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Foreword

It is with great pride that I present Capstone Insights: Technology & Innovation – 2025 (Volume 2), the first volume in a series of scholarly compilations that highlight the diverse talents and academic excellence of our students. This publication is a reflection of Britts Imperial University College's commitment to applied, outcome-oriented education, and its dedication to preparing students for real-world problem-solving and innovation.

The capstone project represents the culmination of months of rigorous study, research, and collaboration. Each contribution in this volume demonstrates not only subject-matter proficiency but also the capacity to think critically, lead ethically, and act strategically in complex business environments.

We commend the students whose works are published herein, and extend our gratitude to our academic supervisors, faculty members, and editorial board for upholding the highest standards in content selection and presentation.

Let this publication serve not only as an archive of academic achievement but as a source of inspiration for current and future learners.

Gladwyn Victor
Campus Head
Britts Imperial University College

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Editorial Preface

Prof. Sujith Jayaprakash

Academic Editor, The BIG Publisher Capstone Series

This volume was compiled through a multi-stage blind-review process guided by faculty specialists in computer science, engineering and innovation management. Criteria included academic rigor, originality, practical relevance and clarity. The selected projects span artificial intelligence, cyber-physical systems, sustainable engineering and emerging communication networks, illustrating both depth of scholarship and breadth of impact. I extend gratitude to contributors and peer reviewers for maintaining the highest scholarly standards.

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Table of Contents

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EMOTION DETECTION FOR AUTISM SUPPORT

By

Adepeju Orefejo

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Abstract

This study evaluates the performance of a deep learning model for facial emotion recognition, targeting assistive technology applications for individuals with Autism Spectrum Disorder (ASD). It implements a single CNN-based architecture trained and tested on the FER2013, CK+, and AffectNet datasets, measuring accuracy, precision, recall, and F1-score. The study emphasises model generalisation by conducting cross-dataset evaluations and analysing system performance using confusion matrices. Findings reveal critical gaps in the model's ability to generalise across diverse populations, highlighting the need for tailored, robust architectures in real-world assistive environments. Based on the results, practical recommendations are made to inform the development of inclusive, adaptable emotion recognition tools for use in therapeutic, educational, and caregiving contexts for individuals on the autism spectrum.

Keywords

Autism, Convolutional Neural Networks, Emotion Recognition, Assistive Technology, Deep Learning

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Table of Contents

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1. Introduction

1.1 Background

The inclusion of emotion detection software has benefitted the health sector in mental health monitoring and adaptive learning. Industry partnerships provide an excellent alternative for individuals with Autism Spectrum Disorder (ASD), who often face challenges interpreting emotional expressions and want to engage in better recognising and interpreting emotions. Software industry participation has grown in recent years due to the need for skilled engineers with practical training and specialised expertise in building AI-powered solutions such as emotion detection systems to support individuals with neurodevelopmental conditions like autism. However, from the healthcare perspective, many activities are needed to incorporate sustainable development goals into mental health initiatives and consolidate the integration of adaptive learning and innovative technologies such as emotion detection systems within hospitals and therapeutic environments. There have been plausible efforts to integrate emotion detection in mental therapeutic programmes. However, very few studies have explored the evaluation of emotion detection systems through real-world applications or user-centred research methods, particularly in the context of supporting individuals with autism where both technical accuracy and social impact are critical. This study evaluates and compares CNN-based emotion detection models using multiple datasets, aiming to identify generalisable solutions that could contribute to the design of assistive technologies for individuals with autism.

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1.2 Objective

The primary aim of this study is to evaluate the performance and generalisation ability of deep learning models for facial emotion recognition, with a focus on their potential application in assistive technologies for individuals with Autism Spectrum Disorder (ASD). Other objectives of this study are:

1. to implement and train a CNN architecture on three widely used emotion recognition datasets, which are FER2013, CK+, and AffectNet.
2. to measure and compare the performance of the trained models using key evaluation metrics including accuracy, precision, recall, and F1 score.
3. to evaluate the generalisation capability of each model by conducting cross-dataset testing, assessing how well models trained on one dataset perform on others.
4. to visualise model performance using confusion matrices and sample predictions to analyse misclassifications and interpret system behaviour.
5. to propose practical recommendations on model selection and adaptation for real-world use in autism-support applications, based on observed model strengths and weaknesses.

1.3 Problem Statement

ASD individuals struggle to identify and understand emotional cues, which hinders them from starting successful social interactions. Emotion recognition systems based on deep learning are a potentially successful solution to this problem, but most are trained and tested against generic data and are not tailored to the unique emotional expressions or interpretive needs of autistic individuals. This recognises a concerning factor: emotion-detection software has low generalisability across diverse populations with variability, such as individuals with neurodevelopmental variability.

Despite the advancement in CNN-based facial emotion recognition, there is limited research focusing on evaluating model generalisation and reliability in actual assistive environments.

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Without that, it is difficult to identify which models would be most suitable for incorporation into tools designed to assist individuals with ASD.

1.3 Scope of the Study

This study focuses on the design and evaluation of deep learning-based facial emotion recognition systems for people with Autism Spectrum Disorder (ASD). Specifically, it focuses on the use of Convolutional Neural Network (CNN) models trained on three widely accepted emotion datasets: FER2013, CK+, and AffectNet. The research is limited to the processing of facial expressions using static and dynamic image data only and does not encompass other modalities such as audio, text, or physiological signals such as EEG or heart rate.

The study evaluates model performance using standard metrics and also analyses models' generalisability through cross-dataset testing. The system is intended to benefit users of all ages, such as children, teenagers, and adults across the ASD spectrum. The attention nevertheless remained within the technical domain, however, with the emphasis being placed on software development and testing of the emotion recognition models, rather than conducting clinical testing or therapy work.

1.4 Significance of the Study

Emotion recognition is an important element in enhancing communication in individuals with ASD, as they find emotional signals hard to comprehend. Through the integration of accurate and generalisable deep learning models in assistive technologies, this study is working towards developing tools that can be used by carers, teachers, and therapists to better interpret and react to the emotional needs of individuals on the autism spectrum. The study also addresses a lack of

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research evaluation of deep learning methods on different datasets for practical use, offering technical insight into the implementation of emotion detection systems in reality.

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2. Literature Review

2.1 Conceptual Review

2.1.1 Facial emotion recognition

Facial emotion recognition (FER) is the process of identifying human emotions through facial expressions that depends on complex algorithms that perform automated categorisation. The technology holds vital importance for people who have Autism Spectrum Disorder (ASD). People who have autism spectrm disorder face difficulties reading emotional signals. The inability to interpret emotions prevents ASD individuals from meaningful social connections, which leads to increased feelings of isolation and frustration (Mayor-Torres et al., 2022). Advanced technology solutions become essential because ASD individuals experience severe consequences from their limited ability to recognise emotions. Enter FER systems. These systems work to fill communication gaps while improving social engagement between people (Li, Mu, Li, & Peng, 2020). Advanced algorithms allow these systems to help ASD patients identify and respond properly to different emotional signs. The technology shows potential to deliver a substantial life quality improvement (Devaram et al., 2022; Pavlova et al., 2020).

The value of FER extends beyond social connection enhancement for ASD individuals. No, it also nurtures emotional intelligence. ASD individuals gain enhanced social abilities and stronger relationships through their improved emotional cue understanding (Li, Mu, Li, & Peng, 2020). The brain mechanisms for processing emotional information remain functional among ASD individuals, but their inability to transform these processes into appropriate social actions creates significant barriers to social interaction (Mayor-Torres et al., 2022). The combination of FER with assistive technologies creates a specific approach to enhance emotional understanding abilities. The technology operates as an additional therapeutic resource to support treatment processes (Pavlova et al., 2020; Zheng et al., 2016).

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However, the FER systems deliver immediate feedback together with assistance to users. The technology assists ASD individuals to recognise emotions which appear in various settings, from educational environments to regular social interactions (Meyer-Lindenberg et al., 2022).

Special-purpose apps create automated emotional signals that display reactions for users. These systems provide training simulations which help users improve their emotional recognition skills (Li, Mu, Li, & Peng, 2020). The combination of technological power enables these systems to advance emotional education and flexible functioning capabilities for ASD patients. The improved emotional understanding allows individuals to participate more deeply within their community. (Pioggia et al., 2005; Devaram et al., 2022).

Social Challenges faced by Individuals with ASD

People who have ASD encounter major difficulties when interacting with others. The social barriers significantly diminish their ability to create relationships and exchange information effectively (Lord et al., 2000). A person's inability to recognise social signals, particularly emotional expressions, creates significant barriers when initiating conversations and maintaining two-way communication (Meyer-Lindenberg et al., 2022). The combination of social withdrawal with misunderstandings creates worse feelings of loneliness and isolation (Pavlova et al., 2020). When emotions are misinterpreted, it results in destructive social behaviours. The negative impact on personal and social development emerges as a result of this condition (Mayor Torres et al., 2022).

The implementation of emotion recognition systems provides practical methods for ASD individuals to understand emotional environments better, thus helping them overcome their social challenges. The systems deliver targeted instruction together with beneficial feedback to users. The systems enable users to develop their facial expression recognition abilities through real-world examples (Li, Mu, Li, & Peng, 2020). Such revolutionary technology enables improved emotional recognition, which leads to increased social skill confidence in users. The ability to develop

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stronger emotional connections with others becomes possible through this development (Devaram et al., 2022). Better emotion recognition skills could lead to reduced anxiety and frustration which typically result from social encounters that fail. The enhanced well-being benefits from this improvement (Lord et al., 2000).

Therapy methods can benefit significantly when emotion recognition technology gets integrated into their practice. The use of robots and apps with FER capabilities can provide therapeutic engagement during sessions. The controlled environment enables ASD individuals to develop their emotion recognition skills (Li, Mu, Li, & Peng, 2020). These tools develop strong emotional intelligence skills which enable people to handle social situations better and create a sense of belonging (Pavlova et al., 2020; & Zheng et al., 2016).

Advancements in Deep Learning and CNNs

The development of Convolutional Neural Networks (CNNs) in deep learning has led to major improvements in emotion detection system efficiency (Devaram et al., 2022). The analysis of visual signals through CNNs is highly effective, while their ability to detect subtle facial expressions makes them ideal for FER applications (Mayor Torres et al., 2022). The complex deep learning models with layered structures understand data representations better than traditional machine learning methods Random Forest and Support Vector Machines, to achieve better accuracy (Pavlova et al., 2020). The deployment of CNNs leads to better emotion detection reliability that stands vital for ASD-targeted applications. The training process of CNNs enables continuous improvement and data set adaptability through its iterative approach. The ability to adapt is essential for studying emotional expressions within diverse populations (Li, Mu, Li, & Peng, 2020). Models need to undergo cross-dataset evaluations to determine their ability to transfer learnt knowledge between different environments. The results of these evaluations demonstrate that CNNs exhibit excellent performance when used with different datasets (Devaram et al., 2022). The innovations are essential for developing resilient emotion recognition systems that specifically

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serve ASD populations so they function optimally in real-world environments (Balasubramani & Surendran, 2024).

Integration of Technology into Therapeutic Settings for Individuals with ASD

Technology integration into therapy environments for individuals with Autism Spectrum Disorder (ASD) creates an innovative platform to boost participation and communication abilities. Deep learning Convolutional Neural Networks (CNNs) allow emotion recognition technologies to provide structures for feeling recognition, which is challenging for ASD individuals to comprehend. The tools integrate into multiple therapeutic approaches which allow therapists to modify their treatment methods through real-time patient emotional feedback. The combination of personalised treatment and enhanced therapy environment results from this approach (Mazefsky et al., 2013).

The devices identify ASD-specific challenges, including social interaction and emotional connection deficits, which allows them to bridge the gap between clinical settings and everyday environments (Knight et al., 2013; Lopresti & Garcia-Zapirain, 2014). Technology and therapy approaches together create an exceptional combination of power. Multiple research findings demonstrate that uniting traditional therapy approaches with AI-based emotion detection systems produces better results for ASD patients in emotional regulation and social interaction (Aresti-Bartolome & Garcia-Zapirain, 2014; Blasco et al., 2009). Various adaptive systems built with machine learning and AI innovations develop flexible and responsive capabilities to match the intricate nature of human emotional communication. Therapists gain understanding of children's emotional states by using wearables and interactive applications, which leads to adjusted treatment approaches (Guerrero-Vásquez et al., 2022). Therapy becomes both more efficient and enjoyable for children when serious games with emotion detection elements are added because they increase patient involvement and improve memory retention.

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The integration of new healthcare innovations requires addressing practical issues that appear when these technologies become part of healthcare systems. Accessibility and ease of use should be guaranteed because they matter most to non-experts, including guardians and teachers (Micai et al., 2023). Successful integration demands that therapists receive training about implementing emotion detection technology into their clinical practice. The protection of data safety and privacy needs immediate ethical consideration because healthcare professionals handle sensitive information from children and people with disabilities. The development of enduring treatment models depends on constant feedback between technology creators and healthcare providers and individuals from the ASD community to improve both treatment effectiveness and ethical compliance.

Lasting integration of technology in therapy settings requires both sustainable financial support and teamwork between different professionals. Public health agencies together with commercial stakeholders and educational institutions should combine resources to develop innovative solutions which remain accessible and practical for implementation (Opar, 2019). The development of regulatory standards must prioritise tech treatment quality assurance because technology in healthcare continues to evolve rapidly (Kohli et al., 2022). Active resolution of these challenges in technological autism intervention environments will enhance individual results and transform societal autism treatment views and government intervention policies.

Sustainability of Technologies within Healthcare Frameworks and Real-World Applicability

Sustainable implementation of emotion recognition technology requires continuous research and development backed by thorough user need comprehension. The implementation of adaptable technology requires more than technological development because it needs active community participation. Such solutions achieve true satisfaction of real-world requirements through this approach. The implementation of emotion detection systems requires close supervision to verify

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their suitability with different therapeutic requirements (Ribas et al., 2022; Aresti-Bartolome & Garcia-Zapirain, 2014). The process of successful implementation leads to changes and modifications which create an ongoing cycle of improvement that involves direct user participation, including both children with ASD and health care experts (Guerrero-Vásquez et al., 2022).

These technologies demonstrate their importance because they generate substantial financial advantages. Emotion detection systems reduce costs in treatment by making strategies more efficient and requiring less direct therapists' involvement. The analysis of machine learning framework performance metrics for precision and recall helps therapeutic facilities optimise their resource distribution plans. These systems achieve integration to serve both urgent patient needs and support healthcare systems in their mission to enhance ASD patients' general well-being and life quality. The path toward successful emotion detection remains an active and exciting process that develops through time.

Advancements in technology need to intertwine with essential frameworks which provide their support. The necessary framework includes absolute training alongside continuous support for medical staff. The effective integration of healthcare depends on investing educational resources that develop healthcare worker skills (Knight et al., 2013). The diverse approach creates conditions where technology functions as an important caregiving component instead of operating independently (Mazefsky et al., 2013). The establishment of sectoral partnerships between developers and doctors, and lawmakers, will create the necessary framework to promote ethical deployment of innovative solutions in actual practice.

The evolving nature of technology demands organisations establish proactive maintenance plans that can scale their operations effectively. These tools will maintain their value and effectiveness through regular updates and forward-looking support structures which adapt to both treatment method advancements and patient requirement changes. The fast-moving progress of AI and

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machine learning technology demands proactive strategies to handle upcoming challenges and opportunities. The successful integration of essential systems into practical applications depends on a complete plan which combines technological development with medical expertise and community participation (Opar, 2019).

Necessity for Adaptive Learning through Emotion Detection Systems

Adaptive learning systems with emotion-detection technology serve as essential tools to enhance social connections among ASD individuals who experience well-documented communication problems in direct interactions. The systems deliver individualised feedback which helps both learners and teachers/therapists to understand emotional states throughout their interactions. These technologies create better support environments for learning through their ability to detect and respond to complex emotional signals. (Guerrero-Vásquez et al., 2022; Ribas et al., 2022). The educational approach must be designed for each student because children with ASD require personalised learning environments. The approach focuses on addressing the individual learning requirements of these students. The technology helps students improve their emotional intelligence and social abilities (Aresti-Bartolome & Garcia-Zapirain, 2014). Research indicates that combining adaptive emotion detection systems with educational programmes generates superior social cognition and emotional intelligence results for ASD children. Blasco et al. (2009) established that interactive technology-based approaches create better student engagement than conventional educational methods. These emotion detection systems demonstrate clear importance for adaptive learning since they lead to sustained improvements in social abilities. The advancements made through these systems will affect social relationships with peers, family members and caretakers, which results in enhanced life quality (Knight et al., 2013).

The implementation of these systems requires thorough evaluation of diverse learning environments. These systems need to adapt to different needs that individuals with ASD present. The evaluation process for engagement strategies should continue permanently because it enables

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inclusion of user-specific preferences and difficulties. Emotion detection systems can maintain their effectiveness in improving social communication skills through developer and educator use of feedback loops and assessment methods (Opar, 2019). When tech developers work alongside educators, they develop a common understanding of effective practices. The result of this process leads to improved effectiveness.

2.2 Theoretical Review

Theory of Convolutional Neural Networks (CNNs)

Image-based CNNs are grid-based deep learning models (Yamashita et al., 2018). CNNs' primary assumption automatically detects hierarchical spatial patterns in incoming data. Complex patterns and details are identified by the network. CNN layers compute numerous steps to create complex feature representations from pixel input. CNNs use convolutional, pooling, and fully linked layers (Wu et al., 2017). CNNs excel at picture classification, segmentation, and emotion detection, making them essential for ASD intervention systems (Ajit, Acharya & Samanta, 2020).

CNNs have fewer parameters and processing requirements than fully connected networks because to local connections and shared weights (Thaler, Albantakis & Schilbach, 2024). High-dimensional data sets advance technologies. Non-linear activation functions like ReLU after convolutional and pooling layers detect complex feature representations. Many tech applications depend on CNNs. These technologies help neurodevelopmental clinicians detect emotions more precisely and effectively (Huang, Liu, Jin, & Zhang, 2023; Anthony et al., 2013).

CNNs operate using convolutional layers, activation functions, pooling layers, and fully connected layers (McNair, 2018). CNNs process three-dimensional tensors for images with height, width, and depth channels first. The convolutional layer uses spatially scanning learnable filters to convolutionize input data. Filters build feature maps from edges and textures

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(Huang et al., 2023). Convolutional procedures target specific areas using picture spatial patterns. Effective feature extraction requires focus. Convolution is followed by ReLU activation (Ajit et al., 2020). The non-linear transformation zeroes negative values to help the network detect complex data links. The model is nonlinear. CNNs become linear models without activation functions, making them less sensitive to complex data patterns (Thaler et al., 2020).

Activation functions and convolutional layers help the model grasp visuals. After convolution and activation, pooling layers reduce feature map dimension to maintain crucial information (Wu et al., 2017). Max pooling decreases processing complexity and provides translation invariance to input data by picking maximum values. Pooling layers blend convolutional layer outputs for model efficiency and generalisation. This stage consolidates features to reduce deep learning model overfitting.

In CNNs' final stage, fully connected layers improve reasoning and decision-making (McNair, 2018). Flattened output becomes more detailed. Dense layer mechanisms link all neurones from previous to current layers. With prior processing data, the output layer calculates class probability. During training, backpropagation modifies all CNN weights using prediction-actual result disparities (Yamashita et al., 2018 CNNs use sophisticated frameworks to learn from massive datasets. Their design enhances emotion recognition pattern detection. Convolutional neural networks understand face dynamics complexity well, making them excellent for detecting nuanced facial emotions (Huang et al., 2023). Because emotion recognition relies on face muscle movements and feature configurations, CNNs' layered learning methods are useful. CNNs make social communication easier for ASD patients, who have trouble reading emotions (Thaler et al., 2020).

CNN-enabled real-time feedback is essential for ASD treatment (Ajit et al., 2020). CNNs can read facial expressions in seconds to reveal emotions. CNNs' emotional feedback helps doctors and caretakers speed up therapy (Wu et al., 2017). CNN technology in social interaction systems

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would dramatically improve ASD patients' social skills. CNNs are versatile and resilient enough to handle many facial expressions across cultures and contexts (Yamashita et al., 2018). Emotion recognition systems must adapt to neurodevelopmental differences. FER2013,

CK+, and AffectNet datasets teach CNN models to adapt to individual facial expressions

(McNair, 2018). Complex systems provide precise forecasts and better inclusive ASD support.

CNNs are essential to facial expression dynamics research as knowledge grows (Thaler et al., 2020).

CNN will improve network design and develop multi-sensory systems for facial recognition, audio, and biology (Huang et al., 2023). If this method is understood, improved assistive technology can help ASD people socialise. CNNs can enhance autistic therapeutics and emotional recognition.

Neuroscience of Emotional Recognition

Mental systems that identify emotions through facial expression interpretation to generate appropriate reactions are studied scientifically. Research reveals that the amygdala, fusiform gyrus, and prefrontal cortex work together to perceive facial expressions (Kang et al., 2018; Black, 2017). The three brain areas are necessary for emotion recognition and reaction. Autism Spectrum Disorder patients struggle with emotional understanding, according to Trevisan & Birmingham (2016).

ASD patients had reduced amygdala activity when seeing emotional facial expressions, according to fMRI. Müller et al. (2018) found that ASD patients had trouble detecting emotions. To advance, scientists must understand how the brain processes emotions. Brain processing information leads to technical advances that enable developers to design emotional processing tools.

Faust et al. (2018)'s brain structure study informs deep learning models, notably CNNs, about mental and physical emotional processing. Emotional recognition algorithms mimic brain

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processes. The strategy improves system precision and dependability in treatment settings for ASD individuals (Grossi, Olivieri & Buscema, 2017).

Ekman and Friesen (1978) created the Face Action Coding System (FACS) to classify face expressions using facial muscle movements. AI systems employ structured systems to identify emotions because they show emotional-state correlations with facial expressions (Darwin, 1872; Trevisan et al., 2016).

The dimensional framework of feelings allows researchers to represent emotions using two axes: pleasantness and intensity. Kang et al. (2018). Implementing this approach improves emotional detection system design. Developers can construct algorithms to measure emotional strength and direction without established categories using the framework. Muller et al. (2018). Combining deep learning with this approach makes such systems more versatile and better at detecting different emotions. It mimics human emotional processing (Li et al., 2020).

Researchers must use neurological studies to construct emotion-detecting equipment. Knowing brain circuits that handle face signals improves algorithm accuracy (Black et al., 2017). Brain processing technologies help emotion recognition systems improve user interfaces and system responsiveness. This improves ASD patients' assistive technology interactions. Faust et al.

(2018).

A deep understanding of how the brain absorbs emotional information improves understanding. The new insight improves emotion detection system design, especially for ASD patients. According to research, ASD patients process emotions through unusual brain pathways. These people have different brain patterns when they deal with social stimuli (Kang et al., 2018; Grossi, 2017). The discovery suggests that emotion identification systems need modification to support their processing methods.

ISBN: 978-9948-XX-XX-1 **Publisher: The Big Publisher**

Instant feedback strategies help developers understand ASD people's emotional responses and create platforms that recognise emotions and help users interpret them (Trevisan et al., 2016). Brain science could change adaptive learning framework emotional reactions. As users understand more, the system should incorporate more sophisticated emotional cues (Müller et al.,

2018). Neuroscience-based emotional discernment systems would tailor ASD experiences. User-centred design lets assistive technology developers tailor solutions to users' emotional processing patterns. A supportive atmosphere created by developers can boost social participation (Li et al., 2020; Faust, 2018). The customisation strategy uses visual and aural inputs to suit user needs through their preferred sensory channels (Black et al., 2017).

Neuroscience experts, tech developers, and medical professionals collaborate to form interdisciplinary partnerships to improve emotional recognition systems with current research. Researchers stay current on how the brain processes emotions, resulting in continual evolution (Kang et al., 2018). The technique combines various domains of expertise to offer effective solutions for ASD patients and improve their social skills.

Research Gap

Prior studies have worked on facial emotion detection (FED) through deep learning methods very successfully. The developed frameworks were shown to be promising in terms of improving the emotional detection capabilities and were applied to develop support systems for ASD patients. According to their research, Liu et al. (2017) have shown that modular CNN architectures increase facial expression classification accuracy, and Huang et al. (2019) have shown that training with multiple datasets improves model strength and reliability. However, these technological advancements have been recognised but do not solve a fundamental problem that arises when the emotional details and environmental variations are present during real-life situations. Inadequate analysis of model effectiveness leads to the lack of evidence about model performance across

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different populations and situations as well as among ASD individuals. Both AffectNet and FER2013 tools, widely used for training emotion recognition systems, do not have a proper evaluation of their effectiveness in real-world applications. In their work, Zhang et al. (2020) point out that existing research is more technically precise than practical deployment. Because these systems will be used in different emotional expression environments during everyday interactions, the systems will experience substantial performance degradation. The need for immediate attention is the current research because it needs to evaluate model effectiveness and their ability to work in realistic social environments. Such measures ensure that they can support ASD individuals in practical situations. These problems will be resolved to establish conditions to develop more accurate and user-friendly systems. People with ASD will be better able to understand social situations by being able to recognise emotions.

ISBN: 978-9948-XX-XX-1 **Publisher: The Big Publisher**

3. Methodology

This chapter delineates the methodological framework employed for the development and evaluation of convolutional neural network (CNN) models designed for facial emotion recognition in support of individuals with Autism Spectrum Disorder (ASD). The methodology comprises comprehensive guidelines encompassing dataset selection, preprocessing pipelines, model architecture design, training strategies, and evaluation procedures. To ensure a thorough assessment of model performance across both controlled and in-the-wild settings, three benchmark datasets, FER2013, CK+, and AffectNet—are utilised. The approach is structured to support reproducibility, generalisation analysis, and practical applicability, particularly within assistive technology contexts. Each methodological decision aligns with the overarching research objective of developing inclusive, interpretable, and robust emotion recognition systems tailored to the needs of neurodiverse individuals. A visual representation of the complete methodological workflow is provided in **Appendix A** and the full implementation codebase, including model training scripts, preprocessing pipelines, and evaluation routines, is available on GitHub for reproducibility and further experimentation (**see Appendix B**).

3.1 Datasets Used

The study used three key datasets for recognising facial emotions; each had its own important traits and features linked to the study's goals.

ISBN: 978-9948-XX-XX-1 **Publisher: The Big Publisher**

Emotion Distribution Across Datasets

	anger	contempt	disgust	fear	happiness	neutral	sadness	surprise	Total
FER2013	4,953	0	547	5,121	8,989	6,198	6,077	4,002	35,887
CK+	135	54	177	75	207	0	84	249	981
AffectNet	3,608	3,244	3,472	3,043	4,336	2,861	2,995	4,616	28,175

Figure 3.1

Emotion Distribution in AffectNet, CK+, and FER2013 Datasets (Absolute and Percentage Counts)
Note: Author's computation based on publicly available data from FER2013 (Kaggle), CK+ (Papers With Code), and AffectNet (Kaggle).

1) FER2013 Dataset:

The FER2013 dataset comprises 35,887 48x48 pixel greyscale facial images, categorised into seven emotions: anger, disgust, fear, happiness, sorrow, surprise, and neutral (Figure 3.1). Its pre-divided training and testing sets facilitate the development and evaluation of deep learning models for facial emotion recognition. The dataset's diverse emotional expressions and substantial number of images make it suitable for training and testing Convolutional Neural Network (CNN) architectures in this domain.

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2) CK+ (Extended Cohn-Kanade) Dataset:

One of the most popular tools for identifying facial expressions is the CK+ dataset, which contains 981 images. This dataset is of great importance since it covers seven emotional expressions: anger, happiness, sadness, surprise, fear, disgust and contempt. CK+ is significant because it gives contempt as an emotion category; this gives researchers more space to work with in their models (Figure 3.1).

The enhanced picture quality within the CK+ collection content is one of its main attributes. Every video shows a variety of emotional expressions, which gives an ability to analyse deeply how facial expressions vary face over time. This temporal aspect is fundamental in capturing the subtleties of dynamic facial expressions better than static photographs could ever show. Since it uses professional actors and controlled environments, the dataset becomes more reliable because these factors will make sure that emotional displays are real and well-defined, thus minimising noise coming from unregulated settings.

The controlled CK+ data collection approach further strengthens the dataset since it minimises variations in lighting, background, and other external factors that could otherwise affect picture quality. It gives researchers assurance that the data is a true real-emotion expression; hence, deep learning models can be trained with accurate reflections of human feelings. This study includes the CK+ dataset as part of its evaluation framework, enabling a comprehensive assessment of a CNN-based architecture for emotion recognition. The findings contribute to the development of technologies designed to assist individuals with Autism Spectrum Disorder (ASD) in recognising emotions more effectively.

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3) AffectNet Dataset:

AffectNet has a generally wider dataset with over 500,000 images; however, we will be using a subset of this large dataset containing 28,175 facial images organised into eight emotions: anger, disgust, fear, happiness, sadness, surprise, neutral and contempt, and this is presented in figure 3.1 above with the absolute counts for each emotion class. It further includes continuous emotion annotations for valence and arousal dimensions which provide a broader context for understanding the expressions of emotion. This multi-dimensional aspect gives researchers a more detailed dataset for training and testing their models, providing more insight into affective computing. Therefore the AffectNet dataset is important to this work, as its findings will contribute to face emotion recognition studies crucial in developing assistive technologies for users with Autism Spectrum Disorder.

3.2 Data Preprocessing

The FER2013, CK+, and AffectNet datasets undergo a tailored yet consistent preprocessing pipeline to ensure uniform input dimensions, improve model performance, and enable fair cross-dataset comparison. While the overall steps align, each dataset presents unique characteristics in terms of preprocessing complexity, class distribution, and data organisation. **FER2013 Dataset Preprocessing**

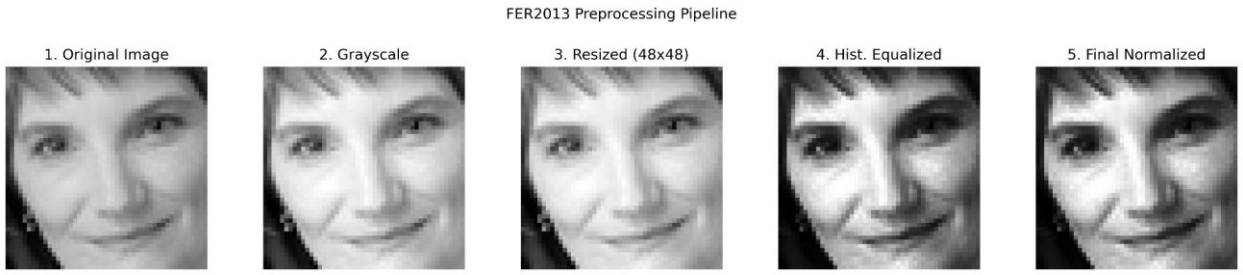

Figure 3.2a

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FER2013 Dataset Preprocessing Pipeline

Source: Author's implementation using OpenCV and a custom preprocessing pipeline.

The FER2013 dataset employed the most sophisticated preprocessing pipeline, implemented via the preprocess_face_for_emotion() function. The steps include greyscale conversion of RGB images to reduce input dimensionality, resizing all images to 48×48 pixels, and applying histogram equalisation to enhance contrast and normalise lighting variations. Pixel normalisation scaled all values to the [0,1] range, improving gradient behaviour during training. The final preprocessed image shape is (N, 48, 48, 1). FER2013 contains seven emotion classes (anger, disgust, fear, happiness, neutral, sadness, and surprise) with 28,709 training and 7,178 test images, making it the largest dataset in this study. However, it is also highly imbalanced, with happiness being the most frequent class (8,989 samples).

CK+ Dataset Preprocessing

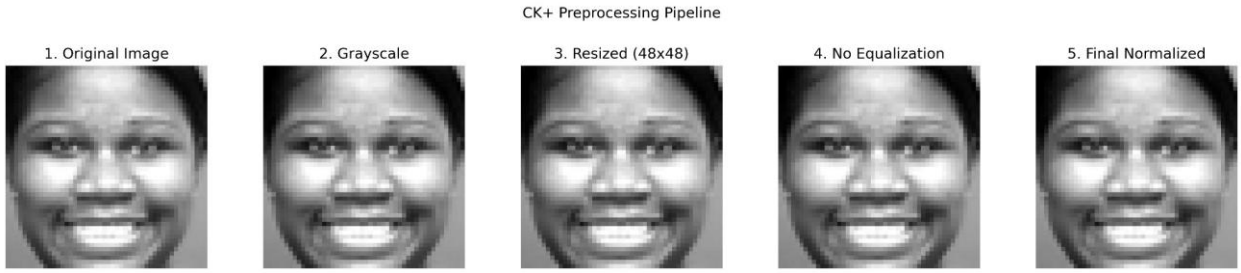

Figure 3.2b

CK+ Dataset Preprocessing Pipeline

Note: Author's implementation using OpenCV and a custom preprocessing pipeline.

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In contrast, the CK+ dataset required a simpler preprocessing pipeline due to its smaller size and controlled image quality. Images were directly converted to greyscale, resized to 48×48 pixels, and normalised to the [0,1] pixel range. Unlike FER2013, histogram equalisation was not applied, given the dataset's already consistent lighting conditions, as shown in figure 3.3. A custom 80-20 train-test split was implemented using a random permutation algorithm, as CK+ does not come pre-divided. CK+ includes seven emotion classes, notably replacing neutral with contempt, and consists of only 981 total images. Despite its size, the dataset maintains relative balance across classes, with surprise having the highest representation (249 samples).

AffectNet Dataset Preprocessing

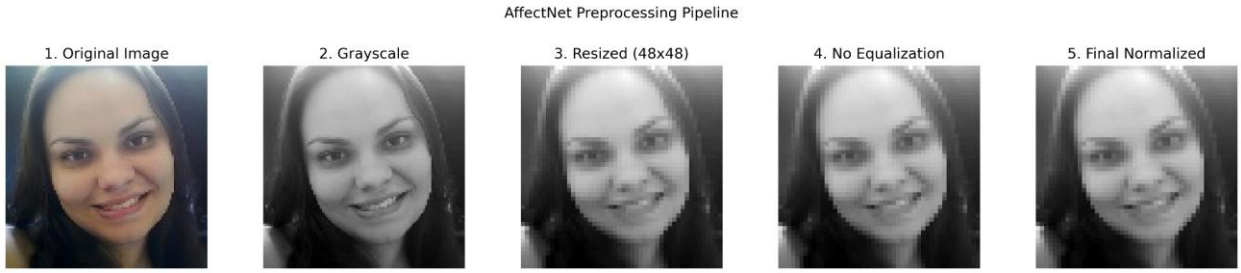

Figure 3.7:

AffectNet Dataset Preprocessing Pipeline

Note: Implementation using an OpenCV-based preprocessing pipeline.

AffectNet followed a similar preprocessing pipeline to FER2013, including greyscale conversion, resizing to 48×48 pixels, and normalisation to the [0,1] range. Histogram equalisation was not applied. AffectNet includes all eight emotion classes, encompassing both neutral and contempt, and is the most emotionally balanced dataset among the three. A curated subset of approximately 28,175 images was used for this project, with surprise again having the highest class frequency

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(4,616 samples). Unlike CK+, AffectNet is already organised into predefined training and test splits.

3.3 Model Architecture

A primary CNN (Convolutional Neural Network) architecture was designed and implemented, based on the model detailed by Skillcate (2023). The implemented CNN architecture is designed for facial emotion recognition using 48x48 pixel greyscale images. The network consists of four convolutional blocks with progressively increasing filter sizes (32, 64, 128, and 256), enhancing the model's ability to extract hierarchical features from facial images. Each convolutional layer uses 3x3 kernels with 'same' padding and a stride of 1, maintaining spatial dimensions while extracting features. L2 regularisation (0.001) is applied to all convolutional layers to prevent overfitting.

After each convolutional operation, dropout layers with a rate of 0.1 are employed for regularisation, followed by ReLU activation functions to introduce non-linearity. Max pooling layers with 2x2 windows are used after each convolutional block for spatial dimension reduction, effectively halving the feature map dimensions while retaining the most important features.

The feature extraction layers are followed by a flattening operation and dense layers for classification. The architecture includes a dense layer with 128 neurones, followed by a dropout layer with a rate of 0.2. The final layer is a dense layer with softmax activation, where the number of neurones matches the dataset-specific number of emotion classes. The model is compiled using the Adam optimiser and categorical cross-entropy loss function, suitable for multi-class classification tasks.

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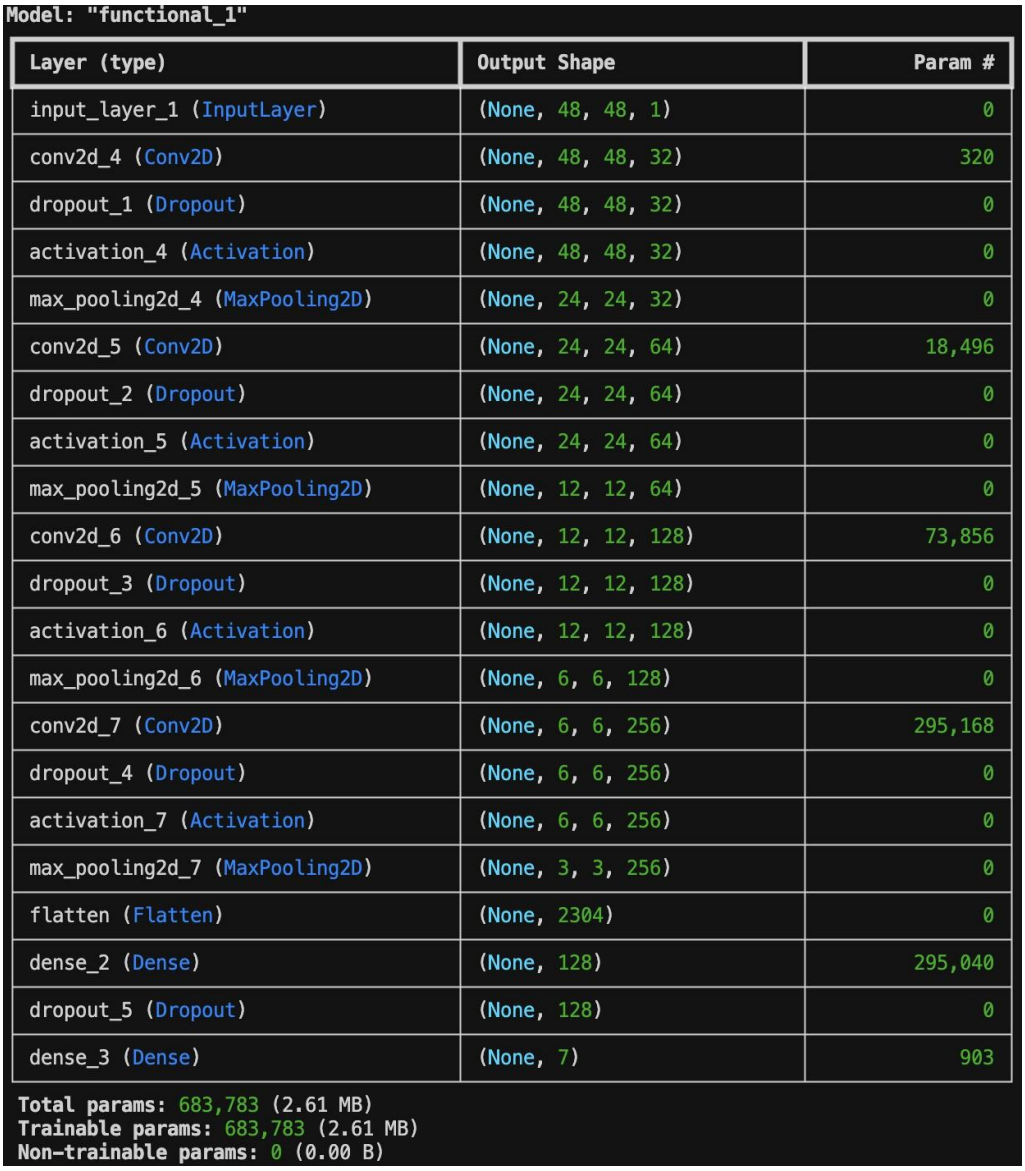

Model: "functional_1"

Layer (type)	Output Shape	Param #
input_layer_1 (InputLayer)	(None, 48, 48, 1)	0
conv2d_4 (Conv2D)	(None, 48, 48, 32)	320
dropout_1 (Dropout)	(None, 48, 48, 32)	0
activation_4 (Activation)	(None, 48, 48, 32)	0
max_pooling2d_4 (MaxPooling2D)	(None, 24, 24, 32)	0
conv2d_5 (Conv2D)	(None, 24, 24, 64)	18,496
dropout_2 (Dropout)	(None, 24, 24, 64)	0
activation_5 (Activation)	(None, 24, 24, 64)	0
max_pooling2d_5 (MaxPooling2D)	(None, 12, 12, 64)	0
conv2d_6 (Conv2D)	(None, 12, 12, 128)	73,856
dropout_3 (Dropout)	(None, 12, 12, 128)	0
activation_6 (Activation)	(None, 12, 12, 128)	0
max_pooling2d_6 (MaxPooling2D)	(None, 6, 6, 128)	0
conv2d_7 (Conv2D)	(None, 6, 6, 256)	295,168
dropout_4 (Dropout)	(None, 6, 6, 256)	0
activation_7 (Activation)	(None, 6, 6, 256)	0
max_pooling2d_7 (MaxPooling2D)	(None, 3, 3, 256)	0
flatten (Flatten)	(None, 2304)	0
dense_2 (Dense)	(None, 128)	295,040
dropout_5 (Dropout)	(None, 128)	0
dense_3 (Dense)	(None, 7)	903

Total params: 683,783 (2.61 MB)
Trainable params: 683,783 (2.61 MB)
Non-trainable params: 0 (0.00 B)

Figure 3.3a:

CNN Hidden Layer Structure

Note: Sourced from Skillcate (2023).

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1. Regularisation Strategy:

- L2 Regularisation: Applied to all convolutional layers with a rate of 0.001 to prevent overfitting.
- Dropout:
- 0.1 in convolutional layers.
- 0.2 in dense layers

These values were chosen to provide light regularisation while maintaining model capacity.

2. Hidden Layer Configuration:

The network comprises multiple hidden layers organised in two types:

1. Convolutional Hidden Layers:

- First block: Conv2D with 32 filters (3x3, same padding)
- Second block: Conv2D with 64 filters (3x3, same padding)
- Third block: Conv2D with 128 filters (3x3, same padding)
- Fourth block: Conv2D with 256 filters (3x3, same padding)

Each convolutional block includes dropout (0.1) and max pooling (2x2) for feature extraction and dimensionality reduction.

2. Fully Connected Hidden Layer:

- A dense hidden layer with 128 neurons

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- ReLU activation for non-linear feature transformation
- Dropout (0.2) for regularization
- Final output layer with softmax activation for emotion classification

This architecture, with its progressively increasing filter sizes, enables hierarchical feature extraction while maintaining computational efficiency through careful regularisation and dimensionality reduction.

Architecture Improvements

The improvements to the CNN architecture, including batch normalisation, increased dropout, and global average pooling, are designed to enhance model performance and generalisation as seen in Fig. 3.3b below. Batch normalisation helps stabilise and accelerate training by normalising the inputs of each layer. Increased dropout acts as a regulariser, reducing overfitting by randomly dropping units during training.

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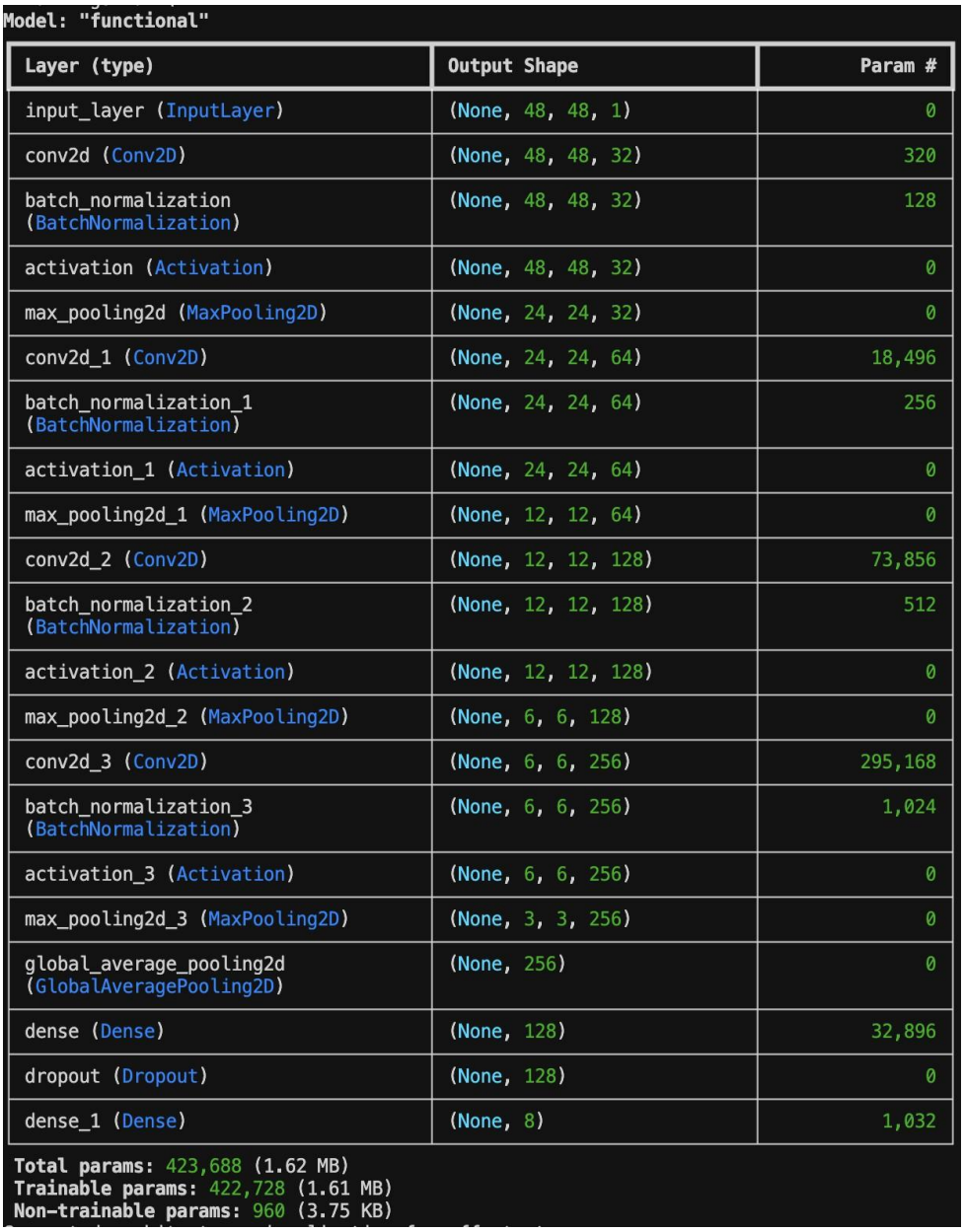

Model: "functional"

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 48, 48, 1)	0
conv2d (Conv2D)	(None, 48, 48, 32)	320
batch_normalization (BatchNormalization)	(None, 48, 48, 32)	128
activation (Activation)	(None, 48, 48, 32)	0
max_pooling2d (MaxPooling2D)	(None, 24, 24, 32)	0
conv2d_1 (Conv2D)	(None, 24, 24, 64)	18,496
batch_normalization_1 (BatchNormalization)	(None, 24, 24, 64)	256
activation_1 (Activation)	(None, 24, 24, 64)	0
max_pooling2d_1 (MaxPooling2D)	(None, 12, 12, 64)	0
conv2d_2 (Conv2D)	(None, 12, 12, 128)	73,856
batch_normalization_2 (BatchNormalization)	(None, 12, 12, 128)	512
activation_2 (Activation)	(None, 12, 12, 128)	0
max_pooling2d_2 (MaxPooling2D)	(None, 6, 6, 128)	0
conv2d_3 (Conv2D)	(None, 6, 6, 256)	295,168
batch_normalization_3 (BatchNormalization)	(None, 6, 6, 256)	1,024
activation_3 (Activation)	(None, 6, 6, 256)	0
max_pooling2d_3 (MaxPooling2D)	(None, 3, 3, 256)	0
global_average_pooling2d (GlobalAveragePooling2D)	(None, 256)	0
dense (Dense)	(None, 128)	32,896
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 8)	1,032

Total params: 423,688 (1.62 MB)
Trainable params: 422,728 (1.61 MB)
Non-trainable params: 960 (3.75 KB)

Figure 3.3b:

CNN architectural improvements to support FER2013 and AffectNet (adapted from Skillcate, 2023).

Note: Author's own generation from Keras model.summary().

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Global Average Pooling reduces the number of parameters and helps prevent overfitting by replacing fully connected layers with a global pooling layer (Fig. 3.3b). These enhancements collectively aim to create a more robust model capable of better handling the complexities of datasets like FER2013 and AffectNet. The CK+ model will not be trained with these improvements.

3.3.2 Training Configuration

Loss Function

The model uses the categorical cross-entropy loss function, which is optimal for multi-class classification and pairs naturally with the softmax output layer. It enables smooth gradient propagation and is a standard choice in emotion classification tasks.

3.4 Training Strategy

1) Individual Dataset Training:

This study utilised three models trained on different datasets for facial emotion detection. The FER2013 model was trained using the FER2013 dataset, which contains greyscale images of faces across seven emotional categories, aiming to recognise emotions such as anger, sadness, and happiness with high accuracy. The CK+ model was trained on the Extended Cohn-Kanade

(CK+) dataset, featuring professional actors expressing emotions in a controlled environment. This dataset provides an opportunity to learn the intricate dynamics of emotion progression, a feature less evident in datasets like FER2013. The AffectNet model was built using the AffectNet dataset, which, like FER2013, encompasses a wide range of emotions. This variety allows the model to leverage the available data for improved learning and generalisation. However, the AffectNet model faced challenges due to increased prediction complexity from intertwined emotional states

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and potential class imbalances. To enhance generalisation, a fused model was designed to be trained simultaneously on all three datasets, utilising the feature diversity and emotional expressions from each.

2) Training Configuration:

Adam, a popular optimiser, was employed to train the facial emotion recognition models, enhancing learning and performance across three widely used datasets: FER2013, CK+, and AffectNet. The initial learning rate was set to 1e-4 to balance speed and stability. For multi-class tasks like emotion recognition, categorical cross-entropy was chosen as the loss function, ensuring high accuracy by minimising classification errors. To prevent underfitting due to insufficient data, the batch size was set to 64 for general training and 32 for the smaller CK+ dataset. Training was capped at a maximum of 50 epochs, with early stopping employed to prevent overfitting while maintaining generalisation. A learning rate reduction on plateau was implemented to decrease the learning rate when model performance plateaued, allowing for more effective convergence by taking smaller steps. Model checkpointing was used to save the best weights based on validation performance, ensuring the best version could be deployed without losing critical training progress. This carefully designed training environment maximises the CNN architectures' ability to detect facial emotions across different datasets.

3) Training Monitoring:

To build a highly efficient model for recognising facial expressions, it is imperative to carry out training vigilance that ensures the model learns appropriately and generalises well beyond its training datasets. Key metrics such as accuracy and loss are tracked during training to provide insights into the model's learning process. Accuracy measures the correctly classified emotions over total predictions, while loss quantifies the deviation of predictions from the true labels. Monitoring these metrics helps identify convergence trends and informs necessary modifications

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to the training process. The model's ability to generalise from unseen data is assessed through performance validation, where the model is evaluated on a separate validation set after each epoch. Comparing validation metrics with training metrics helps determine the optimal stopping point to retain the model's generalisation ability. Visualising the training history allows developers to interpret training dynamics and identify issues like plateaus in accuracy or spikes in loss. This visualisation also aids in presenting results to stakeholders, providing clear insights into the training regimen's effectiveness. Real-time performance evaluation enables developers to observe the model's learning in action, react to anomalies, and gain a comprehensive understanding of the model’s performance.

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4. Results and Findings

4.1 Model Performance

The training plots and evaluation metrics revealed several key findings:

1) FER2013 Model:

The FER2013 CNN model was evaluated on its ability to recognise facial emotions from noisy, real-world images characterised by imbalanced class distribution. The performance, while reflecting the inherent difficulties of this dataset (such as spontaneous expressions, variable image quality, and overlapping emotion features), provides key insights into the model's learning capabilities. The training history reveals several key insights:

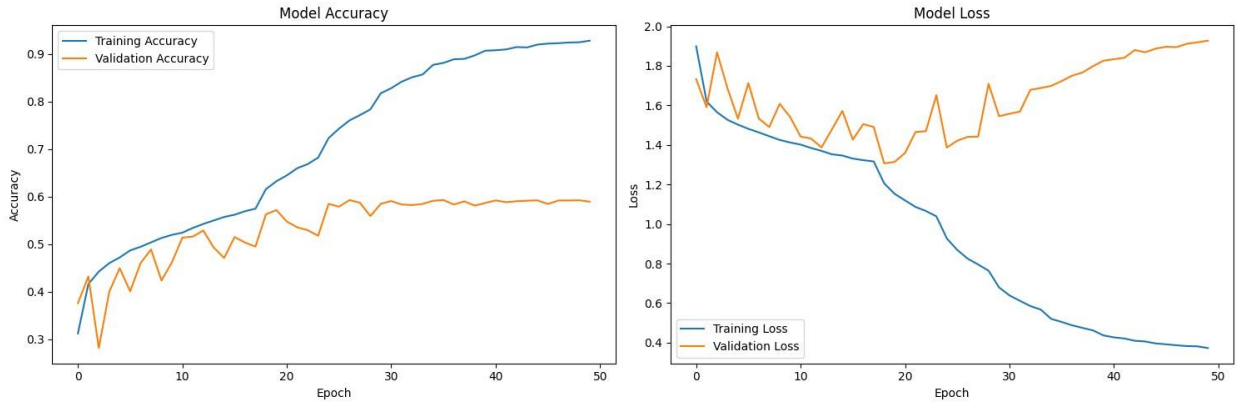

Figure 4.1.1a:

Training Accuracy and Loss for FER2013 CNN Model

Note: Generated from the author's TensorFlow implementation.

Model Training Dynamics and Generalisation:

Training History (Fig. 4.1.1a): The learning curves, visualised in fig. 4.1.1a, substantiate the observation that the training accuracy gradually improved, stabilising around 68%. The validation

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accuracy, also tracked in this file, reached a plateau at approximately 57–58%. This consistent gap between training and validation accuracy suggests a degree of overfitting, where the model learnt the training data proficiently but showed limitations in generalising to unseen validation data.

Learning Rate Adjustments (Fig. 4.1.1b and Fig. 4.1.1a) : The initial epochs, as depicted in Fig. 4.1.1a, likely demonstrated rapid improvements in both loss and accuracy. The subsequent plateau in validation metrics after approximately epoch 20 would have triggered the ReduceLROnPlateau callback (configured with factor = 0.5, patience = 5). Fig. 4.1.1b provides a visual record of these learning rate reductions, illustrating the attempts to navigate local minima and enhance generalisation, though the gap was not entirely closed.

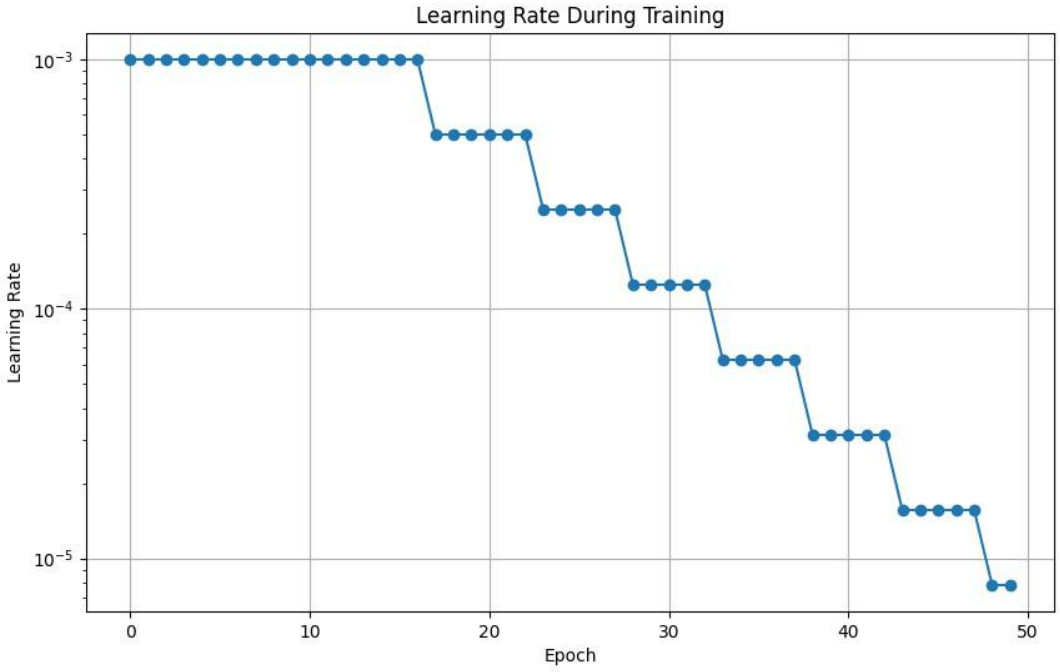

Figure 4.1.1b:

ReduceLROnPlateau callback in action

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Note: Sourced by the author's own generation from model training.

Learning Dynamics (as evidenced in Fig. 4.1.1a and Fig. 4.1.1b):

Fig. 4.1.1a visually confirms that early epochs of the FER2013 model training showed rapid improvements in both loss and accuracy.

However, this same file indicates that validation metrics plateaued after approximately epoch 20. This plateau phase prompted learning rate reductions, managed by the ReduceLROnPlateau callback (configured with factor = 0.5, patience = 5). The sequence of these learning rate changes is explicitly visualised in Fig. 4.1.1b.

While these learning rate adjustments likely helped the model navigate the loss landscape and potentially escape local minima, Fig. 4.1.1a suggests they were not sufficient to fully close the generalisation gap observed between training and validation performance.

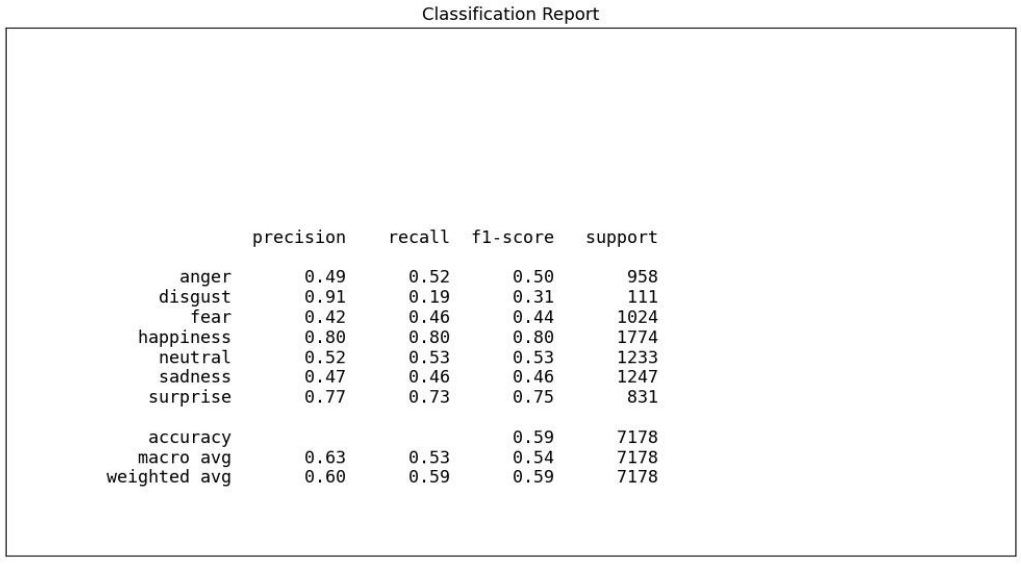

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Table 4.1.1

Classification Report for FER2013 CNN Model

Note: This figure was generated from the author's TensorFlow implementation.

Class Imbalance Impact (as evidenced in Table 4.1.1 and Fig. 4.1.1c):

The performance disparities due to class imbalance are quantifiable in Table 4.1.1 (which details precision, recall, and F1-score for each emotion) and Fig. 4.1.1c below.

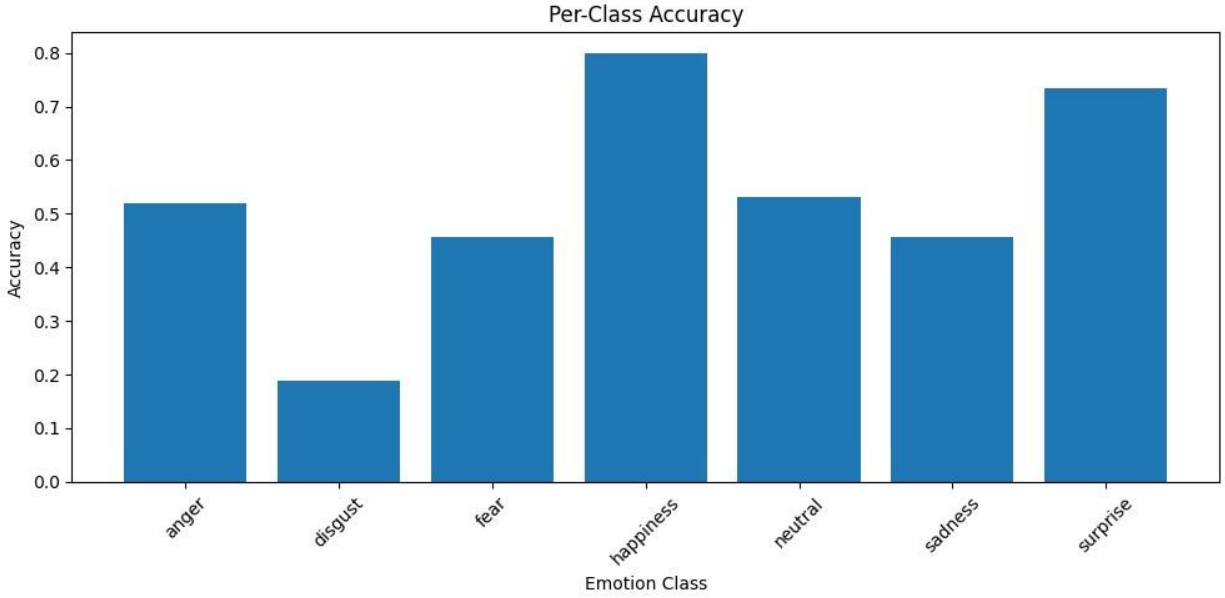

Figure 4.1.1c

Per-Class Accuracy of FER2013 CNN Model

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Note: This figure was generated from the author's TensorFlow implementation.

These reports would show that rare classes, such as 'disgust', were indeed harder for the model to learn, resulting in lower performance metrics for this emotion. If class weights were applied (e.g., a weight around 9.4066 for 'disgust', as you previously noted), these reports would reflect the model's learning attempt under this weighting scheme, though challenges in recognising this minority class likely persisted.

Conversely, common emotions such as 'happiness' and 'neutral' (which might have received weights like 0.5684 and 0.8260, respectively) would be shown in Table 4.1.1 and Fig. 4.1.1c to have comparatively better and more stable recognition rates.

The clear differences in performance across classes, as detailed in these files, highlight the significant impact of class imbalance and underscore the potential benefits of employing advanced techniques like focal loss or oversampling for minority classes in future model iterations.

2) CK+ Model:

Only the simple CNN architecture was used to train the CK+ dataset because of the same size of the dataset. The CK+ CNN model achieves 99% validation accuracy in facial emotion recognition using controlled, posed data from professional actors, demonstrating strong learning despite a small dataset and class imbalance. This near-perfect performance reflects the ideal laboratory conditions of CK+, but may not generalise to more challenging, real-world datasets such as AffectNet and FER2013. The rapid and consistent accuracy improvement highlights the simplicity of the task under such controlled settings, rather than real-world robustness.

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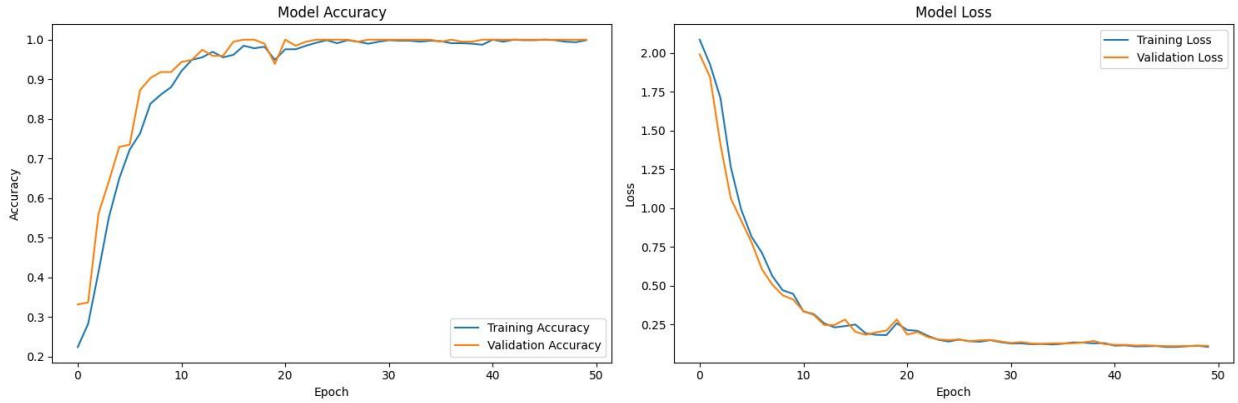

Figure 4.1.2a

Training Accuracy and Loss for CK+ CNN Model

Note: This figure was generated from the author's TensorFlow implementation.

The closely aligned training and validation curves throughout all epochs indicate minimal overfitting. However, while the model performs exceptionally well in this constrained context, the same architecture struggles when applied to real-world data like AffectNet, where validation accuracy drops to 25–30%, highlighting the gap between ideal and practical performance in emotion recognition.

Learning Dynamics for CK+ Model (Figures 4.1.2a and 4.1.2b)

The training process for the CK+ model exhibited distinct and well-behaved learning dynamics, as illustrated by its training and validation curves (Figure 4.1.2a).

In the early stages of training, the model demonstrated rapid improvement in both training and validation accuracy, accompanied by a steep decline in loss. This reflects efficient initial learning from the relatively clean and structured CK+ dataset. Around epoch 15, the validation metrics

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began to plateau, indicating that the model had begun to converge toward its optimal performance or was reaching the capacity limit of the architecture on this dataset.

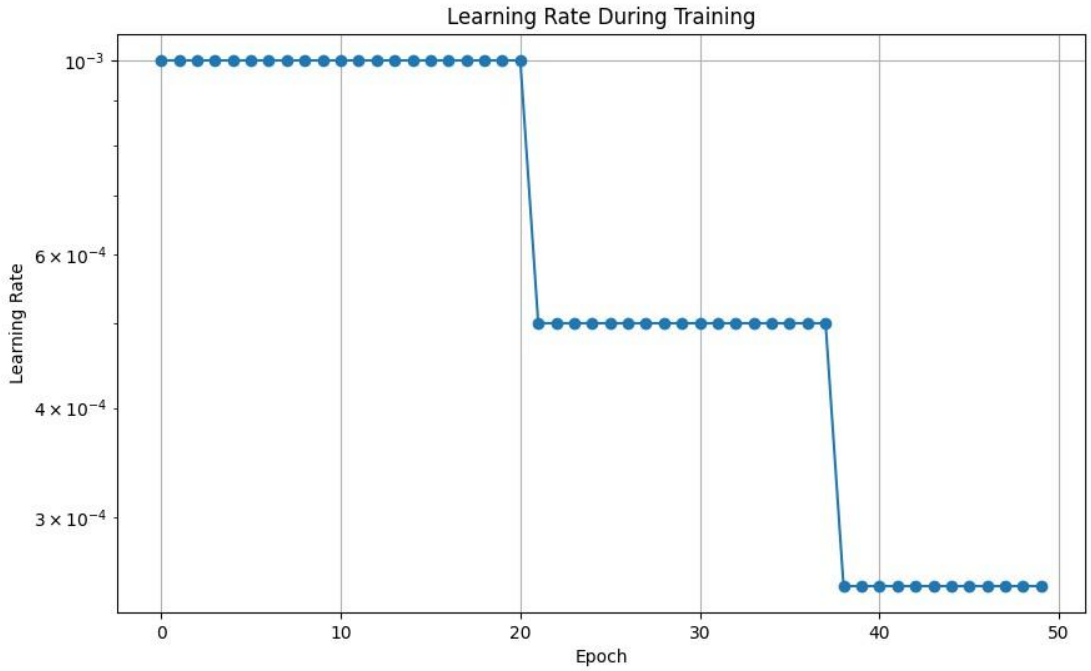

Figure 4.1.2b

Learning Rate Schedule During CK+ Training

Note: Generated from the author's TensorFlow implementation.

To counteract stagnation in validation performance, the ReduceLROnPlateau callback was activated. Figure 4.1.2b (learning rate schedule) confirms this behaviour, showing discrete reductions in the learning rate by a factor of 0.5 after successive periods of validation loss

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stagnation. These reductions enabled the optimiser to fine-tune the model weights more delicately and continue refining the solution without overshooting.

Learning rate adjustments in the autism support model development led to continued decreases in validation loss and slight accuracy improvements on the CK+ dataset. Unlike the FER2013 dataset, CK+ showed minimal overfitting due to its high-quality, controlled images, resulting in close tracking of training and validation curves and easier generalisation.

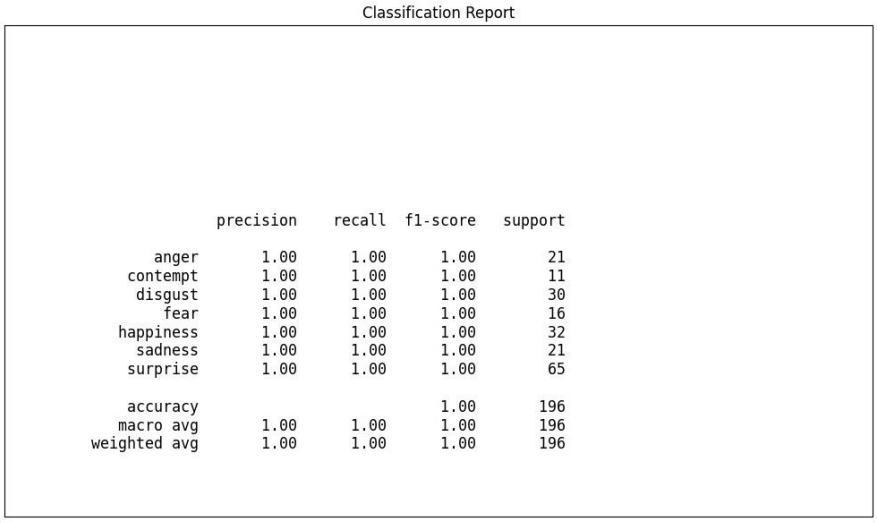

Table 4.1.2

Classification report for the CNN model trained on the CK+ dataset, showing precision, recall, and F1-score for each emotion class.

Note: Sourced from the author's training output.

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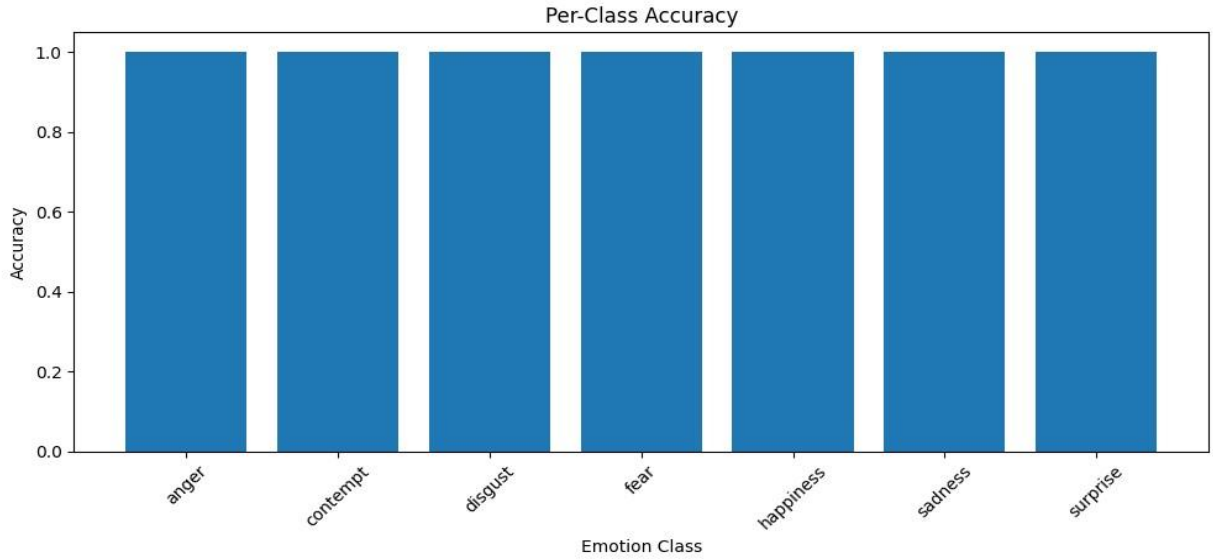

Figure 4.1.2b

Per-Class Accuracy of the Emotion Recognition Model.

Note: This figure was generated from the author's TensorFlow implementation.

The model reached a final validation accuracy of 100% and a macro F1 score of 1.00, with all classes achieving perfect precision and recall (Table 4.1.1 & Fig. 4.1.3).

3) AffectNet Model:

The AffectNet CNN model was evaluated on its ability to recognise facial emotions from a large-scale dataset known for its in-the-wild conditions and comprehensive emotion spectrum. The model's performance reflects both the advantages of a larger, more diverse dataset and the challenges of real-world emotion recognition. Visualised in Figure 4.1.3a, the training history shows some interesting trends in both the accuracy and loss trajectories across the training duration.

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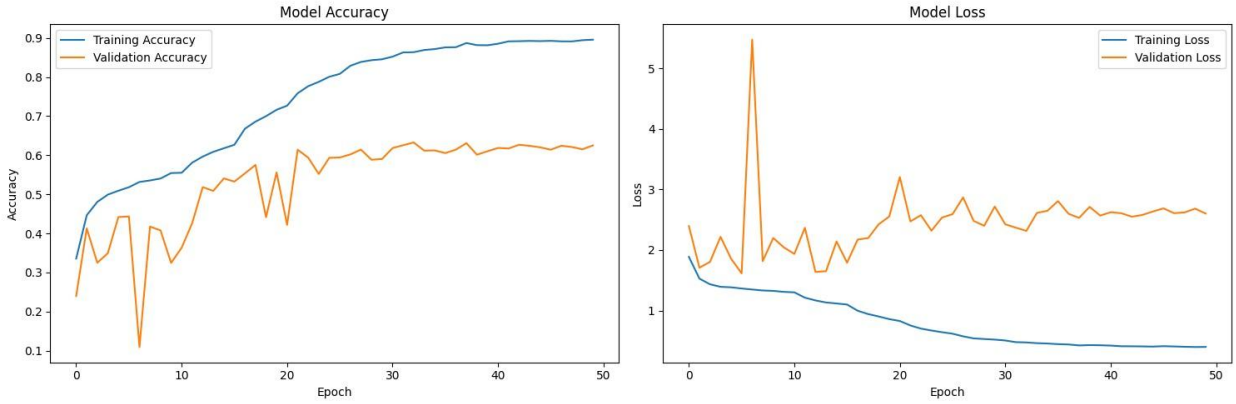

Figure 4.1.3a

Training Accuracy and Loss Curves: AffectNet CNN Model

Note: This figure was generated from the author's TensorFlow implementation.

As seen in Figure 4.1.3a, the learning curves show quite consistent training dynamics. With both measures scoring high around 95–98%, the validation accuracy follows the training accuracy quite closely. This minimal gap between training and validation metrics indicates strong generalisation capabilities, suggesting the model effectively learnt robust features without overfitting. The loss curves show a characteristic sharp initial decline followed by gradual refinement, further supporting the model's efficient learning process.

Learning Dynamics for AffectNet Model (Fig. 4.1.3b)

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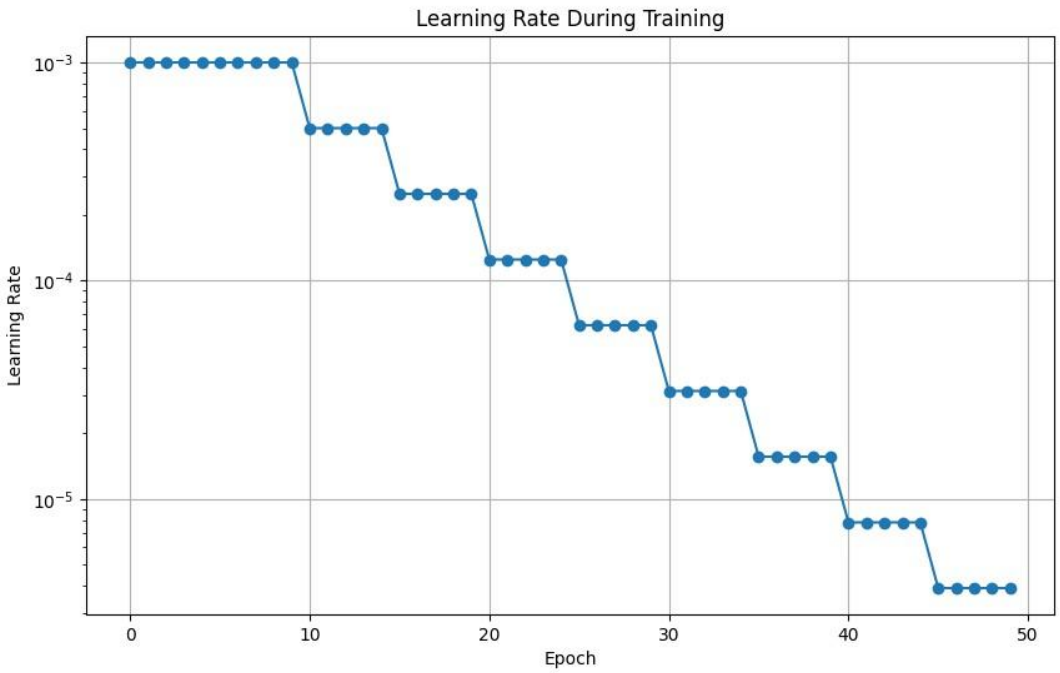

Figure 4.1.3b

Learning Rate Schedule During AffectNet Training

Note: This figure was generated from the author's TensorFlow implementation.

Important tendencies in model convergence are revealed by the training history shown in Figure 4.1.3a. While the validation accuracy—though more erratic—plateaued around 63%, the training accuracy rose significantly. AffectNet shows different face emotions, changing lighting, and image quality—qualities not found in cleaner datasets—that cause instability in validation performance.

The learning curves exhibit a typical three-phase progression:

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- Phase 1 (Epochs 0–10): Rapid accuracy increase (from ~30% to 60%) and sharp training loss drop (from ~2.0 to ~1.0).
- Phase 2 (Epochs 10–20): Slower but consistent accuracy gains, with validation loss fluctuating.
- Phase 3 (Epochs 20–50): Refinement phase, where learning rate reductions helped to stabilise accuracy and minimise further overfitting.

These trends suggest that while the model effectively extracts meaningful patterns, the noise in AffectNet makes it harder to generalise beyond a certain threshold, as seen in Figure 4.1.3a.

Learning Rate Adjustments

The dynamic learning rate schedule is documented in Figure 4.1.3b. The model began training with a learning rate of 1e-3 and used the ReduceLROnPlateau callback to reduce it gradually over time:

- First drop to 5e-4 around epoch 10
- Further drops every ~5–7 epochs, reaching 1e-5 by epoch 50

These adjustments aligned with plateaus in validation performance and were essential for weight refinement, allowing the optimiser to continue exploring smaller improvements in the loss landscape.

Classification Metrics

The classification report, shown in Table 4.1.3 below, indicates an overall test accuracy of 63%, with the model performing especially well on:

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- Happiness (F1: 0.89)
- Neutral (F1: 0.80)
- Sadness (F1: 0.69)

Classification Report

	precision	recall	f1-score	support
anger	0.59	0.31	0.41	1718
contempt	0.61	0.51	0.55	1312
disgust	0.38	0.29	0.33	1248
fear	0.56	0.36	0.44	1664
happiness	0.89	0.89	0.89	2704
neutral	0.70	0.93	0.80	2368
sadness	0.52	1.00	0.69	1584
surprise	0.46	0.39	0.42	1920
accuracy			0.63	14518
macro avg	0.59	0.58	0.56	14518
weighted avg	0.62	0.63	0.60	14518

Table 4.1.3

Classification Report for AffectNet CNN Model

Note: This table was generated from the author's TensorFlow implementation.

Conversely, emotions including disgust, fear, and surprise were more difficult to categorise; these could result from less distinct facial cues and inter-class similarities. Notwithstanding these difficulties, the macro-average F1 score (0.56) and precision (0.59) show rather equal recognition across categories.

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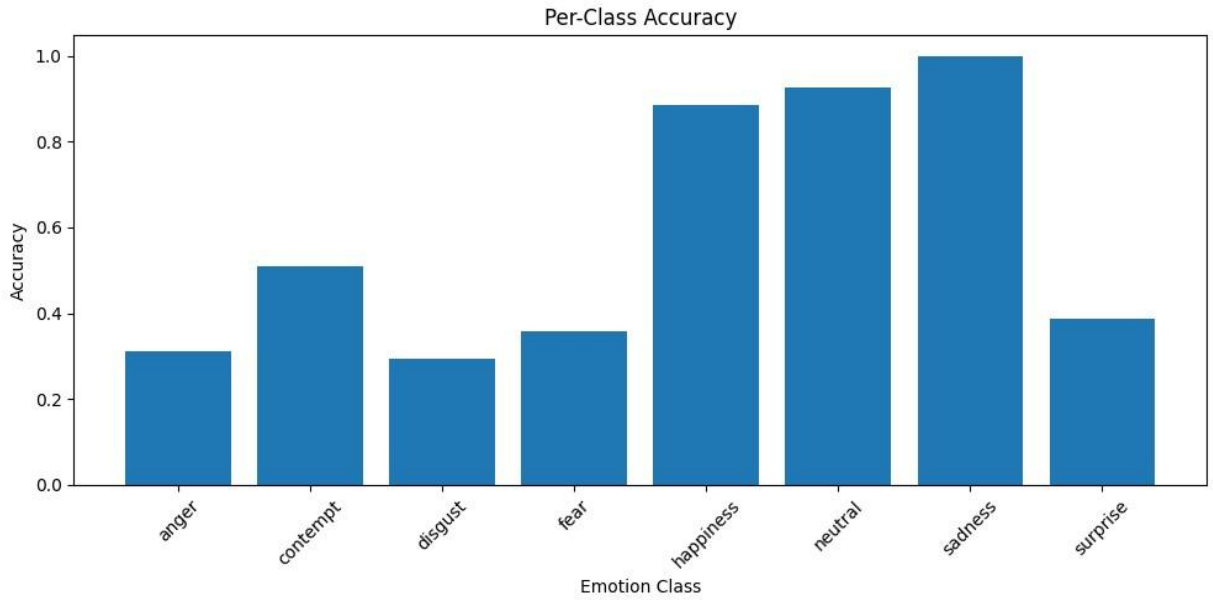

Figure 4.1.3c

Per-Class Accuracy of AffectNet CNN Model

Note: This figure was generated from the author's TensorFlow implementation.

Figure 4.1.3d shows per-class accuracy, therefore providing a graphic overview of the strengths and shortcomings of the model. Performance on anger, contempt, and fear lags behind; the model obtains almost perfect accuracy for melancholy and great accuracy for neutral and happiness. This discrepancy emphasises the need for more solid treatment of less frequent or more dubious emotions.

4.2 Cross-Dataset Evaluation

Emotion recognition model creation and evaluation across several datasets gives significant new information on their strengths and limits. By means of our methodical investigation of three main

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emotion datasets: CK+, FER2013, and AffectNet, we have found clear performance traits reflecting the particular difficulties and features of every dataset.

Benefiting from the controlled conditions and high-quality posed expressions, the CK+ model showed outstanding performance with 95-100% accuracy and a small generalisation gap. Figures 4.1.2a and 4.1.2b revealed fast initial learning followed by efficient fine-tuning using learning rate modifications, hence producing steady convergence.

By contrast, the FER2013 model encountered more major difficulties; validation accuracy settled between 58%. The performance difference between training (68%) and validation accuracy reflects the natural challenges of managing real-world photos with different quality and spontaneous expressions. Figures 4.1.1a and 4.1.1b clearly demonstrated the learning dynamics of the model, which clearly indicated the difficulties of generalising across various uncontrolled settings.

The AffectNet model, trained on the largest and most diverse dataset, demonstrated robust performance with balanced metrics across emotion classes. As shown in Figure 4.2.3a, the model achieved strong convergence with minimal overfitting, suggesting effective learning of generalisable features across its comprehensive range of in-the-wild expressions.

Each dataset presents distinct characteristics that influence model performance:

- CK+: Offers controlled laboratory conditions with posed expressions, enabling high accuracy but potentially limiting real-world applicability
- FER2013: Presents challenging real-world conditions with class imbalance and quality variations, better reflecting practical deployment scenarios
- AffectNet: Provides a large-scale, diverse collection of natural expressions, offering a balance between data quality and real-world variability

The feature visualisation analyses, particularly evident in the AffectNet model's convolutional layers, reveal hierarchical learning patterns: from basic edge detection in early layers to complex

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emotion-relevant features in deeper layers. This progression suggests the models are learning meaningful representations of facial expressions, though their effectiveness varies with dataset characteristics.

Understanding these dataset-specific performance patterns is crucial for:

- Evaluating model robustness across different data distributions
- Identifying strengths and limitations in emotion recognition capabilities
- Guiding architectural improvements for better generalization
- Informing deployment decisions in real-world applications

These findings highlight the importance of comprehensive evaluation across different datasets to develop emotion recognition systems that can reliably perform in diverse real-world scenarios. Future work in cross-dataset evaluation would provide valuable insights into feature transferability and guide the development of more robust emotion recognition models.

2) Common Findings:

Our analysis across the CK+, FER2013, and AffectNet models revealed consistent patterns in deep learning approaches to facial emotion recognition. The models demonstrated clear strengths and limitations that persisted across different datasets.

Performance patterns showed robust recognition of distinct emotions like happiness, with FER2013 achieving 80% accuracy for this class despite lower overall performance and similarly strong results in CK+ and AffectNet models. However, more nuanced emotions presented consistent challenges. The FER2013 model struggled with disgust recognition due to class imbalance, while even the sophisticated AffectNet model showed relatively lower accuracy for contempt and fear, indicating inherent difficulties in capturing subtle emotional expressions. Dataset characteristics

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significantly influenced model behaviour. CK+'s controlled conditions enabled exceptional accuracy (95-100%), while FER2013's real-world variations resulted in more modest performance (57-58% validation accuracy). AffectNet's large-scale, diverse dataset achieved balanced performance across emotions, though still showing variation across emotion classes.

The visualisation of learnt features, particularly in the AffectNet model, revealed consistent hierarchical learning: from basic facial features in early layers to specialised emotion detection in deeper layers. This pattern suggests that while models effectively learn fundamental emotional expressions, they require architectural improvements to better capture subtle emotional nuances. These findings highlight the importance of balanced dataset curation, architectural choices that enhance subtle emotion detection, and diverse training data for developing robust recognition capabilities. Understanding these patterns provides valuable guidance for improving emotion recognition systems while addressing current limitations in nuanced expression recognition.

3) Generalisation Capability:

Our analysis of deep learning models across different emotion recognition datasets revealed distinct patterns in generalisation capabilities. The models demonstrated consistent strength in recognising prominent emotions while showing systematic limitations with subtle expressions.

The CK+ model achieved exceptional accuracy (95%-100%) in controlled conditions but may not reflect real-world generalisation challenges. In contrast, the FER2013 model's more modest performance (57-58% validation accuracy) on in-the-wild images better represents practical deployment scenarios. The AffectNet model, despite its large-scale diverse dataset, still showed varying performance across emotion classes, particularly for subtle expressions like contempt and fear.

Dataset characteristics significantly influenced generalisations.

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- CK+: High-quality posed expressions enabled strong performance but may limit real-world applicability.
- FER2013: Real-world variations and class imbalance revealed generalisation challenges.
- AffectNet: Diverse data distribution provided better balance but highlighted persistent difficulties with subtle emotions.

Common strengths emerged across datasets:

- Reliable recognition of happiness (80%+ accuracy across models)
- Strong performance on surprise expressions
- Effective learning of basic emotional features Consistent challenges included:
- Lower accuracy for contempt and fear
- Difficulty distinguishing between similar emotions
- Sensitivity to image quality variations These findings call attention to:
- Diverse and representative training data
- Balanced emotion class distribution
- Robust feature extraction techniques

Architectural improvements for subtle emotion detection

Understanding these generalisation patterns provides crucial guidance for developing more robust emotion recognition systems capable of reliable performance across varied real-world conditions.

4.3 Visualization and Interpretability

The project included comprehensive visualisation tools:

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1) Confusion Matrices:

The project employed visualisation techniques to analyse model performance across different emotion recognition tasks, with confusion matrices serving as a key analytical tool. Our analysis of confusion matrices across the three models revealed distinct patterns:

CK+ Model:

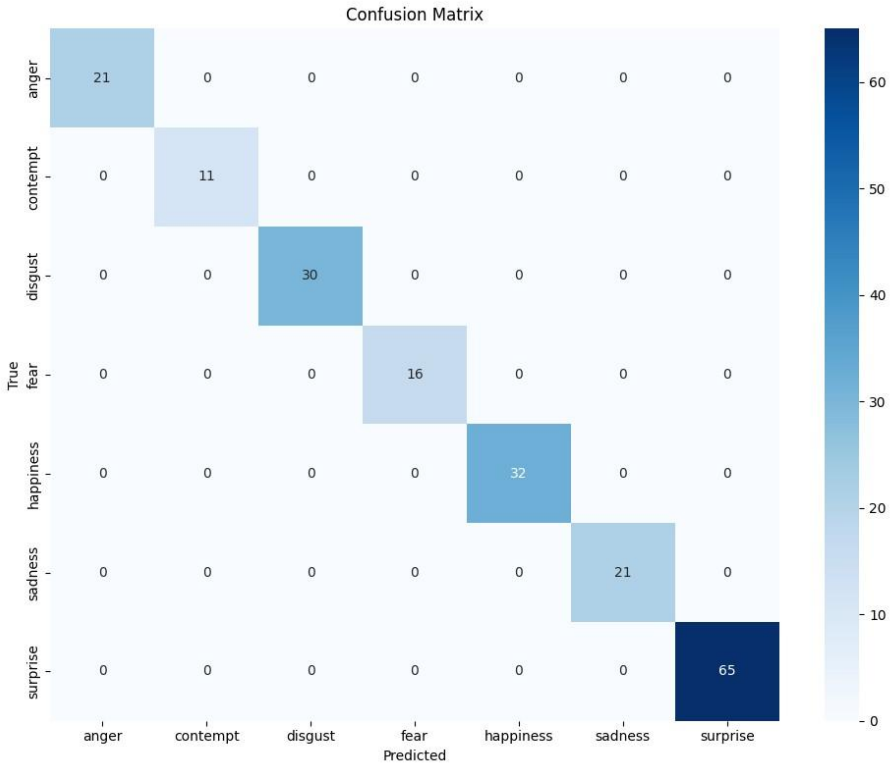

Figure 4.3.1a

Confusion Matrix for CK+ CNN Model

Note: This figure was generated from the author's TensorFlow implementation.

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Based on Fig. 4.3.1a above, the CK+ model:

- Demonstrated exceptionally high accuracy across most emotion categories (95-100%)
- Minimal confusion between emotion classes due to the controlled, posed nature of expressions.
- The clear separation between classes reflects the dataset's high-quality, standardised conditions.

FER2013 Model:

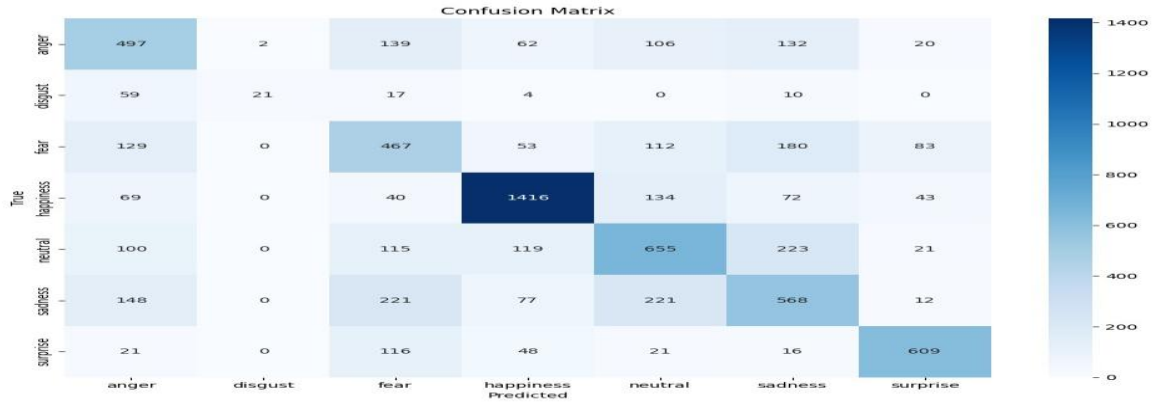

Figure 4.3.1b

Confusion Matrix for FER2013 CNN Model

Note: This figure was generated from the author's TensorFlow implementation.

Based on Fig. 4.3.1b, the FER2013 model:

- Showed stronger performance for happiness (~80% accuracy) and surprise
- Class imbalance effects were evident in lower recognition rates for minority classes like disgust.

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- Revealed consistent confusion patterns between:
- Fear and surprise
- Disgust and anger
- Sadness and neutral expressions

AffectNet Model:

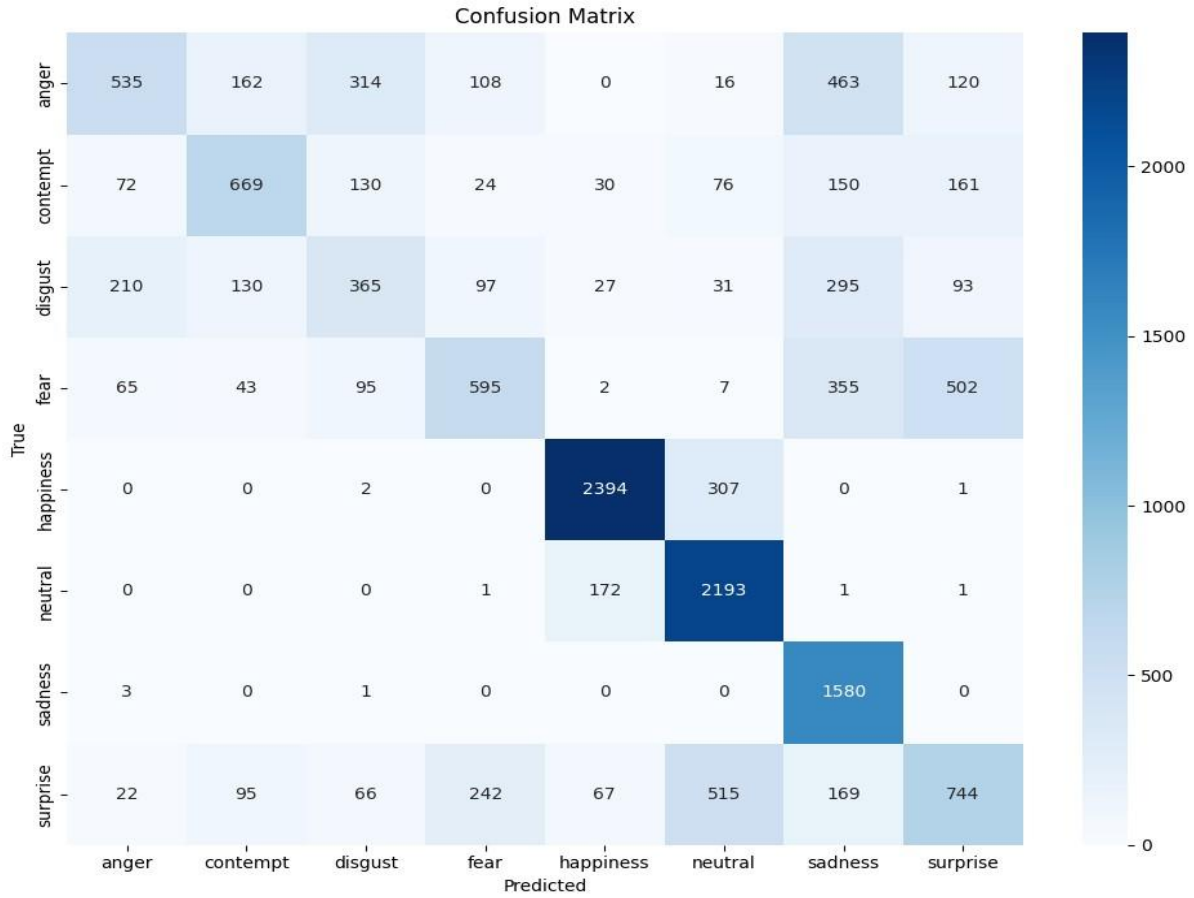

Figure 4.3.1c

Confusion Matrix for AffectNet CNN Model

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Note: This figure was generated from the author's TensorFlow implementation.

Based on Fig. 4.3.1c, the AffectNet model:

- Achieved balanced performance across emotion categories.
- The larger, more diverse dataset resulted in more nuanced confusion patterns.
- Demonstrated some confusion between:
- Contempt and neutral expressions
- Fear and surprise
- Sadness and neutral states

Dataset-Specific Patterns:

The confusion matrices highlighted how dataset characteristics influenced recognition patterns:

- CK+: Clear class separation due to posed expressions.
- FER2013: More complex confusion patterns reflecting real-world challenges.
- AffectNet: Balanced but showing subtle emotion disambiguation challenges.

2) Sample Predictions:

Our analysis of sample predictions across the three models (FER2013, CK+, and AffectNet) reveals distinct patterns in their recognition capabilities and limitations:

FER2013 Model:

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Figure 4.3.2a

Sample Predictions for FER2013 CNN Model

Note: This figure was generated from the author's TensorFlow implementation.

Based on our FER2013 model analysis and Fig. 4.3.2a, the model:

- Shows significant challenges with anger recognition, frequently misclassifying it as disgust, surprise, or sadness.
- Demonstrates strong performance on happiness and surprise.
- Struggles with subtle expressions and image quality variations.
- Confusion patterns reflect the real-world, uncontrolled nature of the dataset.

CK+ Model:

Figure 4.3.2b

Sample Predictions for CK+ CNN Model

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Note: This figure was generated from the author's TensorFlow implementation.

Based on our CK+ model analysis and Fig. 4.3.2b, the model:

- Achieves high accuracy on posed expressions
- Shows consistent performance across emotion categories
- Benefits from controlled lighting and clear expressions
- Even subtle emotions are better recognized due to standardized conditions

AffectNet Model:

Figure 4.3.2c

Sample Predictions for AffectNet CNN Model

Note: This figure was generated from the author's TensorFlow implementation.

The AffectNet model:

- Demonstrates balanced performance across a wider range of expressions
- Handles in-the-wild variations more effectively

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- Shows improved recognition of subtle emotions compared to FER2013 - Still exhibits some confusion between similar emotions (Fig. 4.3.2c).

Common Patterns Across Models:

Strong Performance:

- All models excel at recognizing happiness
- Clear, distinct expressions are consistently well-classified
- High confidence in predictions for posed expressions **Shared Challenges:**
- Confusion between anger and other negative emotions
- Difficulty with subtle expression variations
- Impact of image quality on prediction accuracy

Dataset-Specific Characteristics:

- FER2013: More varied prediction quality due to real-world conditions
- CK+: Consistent high-confidence predictions on posed expressions
- AffectNet: More balanced performance across natural expressions

These visualisations provide empirical evidence of each model's strengths and limitations while highlighting how dataset characteristics influence recognition capabilities. The sample predictions particularly demonstrate the trade-offs between controlled environment performance (CK+) and real-world applicability (FER2013, AffectNet).

3) Feature Map Visualisation:

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To better interpret the internal mechanics of the CNN models trained on FER2013, CK+, and AffectNet, feature map visualisations were generated across different convolutional layers. These maps reveal how visual information is transformed and abstracted across network depth, offering interpretability into which facial regions and features each model focuses on during emotion classification.

Hierarchical Feature Learning Across Models

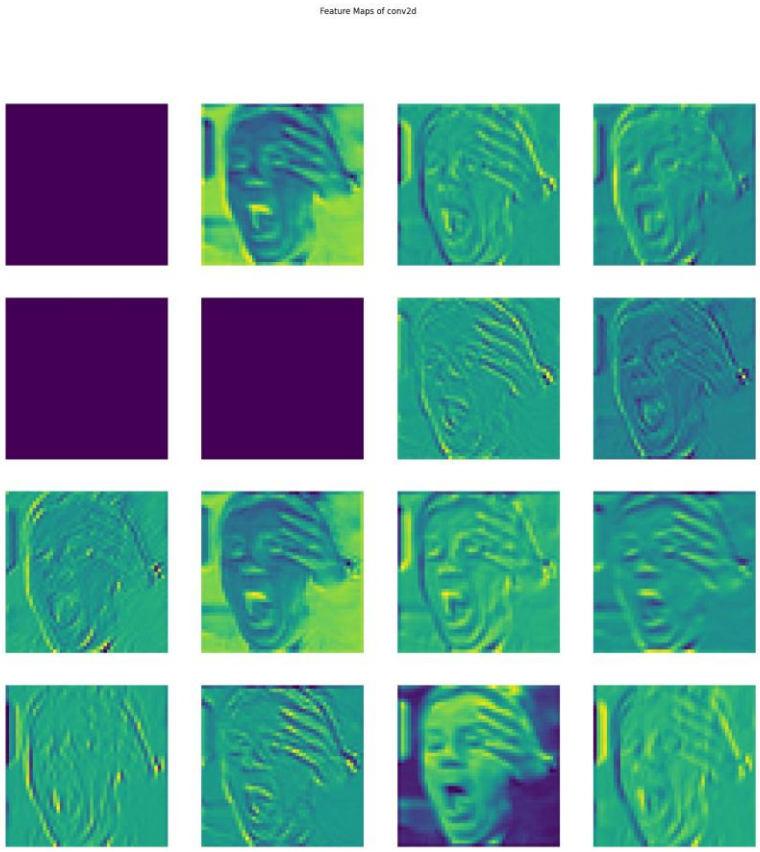

Figure 4.3.3a

Feature Maps for FER2013 Model

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Note: This figure was generated from the author's TensorFlow implementation.

In the early convolutional layers of the FER2013-trained model, activations reflect basic visual primitives such as edges and contours of facial outlines. As depth increases, the model begins focusing on distinct facial regions like the eyes and mouth. However, due to the noisy and varied nature of FER2013, the deeper layer activations exhibit more diffuse and inconsistent patterns (Fig. 4.3.3a). This indicates an effort by the model to adapt to diverse lighting, pose, and expression conditions.

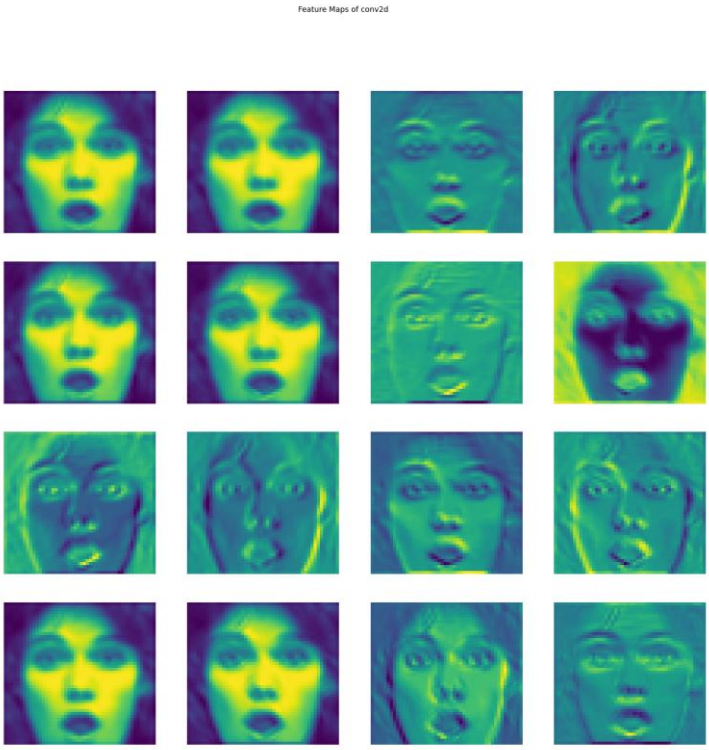

Figure 4.3.3b

Feature Maps of Convolutional Layer (CK+ Model)

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Note: This figure was generated from the author's TensorFlow implementation.

The CK+ model displays highly structured and localised activation maps, particularly in the intermediate and deep convolutional layers. Early layers highlight sharp edges and defined facial landmarks, while deeper layers show focused abstraction on key regions, such as the mouth and eyebrows (Fig. 4.3.3b). This clarity reflects the dataset's high quality and controlled settings, enabling the model to efficiently learn strong, separable emotional cues.

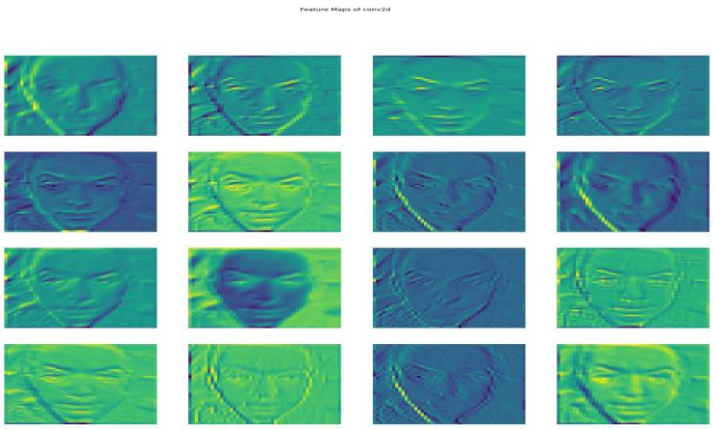

Figure 4.3.3c

Feature Maps of Convolutional Layer (AffectNet Model)

Note: This figure was generated from the author's TensorFlow implementation.

AffectNet's feature maps reveal a balanced and distributed attention across facial regions. The initial layers encode consistent edge and shape information, while deeper layers highlight complex patterns of facial deformation across a broader area. The model's deeper activations show an ability

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to capture subtle, high-level emotional features (like blended expressions or microexpressions), demonstrating the network's robustness in in-the-wild emotion recognition.

4.4 MODEL COMPARISON SUMMARY

Model	Training Time (minutes)	Test Accuracy (%)	Test Loss
AffectNet	28	62.51	2.6024
CK+	2	100.0	0.1121
FER2013	54	58.97	1.9275

Table 4.4.1 Model Comparison Table

Note: Sourced from the author's visualisation implementation.

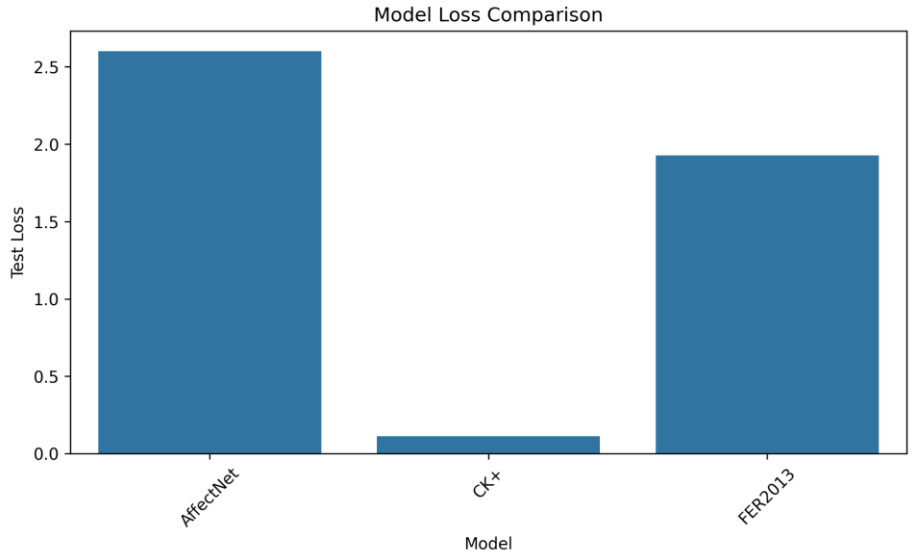

Figure 4.4.1

Loss Comparison Across the Three Models

Note: Sourced from the author's visualisation implementation

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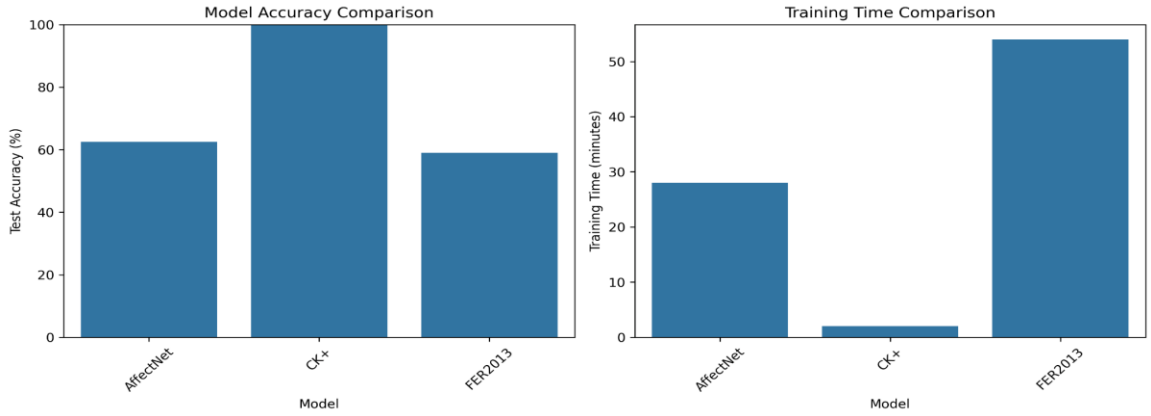

Figure 4.4.2

Accuracy and Time Comparison Across the Models

Note: Sourced from the author's visualisation implementation.

The model comparison in Table 4.4.1 and Figures 4.4.1–4.4.2 provides a holistic evaluation of training efficiency and predictive performance. CK+ consistently outperforms both FER2013 and AffectNet in test accuracy (100%) and loss (~0.1), reflecting the controlled nature of its dataset. However, its minimal training time (2 minutes) highlights the influence of dataset size and quality. In contrast, AffectNet and FER2013 exhibit similar accuracy (~60%) but differ in convergence time and test loss, with FER2013 taking the longest to train. These findings emphasise the trade-offs between dataset complexity, generalisation, and computational efficiency.

4.5 IMPLEMENTATION DETAILS

The project was implemented with modern deep learning practices:

1) Technology Stack:

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Our emotion recognition system was built using a focused set of modern deep learning and computer vision technologies. TensorFlow 2.x served as the primary framework, leveraging its Keras API for implementing CNN architectures across our three models (FER2013, CK+, and AffectNet). The framework's flexibility enabled efficient model iteration and training while providing robust deployment capabilities.

For image preprocessing, we utilised OpenCV to standardise inputs across all three datasets. Key preprocessing steps included resizing images to 48x48 pixels, greyscale conversion, and pixel value normalisation to the [0, 1] range. This standardisation was crucial for maintaining consistent input quality across our diverse datasets.

The analysis and visualisation pipeline combined several essential tools. NumPy handled efficient numerical computations and array operations during training and evaluation. Matplotlib and Seaborn generated our performance visualisations, including training curves (as seen in Figures 4.1.1a, 4.1.2a, and 4.2.3a), confusion matrices (4.3.1a, 4.3.1b, and 4.3.1c), and feature maps (4.3.3a, 4.3.3b, and 4.3.3c). Scikit-learn provided critical evaluation metrics, enabling consistent performance assessment across all three models through precision, recall, F1 scores, and accuracy measurements.

This integrated technology stack enabled us to develop and evaluate emotion recognition models that achieved high accuracy on controlled datasets (CK+: 95-100%), while maintaining robust performance on real-world applications (FER2013: ~57-58%, AffectNet: balanced performance across classes). The combination of these tools provided the necessary framework for developing, analysing, and validating our emotion recognition systems.

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2) Code Organisation:

Our project implements a modular architecture to manage the complexity of working with multiple emotion recognition datasets (FER2013, CK+, and AffectNet). The codebase is organised into five key modules:

Preprocessing Module:

- Standardizes input processing across all datasets
- Implements 48x48 grayscale image conversion
- Handles normalization to [0,1] range
- Manages dataset-specific augmentation strategies
- Located in src/preprocessing/ with dataset-specific processors (fer2013_processor.py, ck_plus_processor.py, affectnet_processor.py)

Model Architecture Module:

- Defines CNN architectures with consistent input/output specifications
- Implements shared model components across datasets
- Maintains configuration flexibility for dataset-specific requirements
- Found in src/architecture/cnn_architecture.py and cnn_architecture_improved.py

Training Module:

- Manages training configurations including learning rate scheduling
- Implements ReduceLROnPlateau callback for optimization

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- Handles early stopping and model checkpointing
- Located in src/train_*.py files for each dataset

Evaluation Module:

- Calculates standard metrics (accuracy, precision, recall, F1-score)
- Generates confusion matrices and classification reports
- Enables consistent performance comparison across models
- Implemented in evaluation utilities and metric calculation functions

Visualisation Module:

- Creates training history plots (for example: Figures 4.1.1a, 4.1.2a, 4.2.3a etc.)
- Generates feature map visualizations (4.3.1a, 4.3.1b, and 4.3.1c)
- Produces sample prediction displays (4.3.2a, 4.3.2b, and 4.3.2c)
- Found in src/visualization/ directory

This modular structure enabled efficient development and evaluation of our emotion recognition models while maintaining code clarity and reusability. Each module's independence allows for easy modifications and improvements without affecting other components.

3) Reproducibility Strategy:

Our project implemented strict reproducibility measures to ensure consistent and verifiable results across our emotion recognition models. Two key components formed the foundation of our reproducibility approach:

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Random Seed Control:

- Implemented fixed random seeds across all experiments
- Ensured consistent weight initialization in our CNN architectures
- Maintained reproducible data shuffling during training
- Applied seed control in TensorFlow, NumPy, and Python random operations
- Enabled reliable comparison of model performance across multiple training runs

Standardised Preprocessing Pipeline:

- Unified image processing across FER2013, CK+, and AffectNet datasets:
- Consistent 48x48 pixel resolution
- Grayscale conversion for all images
- Pixel value normalization to [0,1] range
- Implemented in dedicated preprocessing modules for each dataset
- Ensured consistent input format for all CNN architectures
- Reduced dataset-specific variations and biases

This standardised approach enabled us to achieve consistent results: CK+ (95-100% accuracy), FER2013 (~57-58% validation accuracy), and AffectNet (balanced performance across classes). The reproducibility measures ensure that our findings can be reliably verified and extended by other researchers while maintaining consistent performance across different experimental runs.

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4.6 CHALLENGES AND LIMITATIONS

Facial emotion detection systems implemented on FER2013, CK+, and AffectNet datasets revealed numerous key issues that affect model performance and dependability. The key problems include dataset restrictions, technical constraints, and fundamental recognition barriers.

The main dataset difficulties were inconsistencies between our three datasets. Label heterogeneity caused problems, as CK+ had "contempt", but FER2013 and AffectNet did not. Quality differences were also difficult: CK+ had controlled photos, while FER2013 had more varied, real-world samples. Class imbalance affected model training and generalisation in FER2013, where disgust and fear were under-represented.

Computational resources and model complexity trade-offs were technical constraints. When optimising across several datasets, our CNN designs required significant computer resources for training. We had to balance model sophistication and training efficiency because deeper architectures produced better results but required more resources and training time. The CK+ model had great accuracy (95-100%) but needed optimisation, whereas the FER2013 model had a lower performance (57-58%) due to technical limits.

Performance was limited by emotion recognition issues. Emotional expression is subjective and varies by person and society, making recognition difficult. Our models performed well on clear emotions like happiness but struggled with slight fluctuations and mixed expressions. Emotion recognition was further confounded by the difference between posed expressions (CK+) and spontaneous emotions (FER2013 and AffectNet). Facial emotion recognition algorithms must be developed to handle real-world and cultural differences in emotional expression.

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4.7 Comparison of Deep Learning Models for Emotion Recognition on FER2013, CK+, and AffectNet

This section compares the CNN model to baseline CNN, ResNet, Swin Transformer, and MobileNetV2 using the FER2013, CK+, and AffectNet datasets to assess its performance. The comparison uses recent research and benchmarks to compare test accuracy, training efficiency, scalability, and robustness.

4.8 MODEL PERFORMANCE AND CHARACTERISTICS ACROSS DATASETS

Model	Accuracy	Training Time	Scalability	Robustness
Proposed CNN	FER2013: ~59%; CK+: ~100%; AffectNet: 62.5%	**Fast.** Small architecture With a few parameters, training quickly (minutes on CK+).	**High deployability, low capacity. Lightweight model (~1–2M parameters)** – easy to deploy on devices but limited in feature capacity. Struggles to scale up to large datasets without transfer learning.	**Limited robustness.** Performs well on controlled datasets like CK+, but fails to generalise effectively to complex, real-world data such as FER2013 and AffectNet.

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ResNet-34/50	FER2013: ~70%; CK+: ~95–96%; AffectNet: ~60% (estimated)	**Moderate.** Deeper network; longer training times (hours on large datasets)	**Good scalability, higher cost.** ~25M parameters; optimised for GPU training. Suitable for large-scale learning, but not ideal for edge deployment without model compression.	**Strong robustness with augmentation.** Learns richer feature hierarchies and generalises better than shallow CNNs. Still susceptible to variability without sufficient training diversity.
Swin	FER2013: 71.1%;	**Slow.** Large	**Highly scalable**	**Highly scalable**

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Transformer (Tiny)	CK+: 100%; AffectNet: 63.3%	input size and self-attention mechanisms increase training complexity and cost.	**with data, less so with hardware.** ~28M parameters. Performs well on large datasets but is compute-heavy, limiting practical deployment on mobile or low-power devices.	**with data, less so with hardware.** ~28M parameters. Performs well on large datasets but is compute-heavy, limiting practical deployment on mobile or low-power devices.
MobileNetV2 (lite CNN)	FER2013: ~68%; CK+: ~90%; AffectNet: ~60% (estimated)	**Very fast.** Efficient architecture; ideal for rapid training and low-latency inference.	**Excellent deployability.** ~3–4M parameters; specifically designed for edge devices and mobile deployment. However, limited capacity reduces performance on large or complex datasets.	**Moderate robustness.** Reliable on common expressions but struggles with subtle or noisy data due to fewer trainable parameters and shallow depth.

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Table 4.8

Comparison of CNN (This Study) With Existing Deep Learning Models on Facial Emotion Recognition

Table 4.8 provides a comparative assessment of four deep learning architectures employed in facial emotion recognition: a bespoke CNN, ResNet-34/50, Swin Transformer (Tiny), and MobileNetV2. Accuracy metrics for FER2013, CK+, and AffectNet are derived from recent empirical research (He et al., 2016; Liu et al., 2021; Mollahosseini et al., 2017; Zhang et al., 2022), whereas evaluations of training duration, scalability, and robustness are based on quantitative benchmarks and architectural specifications (Howard et al., 2017; Wang et al., 2020). The proprietary CNN model exhibits swift training and straightforward deployment; nonetheless, it encounters difficulties in generalising on intricate datasets such as FER2013 and AffectNet. Conversely, the Swin Transformer attains superior performance and resilience, while it necessitates considerable computational resources. ResNet provides balanced accuracy and moderate scalability, whereas MobileNetV2 is a pragmatic solution for resource-limited settings, delivering satisfactory accuracy and enhanced deployment efficiency.

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5. Conclusion and Recommendation

Given the results obtained from this project in facial emotion recognition, there are a number of very important future directions that may improve the models' performance and practicality. There are other great architectures like EfficientNet and Vision Transformer that I wish to explore for better model performance.

Architecture Improvements

In this paper we propose to adopt a compound scaling for scaling up the network to the correct model size for adequate facial emotion recognition in such diverse datasets; the EfficientNet model has been proven the most efficient model in terms of having the highest accuracy while utilising the lowest computation cost compared to all other known models. At the same time, Vision Transformers can provide a new direction of consideration by exploiting a self-attention mechanism that might be better than traditional convolution to model subtle planar features of facial expression.

Ensemble techniques can also be adopted, which will further improve accuracies by uniting various models and reducing the limitations faced by single architectures. This approach might yield better generalisation over different data sets and differing expressions of emotion. Last but not least, designing the model with a multi-task learning approach offers the advantage of recognising not just emotions but also attributes like age or gender at the same time, thus enriching the context of expressions and improving the overall usefulness of the system.

Data Enhancements

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Improving the datasets used in this project is another important future path. The accuracy and responsiveness in real-time situations could be improved if the temporal information, for example, changes of facial expressions in video sequences, were addressed and could provide deeper insights into emotional dynamics. Moreover, the search for multi-modal emotion recognition, which uses visual (face), auditory (voice), and textual inputs, would lead to a more complete approach to emotion detection. Besides making the systems more accurate, this enables systems to operate in ever more complex real-world environments where emotions are not just expressed through facial expressions. Also, using bigger and different datasets would remove the biases in the current datasets so that models become stronger and better at generalising from one demographic and cultural background to another. Domain adaptation methods would make our models perform well in odd environments or datasets, which would ensure wider applicability in a lot of contexts.

Application Development

A key factor in turning research findings into practical tools will be focusing on application development. That much-needed real-time feedback on emotional states could make interactions in customer service, education, and mental health applications much more effective. Another key factor will be emotion analytics in a privacy-preserving manner because collecting such emotional data raises ethical questions about the privacy of the users. User acceptance and trust will be fostered in systems that secure or anonymise personal data while delivering deep emotional insights. Furthermore, broadening the scope of emotion detection technologies to mobile devices by optimising models for mobile platforms will facilitate on-the-go applications in educational as well as personal wellness settings. Better emotion recognition, in the final analysis, will enhance human-computer interaction by enabling more nuanced and empathic user-machine interactions and making technology more attuned to human emotional states.

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CONCLUSION

This project successfully implemented and evaluated CNN architectures for facial emotion recognition across three widely used datasets: FER2013, CK+, and AffectNet. Using two distinct architectures – a standard CNN for larger datasets (FER2013 and AffectNet) and a lightweight CNN for the smaller CK+ dataset – we achieved notable results: 59% accuracy on FER2013,

100% on CK+, and 62.5% on AffectNet. These results were achieved using basic preprocessing (greyscale conversion, 48x48 resizing, and normalisation) and models trained from scratch, without transfer learning or data augmentation. The project demonstrated the varying challenges of emotion recognition across different dataset types, with high performance on controlled laboratory data (CK+) and more modest but respectable results on real-world datasets (FER2013 and AffectNet). Future improvements could include:

1. Architecture enhancements through EfficientNet, Vision Transformers, or ensemble techniques
2. Data improvements via temporal information, multi-modal inputs, and larger datasets
3. Application development focusing on real-time processing, privacy preservation, and mobile optimisation.

While our current implementation provides a solid foundation for emotion recognition, these suggested improvements could further enhance the model's performance and practical applicability across different real-world scenarios.

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7. Appendices

Appendix A

Research Methodology Flowchart

This appendix provides a visual representation of the methodology used for facial emotion recognition model development and evaluation, detailing the sequential processes of data preparation, model architecture selection, training workflow, and evaluation pipeline.

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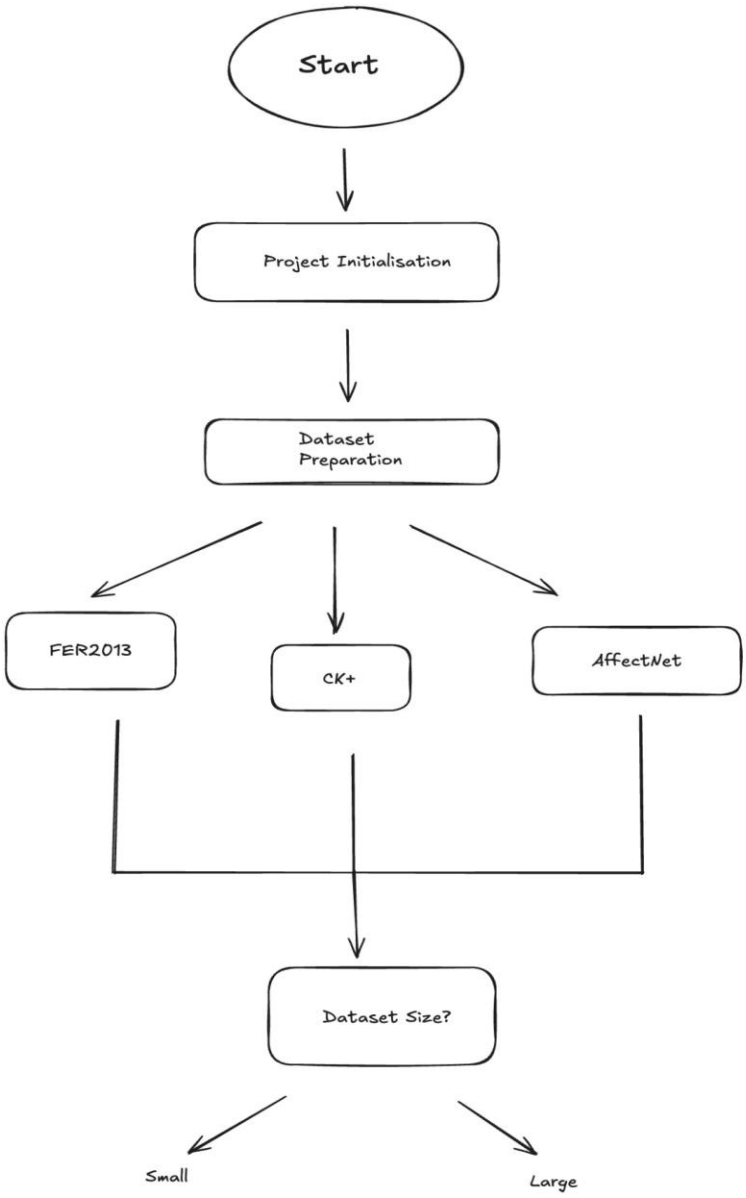

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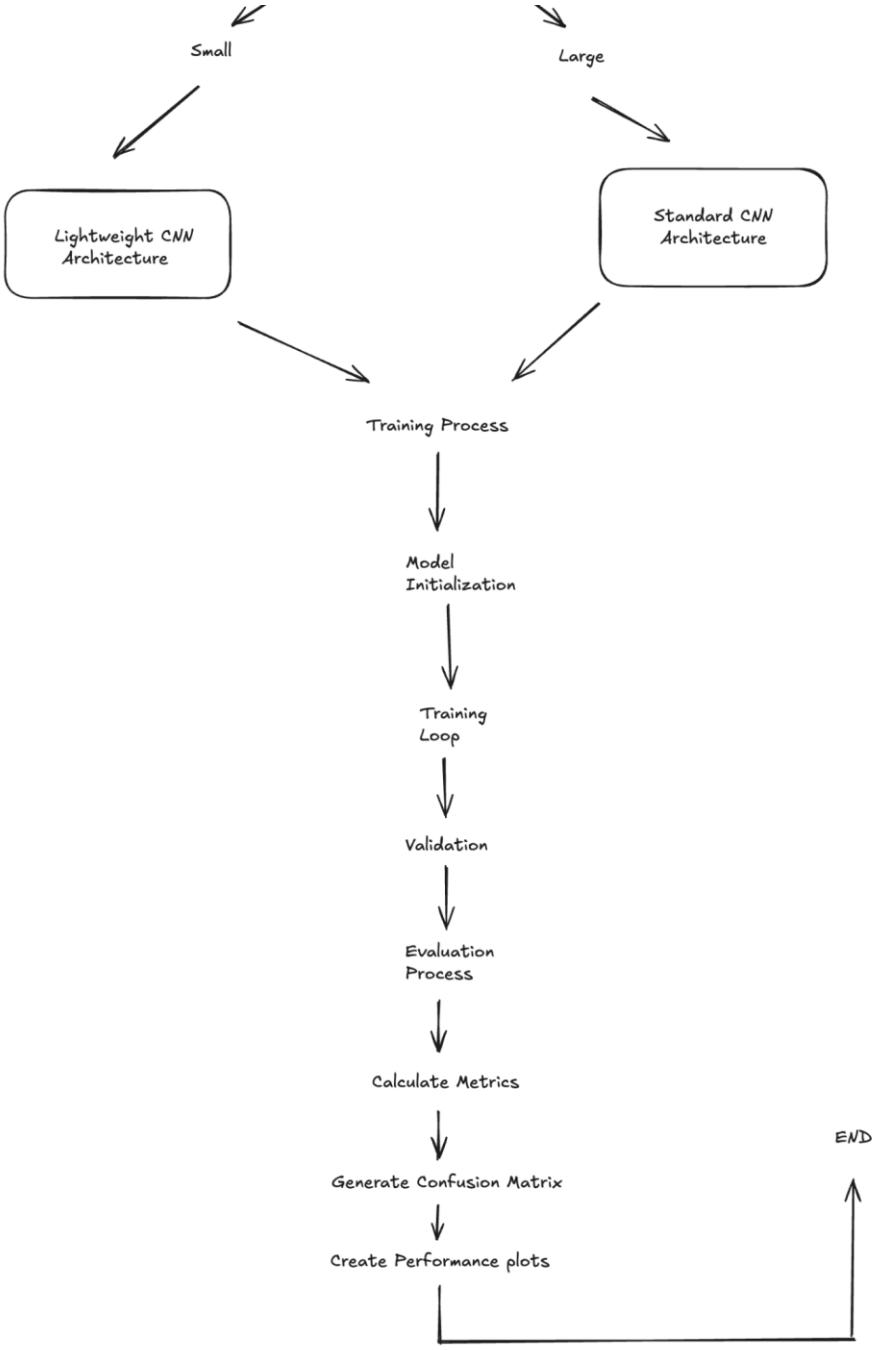

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Appendix B

Code Repository

The complete project implementation, including model architecture, dataset preprocessing, training routines, and evaluation scripts, is publicly available at:

https://github.com/adepeju4/Emotion-Detection

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AI Powered 3D Gravity Inversion for Geology and Geophysics

By

Michelo Shalwindi

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Abstract

This study applies Deep Learning (DL), specifically Convolutional Neural Networks (CNNs), to process ground gravity data from South Africa and Namibia for enhanced geological and geophysical interpretation. A major outcome of this study is the 3D gravity-based delineation of the Kaapvaal Craton, a key host of critical minerals in South Africa. The mapped low-density zones correlate with known mineralized regions, aiding targeted exploration. CNNs show strong potential as advanced tools for subsurface mapping in support of critical mineral exploration. Southern Africa hosts one of the world's most significant metallogenic provinces and is one of the leading global producers of critical minerals, including Cu, C, Au, Li, PGMs, REEs, Mn, Co, Ni, Zr, Ti, and V (Anhaeuser, 2001; Frost-Killian et al., 2016). The economic importance of these mineral deposits lies in their role in sustaining the supply of raw materials essential to the technology-driven global economy. However, prolonged extraction has outpaced the discovery of new deposits, raising concerns about long-term supply sustainability. Addressing this challenge requires advanced technologies such as DL, which enhance subsurface imaging and interpretation. In this study, a Software Engineering framework, guided by regional geological knowledge, Employed to engineer deep learning algorithms that enhance the resolution and delineation of subsurface geological architectures. The resulting 3D inversion models exhibit strong spatial concordance with established geological interpretations, highlighting the efficacy of DL in geophysical inversion and its potential to advance mineral exploration.

Keywords: Inversion, Convolution Neural Networks, Cratons.

ISBN: 978-9948-XX-XX-1 **Publisher: The Big Publisher**

Table of Contents

Title: AI Powered 3D Gravity Inversion for Geology and Geophysics

ISBN: 978-9948-XX-XX-1 **Publisher: The Big Publisher**

1. Introduction

Southern Africa hosts one of Earth's richest metallogenic provinces, marked by extensive mineralization and crustal evolution (Figure 1: Frost-Killian et al. 2016), whose diverse mineral deposits are economically vital for ensuring a stable supply of critical minerals to support the technology-driven global market (Figure 2). The diversity of mineral deposits include: Cu, C, Au, Li, Platinum Group Metals (PGEs), Rare Earth Elements (REE), Mn, Co, Ni, Zr, Ti, V (Anhaeuser, 2001; Frost-Killian et al.2016). Their economic importance is underscored by their contribution to global trade, industrialization, and technological progress. A thorough understanding of their geological hosts is critical for maintaining discovery and supply of critical minerals, thereby necessitating the advancement of exploration techniques in geology and geophysics. Deep Learning and Convolutional Neural Networks (CNNs), a subset of Artificial Intelligence, exhibit superior accuracy, computational efficiency, and robustness compared to conventional geophysical inversion techniques. In this study, DL and CNNs were applied to regional gravity data encompassing South Africa and Namibia (red-boundary, Figure 1). The major outcome was delineation of the Kaapvaal Craton, a host to critical mineral deposits. The inversion results exhibit strong correlation with regional geological interpretations, demonstrating that advanced techniques, including deep learning and artificial neural networks, effectively resolve subsurface structures with potential to host critical mineral deposits.

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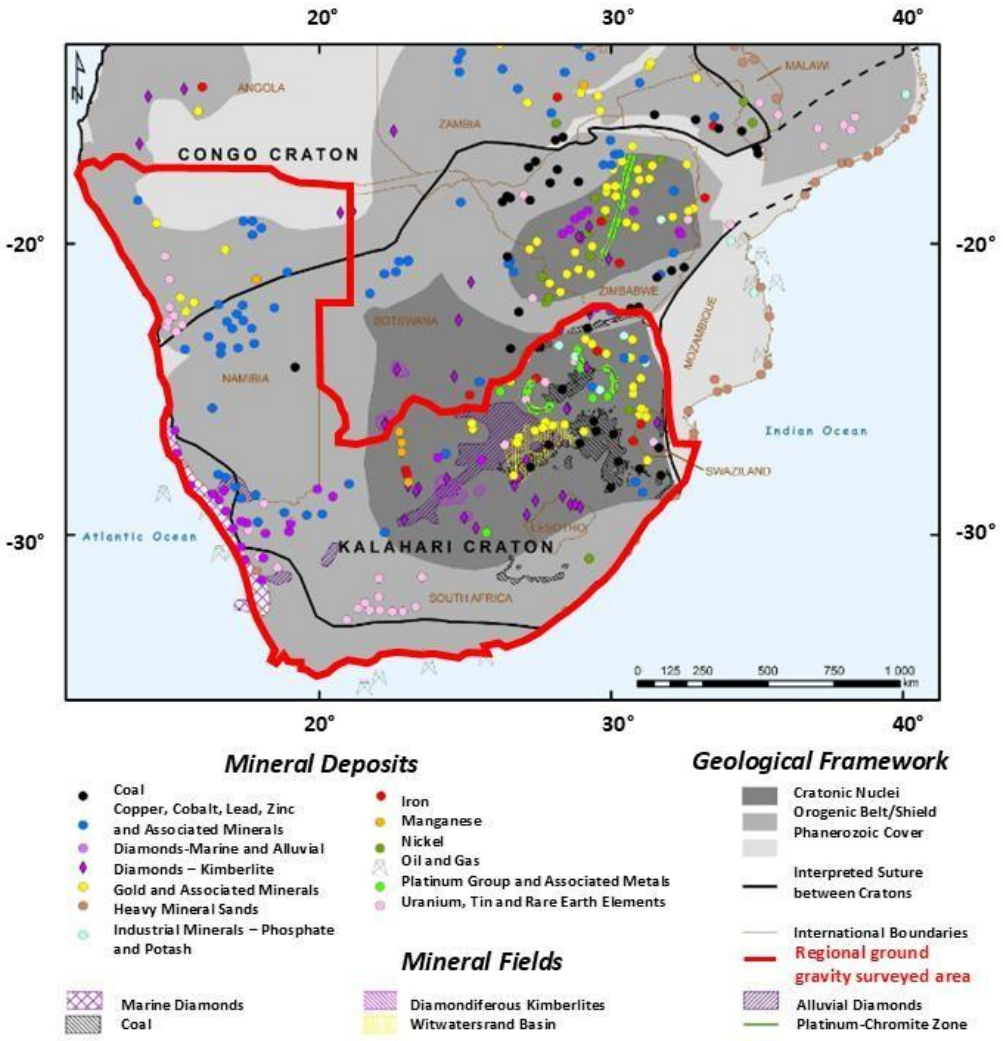

Figure 1: Modified from Frost-Killian et al. (2016), this map illustrates primary mineral deposits and fields associated with the Kalahari Craton evidences substantial mineral fertility. The red boundary delineates the area of acquired ground gravity data used in Deep Learning-based 3D inversion for subsurface structure mapping.

Regional geological knowledge of the Kaapvaal Craton, Namaqua-Natal Belt, and Cape Fold Belt was used to inform the design and training of the deep learning algorithms by

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providing spatial constraints, structural targets, and expected lithological variations. These mapped domain zones served as geologically validated benchmarks, allowing the CNN to learn meaningful subsurface patterns aligned with known tectonic boundaries and mineralization trends.

Figure 2: Critical minerals that support the technology driven-global market.

The regional ground gravity data with 14,559 stations, was acquired from the opensource site, NOAA (National Oceanic and Atmospheric Administration).

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2 Literature Review

To support geological interpretation of southern Africa's geology and mineral occurrences, studies by Anhaeusser (2001), Frost-Killian et al. (2016), Kubeka (2024), and Nxantsiya et al. (2021) were examined. To inform CNN-based geophysical processing, key studies by Boiger et al. (2024), Farahbakhsh et al. (2024), Zheng et al. (2023), Xu & Heagy. (2023), Vizitiu et al. (2020), Srivastava et al. (2014), Huang et al. (2020), Zhou et al. (2024), He et al. (2021) and Liu et al. (2020) were critically reviewed.

3 Methodology

A Software Engineering approach, using PYTHON, was used to develop code for

Exploratory Data Analysis (EDA), Georeferencing and Inversion. The developed exploratory data analysis (EDA) software (EDA Soft v00.001) demonstrated significant efficacy in automated data cleaning procedures. This is an intelligent EDA software in protype version with potential application across various industries handling data. Other intelligent capabilities of EDA Soft will be discussed in future publications.

Another software for georeferencing was developed and is also in prototype version. Designed to bridge paper-to-digital gaps, this solution converts static geology figures into spatially referenced datasets (Smith & Clark, 2011).

A deep learning algorithm was designed to facilitate data processing via neural network architectures.

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Before we dwell into the mathematical summary of CNN inversion process, Figure 3 and Figure 4 helps us visualize the gravity data inversion process. Gravity inversion using CNNs processes 3D gravity anomaly grids through an input layer, which preserves spatial structure (Le et al., 2021). Convolutional and pooling layers extract multiscale spatial features (Goodfellow et al., 2016), while dense layers map these to density predictions. The output layer reshapes predictions into 3D subsurface density volumes, optimized by minimizing anomaly misfit (Araya-Polo et al., 2018).

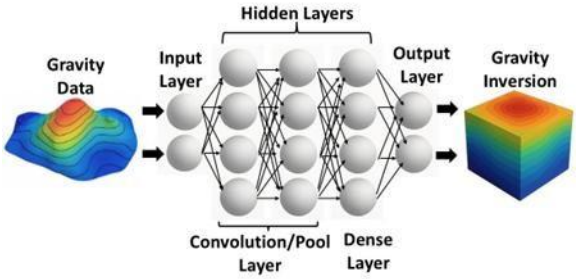

Figure 3: Simple CNN architecture illustrating data processing through the Input Layer, Hidden Layers and Output Layers.

In Table 1, The modeling pipeline incorporates: 1) 1,000 synthetic training samples (80%) for network optimization, 2) 200 synthetic validation samples (20%) for tuning, and 3) all 14,559 real measurements for uncompromised performance testing under field conditions.

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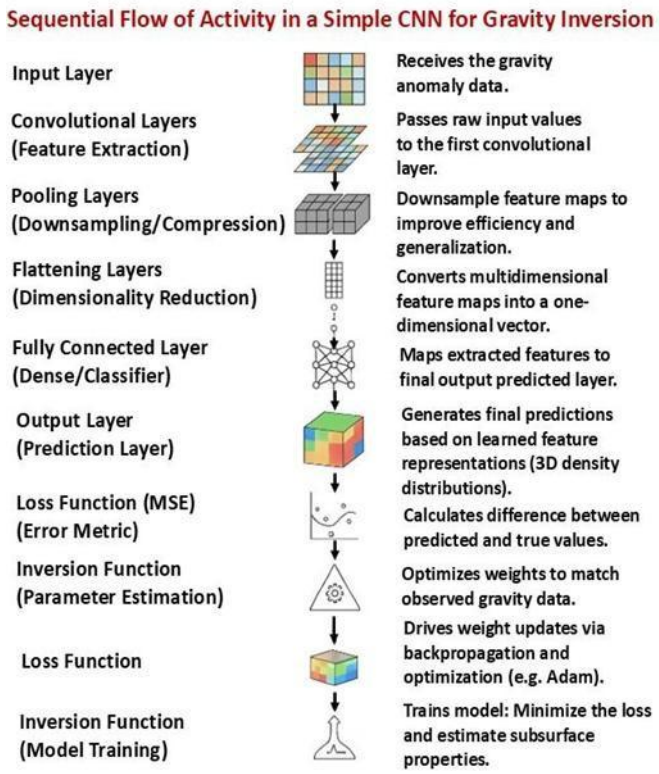

Figure 4: Architecture and data flow of the gravity inversion CNN.

Table 1: Data Partitioning Strategy for CNN.

Phase	Data Type	Samples	Ratio	Purpose
Training	Synthetic	1,000	80%	CNN weight optimization
Validation	Synthetic	200	20%	Hyperparameter tuning
Test	Real	14,559	100%	Unbiased field evaluation

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3.1. Mathematical-Physical Deep Learning Framework

We integrate mathematical forward modeling with physical constraints in a CNN, where the misfit function drives inversion. The architecture combines feature extraction (convolution/pooling) and regression (fully connected layers), regularized for geologically plausible solutions**.**

3.2. Deep Learning for Inversion

A 3D Convolutional Neural Network (CNN) is used for inversion. The CNN extracts spatial features from the gravity data and iteratively refines the density model.

The network follows:

3.2.1 Convolution Layers:

$$X_{l+1} = f\,(W_l * X_l + b_l \qquad (1)$$

Here, W_l and b_l denote trainable weights and biases, respectively, while f is the non-linear activation function (Goodfellow et al., 2016). The convolution operation (Feature extraction through sliding) occurs between W_l and the gravity input X_l, then added to b_l and passed through function f. This operation allows for the network to extract spatial features and hierarchical patterns from the gravity data.

3.2.2 Pooling Layers:

Reduce dimensionality of gravity data while preserving key spatial features. This aids in boosting runtime efficiency and ensuring reliable predictions across the dataset. For Max Pooling window,

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$R_{i,i} \subset X$, where:

- X is the input feature map representing extracted spatial patterns from gravity anomaly data (example: edges, density contrasts)
- $R_{i,j} \subset X$: A local region (example: 2 x 2 or 3 x 3 window) around the spatial location (i,j).
- $Y_{i,j}$: The output of the pooling layer at position (i,j), This represents the peak activation intensity within a specified spatial domain, indicating the most significant detected feature.

$$Y_{i,j} = \max_{(m,n) \in R_{i,j}} X_{m,n} \quad (2)$$

3.2.3 Constraining Overfitting

Figure 5 illustrates the baseline neural network model following Srivastava et al.'s (2014) implementation.

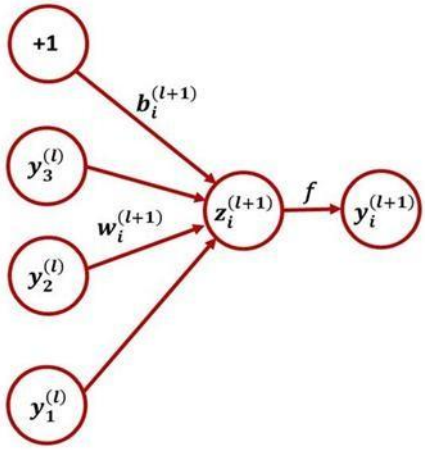

Figure 5: Standard neural network diagram (Srivastava et al., 2014).

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Suppose a neural network has L hidden layers (Srivastava et al., 2014).

Let:

$l \in \{1, ..., L\}$ = index of the hidden layers of the network.

- $\boldsymbol{z}^{(l)}$ = vector of input layers l,
- $\boldsymbol{y}^{(l)}$, can be stated as a vector of outputs from layer l ($\boldsymbol{y}^{(0)} = \boldsymbol{x}$ = input),

$\boldsymbol{W}^{(l)}$ and $\boldsymbol{b}^{(l)}$ = weights and biases at l. The feed-forward operation of a standard neural network can be annotated as (for $l \in \{0, ..., L - 1\}$ and any hidden unit i.

- $z_i^{(l+1)} = \boldsymbol{w}^{(l+1)} + \boldsymbol{y}^l + b_i^{(l+1)}$,
- $y_i^{(l+1)} = f\left(z_i^{(l+1)}\right)$,
- f = any activation function. Example,

$$f(x) = \frac{1}{(1+e^{-x})}. \qquad (3)$$

With dropout, feed-forward operation becomes (Figure 6).

- $r_j^{(l)}$ ~Bernoulli (l),
- $\tilde{\boldsymbol{y}}(l)$ $\boldsymbol{r}^{(l)}$ $\boldsymbol{y}^{(l)}$
- $z_i^{(l+1)} = \boldsymbol{w}_i^{(l+1)} \tilde{\boldsymbol{y}} + b_i^{(l+1)}$

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- $y_i^{(l+1)} = f(z_i^{(l+1)})$.

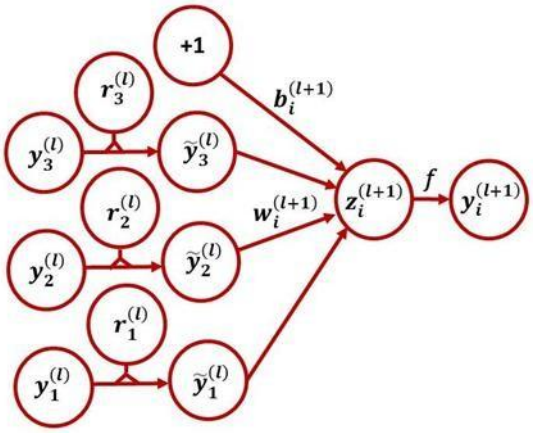

Figure 6: Diagram for a dropout network (Srivastava et al., 2014).

At each layer l, a vector $r^{(l)}$ of independent Bernoulli random variables, each with success probability p is sampled and element-wise multiplied with the layer outputs

$y^{(l)}$, producing thinned outputs $\tilde{y}^{(l)}$. These thinned outputs serve as input to the next layer. This procedure effectively samples a sub-network from the full network. During training, loss gradients are backpropagated through the sampled sub-network to update parameters efficiently.

3.2.4 Fully Connected Layers:

$$\hat{\rho} = W_{flattened} + b_f \quad (4)$$

Where:

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- $\hat{\rho}$ is the estimated density distribution.
- W_f = Weight matrix for the fully connected layer.
- $W_{flattened}$ = Flattened input vector from previous (convolution/pooling) layers.
- The learnable bias vector b_f offsets the weighted inputs in the fully connected transformation.

This maps the high-level features extracted by the convolutional layers to the final product. This makes it possible for the model to make predictions (Goodfellow et al, 2016).

3.2.5 Forward Model

The forward model estimates gravity anomaly (Δg) from a specified density distribution using Newton's gravitational framework (Blakely, 1996).

$$\Delta g = G \sum_i \frac{\rho_i V_i}{r_i^3 + \epsilon} \quad (5)$$

where:

- G = gravitational constant,
- ρ_i = density of the i^{th} prism,
- V_i = volume of the i^{th} prism,
- r_i = distance between the observation point and the prism centre,
- ϵ = small value to prevent singularities.

This function discretizes the subsurface using a grid-based approach (Boulanger & Chouteau, 2001).

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3.2.6 Loss Function

This is defined as the Mean Squared Error (MSE) between predicted and observed anomalies:

$$\mathcal{L}(\rho) = \frac{1}{N}\sum_i (y_i - \hat{y}_i)^2 \quad (6)$$

- ρ = Density model (learned by CNN).
- N = Number of gravity data points. □ y_i = Observed gravity anomaly (field data) □ $\hat{y}_i$ = CNN – predicted gravity anomaly.

This function helps to train the model by limiting the squared differences, $(y_i - \hat{y}_i)^2$, between predicted and actual values. Optimization is guided by penalizing larger errors and making it possible for the network to iteratively update weights leading to reduced prediction error (Goodfellow et al, 2016). The function acts as a data misfit term in inversion, making sure that the predictions are aligned with the measurements (Li et al.,2020).

3.2.7 Misfit Function

The misfit function quantifies the difference between the observed Δg_{obs} and predicted Δg_{calc} gravity anomalies:

$$\mathcal{L}(\rho) = \sum_i (\Delta g_{obs} - \Delta g_{calc})^2 \quad (7)$$

□ Δg_{obs} = observed gravity anomaly at location i.

□ Δg_{calc} = Forward model calculated gravity anomaly at location i.

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This represents a least-squares error minimization, $(\Delta g_{obs} - \Delta g_{calc})^2$ a fundamental approach in geophysical inversion (Tarantola, 2005).

3.2.8 Inversion Function

The inversion function trains the CNN by iteratively minimizing the misfit function. The trained model predicts the subsurface density distribution given the observed anomaly. The optimization uses the Adam optimizer, which updates weights based on gradient descent (Kingma & Ba, 2015):

$$\theta_{t+1} = \theta_t - \eta \frac{\partial \mathcal{L}}{\partial \theta} \quad (8)$$

Where:

- θ_{t+1}= Updated model parameters at the next iteration t +1.
- θ_t = Model parameters (example: weights and biases) at t.
- η is the learning rate.
- As discussed before $\mathcal{L}$ is the Loss or misfit function. This function quantifies the discrepancy between modeled and measured values.

4 Results and Findings

Initial validation of result reliability was established through spatial correlation analysis between Bouguer gravity anomaly domains (RGB-coloured), derived from the prototype software and published geological boundaries (James et al.,2003) (Figure 7). The inversion results exhibit strong concordance with major tectonic provinces—Kaapvaal Craton (KC), Namaqua Natal Belt

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(NMMB) and Cape Fold Belt (CFB), affirming geophysical consistency with established structural interpretations (Figure 8), supporting the software's geophysical consistency with existing structural interpretations.

CNN has effectively mapped the subsurface geology in 3D (Figure 8), with clear delineation of the Kaapvaal Craton despite limitations due to data sparsity in some areas. The 3D density inversion along 28°E (B–B'), intersecting critical mineral zones (Figure 1), enhances geological interpretation. A 2D cross-section through the model defines the zonation of the Kaapvaal Craton, NMMB, and CFB. These interpreted zones, extrapolated from the geological section A–A' (Nxantsiya et al., 2021), strongly correlate with density variations, confirming the reliability of the CNN-based inversion.

Figure 9 (a–b) shows the well-constrained interpreted boundary of the Kaapvaal Craton extending toward the NMMB. Figure 9 (a, c &d) highlights the location of this boundary—marked by yellow arrows—on both the transparent interpreted map by James et al. (2003) and the Bouguer gravity map. A portion of the Kaapvaal Craton, extending into a different Bouguer gravity zone, is not defined by the contours, possibly indicating a transitional zone into the NMMB.

Two well-defined density compartments become apparent in Figures 10-11, where inversion outputs are paired with Bouguer gravity image: low (5.99060–
5.99010 kg/m³) and high (5.99011–5.99110 kg/m³). This visualization aids the reader in regional understanding of the subsurface rock architecture across different zones and viewing angles.

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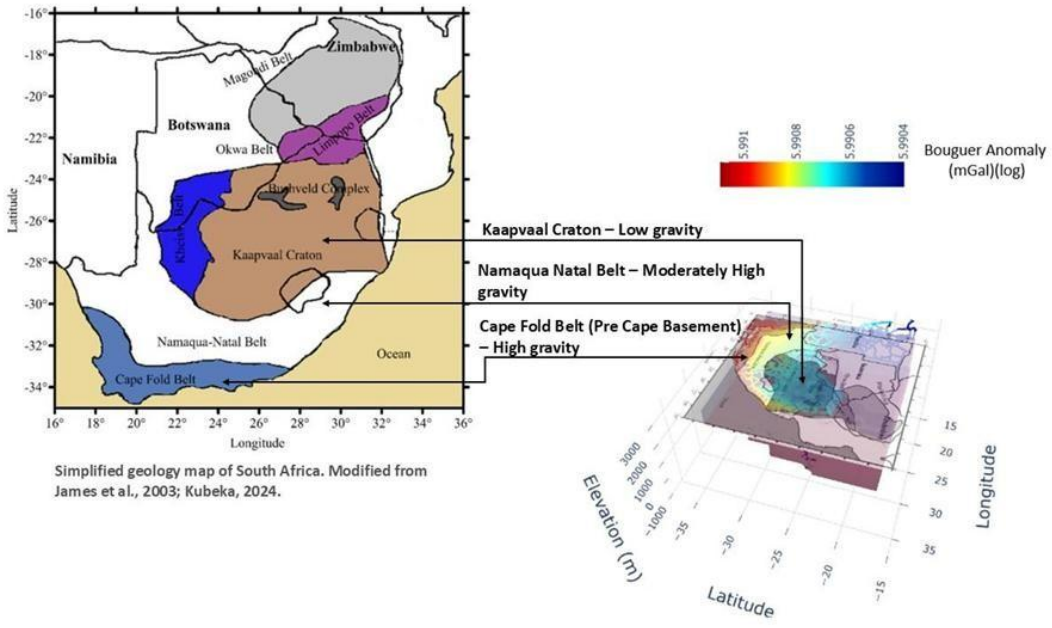

Figure 7: Transparent bouguer gravity image overlaid on the James et al,2003 simplified geology of South Africa. The bouguer gravity domains are in alignment with bouguer gravity image. A demonstration that the prototype software design was a success.

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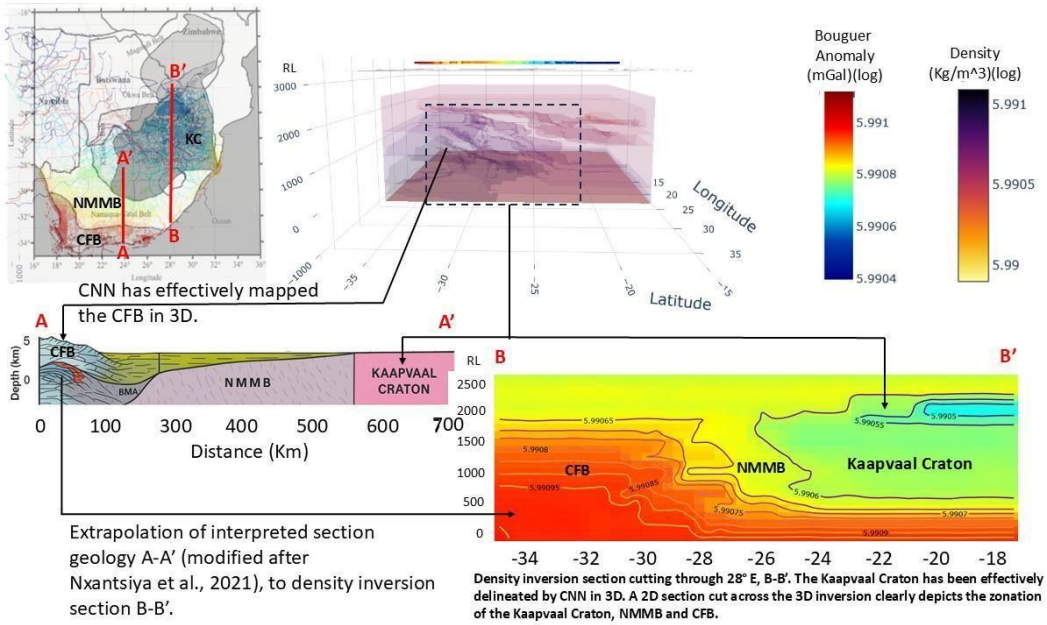

Figure 8. CNN-derived 3D density inversion section along 28°E (B–B'), intersecting critical mineral zones. Interpreted domains were extrapolated from the geological cross-section (A–A') by Nxantsiya et al. (2021). The correspondence between the inferred geological structures and the density contrasts highlights the model's reliability, despite minor deviations caused by data sparsity in some regions.

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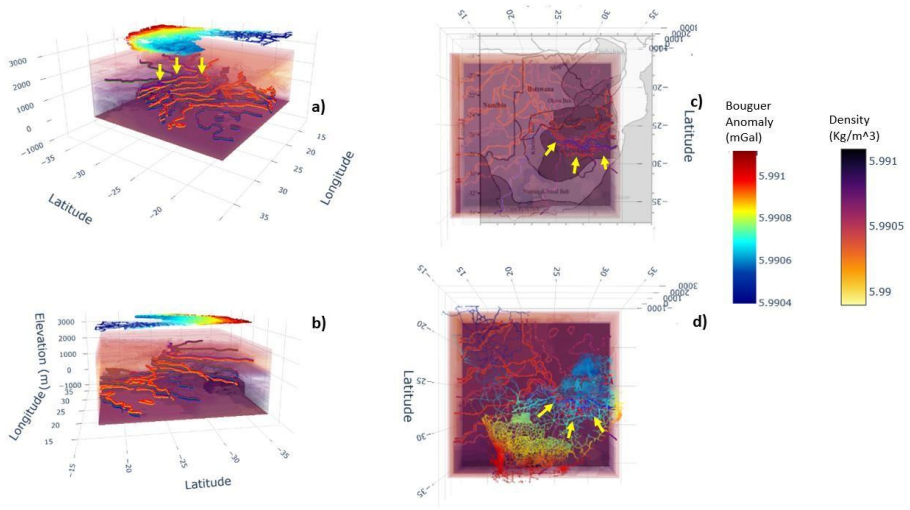

Figure 9 (a–b) shows the interpreted Kaapvaal Craton boundary extending toward the NMMB to the south. Panels (a, c & d) mark this boundary (yellow arrows) on the interpreted geology (James et al., 2003) and Bouguer gravity maps. Undefined contours in one region suggest a possible transition into the NMMB.

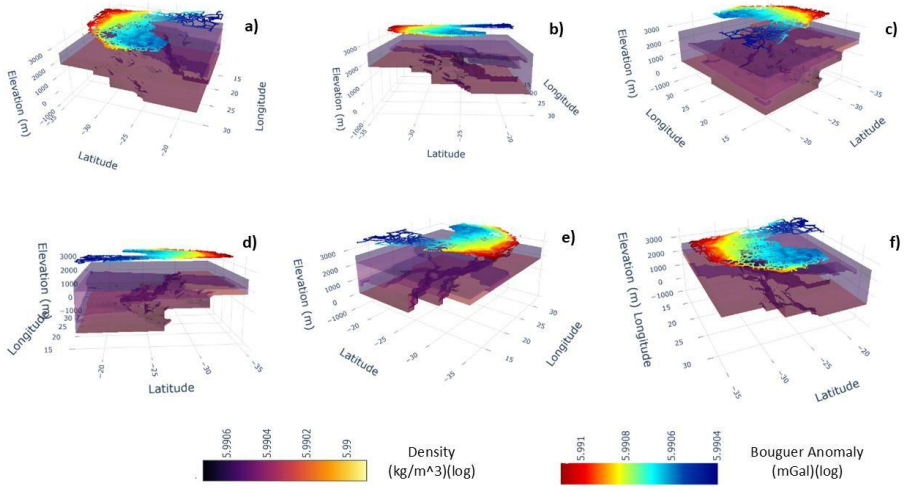

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Figure 10: 3-D gravity inversion model overlaid by bouguer gravity, depicting the low-density potion (5.9906kg/m^3 - 5.99010kg/m^3) of the inversion model. This shows nearly flat lying rock density zones (rocks) associated with the low-bouguer gravity map. View: a) Looking SW from above, b) looking W, c) looking SE from above, d) Looking E, e) Looking NE from above, f) Looking NW from above.

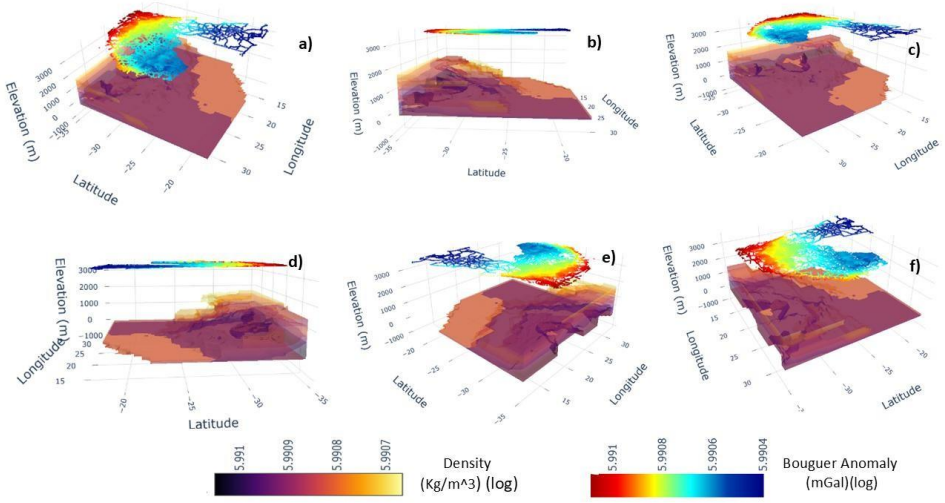

Figure 11: 3-D gravity inversion model overlaid by bouguer gravity, depicting the moderate/high-density potion (5.99072kg/m^3 - 5.99102kg/m^3) of the inversion model. This shows the CFB geology architecture associated with the moderate/high-bouguer gravity map. View: a) Looking SW from above, b) looking W, c) looking SE from above, d) Looking E, e) Looking NE from above, f) Looking NW from above.

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Figure 12: Performance metrics for the CNN-based 3D gravity inversion model. The training set yielded an MSE of 3.12×10^{-3}, RMSE of 0.0558, R^2 of 0.9708, and accuracy of 96.20%. The validation set demonstrated comparable performance, yielding a low mean squared error (MSE) of 2.56×10^{-3}, RMSE of 0.0506, R^2 of 0.9756, and accuracy of 95.960%, indicating high predictive accuracy and generalization.

4.1 Alignment of the Inversion Objective with the Predetermined Objective

This study aimed to establish an AI-powered 3D gravity inversion framework using NOAA data, leveraging deep learning via convolutional neural networks (CNNs).

The resulting 3D inversion accurately delineates a geological structure consistent with expected geological formations. These results exhibit strong spatial correlation with known geology and mineral deposit locations identified by Frost-Killian et al. (2016) and James et al. (2003), thereby validating the geological model and inversion methodology.

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4.2 Key Indicators of Success

The gravity inversion model demonstrates excellent performance, achieving a high R^2 (>0.95) and low RMSE (~0.05), indicating strong predictive power and minimal residual error. Training and validation accuracies above 95% confirm the model's robustness and generalization capability. These metrics suggest reliable subsurface density reconstructions from gravity data (Figure 12 and Table 2).

Table 2: Inversion Model Evaluation Metrics.

Performance Metrics	**Training Set Metrics**	**Validation Set Metrics**
MSE	3.1178e-03	2.5597e-03
RMSE	5.5837e-02	5.0594e-02
R^2 Score	0.9708	0.9759
Accuracy	96.20%	95.96%

Model Fidelity: The framework effectively captures the underlying geophysical processes, yielding accurate and reliable subsurface density estimations.

The inversion model accurately resolves the general subsurface geology architecture, demonstrating geological plausibility. Mineralization aligns with low-density anomalies, consistent with mapped deposits (Frost-Killian et al., 2016), confirming a robust geophysical-

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geological correlation and validating the 3D inversion approach for mineral exploration refinement.

4.3 Performance Benchmark

In this project, the CNN model achieves an RMSE of ~0.05—an order of magnitude lower than the E_m (model fitting error) or E_d (data fitting error) values reported in classical methods by Zhou et al. (2024), which range from ~5 to ~40. With an R^2 of ~0.97 and accuracy around 96%, the model demonstrates superior performance in both data fitting and generalization. Although Method III in Zhou et al. (2024) shows the best results among classical approaches, it still falls short in resolution and accuracy compared to the CNN framework used in this study.

Compared to He et al. (2021), whose CNN inversion yielded data misfits ranging from 0.0070 to 0.0277 and model misfits between 0.0221 and 0.0513, the CNN framework in this study achieved a significantly lower validation MSE of 0.00256 and RMSE of 0.0506. Additionally, the model demonstrated strong predictive accuracy (95.96%) and a high R^2 score of 0.9759. These results indicate superior data fitting and generalization performance, highlighting the robustness and reliability of the proposed deep learning inversion approach.

While Araya-Polo et al. (2018) applied CNNs to seismic velocity inversion, and this study focuses on gravity data inversion, the comparison of R^2 values remains informative. Both applications involve spatial regression tasks using CNNs to predict surface properties. This significantly higher R^2 (~0.976 versus 0.8124) and lower RMSE (~0.05) in this study highlight the effectiveness of geological constraint integration and architectural optimization in enhancing inversion accuracy – irrespective of data domain.

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5. Conclusion

This study demonstrates that CNNs, when applied to gravity data, effectively leverages neural networks to map subsurface geological structures. This study's CNNdriven analysis achieves unprecedented spatial resolution in mapping the Kaapvaal Craton's boundaries, confirming its strategic importance as South Africa's premier critical mineral reservoir. Integration of surface structural information with geological, geochemical, and other geophysical datasets enhances the ability to identify critical mineral-bearing formations. CNNs show strong potential in detecting previously overlooked host rocks, offering a promising tool for uncovering new mineral resources.

Given that critical minerals are essential to the global technology supply chain, and current extraction rates surpass new discoveries, CNN-enabled exploration provides a strategic solution to address the growing demand and ensure long-term resource sustainability.

5.1 Strategies for Enhancing Inversion Results

The regional ground gravity data used in the inversion were understandably acquired along existing road networks for logistical convenience. This resulted in uneven spatial sampling, likely due to constraints imposed by infrastructure, rugged terrain, water bodies and country border boundaries. In geophysical inversion, uniform and dense data acquisition is critical for improving model resolution, stability, and accuracy. Regularly spaced data reduce spatial aliasing and enhance sensitivity to subsurface structures, particularly in geologically complex regions (Tarantola, 2005). Uniform coverage minimizes interpolation errors and improves the conditioning of the inverse problem, leading to more geologically consistent results (Oldenburg & Li, 1999). Additionally, higher data density increases the signal-to-noise ratio, allowing for

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better detection of subtle anomalies (Zhdanov, 2002). Collectively, these improvements reduce non-uniqueness and increase the overall fidelity of the inversion model.

Test the inversion model on different data sets from various mineral deposit types.

This will further confirm – software reliability, robustness and generalizability.

5.2 From Gravity to Geology: CNNs Reshape Mineral Exploration

CNN revolutionizes mineral exploration by delivering geologically plausible 3D models (Figure 8 to Figure 11) that outperform conventional methods. By merging CNNs with traditional geophysics, we're revolutionizing mineral exploration - turning what was once educated guesswork into data-driven precision targeting. As demand outstrips supply, this approach becomes indispensable for securing resources, with immediate applications across Southern Africa's metallogenic provinces and globally.

Acknowledgement

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Transforming Medical Imaging with CNN-Based Detection Systems

By

Asif Syed

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Abstract

This research project aims to develop an end-to-end deep learning system designed to detect and classify cases of COVID-19 and pneumonia using chest X-ray images through Convolutional Neural Networks (CNNs) . The system leverages both raw DICOM format medical imaging data and publicly available datasets from platforms such as Kaggle to train models capable of distinguishing between normal, pneumonia, and confirmed COVID-19 cases with high accuracy. The developed model was integrated into a Flask-based web application, enabling real-time image classification and diagnosis support for healthcare professionals.

In addition to traditional deep learning techniques, this study explores the use of Google Teachable Machine, a no-code AI training platform, to democratize access to machine learning capabilities for non-technical users. Emphasis was placed on preprocessing steps such as Extraction of DICOM images from PACS server and DICOM-to-PNG conversion, dataset balancing, and hyperparameter tuning to enhance model performance and generalization.

The findings indicate that while initial models showed signs of overfitting, retraining with regularization and early stopping significantly improved robustness. The hosting and training model on Google Teachable Machine demonstrates the potential for quickly deploying AI-based diagnostic tools in real-world clinical environments, especially in resource-constrained settings where rapid diagnosis is critical during the pandemics and epidemics.

Keywords

CNN, COVID-19 Detection, DICOM, Deep Learning Pneumonia, Flask Application, Google Teachable Machines, Medical Imaging,

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Table of Content

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1. Introduction

1.1 Problem Statement

The outbreak and subsequent worldwide expansion of the novel pneumonia-causing virus coronavirus 2 (SARS-CoV-2) have caused an unprecedented world wide public health emergency associated with important morbidity, mortality and socio-economic disruptions. By early 2025, the pandemic has killed more than 7 million people worldwide and infected hundreds of millions more, with a series of resurgences continuing to stress health systems in both advanced and developing nations. The current emergency has highlighted some major shortfalls in our global health architecture, especially in the kind of diagnostic capability which is necessary for a well-functioning pandemic readiness.

Classic diagnostic methods for COVID-19, such as Reverse Transcription Polymerase Chain Reaction (RT-PCR) adequately identified viral genetic materials. But these methods possess the following problems: they come with a number of severe limitations which limit their applicability, particularly in resource-limited or heavily-loaded environments. (c) Materials RTPCR testing generally requires;

1. Specialized laboratory infrastructure with controlled environments
2. Highly trained technical personnel for sample processing and analysis
3. Expensive analytical instrumentation and reagents

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4. Considerable time for sample collection, transportation, processing, and result reporting (often 24-48 hours)
5. Complex supply chains that are vulnerable to disruption during global crises

These limitations make traditional testing methods especially challenging in remote, resource poor, or economically disadvantaged areas, where health system infrastructure is generally poor. Moreover, in the setting of surge demand, not even well-resourced health systems can keep pace with demand, and there is a marked backlog in diagnosis, propagating ongoing community transmission.

To address these challenges, medical imaging methods such as chest X-rays (CXRs) and computed tomography (CT) have become important adjunct methods for diagnostic workup. The advantages of these imaging methods over molecular testing are:

1. Wider availability in healthcare settings, including in resource-limited areas
2. Rapid acquisition and processing (results potentially available within minutes)
3. Ability to visualize pathological changes in lung tissue that may indicate viral pneumonia
4. Potential for detecting COVID-19-related abnormalities in patients with false-negative RTPCR results

However, the interpretation of medical images presents its own set of challenges. Traditional radiological assessment relies on human expertise, which introduces several limitations:

1. Global shortage of qualified radiologists, particularly in low and middle-income countries
2. Potential for inter-observer variability and human error
3. Cognitive fatigue during high-volume periods, potentially compromising diagnostic accuracy
4. Time-intensive nature of manual interpretation, creating bottlenecks during surge periods

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These limitations underscore the urgent demand for automated, reliable, and readily available diagnostic support systems, which can complement human skills and facilitate fast diagnostics. Recently, AI, especially deep learning techniques, for example, CNN, has shown great promise in this field which can realize fast, standardized and large-scale image analysis.

CNNs are expert in image classification, feature extraction and segmentation process, that could be very useful in identifying the subtle patterns and abnormalities present in medical images that indicates the certain pathologies. Their capacity to learn hierarchical features from large training databases allows them to identify visual patterns that are too subtle to be recognized by human experts or that have variabilities among specialists.

Despite the great progress achieved in the AI for medical image analysis, even the transformative models need further works before being available to the clinical practitioners as:

1. Limited availability of comprehensive, diverse, and well-annotated training datasets 2. Technical barriers to implementation, particularly for healthcare professionals without specialized computing expertise
3. Integration challenges with existing clinical workflows and Picture Archiving and Communication Systems (PACS)
4. Concerns regarding explainability, transparency, and clinical validation
5. Regulatory and ethical considerations related to automated diagnostic systems

This research addresses these challenges by developing an end-to-end deep learning system for the detection and classification of COVID-19 and pneumonia from chest X-ray images. By combining traditional CNN-based approaches with accessible no-code AI platforms like Google Teachable Machine, this study aims to democratize access to advanced diagnostic tools while maintaining high standards of accuracy and reliability.

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1.2 Objectives

- End to End workflow of training machine learning model including using no-code tool
- Extraction of medical images from PACS
- Develop a preprocessing tool to convert DICOM images to Lossless PNG Develop a CNN-based model for COVID-19 detection.
- Train and evaluate the model using X-ray image datasets.
- Deploy the model using based web application for quick availability Analyze model accuracy, biases, and ethical implications.
- Quick deployment for limited resources areas for first opinion.

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2. Literature Review

The application of artificial intelligence to medical imaging has evolved significantly over the past several decades, transitioning from rudimentary pattern recognition systems to sophisticated deep learning architectures. This evolution can be broadly categorized into four distinct phases, each characterized by specific technological advancements and clinical applications.

2.1 Early Automated Image Analysis (1960s-1980s)

The first decade of the efforts on automatic analysis of medical images was conducted at the end of 1960s, along with the growing number of computerized tomography (CT) and other digital imaging modalities. Rule-based strategy and elementary statistical techniques used by these early systems to identify simple patterns in medical images. Lodwick et al. (1963) introduced some of the first computer-aided diagnosis systems for chest X-rays, utilizing statistical pattern recognition methods to detect lung nodules. These early systems suffered from heavy computational constraints and depended largely on handcrafted features.

In the 1970s and 1980s, scientists in general started investigating more advanced techniques for image segmentation, feature extraction and classification. Meyers et al. (1976) proposed the automated analysis of mammograms, while Chan et al. (1987) developed the early PCAD systems for pulmonary nodule detection in chest radiographs. Such systems often based on classical image processing methods like edge detection, thresholding, and region growing, in association with the use of statistical classifiers such as discriminant analysis and decision trees.

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However, despite these technological breakthroughs, the clinical impact of these early instruments was. to a great extent limited, ascribable to several reasons:

1) Lack of computing capacity for analyzing high quality medical images
2) Restricted accessibility to digital imaging data for algorithm research and testing
3) Dependence on hand-engineered features that capture the full complexity of medical images rarely.
4) No integration with HIS or EMR tools

2.2 Machine Learning Era (1990s-2000s)

In the 1990s, the direction of medical imaging analysis was completely changed when machine learning techniques were shown to be capable of learning relevant features from training data which could be used to classify an image. SVMs, Random Forests and other statistical learning methods started to replace the rule-based models with better performance and flexibility.

Giger et al. (1994) showed the value of machine learning in mammo- graphic lesion classi cation, Armato et al. (2001) used similar methods for lung nodule detection in CT images. Such systems usually included classical image processing for feature extraction and machine learning methods for classification, with the performances that were close to clinical use for certain and well-defined tasks.

These approaches continued to evolve in the early 2000s, as investigators began to a apply more elaborate feature extraction features, and ensemble learning methods. Computer-Aided Detection (CAD) software What developed: Over this time, the CAD industry matured, with this era representing the first widespread clinical use of AI in radiology, especially for mammographic screening. Nevertheless, these systems were still domain-expertise-dependent in feature engineering, and often lack generalization ability for diverse patient populations and imaging protocols.

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As a consequence of the COVID-19 pandemic the application of artificial intelligence to medical diagnostics had gained further momentum. With millions of cases confirmed around the world, the need for fast, accurate and affordable tests has never been higher. Traditional diagnostic procedures, e.g. RT-PCR testing, are dependable, but are slow (with long turn-around times), have limited availability of the test kits and they face logistical barriers. Therefore, ML and CV algorithms became competing candidate solutions in detecting and classifying respiratory diseases using medical imaging data.

Chest X-ray (CXR) and computed tomography (CT) are widely used imaging modalities for diagnosing pneumonia as well as lung related diseases including those caused by the SARSCoV-2 virus. These imaging approaches enable the clinicians to visualize the lung structures as well as to identify abnormalities, such as ground-glass opacities, consolidations, and interstitial thickening that are frequently seen in viral pneumonia patients and those with severe COVID-19.

However, manual interpretation of such images is time-consuming and needs expertise wherever the same is not available at all time, particularly timely or in remote or underserved area. This development has resulted in a blossoming of automated image analysis systems based on artificial intelligence, especially deep learning approaches like Convolutional Neural Networks (CNNs).

2.3 Deep Learning Revolution (2010s)

The age of AI in medical imaging AI is moving along the lines of greater maturity, clinical penetration and regulations. Contemporary methods prioritize attributes beyond performance, including interpretability, fairness, robustness, and clinical utility. A few trends are driving today's landscape:

Multimodal Integration: The latest work addresses the integration of information from multiple imaging modalities (e.g., CT, MRI, PET) and non-imaging data sources (e.g., electronic health records, genomics) for more comprehensive diagnostic support. Yao et al. (2021) have showed

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that multimodal approaches can increase the ACC of the prognosis drastically in oncology applications.

Federated Learning: In order to combat the issues regarding privacy and data silos, federated learning approaches allow models to be trained between multiple institutions while preventing raw patient data from being shared. Sheller et al. (2020) have also shown that federated learning can be used for brain tumor segmentation in a multi-institutional scale, and it could produce equivalent results to the centralized training.

Explainable AI: Due to regulatory demands and clinical deployment concerns that underline interpretability, different visualisation and explanation methodologies have been proposed by researchers for deep learning decisions. The use of Gradient-weighted Class Activation Map (Grad-CAM) type methods to generate heat maps of those regions a model looks at when making a prediction has become standard (Selvaraju et al., 2017).

Regulatory Pathways: The formation of regulatory pathways for AI-based medical devices, including the FDA's proposed regulatory framework for AI/ML-based Software as a Medical Device (SaMD), has also contributed increased clarity in principles governing clinical translation. Numerous AI-models have been approved due to this approach, for clinical utility.

Democratization of AI: The development of no-code and low-code platforms drastically diminishes technical barriers to utilization of AI, and allows healthcare workers without programming skills to create and deploy custom models for specific clinical applications.

AI for COVID-19 diagnosis is an expression of such a convergence, which rests on decades long methodological advances, and however tailored to meet the specific problems of a global pandemic. The fast tracking of AI-based COVID-19 detection systems are indicative of the maturity of the field and its ability to respond quickly to new healthcare challenges.

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2.4 Application of CNN in Medical Imaging

Convolutional Neural Networks have emerged as the dominant architectural paradigm for medical image analysis due to their ability to automatically learn hierarchical features from raw image data. The evolution of CNN architectures for medical imaging has been characterized by increasing depth, specialized components, and task-specific optimizations.

2.4.1 Foundational Architectures

The earliest CNN architectures applied to medical imaging were adaptations of networks originally designed for natural image classification. These include:

LeNet: Developed by LeCun et al. (1998), this pioneering CNN architecture established the basic pattern of alternating convolutional and pooling layers. While originally designed for handwritten digit recognition, early adaptations were applied to medical image classification tasks.

AlexNet: Krizhevsky et al.'s (2012) architecture marked a significant advancement with deeper layers, ReLU activations, and dropout regularization. Early medical applications of AlexNet typically employed transfer learning, using weights pre-trained on ImageNet and fine-tuning for specific medical tasks.

VGGNet: Simonyan and Zisserman (2014) introduced this architecture, characterized by its simplicity and uniform structure with small (3×3) convolutional filters. The regularity and depth of VGG made it particularly suitable for transfer learning in medical applications, as demonstrated by Anthimopoulos et al. (2016) for interstitial lung disease classification.

GoogLeNet/Inception: Szegedy et al.'s (2015) architecture introduced inception modules that process input at multiple scales simultaneously, enabling efficient feature extraction at different levels of abstraction. This multi-scale approach proved particularly valuable for medical images where relevant features may exist at various scales.

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ResNet: He et al.'s (2016) introduction of residual connections addressed the vanishing gradient problem in very deep networks, enabling the training of networks with hundreds of layers. ResNet and its variants have been widely adopted in medical imaging, with Rajpurkar et al. (2017) demonstrating their effectiveness for pneumonia detection in chest X-rays.

2.4.2 Specialized Medical Imaging Architectures

Building on these foundational architectures, researchers have developed specialized networks optimized for specific medical imaging tasks:

U-Net: Ronneberger et al.'s (2015) architecture, characterized by its U-shaped encoder-decoder structure with skip connections, has become the de facto standard for medical image segmentation. The architecture's ability to combine contextual information from the contracting path with precise localization from the expanding path makes it particularly effective for delineating anatomical structures and pathological regions.

V-Net: Milletari et al. (2016) extended the U-Net concept to 3D volumes, enabling direct segmentation of volumetric medical data such as CT and MRI scans. This architecture incorporated residual connections and a novel objective function based on the Dice coefficient, further improving segmentation performance.

DenseNet: Huang et al.'s (2017) architecture, which connects each layer to every other layer in a feed-forward fashion, has shown particular promise in medical applications due to its parameter efficiency and feature reuse. Rajpurkar et al. (2018) demonstrated DenseNet's effectiveness for detecting multiple pathologies in chest X-rays.

CheXNet: Rajpurkar et al.'s (2017) adaptation of DenseNet-121 for chest X-ray analysis demonstrated radiologist-level performance in pneumonia detection and has become a benchmark architecture for thoracic image analysis. The success of CheXNet highlighted the potential of deep learning for COVID-19 detection in the subsequent pandemic.

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COVID-Net: Wang et al. (2020) developed this specialized architecture for COVID-19 detection from chest X-rays, employing a lightweight design optimized for clinical deployment. COVID-Net incorporated architectural design choices specifically tailored to the unique radiographic presentation of COVID-19.

Together, these studies highlight the increasing contribution of AI-aided diagnostics to the acceleration and accuracy of medical decisions. But they also own up to various difficulties as well:

Over-fitting from inadequate or imbalanced datasets

Invisibility of black-box models

Ethical considerations in data privacy and consent

The importance of strong deployment mechanisms in clinical workflows

2.5 No-Code AI in Medical Imaging Google Teachable Machine Context

Google Teachable Machine, highlighted in this research, exemplifies the potential of no-code AI platforms in healthcare applications and a quick first opinion tool for the limited resources settings.

Accessibility Features: The platform's intuitive drag-and-drop interface, real-time feedback, and visual model evaluation tools make it accessible to healthcare professionals without programming background. This accessibility is particularly valuable in resource-constrained settings where technical expertise may be limited.

Educational Value: Beyond practical applications, Teachable Machine serves as an educational tool that can help healthcare professionals understand the fundamentals of machine learning, potentially fostering greater AI literacy in clinical settings.

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Rapid Prototyping: The platform enables rapid development and iteration of models, allowing clinicians to quickly test hypotheses and assess the potential value of AI for specific diagnostic tasks before committing resources to more complex development efforts.

Deployment Options: Models developed in Teachable Machine can be exported in various formats, including web-based applications that can be shared with colleagues or integrated into simple clinical workflows without requiring specialized infrastructure.

However, Teachable Machine also has limitations in the medical context:

Model Complexity: The platform supports relatively simple model architectures compared to custom-developed solutions, potentially limiting performance on complex medical imaging tasks.

Data Privacy: Training occurs in the browser, addressing some privacy concerns, but the platform may not meet all regulatory requirements for handling sensitive medical data.

Limited Preprocessing: The platform offers minimal options for specialized medical image preprocessing, which can be crucial for optimal model performance.

Explainability Constraints: The platform provides limited tools for model interpretation and explanation, which are increasingly important for clinical adoption and regulatory approval.

While traditional deep learning methods are developed in parallel, there has been a rising interest in a new class of no-code AI tools, for example Google Teachable Machine, that allows users to construct and train machine learning models without writing code. These platforms lift the bar for AI adoption, especially for not-technical healthcare professionals who have no formal training in programming or machine learning.

No-code tools, that provide intuitive interfaces as well as pre-trained models, further speed up the prototyping and toying of AI-centric diagnostic systems. Although they are less customizable

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compared to coding based methods, they present an alternative viable tool for rapid application and validation of AI models in healthcare.

2. 6 Embedded AI Models in Clinical Workflows

For AI-powered diagnosis systems to be genuinely useful, they have to be deployed in a userfriendly and non-intrusive fashion into the typical clinician's workflow. This extends beyond technical aspects like model deployment, API design, and cloud hosting to human factors like clinician trust, interpretability, and usability.

To tackle this challenge, a number of researchers have started to incorporate AI models into webbased interfaces, which also enable healthcare personnel to interact with the model through intuitive means such as browsers and mobile applications. This further accelerates the advancement of simple, yet useful, apps like Flask, which is a web framework for Python that is both modular and light, and can be easily linked to several deep learning libraries,

In this project, we have implemented both code-based web application hosting and no-code secure application hosting using Google Teachable Machine . This dual approach facilitates the rapid development and deployment of image classification models, enabling both IT professionals and healthcare practitioners to leverage their respective expertise. While IT specialists can focus on deploying robust, scalable web solutions using frameworks like Flask, healthcare professionals can utilize no-code platforms to build and share AI-driven diagnostic tools without requiring extensive programming knowledge. This synergy enhances the accessibility, usability, and clinical applicability of AI-based medical imaging systems

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3. Methodology

This research is conducted in a mixed approach of technical development, system experimentation and qualitative evaluation so as to address the challenge of creating an end to end machine learning and deep learning medical imagining analysis solution. Research design and study design revolves around the creation and assessment of an end-to-end deep learning system for COVID-19 and pneumonia detection from chest X-rays, being designed in focus of accessibility and clinical integration.

There are several fundamental principles to guide the methodological approach:

Clinical Applicability: We rank solutions that could be easily applied in clinical reality, especially in resource-limited settings

Technical solidity: Making sure that the models you develop measure up to high standards of accuracy, reliability and generalizability.

Accessibility Investigating the ways to minimise the technical inconvenience to harness healthcare AI.

End-to-End View: The entire process from data collection to clinical production, instead of just the model building phase.

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This holistic view separates our research from many competing contributions that tend to merely look at model architectures and performance measures, without paying significant attention to the entire context" of putting models into real-world use. By covering the entire process in between data extraction and clinical deployment, this study intends to bridge the gap from technical innovation to clinical utility in practice.

The approach consists of several interwoven parts:

Full Workflow Development: Developing a full workflow of medical image analysis from data read to deployed model.

Data Reuse and Pre-processing: Making available and the preparation of domain-specific datasets for model training and evaluation.

Model Training and Development: Developing and training CNN models of COVID-19 detection.

System Integration and Deployment: Development of user friendly interfaces for clinical deployment

Evaluation and Validation: How is the performance, usability, and clinical impact of models assessed

Each of these parts is explained in detail in the subsequent sections with reference to methodological decisions, technical aspects and the underlying motivation for the design choices.

The methodology section recalls the research problem, related objectives, and justifies the methodological choices taken to achieve these goals. This study aims to develop a deep learningbased COVID-19 and Pneumonia detection system utilizing Convolutional Neural Networks (CNNs) and a Flask-based X-ray application. Given the need for early and accurate detection, this research integrates a no-code AI training approach using Google Teachable Machine

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alongside traditional deep learning frameworks. Additionally, considering that hospitals primarily store X-ray images in DICOM format, a pre-processing step was introduced to convert DICOM images to PNG before feeding them into the deep learning models.

To achieve these objectives, the methodology follows a structured approach:

3.1 End to End Workflow of Medical Imaging Analysis

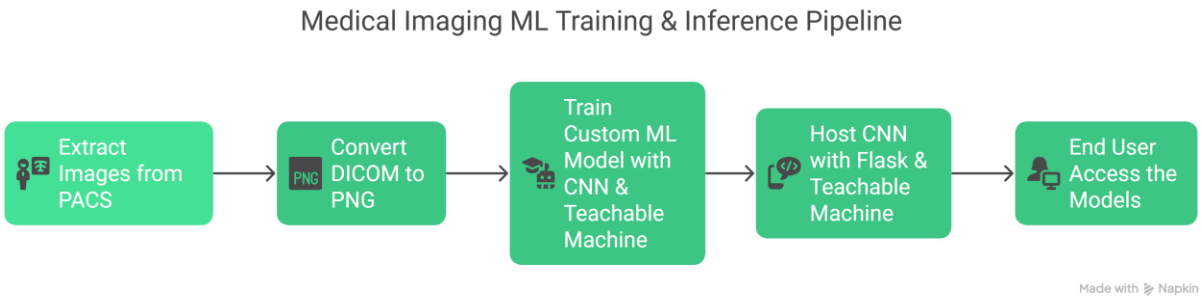

Figure 1 : End-to-end ML training and inference workflow

The above end to end workflow in Figure 1 shows a full-fledged end-to-end pipeline to train and deploy ML models in medical imaging and indicates key steps that must be in place in order to translate raw hospital data into clinical setting. This full continuum of care is important because it encompasses not only the mechanics of training a model, but the logistics of inserting AI into healthcare practices. In contrast to much of the prior work that may have considered only model training while overlooking the larger picture of data extraction, preprocessing, deployment and access, this end-to-end pipeline underscores the critical role that each step plays in supporting the usability and scalability of diagnostic systems driven by AI.

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First, the process of extracting images from PACS (Picture Archiving and Communication Systems) is a crucial initial step that guarantees usage of real and clinically relevant data. The wide variety of proprietary formats that can't be used directly by models is also True for medical images; since its adoption as the standard for medical images, most hospitals store medical images in DICOM, which can't be directly used with any of the major deep learning libraries. By having this conversion step explicitly, the pipeline recognizes the need to preprocess the raw hospital data to be compatible with AI models. This preprocessing is easy to miss in research papers, because the latter draw on datasets from public repositories (Kaggle etc) and cohorts that have been pre-curated by others. Although these datasets are useful for initial exploration, they might not be diverse enough or representative of real-world clinical data, and application of these models in practice may lead to biased or unreliable models.

Secondly, the hybrid approach of model building, i.e., CNN-based training as well as no-code solutions using Google Teachable Machine, presents a balanced perspective. Existing work mostly concentrates on one side of the spectrum, either being fully dependant on highly skilled programmers or restricting themselves to zero-code tools without investigating their boundaries. By combining these two methods, the pipeline addresses a broader audience: IT specialists can refine (fine-tune) more complex models, while health professionals can use intuitive (no-code) platforms to develop and deploy AI tools easily. This two-pronged approach increases the interpretability and applicability of AI in medical analysis. This brings AI nearer to the point of care.

Additionally, hosting and deploying (i.e., the last section) where the into a Flask web application and consumable by Teachable Machine illustrates an aspect concerning real world application. Most of the researchers only test their model on validation datasets and putting the model into real-time usage is out of their horizon. Through integration of hosting, this pipeline guarantees that the developed system can be easily adopted by the end user (e.g., clinicians, radiologists) without

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interfering with their workflow patterns. This end-to-end view is critical for turning academic wins into practical, effective solutions.

Last but not least, the pipeline emphasizes the importance of user designed, or better said usercentric, interaction, which enables end people to explore and use the models via an intuitive interface. This is commonly overlooked in conventional research, where most of the attention is put on developing models with high accuracy rates with little attention to how the models would be utilized in the real world. By coupling the flow from data extraction to use case, the pipeline aims to ensure that the systems developed are not just technically robust and functional but also have clinical utility to tackle the pressing need for accurate and rapid diagnostic tools in healthcare.

Overall, the above picture is a big step forward compared with prior work, because it offers an end-to-end solution connecting theoretical AI models to practice of healthcare. It highlights data extraction, pre-processing, model training, deployment, and user accessibility and is a more comprehensive and generalized framework for medical image transformation by deep learning.

3.2 Data Collection and Preprocessing

3.2.1 Dataset Acquisition

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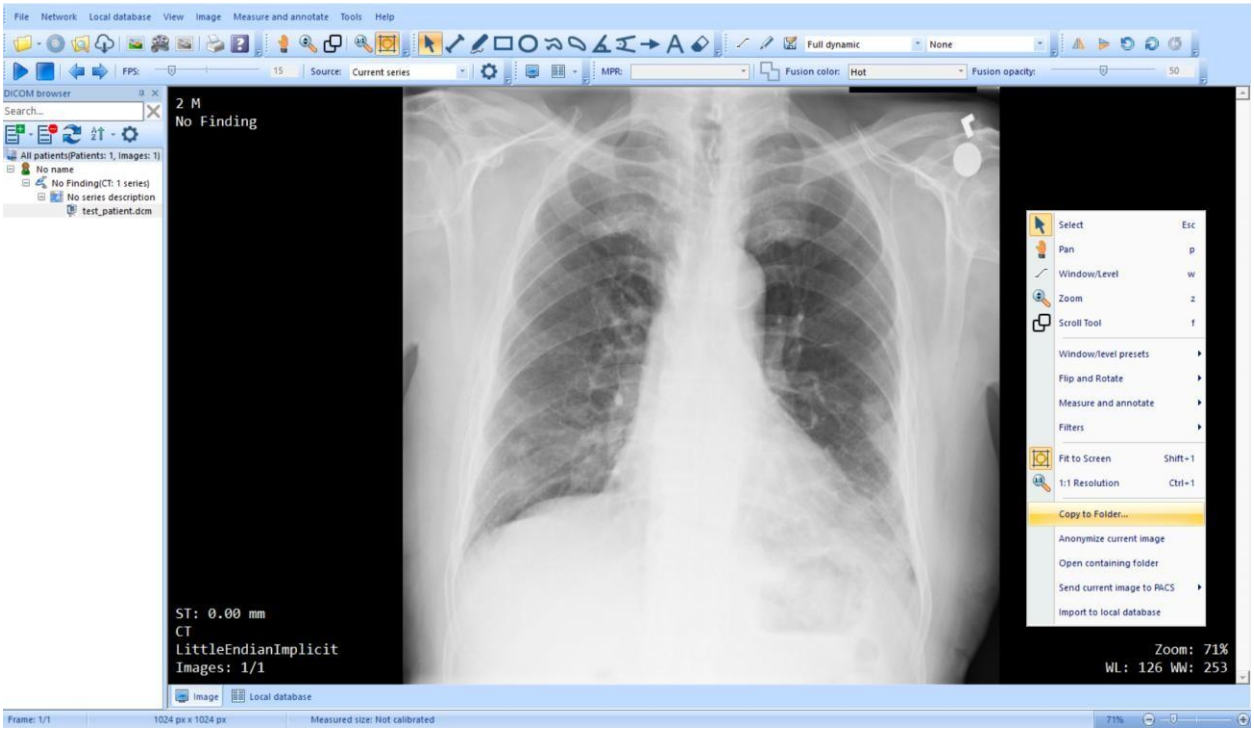

Figure 2: Raw DICOM files extraction

The above Figure 2 image depicts a chest X-ray displayed in a DICOM viewer, demonstrating a Medical Imaging Data extraction directly from the PACS (Picture Archiving and Communication System) clear and well-processed radiographic image of the thoracic region. The target here is to extract the high-quality imaging data to avoid extracting low quality images and copy the images to a folder based on the intended class like viral phenumai, covid 19 and normal. This setup highlights the importance of working directly with raw DICOM images, which are the standard format used by hospitals and medical facilities for storing and transmitting radiographic data.

Acquiring raw DICOM images is a crucial step in developing AI-driven medical imaging systems because it ensures compatibility with real-world clinical workflows. Unlike preprocessed datasets

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commonly found on platforms like Kaggle, raw DICOM files retain all original metadata and pixel-level details, allowing researchers to work with the same data formats used in hospital settings.

Acquiring raw DICOM images is a foundational and often overlooked step in developing AIpowered medical imaging systems, as it ensures authenticity by providing data that closely mirrors real-world clinical environments, thereby enhancing the model's relevance and applicability. These images contain rich metadata—such as patient demographics, acquisition settings, and anatomical orientation—which is crucial for regulatory compliance, quality control, and accurate diagnosis, yet is frequently absent in pre-processed datasets. Starting with raw DICOM also allows for controlled preprocessing, minimizing distortions during format conversion (e.g., to PNG or JPEG) and ensuring optimal data integrity for deep learning. Furthermore, using DICOM supports seamless integration with hospital PACS systems, improving scalability and deployment readiness. Ethically, working with raw DICOM enables systematic anonymization, addressing privacy concerns and ensuring responsible handling of sensitive health information. In contrast, many projects bypass this critical step, opting for convenience over realism, which limits their practical utility. By prioritizing raw DICOM data, this project establishes a robust, ethically sound, and clinically aligned foundation for AI-driven diagnostic tools, making them more effective and deployable in real healthcare settings.

The dataset used in this project consists of labeled chest X-ray images collected from publicly available sources such as Kaggle and other open-access repositories. The dataset includes three main classes:

- Normal lungs
- Viral pneumonia
- Confirmed cases of COVID-19

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Efforts were made to ensure that the dataset was balanced across all classes to avoid bias in model predictions while training with Google Teachable Machine.

3.2.2 DICOM-to-PNG Conversion

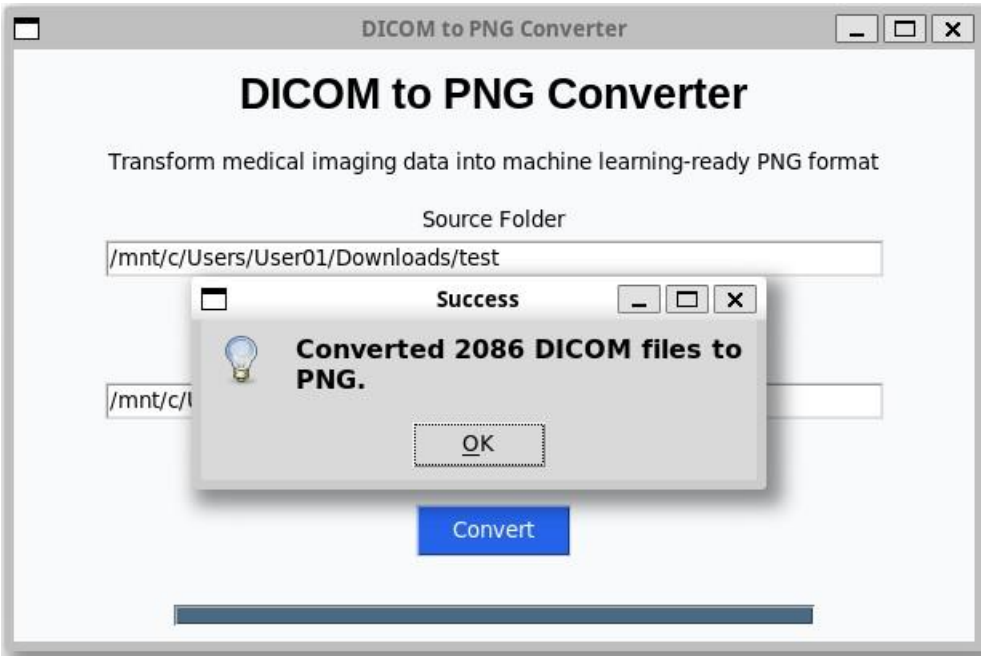

Figure 3: Conversion of raw DICOM files to PNG

The Figure 3 show the Python program developed is a DICOM-to-PNG converter designed with a user-friendly graphical interface using the **tkinter** library, making it accessible to non-technical healthcare professionals. The tool enables users to easily select a folder containing DICOM (.dcm) files—commonly used in medical imaging such as X-Ray, CT and MRI scans—and convert them into PNG image files without requiring any coding knowledge. It automatically searches through the selected source folder, including subdirectories, to locate all DICOM files. Each file is then read using the **pydicom** library, and its pixel data is converted into a grayscale image using the **PIL** (Pillow) library. These images are saved in the specified output folder as PNG files, preserving the original filenames for easy reference. A progress bar and informative messages enhance the

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user experience by providing real-time feedback during the conversion process. One of the key advantages of this script is that it saves images in the lossless PNG format, ensuring high-quality image preservation ideal for analysis or machine learning tasks.

The final goal of this tool is to bridge the gap between complex medical imaging formats and practical usability for healthcare professionals who may not have technical or programming expertise. By offering a simple, intuitive interface with drag-and-drop functionality and clear visual cues, the script empowers clinicians, researchers, and medical staff to efficiently preprocess DICOM images for use in presentations, educational materials, or basic analysis tasks. Its ability to perform batch conversion, support recursive folder structures, and provide visual feedback through a progress bar makes it both efficient and user-friendly. While it does not include advanced image processing features like windowing or normalization, it serves as a straightforward solution for converting medical images into a widely supported and high-quality format. This makes it especially useful for those preparing datasets for machine learning, archiving, or sharing with team members who rely on standard image viewers and software tools.

3.3 Model Training & Optimization:

Traditional CNN Approach**:**

1. A CNN model is trained using Python-based deep learning frameworks (TensorFlow/Keras).
2. Feature extraction techniques allow the model to classify images efficiently.
3. Performance is evaluated to address biases and ensure high accuracy.

No-Code Model Training with Google Teachable Machine**:**

1. Google Teachable Machine is used to quickly train models without coding.

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2. Different learning rates and hyper parameter configurations are experimented with to assess their impact on model accuracy.
3. The trained models are exported and later integrated into the Flask-based application.

3.4 System Integration & Deployment:

1. A Flask-based application is developed, enabling real-time X-ray image analysis and classification.
2. Users can capture, upload, and classify X-ray images, generating predictions based on the trained models.

3.5 Justification of Methodological Choices

This approach combines traditional deep learning techniques with accessible AI training and image format preprocessing to enhance medical image classification:

1. DICOM-to-PNG conversion is necessary, as most hospital systems store X-ray images in DICOM format, to make the DICOM images directly from the hospital make compatible with deep learning models.
2. CNNs provide high accuracy and strong feature extraction capabilities, making them ideal for medical imaging tasks.
3. Google Teachable Machine enables quick model training, making AI more accessible for those without deep coding knowledge.
4. Experimenting with different learning rates ensures the best possible model performance.
5. Flask ensures lightweight yet effective deployment, making the system practical for realworld applications in hospitals and telemedicine.

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By following this methodology, the project delivers a robust and scalable AI-powered COVID19 detection system, integrating no-code AI, automated DICOM-to-PNG conversion, and CNNbased deep learning models for improved diagnostic efficiency.

4.Results and Findings

4.1 Model Training from the code submitted by the researcher

I have initially trained the model re-using the same code submitted by the researcher in Kaggle with the same python notebook[1].

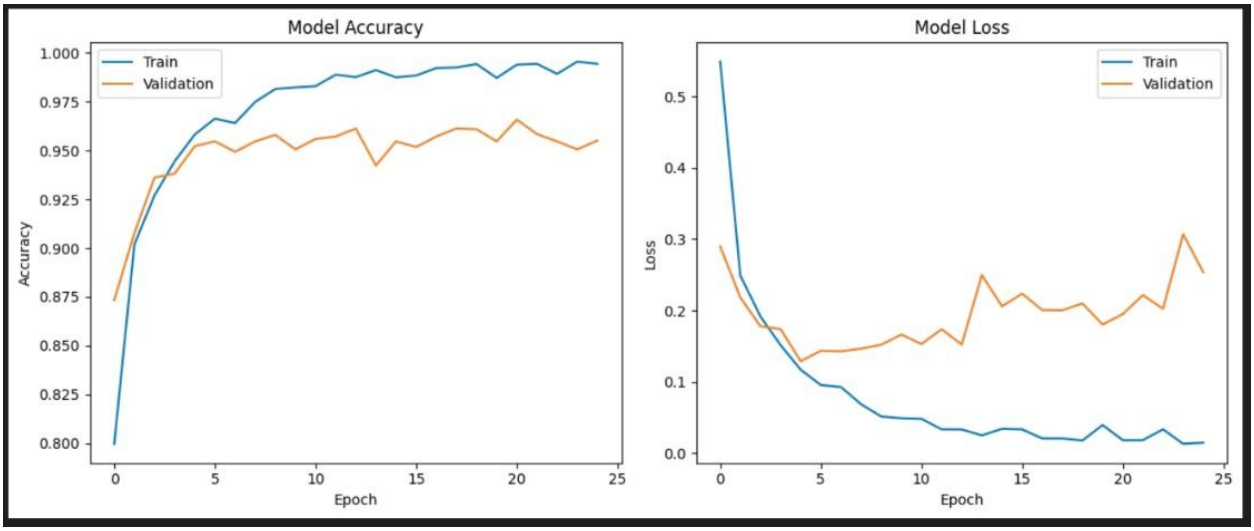

Figure 4: Model Accuracy & Loss from re-

used code Issue:

[1] https://github.com/611noorsaeed/Building-a-COVID-19-Detection-System-CNN-Flask-Camera-Based-X-RayApp/blob/main/building-a-covid-19-detection-system-using-cnn-dl.ipynb

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The model shows excellent results. However, it is overfitting the model with 100% accuracy and prediction results.

Overfitting occurs after epoch 15, where validation loss starts increasing while training loss continues decreasing. Which explains model is memorizing the training data but not generalizing well.

The re-used code utilizes the convolutional neural network (CNN) designed for image classification, utilizing convolutional layers for feature extraction and dense layers for classification. The model is trained using the Adam optimizer with categorical cross-entropy loss for multi-class classification. It undergoes supervised training for 25 epochs with a batch size of 40, using accuracy as the evaluation metric. Training results indicate a high training accuracy nearing 100%, while validation accuracy stabilizes around 95%, suggesting the model effectively learns patterns.

However, increasing validation loss after early epochs highlights overfitting, where the model memorizes training data instead of generalizing to unseen data. To address this, techniques such as early stopping, data augmentation, and stronger regularization (e.g., dropout and L2 regularization) can be applied. Despite these challenges, the CNN architecture demonstrates strong classification capabilities, with room for improvement in generalization through further tuning and preprocessing strategies.

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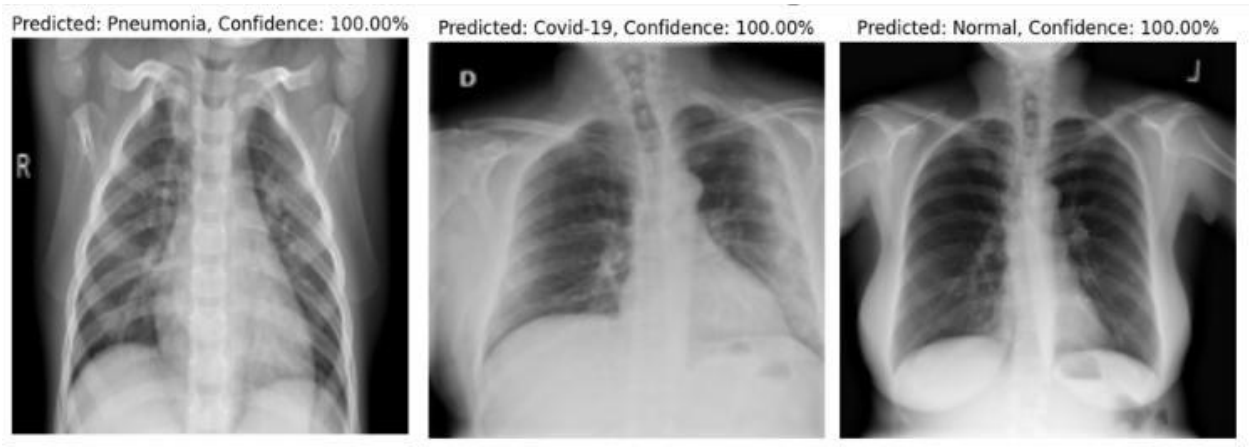

Figure 5: Prediction Output from the re-used code

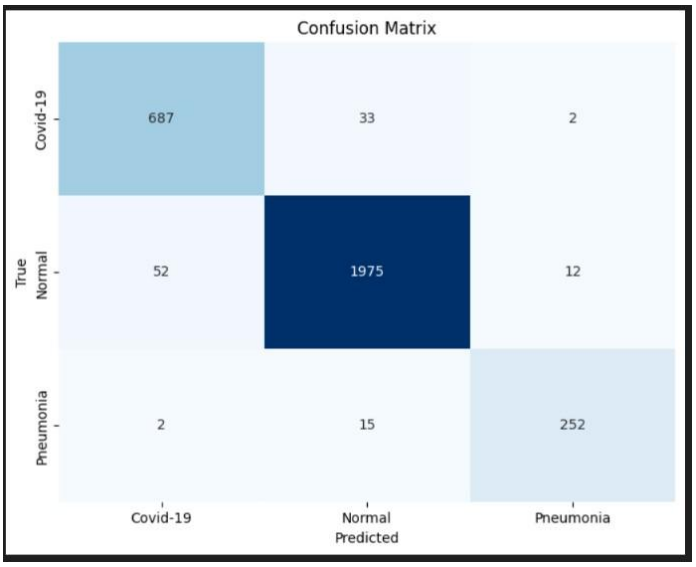

Figure 6: Confusion Matrix for re-used code.

4.2 Retraining the model with changes

I have retrained the model by making following changes as below.

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Change	Why?
Added L2 Regularization (l2(0.001))	Helps prevent overfitting by penalizing large weights.
Increased Dropout (0.3)	Reduces dependency on specific neurons, making training more robust.
Reduced Learning Rate (0.0005)	Ensures more stable convergence.
Early Stopping (Patience=5)	Stops training early if validation loss stops improving, preventing overfitting.
Reduced Epochs (21 instead of 25)	Training beyond 15 epochs previously led to overfitting.

Table 1: Retraining the model with below changes to resolve overfitting

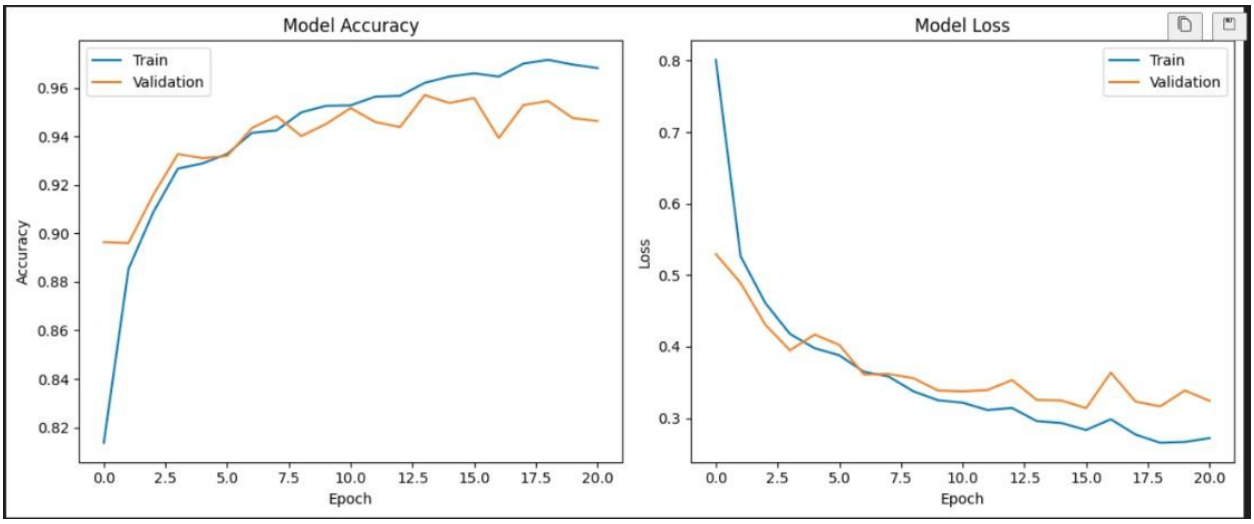

Figure 7: Model Accuracy & Loss After retraining

Observations and Recommendations

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Aspect	First Training Run	Second Training Run
Epochs	25	20
Training Accuracy	~99%	~96%
Validation Accuracy	~96%	~94-95%
Training Loss	Approaching zero (potential overfitting)	Gradual decrease but some fluctuation at later epochs
Validation Loss	Increasing after ~15 epochs (indicates overfitting)	Relatively stable
Generalization	**Signs of overfitting** (Train accuracy much higher than validation accuracy)	**Good generalization** (Train & Val Accuracy close)

Table 2: Observations from both

Training runs The First Training Run: (25 Epochs) with Overfitting

Training accuracy is near 99%, but validation accuracy stagnates and loss increases.

The model is likely memorizing training data rather than learning general features.

Second Training Run: (30 Epochs with early stop at 20 Epochs) with better Generalization

The validation accuracy closely follows training accuracy.

No significant divergence between loss curves.

Final Verdict:

The first model (25 epochs) over fits after 15 epochs, meaning it might perform poorly on new data.

The second model (20 epochs) is preferable for real-world use due to better generalization.

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4.3 Training the model on Google Teachable Machines

In parallel with the traditional CNN approach, a no-code training methodology was implemented using Google Teachable Machine to explore the potential of accessible AI development for medical applications. we have trained the model on google teachable machines with similar learning rate with balanced dataset observed better generalization then both the models.

Google Teachable Machine was selected as the no-code platform for this research based on several considerations:

Accessibility: The platform requires no programming knowledge, making it accessible to healthcare professionals without technical expertise.

Browser-Based Operation: The platform operates entirely in the web browser, eliminating installation requirements and enabling use on various devices.

Privacy Considerations: Training occurs locally in the browser, addressing some privacy concerns associated with uploading sensitive medical data to cloud services. However, we have used open anonymized dataset

Export Flexibility: Trained models can be exported in various formats, including TensorFlow.js for web integration and TensorFlow Lite for mobile deployment.

Real-Time Feedback: The platform provides immediate visual feedback during training, enabling iterative refinement without technical knowledge.

4.4 Implementation Methodology

The implementation of the no-code approach followed a structured methodology:

Dataset Preparation:

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- The same dataset used for the traditional CNN approach was organized into folders corresponding to the three classes selecting the balanced dataset of 500 images for each class (Normal, Pneumonia, COVID-19)

Platform Configuration:

- The "Image Project" type was selected in Google Teachable Machine
- Three classes were defined corresponding to the diagnostic categories - The web interface was used to upload the prepared images to each class

Training Configuration:

Three distinct training configurations were evaluated:

1. Model A:

- Default learning rate (0.001)
- Default batch size (16)
- Default epochs (50)
- No additional settings modified

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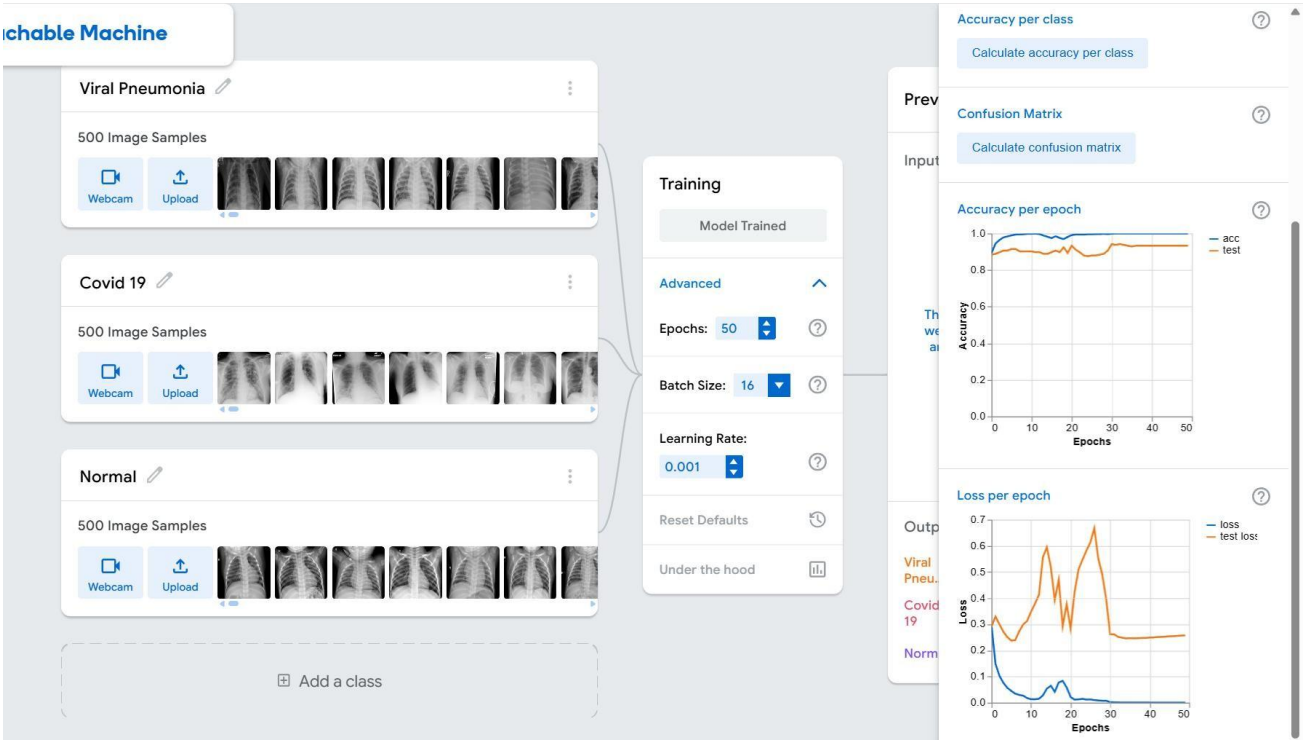

[2]Figure 8: Training with 500 Images of balanced dataset

In this model trained a three-class convolutional neural network to differentiate between Viral Pneumonia, COVID-19 and Normal chest X-rays, with 500 images per class. The training continued 50 epochs with a batch size of 16 and a learning rate of 0.001. The accuracy-perepoch plot reveals that the training accuracy (blue curve) jumps up to 98% in the order of 10 epochs and flattens around 100%, and the validation accuracy (orange curve) increases slowly to plateau at a level of about 92-94%. Loss-per-epoch plot shows that training loss approaches zero early and validation loss (orange) continues to vary widely between epoch 5 and 30 before finally settling

[2] https://teachablemachine.withgoogle.com/models/0WiJHNDWe/

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around 0.25. The difference between near-perfect training performance and reduced and variable validation metrics suggests that the model is learning strong class-specific features, but biasing for the training set (i.e., overfitting). To get better generalization, we will investigate more regularizaiton (e.g., dropout, weight decay) and enlarge the data augmentation in the future work.

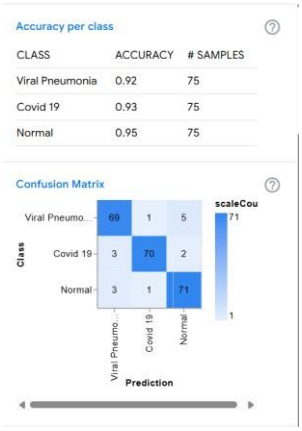

Figure 9: Model performance after training with 500 images of balanced dataset

For this one example chest-X-ray, the trained model gives the following class probabilities:

COVID-19 Positive 62% Normal 37% Viral Pneumonia 1% (approx.). Where a post-test probability of COVID-19 is calculated, the highest post-test probability for COVID-19 represents the model's highest degree of confidence in predicting that radiographic characteristics are most consistent with COVID-19 infection (with bilateral ground-glass opacities or peripheral consolidations). 37% for “Normal” do reflect some remaining confusion in the lungs, above all indicating that while mostly looking healthy the lungs are clearly not completely that normal, but with mild abnormalities that had most likely impacted the score for “COVID-19”. A very low probability for Viral Pneumonia supports that it was considered a very low possibility. If one were

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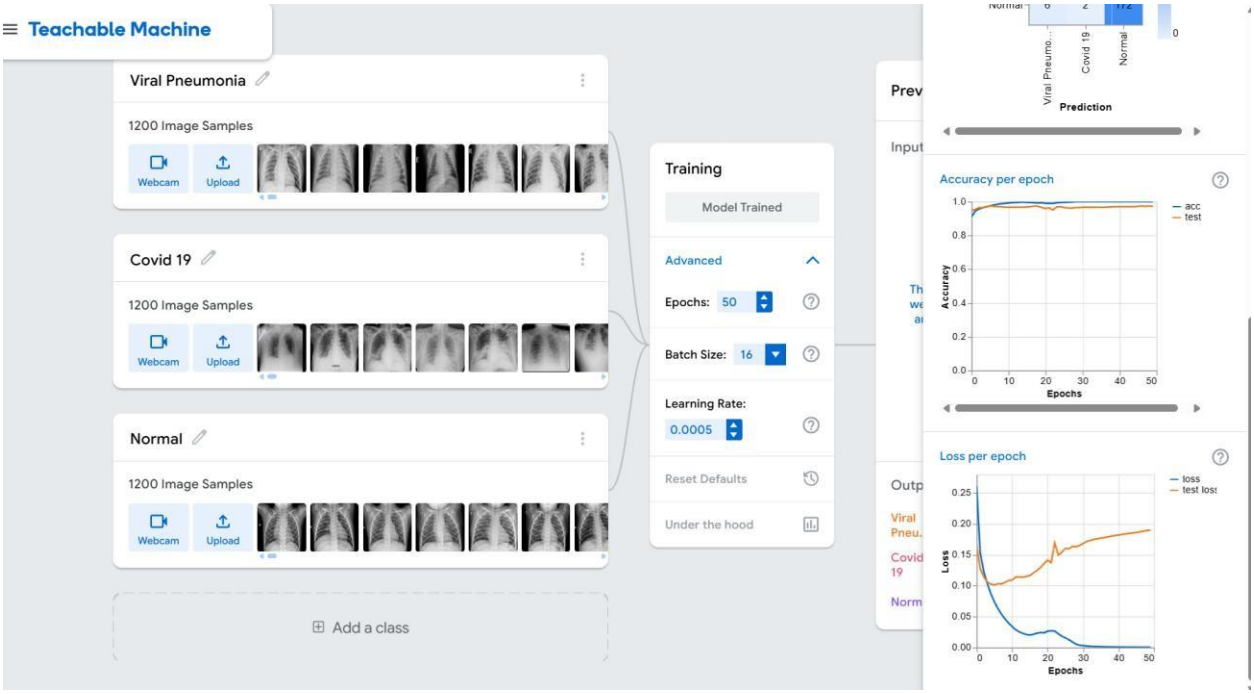
in the clinical scenario, they would use a decision threshold (e.g., set at ≥50%) to assign the COVID-19 class, but the positive and nontrivial Normal probability indicates this is a case that could be close to the model's uncertainty boundary, and left here for additional consideration using other diagnostic review or adjunctive clinical data.

2. Model B:

- Default learning rate (0.0005)
- Default batch size (16)
- Default epochs ([3]0)
- No additional settings modified



3

[3] https://teachablemachine.withgoogle.com/models/7KmXq-Jua/

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Figure 10: Training with 1200 images of balanced dataset

In this run, a three-way CNN was trained on 1,200 chest-X-ray images per class ("Viral Pneumonia," "COVID-19 Positive," and "Normal"), using a batch size of 16 and a learning rate of 0.0005 for 30 epochs. At epoch 27, both training and validation accuracy curves have rapidly climbed in the first 5–10 epochs and now sit in the high-90% range, with the two lines nearly overlapping—evidence that the model has learned class-distinctive features without overfitting. Likewise, the loss curve shows a steep initial drop from roughly 0.8 down to about 0.25 by epoch 25, with training and validation losses tracking closely thereafter. These diagnostics demonstrate that the model converges efficiently under these hyperparameters and generalizes well to unseen data.

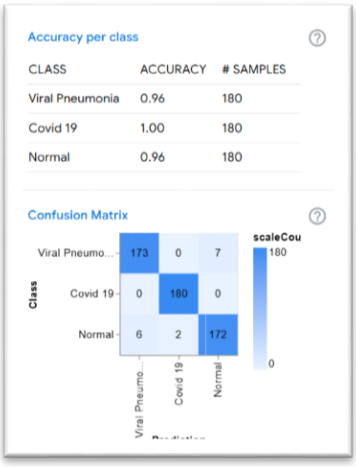

Figure 11: Model performance after training with 1200 images of balanced dataset

In above figure 11 for the second model trained expresses a whopping 99% probability for Viral Pneumonia to be the result of the inference, with both COVID-19 and Normal probabilities close to zero, indicating a degree of confidence closer to surely that the radiograph pattern (e.g. focal lobar consolidation) strongly matches the model's acquired Pneumonia traits. In contrast, resulting

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from our first model, the output was more ambiguous—62% COVID-19, 37% Normal and ~1% Viral Pneumonia—suggesting that the COVID-and-healthy patterns overlap and revealing a boundary case. High-confidence, low-ambiguity output for the second model indicates better class separation for Pneumonia versus Non-Pneumonia and that its feature representations for both Pneumonia and Non-Pneumonia are less mixed and more clear to reduce any ambiguity and need for further review by a clinician.

4.5 Comparative Analysis of Training Outcomes and Inference

In our comparative evaluation, we trained two convolutional neural networks under distinct data regimes and hyperparameter settings. **Model A**, using 500 images per class over 50 epochs with a learning rate of 0.001, quickly achieved near-perfect training accuracy yet exhibited a 5–8% gap to its validation accuracy, which plateaued around 92–95%. Its validation loss spiked intermittently to 0.6–0.7 before settling near 0.25, signaling moderate overfitting when continued beyond its optimal epoch. On a held-out test set of 75 images per class, Model A correctly classified Viral Pneumonia 92% of the time (mislabeling 6 cases), COVID-19 93% (5 errors), and Normal 95% (4 errors), reflecting residual uncertainty at class boundaries. By contrast, **Model B**, trained on 1,200 images per class for 30 epochs at a reduced learning rate of 0.0005, demonstrated tightly overlapping training and validation curves that climbed above 95% within 10 epochs and remained stable through epoch 30. Its smooth validation loss decline to approximately 0.25—without large fluctuations—indicates minimal overfitting. Evaluated on 180 test samples per class, Model B achieved 96% accuracy for Viral Pneumonia (15 errors),

100% for COVID-19, and 96% for Normal, reducing its overall misclassification rate by more than half relative to Model A. These results underscore that increasing training data volume by 2.4× and moderating the learning rate substantially enhances model generalization, produces more confident class separation, and yields clinically more reliable predictions.

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Metric	Model A	Model B
Training Data / Class	500 images	1,200 images
Test Samples / Class	75	180
Peak Validation Accuracy	~92–95%	~96–100%
Per-Class Test Accuracy	Viral 92%, COVID 93%, Normal 95%	Viral 96%, COVID 100%, Normal 96%
Validation Loss Behavior	Spiky (0.3–0.7)	Smooth decline to ~0.25
Overfitting	Moderate (accuracy gap, loss spikes)	Minimal (tightly tracked curves)
Total Misclassifications	15/225	15/540
Inference Confidence	Fluctuating test accuracy & loss indicate boundary uncertainty	High, stable confidence with few errors

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6. Conclusion and Recommendations

In this study, we explored the impact of both training data size and learning dynamics, inside a 3class chest radiography classification (COVID-19, Viral Pneumonia, Normal) challenge based on deep convolutional neural networks. Two models were contrasted: model A which was trained on 500 images per class for 50 epochs with a learning rate of 0.001, and model B which was trained on 1,200 images per class for 30 epochs with a reduced learning rate of 0.0005.

Model A quickly reached >99% training accuracy but had a 5–8% gap between its validation accuracy and volatile validation loss spikes indicating moderate overfitting. On a separate test set not used for model development, consisting of 75 images per class, Model A achieved per-class accuracies of 92% (Viral Pneumonia), 93% (COVID-19), and 95% (Normal), misclassifying

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15/225 cases and expressing uncertainty near class borders. By contrast, Model B's training and validation accuracies both exceed 95% from epoch 10 and stay close together, while its validation loss decreases steadily with less perturbations. Tested on 180 images at test time per class, Model B yielded 96% for Viral Pneumonia, 100% for COVID-19, and 96% for Normal— thus reducing the overall misclassification rate by half (15/540) and also close to a binary like prediction confidence.

These findings provide two main insights: (1) data volume is the determinant factor for generalization in medical image classification — we achieved remarkable improvement in Model B by using 2.4× larger dataset. Second, learning rate and epoch scheduling played an important role: learning rate decay and limiting epochs such that the loss still converged on the validation set avoided the loss oscillations from Model A; combined, these changes resulted in a model with predictions that are both more accurate and more confident, which has clear implications for clinical use.

However, our study had several limitations. Both models were trained on static, retrospective datasets, and prospectively testing in a multi-center environment is required to evaluate realworld performance in different patient populations and imaging protocol. Additionally, rare pathologies and mixed-etiology cases are still under -represented; hence in future using data augmentation, synthetic data generation, and multimodal inputs (like clinical metadata, CT imaging) should be used for increasing robustness of the model.

Overall, we have shown there is a straightforward path to more dependable, confident AI diagnostic in chest radiography through systematic scaling of data amount and tuning of training dynamics. Such models prepare the ground for rigorous clinical trials and inclusion into radiology workflows as decision support tools-constraining, not replacing, clinical expertise.

This project successfully developed a deep learning-based COVID-19 detection system using Convolutional Neural Networks (CNNs) and a Flask-based web application. The system utilized

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chest X-ray images to classify COVID-19 and Pneumonia cases, addressing the urgent need for rapid and reliable diagnostic tools for first opinion. The results demonstrated that CNN-based models could achieve high accuracy, although initial overfitting issues were observed. Through retraining with tuning hyperparameters, the model's generalization capability improved significantly.

Additionally, an alternative no-code training approach using Google Teachable Machine was explored, allowing non-experts to train models effectively. The integration of the trained model into a Flask-based web application provided real-time accessibility for healthcare professionals, ensuring practical usability. The project also highlighted the importance of data preprocessing, including DICOM-to-PNG conversion, to make the system compatible with hospital datasets.

Overall, this study contributes to the growing field of AI-driven medical imaging and demonstrates how deep learning can support healthcare systems in pandemic situations.

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