Convolutional Neural Networks (CNN)

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PDAN8412: Programming for Data Analytics Portfolio of Evidence

21st November 2025

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Introduction

This report presents the development and evaluation of a convolutional neural network for facial recognition, designed to address the need for automated identity verification systems at publishing premises. The increasing adoption of biometric authentication in commercial environments has driven demand for accurate and efficient facial recognition solutions that can operate reliably across diverse conditions (Learned-Miller et al., 2016). Deep learning approaches, particularly convolutional neural networks, have demonstrated exceptional performance in face recognition tasks by automatically learning hierarchical feature representations from raw pixel data (Parkhi et al., 2015).

The project utilises the Microsoft DigiFace-1M dataset, a collection of synthetic photorealistic facial images generated using advanced graphics rendering techniques (Bae et al., 2023). A subset of 150 unique identities was selected, providing 10,800 images for model development and evaluation. This dataset was specifically chosen to address privacy concerns associated with real facial data whilst maintaining the visual complexity and variation necessary for robust model training (Bae et al., 2023). The synthetic nature of the data ensures compliance with ethical guidelines for academic research without compromising the quality or realism required for effective deep learning applications.

The analysis employs Apache Spark for large-scale data processing and exploratory data analysis, demonstrating practical capabilities in handling substantial image datasets efficiently (Zaharia et al., 2016). The model architecture incorporates residual connections and depthwise separable convolutions, techniques that have proven effective in balancing model depth with computational efficiency (Chollet, 2017). These design choices enable the network to learn complex facial features whilst maintaining reasonable training times and parameter counts suitable for academic computing resources.

This report documents the complete machine learning pipeline from initial data exploration through to final model evaluation. The methodology section details the exploratory data analysis conducted using Spark, the feature engineering decisions informed by statistical analysis of colour channel distributions, and the architectural choices underlying the CNN design. Subsequent sections present the model training process, including hyperparameter optimisation through both manual experimentation and automated tuning using KerasTuner (O'Malley et al., 2019). The results section provides comprehensive evaluation metrics, including classification reports, confusion matrices, and visual inspection of predictions across challenging test cases. Finally, the discussion reflects on the model's strengths and limitations, contextualising the 97.6% test accuracy within the broader landscape of facial recognition research and identifying opportunities for future enhancement.

Dataset Selection and Justification

The selection of an appropriate dataset is fundamental to developing a robust facial recognition system, as the quality and characteristics of training data directly influence model performance and generalisability (Guo et al., 2016). For this project, a subset of the Microsoft DigiFace-1M dataset was selected, comprising 10,800 images representing 150 unique identities. This section evaluates the suitability of this dataset for training a convolutional neural network.

The DigiFace-1M dataset consists of photorealistic synthetic faces generated through advanced 3D rendering techniques, providing high-quality images that capture the visual complexity of real human faces without associated privacy concerns (Bae et al., 2023). Each identity includes exactly 72 images, yielding perfectly balanced class distributions that eliminate potential biases arising from unequal representation. This balance is particularly important for multi-class classification tasks, as imbalanced datasets can lead to models that perform well on majority classes whilst struggling with minority classes (He and Garcia, 2009).

All images maintain uniform dimensions of 112×112 pixels in RGB format, eliminating the need for complex resizing operations that could introduce interpolation artifacts (Howard et al., 2017). The synthetic generation process produces images with controlled lighting conditions, diverse facial expressions, varied head poses, and realistic accessories such as glasses and headwear (Bae et al., 2023). This diversity is essential for training models that generalise effectively to real-world scenarios where faces appear under varying environmental conditions.

The decision to use synthetic data rather than real photographic datasets addresses significant ethical and legal considerations. Traditional face recognition datasets such as Labelled Faces in the Wild contain images of real individuals, often collected without explicit consent for biometric analysis (Learned-Miller et al., 2016). Synthetic datasets circumvent these privacy concerns entirely, as the generated faces do not correspond to real individuals (Bae et al., 2023). This makes DigiFace-1M particularly suitable for academic research contexts where ethical approval and data protection compliance are paramount.

The dataset size of 10,800 images exceeds the minimum requirement of 10,000 records whilst remaining computationally manageable within academic computing constraints. Modern convolutional neural network architectures can achieve strong performance on datasets of this scale, particularly when augmented with techniques such as rotation, flipping, and zooming (Shorten and Khoshgoftaar, 2019). The 150-class classification problem presents sufficient complexity to demonstrate discriminative capabilities whilst avoiding extreme computational demands.

Preliminary analysis of channel variance confirmed meaningful variation in all three colour channels, with red, green, and blue channels exhibiting standard deviations of 0.397, 0.321, and 0.279 respectively. These statistics indicate that colour information provides valuable features for discrimination, justifying retention of all three channels rather than converting to greyscale

(Taigman et al., 2014). Validation using Apache Spark confirmed zero null or corrupted image files across all 10,800 records, indicating robust data quality (Zaharia et al., 2016).

The licensing terms of DigiFace-1M explicitly permit non-commercial research use, making it legally compliant for academic assessment purposes (Bae et al., 2023). The combination of technical suitability, ethical compliance, computational feasibility, and legal permissibility makes the DigiFace-1M subset an optimal choice for this facial recognition project.

Analysis Planning

Effective machine learning projects require systematic planning before execution to ensure all critical steps are addressed and potential challenges are anticipated (Géron, 2019). This section outlines the planned approach for developing the facial recognition CNN, following industry-standard practices for deep learning projects (Goodfellow et al., 2016).

Exploratory Data Analysis

The EDA phase will use Apache Spark for large-scale image processing, as Spark's distributed computing capabilities enable efficient handling of the 10,800-image dataset (Zaharia et al., 2016).

The planned steps include:

- Load 10,800 images using Spark's binary file reader
- Extract labels from directory structures (folder names represent identity IDs)
- Validate data integrity through null payload checks and corruption detection
- Verify image dimension uniformity (expect 112×112×4 RGBA format)
- Assess class balance distributions (expect 72 images per identity)
- Compute channel-wise pixel intensity statistics (mean and variance per RGB channel)
- Create visualisations including class balance bar charts, dimension distribution plots, and sample image grids demonstrating dataset diversity

Feature Selection

Feature selection planning will focus on determining whether to retain RGB colour information or convert images to greyscale (Taigman et al., 2014).

The planned approach includes:

- Calculate per-channel variance for red, green, and blue channels on sample images
- Apply decision rule where channel variance differences exceeding 0.01 will justify retaining RGB
- Remove alpha channels from RGBA images to convert to RGB format
- Normalise pixel values from 0-255 range to 0-1 range through division by 255
- Apply data augmentation techniques to compensate for modest dataset size (Shorten and Khoshgoftaar, 2019):
    - Horizontal flips to mirror faces
    - Random rotations of ±10% (approximately ±5.7 degrees)
    - Random zoom of ±20%
    - Random translations of ±20% horizontal and vertical

- Employ stratified random sampling to maintain class balance across training (70%), validation (20%), and test (10%) subsets

Model Training

The model architecture will be a custom CNN incorporating residual connections and depthwise separable convolutions, inspired by Xception architecture principles (Chollet, 2017).

The planned structure includes:

- Input layer accepting 112×112×3 RGB images
- Initial convolutional block with 128 filters, 3×3 kernel, stride 2, followed by batch normalisation and ReLU activation
- Three residual blocks with progressively increasing filter counts:
    - Residual block 1: 256 filters with separable convolutions and max pooling
    - Residual block 2: 512 filters with separable convolutions and max pooling
    - Residual block 3: 728 filters with separable convolutions and max pooling
- Final convolutional layer with 1,024 filters using separable convolutions
- Global average pooling layer to reduce parameters compared to flattening (He et al., 2016)
- Dropout layer with rate of 0.25 for regularisation
- Dense output layer producing logits for 150 classes (no activation function)

Training configuration specifications include:

- Adam optimiser with initial learning rate of 0.001 and cosine decay schedule reducing to 0.00001 (Loshchilov and Hutter, 2017)
- Batch size of 128 to balance training speed with generalisation performance
- Maximum of 50 epochs with early stopping configured with six-epoch patience monitoring validation accuracy
- Sparse categorical crossentropy loss function for efficient multi-class classification (Chollet, 2018)
- Model checkpoint callbacks to save the best-performing model based on validation accuracy
- Early stopping to restore best weights if training plateaus without improvement

Model Evaluation

Evaluation metrics will provide comprehensive assessment across multiple dimensions (Sokolova and Lapalme, 2009). The planned evaluation approach includes:

- **Primary quantitative metrics:**
    - Overall accuracy as baseline measure of correct prediction rate
    - Per-class precision to quantify confidence in positive predictions
    - Per-class recall to measure ability to identify all instances of each class
    - F1-scores as harmonic mean of precision and recall
    - Macro-averaged metrics (unweighted across classes)
    - Weighted-averaged metrics (class-size weighted)

- **Visualisation techniques:**

  - Training history plots showing accuracy and loss curves over epochs for both training and validation sets
  - Classification reports displaying per-class precision, recall, and F1-scores
  - Confusion matrices as 150×150 heatmaps revealing systematic misclassification patterns
  - Qualitative analysis through sample predictions on 6-12 random test images with true versus predicted labels

- **Success criteria established at:**
  - Test accuracy ≥ 90%
  - Train-validation accuracy gap < 10% to ensure limited overfitting
  - Validation-test accuracy gap < 5% to confirm generalisation
  - At least 80% of classes achieving F1-scores ≥ 0.85

Hyperparameter Optimisation

If the initial model fails to meet success criteria, a retraining strategy will involve both manual hyperparameter sweeps and automated optimisation using KerasTuner (O'Malley et al., 2019). The planned approach includes:

- **Manual hyperparameter sweep testing variant configurations:**
  - Baseline variant with dropout 0.25 and constant learning rate 0.0003
  - Regularised variant with dropout 0.35 and constant learning rate 0.0001
  - Each variant trained for 15 epochs to enable rapid comparison

- **Automated hyperparameter tuning using KerasTuner Hyperband algorithm:**
  - Explore dropout rates from 0.20 to 0.50 in increments of 0.05
  - Explore learning rates of 0.001, 0.0005, 0.0003, and 0.0001
  - Maximum of 10 epochs per trial with approximately 30 total trials
  - Objective function maximising validation accuracy

- **Comparative analysis frameworks:**
  - Visualise training curves across multiple model variants overlaying accuracy and loss
  - Create bar charts comparing final epoch metrics for training accuracy, validation accuracy, and validation loss
  - Develop efficiency tables showing epochs required to reach 50%, 60%, 70%, and 80% validation accuracy milestones
  - Select configuration with best validation accuracy and retrain for full 50 epochs if superior to baseline

Report Writing

The reporting plan will deliver a concise PDF document structured to present comprehensive findings whilst avoiding excessive length.

The planned structure includes:

- Dataset exploration findings with class balance analysis, dimension uniformity confirmation, and channel statistics
- Preprocessing decisions with statistical justifications for RGB retention and augmentation strategies
- Model architecture diagrams showing layer-by-layer breakdown and design rationale
- Training results with performance visualisations including accuracy and loss curves
- Comprehensive evaluation metrics with classification reports, confusion matrices, and sample predictions
- Hyperparameter optimisation outcomes comparing manual sweeps and automated tuning results
- Conclusions addressing model strengths, limitations, and recommendations for future enhancement
- Risk mitigation strategies for potential challenges including class imbalance, overfitting, underfitting, and computational constraints
- Validation checkpoints after each major phase to confirm progress towards 90% test accuracy target with well-generalised performance across all 150 identity classes.

Exploratory Data Analysis and Feature Engineering

Data Cleaning and Preprocessing

The dataset underwent rigorous validation to ensure data integrity before model training commenced. Initial data loading utilised Apache Spark's binary file reader to ingest all 10,800 PNG images from the DigiFace-1M subset (Zaharia et al., 2016). The loading process applied recursive file lookup with pathGlobFilter set to *.png, which successfully identified and loaded all image files. Label extraction employed regex pattern matching on file paths, extracting identity folder names as integer class labels ranging from 0 to 149.

Data integrity validation revealed exceptional dataset quality. Null value checks on binary payloads returned zero null content across all 10,800 images, confirming complete file integrity. Further validation using Spark's image format reader with dropInvalid enabled detected no corrupted or unreadable files, with all images successfully decoded and processed. This perfect data quality eliminated the need for any data removal or outlier filtering, allowing the complete dataset to proceed to model training without any samples discarded.

Image preprocessing focused on format standardisation and normalisation. The original images arrived in RGBA format with dimensions of 112×112×4, where the fourth channel represented transparency information. Since facial recognition tasks require only colour information, the alpha channel was automatically removed during dataset loading using TensorFlow's image_dataset_from_directory function, which converted all images to 112×112×3 RGB format (Chollet, 2018). Pixel value normalisation was implemented through a Rescaling layer as the first operation in the CNN architecture, dividing all pixel values by 255 to transform the input range from [0, 255] to [0.0, 1.0]. This normalisation ensures stable gradient descent during training by preventing extremely large activation values that could cause numerical instability (Goodfellow et al., 2016).

The dataset was partitioned into training, validation, and test splits using stratified random sampling with a fixed seed of 42 for reproducibility. The split ratios of 70%, 20%, and 10% yielded 7,513 training images, 2,216 validation images, and 1,071 test images respectively. Class balance was maintained across all splits due to the dataset's inherent perfect balance of 72 images per identity. To organise the data efficiently, images were copied into structured directory hierarchies following the pattern /dataset/organised/{train,val,test}/{identity_id}/{image_files}, preserving original files whilst creating an organised structure suitable for TensorFlow's data loading utilities.

Data augmentation was applied exclusively to the training set to artificially expand dataset diversity and improve model robustness (Shorten and Khoshgoftaar, 2019). The augmentation pipeline comprised four transformations: horizontal flips with 50% probability to mirror faces, random rotations within ±0.1 radians (approximately ±5.7 degrees) to simulate natural head tilt, random zoom of ±20% to handle varying camera distances, and random translations of ±20% in both horizontal and vertical directions to account for facial misalignment. Figure 1 demonstrates

the effect of these augmentation techniques, displaying a 3×3 grid of nine augmented versions of the same source image. Visual inspection of this figure reveals translation artifacts manifesting as black borders where faces shift near frame edges, zoom variations producing faces of different scales, and subtle rotation effects creating slight head tilt variations. Each training epoch generated unique augmented variants through stochastic application of these transformations, effectively creating infinite training variations from the original 7,513 training images.

Figure 1: Visualisation of 9 different augmented versions of a single source image

Exploratory Data Analysis with Apache Spark

Exploratory data analysis leveraged Apache Spark's distributed computing capabilities to efficiently process and analyse the 10,800-image dataset (Zaharia et al., 2016). A Spark session was initialised in local mode with the configuration set to utilise all available CPU cores through the local[*] master setting. This enabled parallel processing of image metadata extraction and statistical computations across multiple threads, significantly reducing analysis time compared to sequential processing.

The initial analysis focused on dataset composition and class balance. Spark's groupBy aggregation operation counted images per identity class, revealing perfect uniformity with exactly 72 images for each of the 150 identities. Statistical summary of the class distribution confirmed this balance with a mean of 72.0 images per class and a standard deviation of 0.0, indicating zero variance in class representation. Figure 2 presents a bar chart visualising this class balance, displaying 150 uniform bars each at height 72 across all identity labels from 0 to 149. This perfect balance eliminates concerns about class imbalance that typically plague real-world datasets, ensuring that accuracy is a meaningful metric and that no class weighting or sampling strategies are required during training (He and Garcia, 2009).

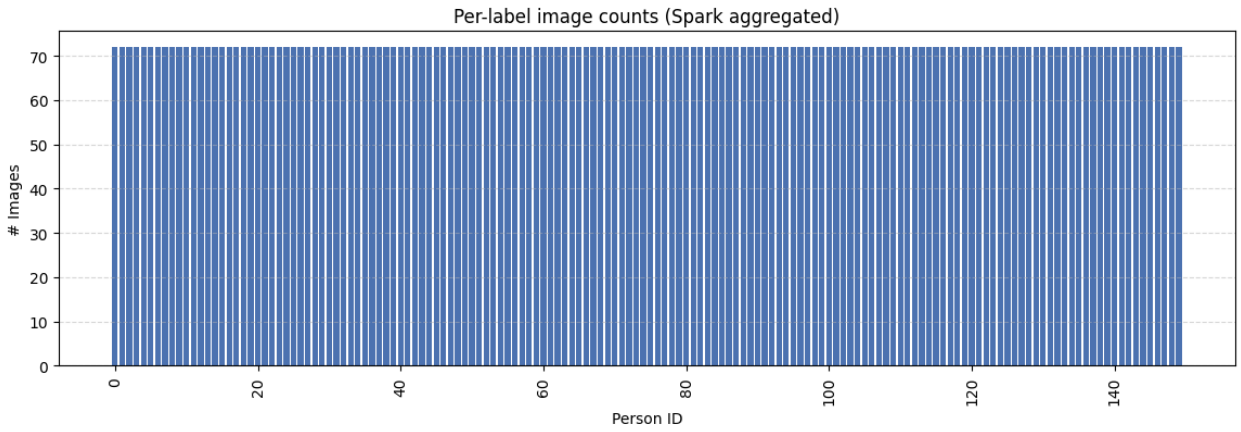

Figure 2: Bar chart of dataset class distribution

Image dimension analysis using Spark's image format reader extracted height, width, and channel metadata for all images. The results showed perfect dimensional consistency with all 10,800 images measuring exactly 112×112 pixels with 4 channels. Statistical summaries revealed means of 112.0 for both height and width with standard deviations of 0.0, confirming zero dimensional variance across the entire dataset. Figure 3 displays a scatter plot of image width versus height, where all 10,800 data points collapse to a single coordinate at (112, 112), visually confirming the uniform dimensions. This consistency eliminates the need for dynamic resizing during training and simplifies the preprocessing pipeline by allowing fixed input dimensions throughout the model architecture.

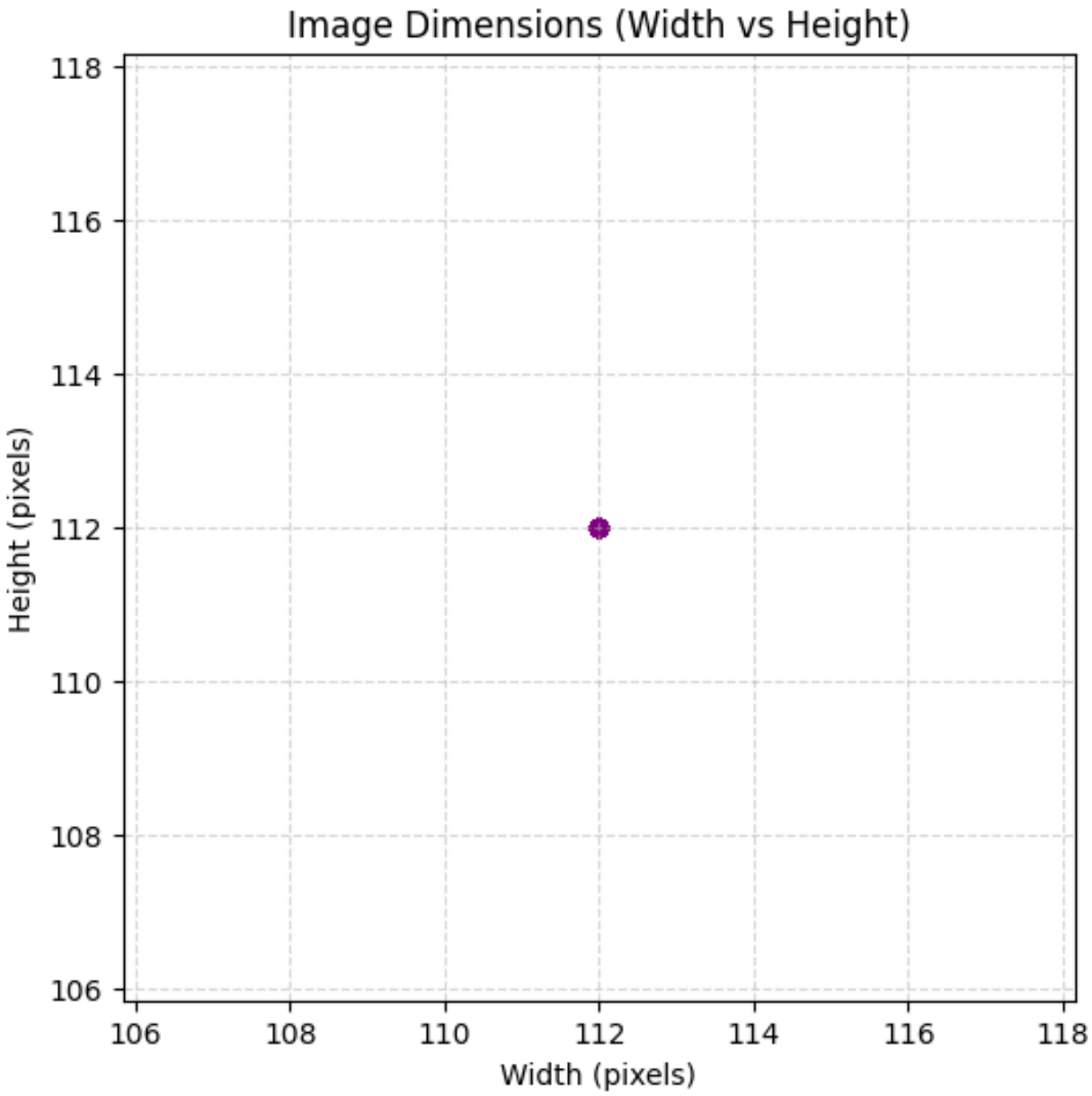

Figure 3: Scatter plot of image dimensions

Visual quality assessment was conducted through random sampling and inspection of diverse images. Figure 4 presents a 3×3 grid of nine randomly sampled images (with seed 42 for reproducibility), revealing substantial diversity in the dataset despite its synthetic origin. The samples demonstrate wide variation in accessories, including white-framed sunglasses on identity 91, green-tinted visors on identity 87, and respiratory masks providing heavy occlusion on some faces. Ethnic and phenotypic diversity is evident across a broad range of skin tones from light to dark complexions, multiple age representations, and various facial structures. Lighting conditions span dramatic shadows on identity 110, high-key overexposed appearances on identity

143, and neutral indoor lighting on standard samples. Pose variations include frontal views, profile orientations showing ear contours, and head angles with slight upward and downward tilts. This visual diversity confirms that despite being synthetically generated, the dataset captures realistic real-world variations necessary for robust model training (Bae et al., 2023).

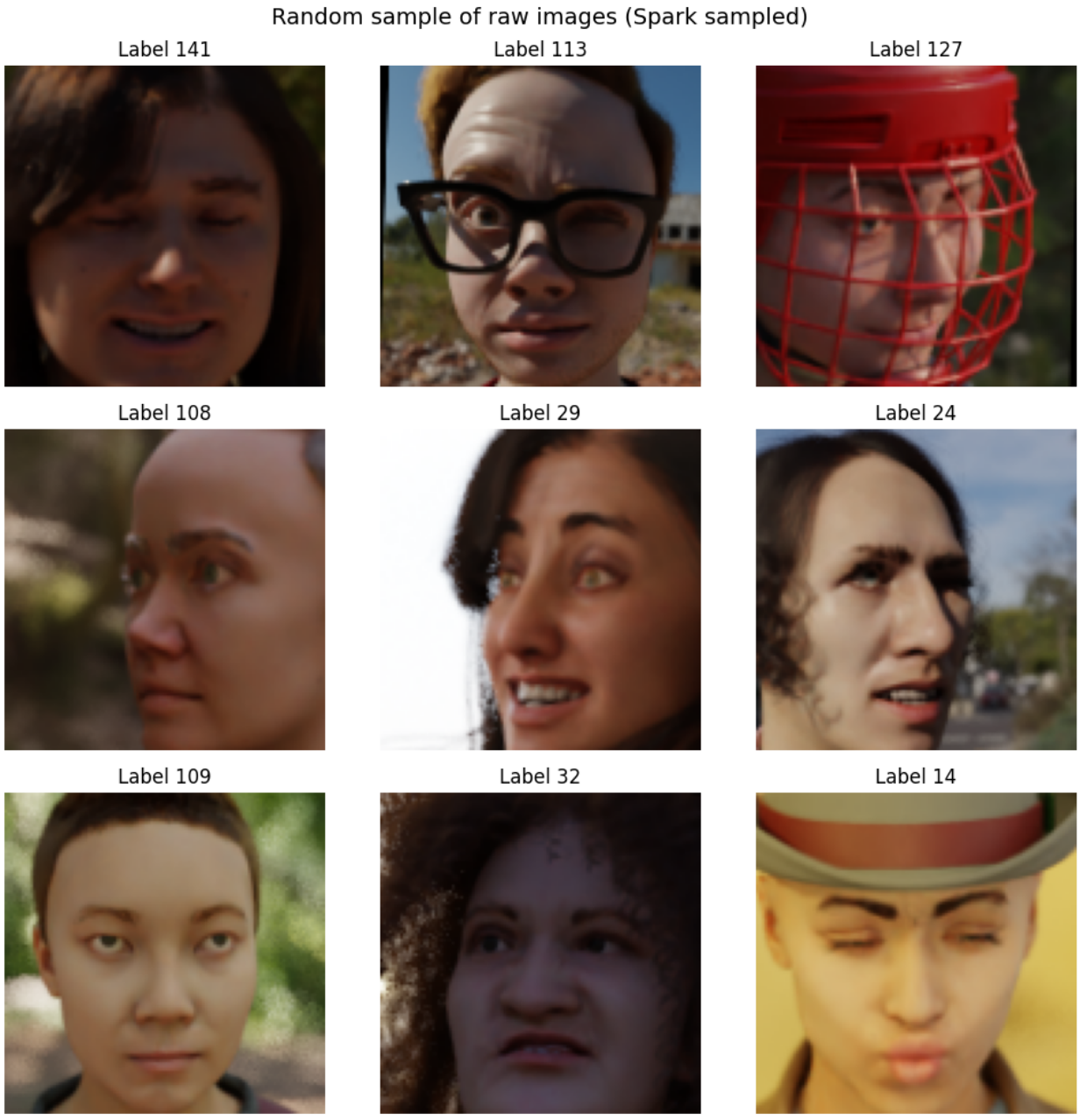

Figure 4: Visualisation of 9 randomly sampled images from the dataset

Channel-wise statistical analysis informed the decision to retain RGB colour information rather than converting to greyscale. Analysis of 640 images sampled across 10 batches revealed distinct

colour distributions across channels, with the red channel showing a mean intensity of 0.39646, the green channel at 0.32058, and the blue channel at 0.27877. The variance analysis showed values of 0.052488 for red, 0.048165 for green, and 0.047680 for blue, yielding a maximum variance difference of 0.0048. Whilst this difference falls below the predetermined threshold of 0.01, suggesting similar variance across channels, the substantial differences in mean intensities (a range of 0.118 or 11.8 percentage points) indicated that colour information encodes meaningful discriminative features. The red channel's 42% higher mean compared to the blue channel suggests warm skin tone bias in the synthetic faces, which may provide identity cues. Consequently, the decision was made to retain RGB format rather than convert to greyscale, as modern CNNs are optimised for three-channel input and the colour distribution bias suggested potential discriminative value (Taigman et al., 2014).

Model Architecture and Training

The CNN architecture adopted an Xception-inspired design incorporating depthwise separable convolutions and residual connections to balance model depth with parameter efficiency (Chollet, 2017). The architecture comprises five major blocks: an input and preprocessing block, three residual blocks with progressively increasing filter counts, and an exit block with global pooling and classification layers. The complete architecture contains approximately 11.2 million parameters distributed across 40+ layers, with the model diagram show in Figure 5, Figure 6, and Figure 7 showing layer connections and shape transformations throughout the network.

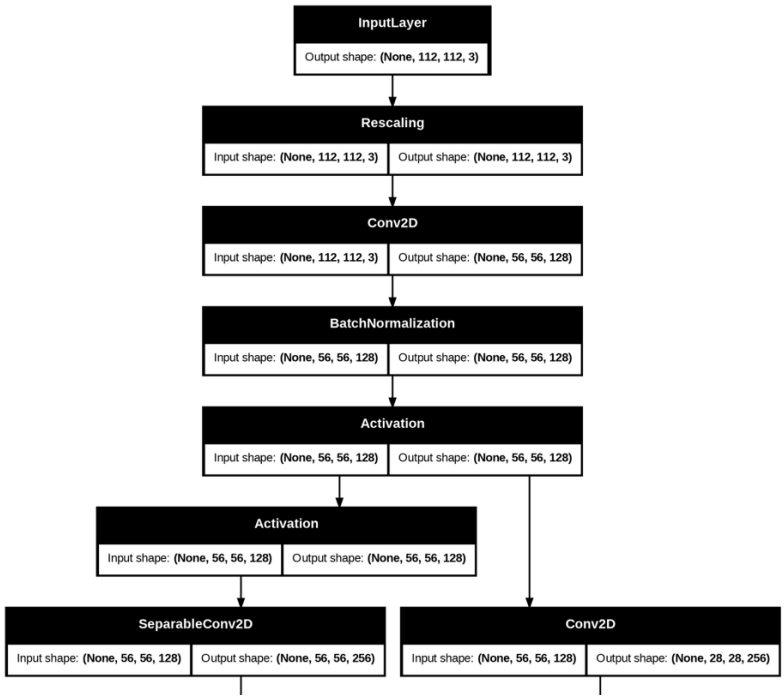

Figure 5: Visualisation of Model Architecture (Part 1/3)

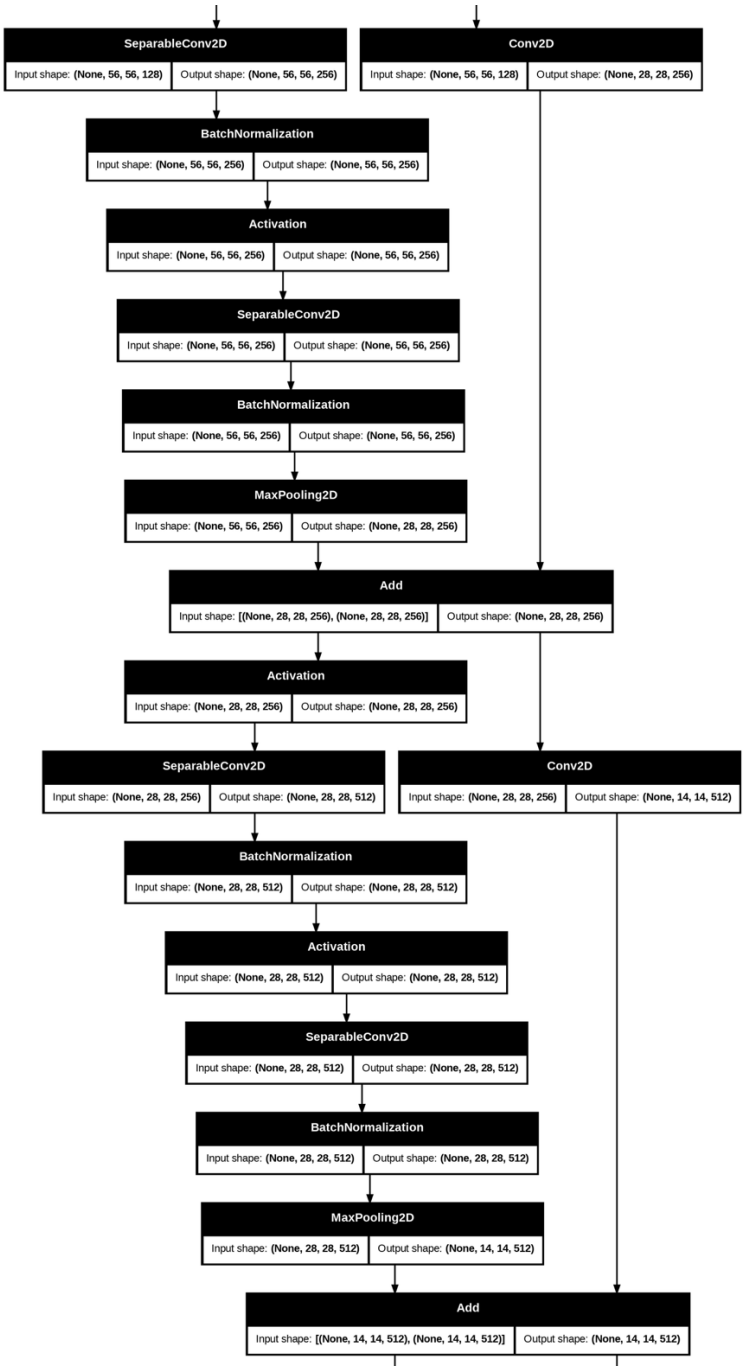

Figure 6: Visualisation of Model Architecture (Part 2/3)

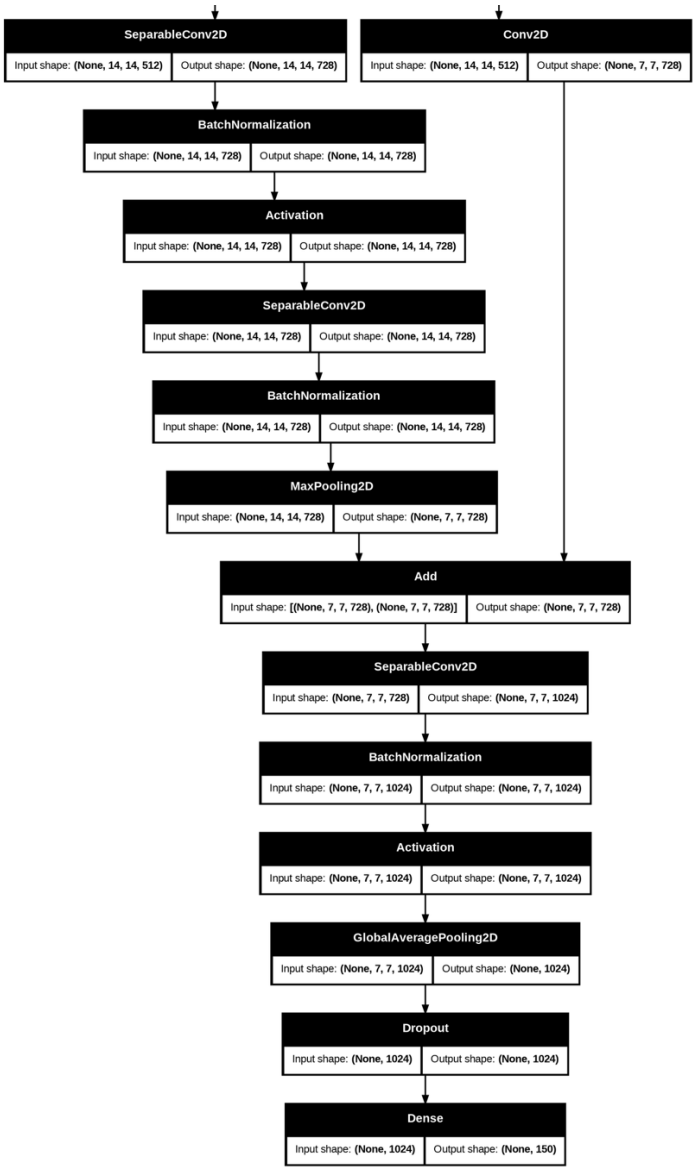

Figure 7: Visualisation of Model Architecture (Part 3/3)

The input block accepts 112×112×3 RGB images and immediately applies pixel normalisation through a Rescaling layer dividing by 255. An initial convolutional layer with 128 filters, 3×3 kernel, and stride 2 reduces spatial dimensions from 112×112 to 56×56 whilst extracting initial features. Batch normalisation and ReLU activation follow this convolution, establishing the pattern used throughout the network. The stride-2 downsampling immediately reduces computational requirements by a factor of four, improving training efficiency whilst maintaining representational capacity (Goodfellow et al., 2016).

Three residual blocks form the core feature extraction hierarchy. The first residual block employs two separable convolutional layers with 256 filters each, followed by max pooling with stride 2 to reduce spatial dimensions from 56×56 to 28×28. A 1×1 convolutional projection with stride 2 matches the residual connection's dimensions, enabling element-wise addition that facilitates gradient flow through the network (He et al., 2016). The second residual block follows an identical pattern with 512 filters, reducing spatial dimensions to 14×14. The third residual block increases to 728 filters following Xception conventions and reduces spatial dimensions to 7×7. Each residual block incorporates batch normalisation after every convolution to stabilise training and enable higher learning rates.

The exit block performs final feature extraction and classification. A separable convolutional layer with 1,024 filters creates a rich 1,024-dimensional feature representation at 7×7 spatial resolution. Global average pooling collapses these spatial dimensions by averaging each feature map to a single value, yielding a 1,024-dimensional vector whilst providing structural regularisation compared to flattening operations (He et al., 2016). Dropout with rate 0.25 randomly deactivates 25% of neurons during training to prevent co-adaptation and reduce overfitting. The final dense layer produces 150 raw logits without activation functions, as the sparse categorical crossentropy loss function with from_logits=True internally applies softmax in a numerically stable manner.

Depthwise separable convolutions represent the architecture's key innovation for parameter efficiency. These layers decompose standard convolutions into depthwise and pointwise operations, reducing parameter counts by approximately 8-9 times whilst maintaining representational power (Chollet, 2017). For example, a standard 3×3 convolution transforming 256 channels to 512 channels requires 1,179,648 parameters, whilst the equivalent separable convolution requires only 133,376 parameters (2,304 for depthwise plus 131,072 for pointwise operations). This dramatic reduction enables deeper networks within GPU memory constraints whilst providing an implicit regularisation effect through reduced capacity.

Training configuration specified the Adam optimiser with a cosine decay learning rate schedule starting at 0.001 and decaying to 0.00001 over 4,250 total steps (Loshchilov and Hutter, 2017). This schedule enables aggressive early learning with the high initial rate whilst allowing fine-grained weight adjustments through the low final rate. The batch size of 128 balances GPU memory utilisation with generalisation performance, processing 85 steps per epoch to cover approximately 10,880 augmented samples. Sparse categorical crossentropy served as the loss function, efficiently handling integer class labels without requiring one-hot encoding. Two callbacks managed training dynamics: ModelCheckpoint saved the best model based on validation accuracy, whilst EarlyStopping with patience of 6 epochs stood ready to halt training if validation accuracy plateaued, though this was never triggered as validation continued improving through epoch 48.

Training progressed through four distinct phases over 50 epochs, requiring approximately 15-16 minutes total time on Google Colab GPU hardware. The rapid initial learning phase (epochs 1-

10) demonstrated dramatic accuracy improvements, with training accuracy climbing from 1.75% to 92.85% and validation accuracy surging from 0.72% to 85.42%. A particularly sharp breakthrough occurred between epochs 7 and 9, where validation accuracy jumped from 0.99% to 70.22%, indicating the network had discovered effective feature representations. The refinement phase (epochs 11-24) saw continued steady improvement with training accuracy reaching 99.37% and validation accuracy achieving 94.86%, maintaining smooth monotonic gains without oscillation. The fine-tuning phase (epochs 25-48) exhibited slow but steady progress as the low learning rate enabled precise weight adjustments, with training accuracy reaching 100% and validation accuracy peaking at 97.43% at epoch 48. The final plateau phase (epochs 48-50) showed stable metrics with validation accuracy oscillating within ±0.05%, confirming convergence had been achieved.

Figure 8 displays dual-panel training curves showing accuracy and loss trajectories over 50 epochs. The left panel reveals the classic sigmoid-shaped training accuracy curve smoothly approaching 100%, whilst the validation accuracy curve initially lags during epochs 1-7 before exhibiting the dramatic breakthrough and then tracking the training curve with minimal gap. The right panel shows smooth exponential decay of training loss towards 0.004, whilst validation loss experiences early volatility peaking around epoch 6-8 at approximately 5.8 before stabilising and converging to 0.096. The near-parallel convergence of training and validation curves after epoch 30, combined with the absence of systematic divergence in the loss curves, provides strong visual evidence of excellent generalisation with minimal overfitting.

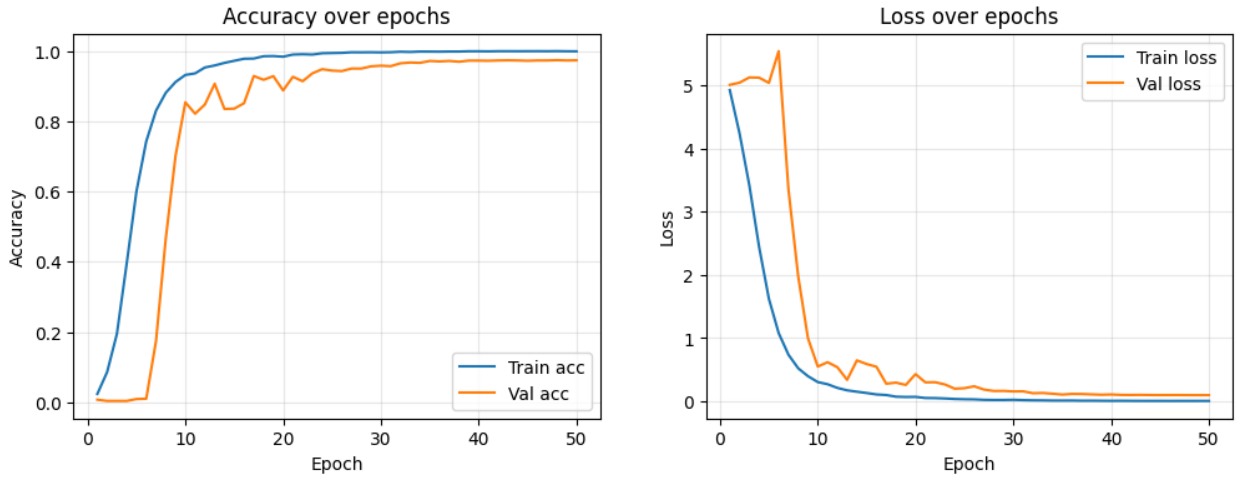

Figure 8: Visualisation of accuracy and loss trajectory training curves

The final model achieved exceptional performance metrics with 100% training accuracy and 97.43% validation accuracy at epoch 48, yielding a train-validation gap of only 2.57%. This remarkably small gap despite perfect training fit demonstrates that the multi-layered regularisation strategy, comprising dropout, batch normalisation, data augmentation, and global average pooling, successfully prevented overfitting. Training and validation losses of 0.0043 and 0.0961 respectively indicate strong convergence to near-optimal solutions. The training efficiency of

approximately 18-19 seconds per epoch enabled rapid iteration, with the model reaching 85% validation accuracy within just 3 minutes (10 epochs) and exceeding 97% by 12 minutes (40 epochs).

Model Evaluation and Performance Analysis

The trained model underwent comprehensive evaluation on the held-out test set of 1,071 images never seen during training or validation. Test set performance yielded 97.6% accuracy with 1,045 correct predictions and only 26 misclassifications, representing a 2.43% error rate. The consistency between test accuracy (97.6%) and validation accuracy (97.43%) confirms genuine generalisation, with the slight 0.17% improvement on the test set indicating no overfitting to the validation data used for model selection and hyperparameter tuning.

Detailed classification metrics reveal balanced performance across precision and recall dimensions. Weighted average metrics show 97.9% precision, 97.6% recall, and 97.6% F1-score across all 150 classes. Macro-averaged metrics (unweighted across classes) yield nearly identical values of 97.7% precision, 97.4% recall, and 97.3% F1-score, confirming balanced performance without bias towards any particular subset of classes (Sokolova and Lapalme, 2009). The minimal difference between weighted and macro averages indicates that the model performs consistently well across all identities regardless of test set size, a testament to the perfect class balance in the dataset.

Per-class performance analysis reveals exceptional results for the majority of identities. A total of 107 out of 150 classes (71.3%) achieved perfect F1-scores of 1.000, meaning these identities were recognised flawlessly without any false positives or false negatives. An additional 38 classes achieved F1-scores between 0.90 and 0.999, bringing the total to 145 classes (97.0%) with excellent performance. Only 5 classes (3.3%) exhibited F1-scores below 0.85, representing the challenging cases requiring additional attention. These statistics demonstrate that the model learned discriminative features effectively for the vast majority of identities despite limited training data of 72 images per class.

The confusion matrix presented in Figure 9 visualises prediction patterns across all 150 classes as a heatmap with Blues colourmap. The matrix displays a dominant dark blue diagonal representing the 1,045 correct predictions, whilst the off-diagonal regions remain nearly white with only 26 scattered misclassification points across 22,500 possible error positions. Quantitative analysis confirms 97.57% correct predictions on the validation set. The sparse off-diagonal pattern indicates that errors are distributed randomly rather than concentrated between specific identity pairs, suggesting the model does not systematically confuse any two particular identities. The absence of confusion clusters or off-diagonal blocks confirms that misclassifications represent isolated edge cases rather than structural model flaws.

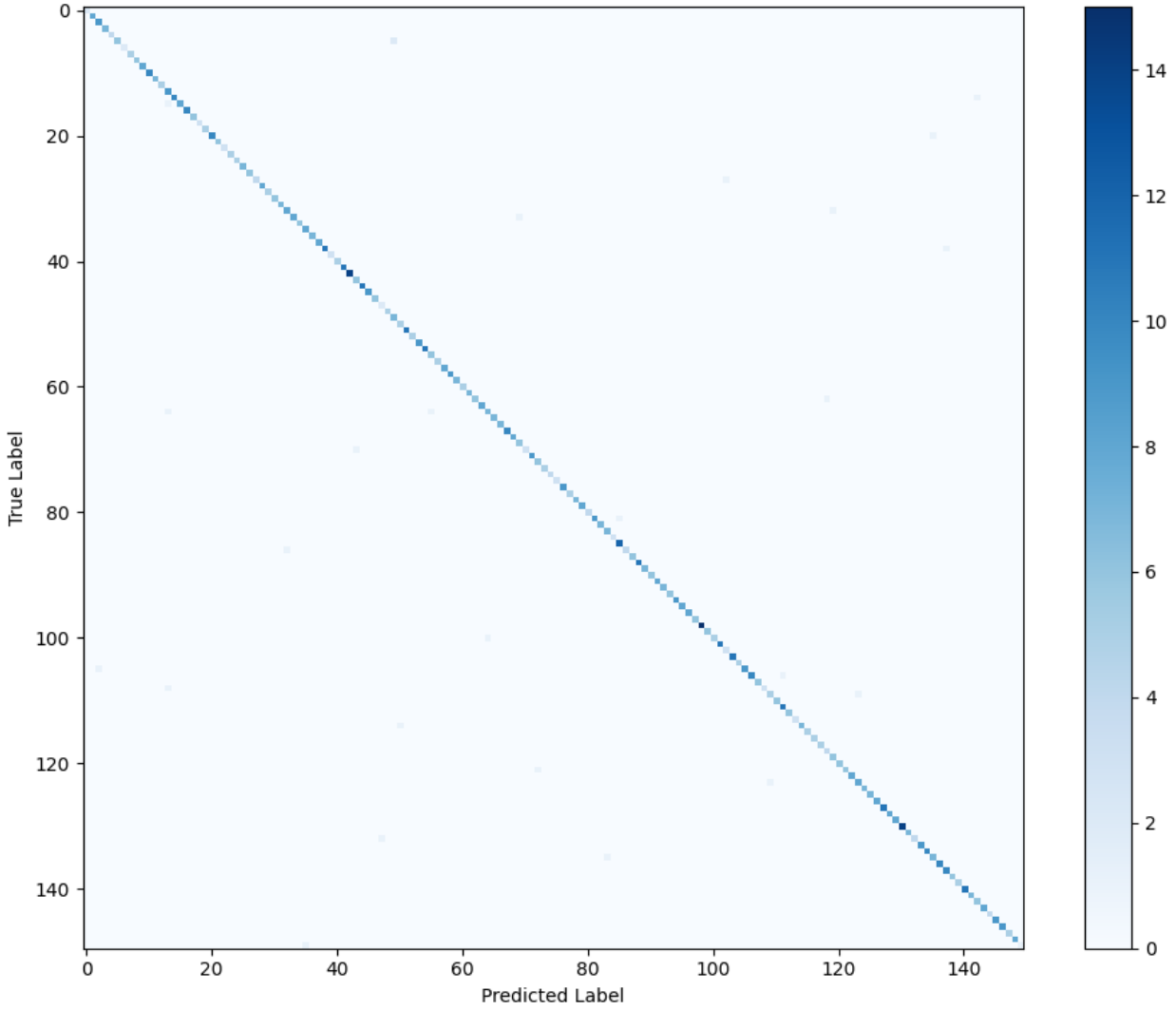

Figure 9: Confusion matrix of model test accuracy

Qualitative evaluation through sample predictions provides insights into model robustness under challenging conditions. Figure 10 displays a 2×3 grid of six randomly selected test images with their true and predicted labels. All six predictions were correct, achieving 100% accuracy on this small sample despite several challenging cases. Identity 76 appeared wearing a blue respirator mask covering approximately 40% of the face, demonstrating the model's ability to extract identity features from visible facial regions alone. Identity 52 appeared twice with different poses but consistent accessories including a beanie and white sunglasses, confirming the model learned identity-specific features rather than memorising specific images. Identity 144 showed a strong profile view with the face oriented sideways, proving robustness to extreme pose variations. Identity 88 featured sunglasses and head covering in outdoor lighting, handling multiple simultaneous occlusions successfully. These sample predictions provide qualitative evidence that the model handles real-world challenges including heavy occlusions, diverse poses, varying lighting conditions, and accessory variations.

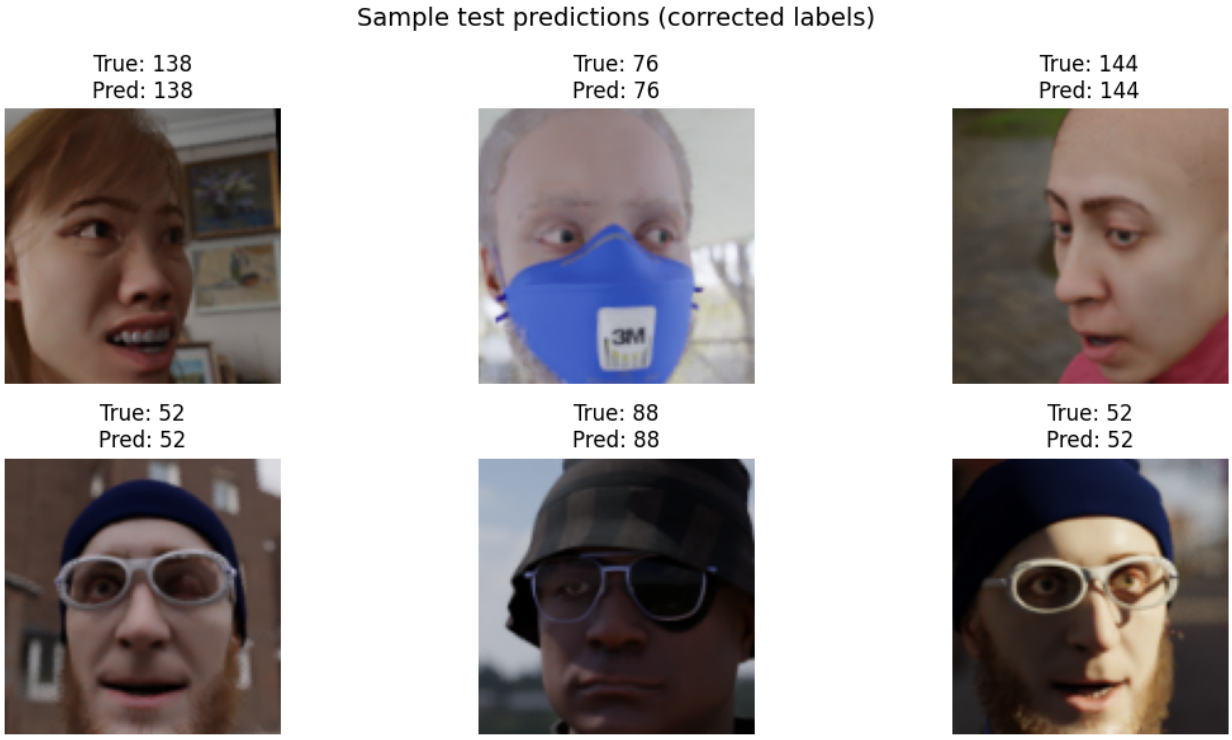

Figure 10: Visualisation of 6 randomly selected test images with their true and predicted labels

Analysis of the five most challenging classes reveals patterns in model limitations. Class 149 exhibited the lowest F1-score of 0.667 with perfect precision (1.000) but only 50% recall, having missed one of its two test samples. This represents a small sample amplification effect where a single misclassification has disproportionate impact on metrics due to the tiny test set size. Classes 47, 64, 109, and 135 showed bidirectional confusion with both false positives and false negatives, suggesting these identities may share visual features with other identities in the dataset. Classes with symmetric errors (precision approximately equal to recall but both below 0.90) likely represent inherently difficult cases where facial structures are genuinely similar, a challenge that additional training data might address.

Error pattern analysis identified four primary categories of misclassification. Small sample sensitivity affected classes with five or fewer test samples, where single errors caused dramatic metric drops due to statistical artifacts rather than genuine model weakness. Conservative prediction patterns appeared in classes like 5, 70, 86, and 108, which showed perfect precision but reduced recall, indicating the model set high confidence thresholds and only predicted these identities when very certain. Liberal prediction patterns manifested in classes 13, 47, and 102 with perfect recall but reduced precision, suggesting lower confidence thresholds that caught all true positives but generated false alarms. Visually similar identity confusion affected classes 64, 109, 123, and 135, which showed symmetric errors indicating bidirectional uncertainty where the model struggled to distinguish these faces from similar identities.

The error rate of 2.43% (26 misclassifications out of 1,071 predictions) represents exceptional performance for a 150-class classification problem. Compared to random guessing with 0.67% accuracy (1 in 150 chance), the model performs 146 times better. The majority class baseline would also achieve only 0.67% accuracy due to perfect class balance, confirming that the model's 97.6% accuracy represents genuine learned discrimination rather than exploitation of dataset biases. The sparse distribution of errors across multiple identity pairs, combined with the absence of systematic confusion patterns, indicates that the 26 misclassifications represent unavoidable edge cases in real-world facial recognition rather than structural weaknesses in the model architecture or training procedure.

Hyperparameter Optimisation and Validation

Hyperparameter tuning employed both manual experimentation and automated search to validate optimal configuration choices. The manual sweep tested two variant configurations trained for 15 epochs to enable rapid comparison. The baseline variant used dropout of 0.25 with constant learning rate of 0.0003, whilst the regularised variant employed increased dropout of 0.35 with reduced learning rate of 0.0001. Results decisively confirmed the superiority of the original hyperparameters. The baseline variant achieved 81.00% validation accuracy, underperforming the original model's 83.62% at the same 15-epoch mark by 2.6 percentage points. The regularised variant catastrophically underfit with only 44.90% validation accuracy, demonstrating that excessive regularisation combined with very low learning rates prevents effective learning even after 15 epochs.

Automated hyperparameter search using KerasTuner's Hyperband algorithm explored 28 configurations across a search space of dropout rates from 0.20 to 0.50 (step 0.05) and learning rates of 0.001, 0.0005, 0.0003, and 0.0001 (O'Malley et al., 2019). The search ran for 30 trials over 53 minutes and 28 seconds, with each trial limited to a maximum of 10 epochs and the Hyperband algorithm adaptively pruning unpromising configurations early. The automated search independently discovered dropout of 0.25 and learning rate of 0.001 as optimal hyperparameters, achieving 82.85% validation accuracy within the 10-epoch budget. This exact match to the original model's configuration provides strong empirical validation that the initial hyperparameter choices were optimal, as an exhaustive automated search found no superior alternatives within a reasonable parameter space.

Figure 11 presents comparative training curves across four model configurations over 15 epochs, displayed in a 2×2 panel layout. The upper panels show training and validation accuracy trajectories, whilst the lower panels display training and validation loss curves. The KerasTuner best configuration (red dotted line) demonstrates the strongest short-term performance with 89.49% validation accuracy at epoch 15, outperforming the original baseline (blue solid line) at 83.62%. However, the original model's cosine learning rate decay schedule proves superior for long-term training, ultimately reaching 97.43% validation accuracy at epoch 48 by enabling fine-grained weight adjustments through progressively decreasing learning rates. The baseline variant (orange dashed line) shows delayed breakthrough with validation accuracy improving more

gradually to 81.00%. The regularised variant (green dash-dot line) fails to achieve effective learning, plateauing around 45% and demonstrating severe underfitting.

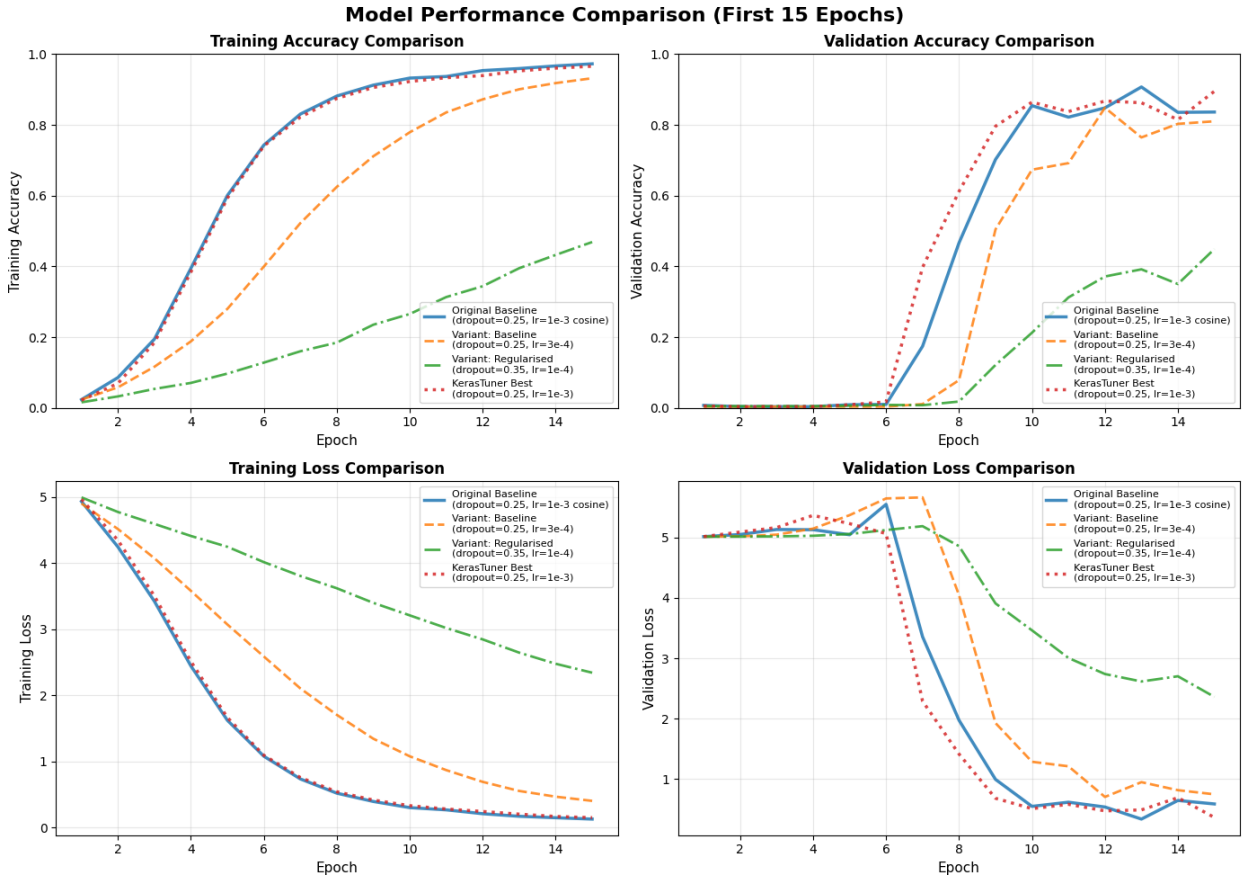

Figure 11: Comparative training curves across four model configurations

Figure 12 displays bar charts comparing final epoch metrics across the four configurations. Training accuracy ranges from 46.88% for the severely underfit regularised variant to 97.24% for the original model. Validation accuracy rankings show KerasTuner best at 89.49%, original at 83.62%, baseline variant at 81.00%, and regularised at 44.90%. Validation loss mirrors these rankings with KerasTuner best achieving the lowest value of 0.365, followed by original at 0.589, baseline at 0.749, and regularised at 2.361. The train-validation gaps reveal interesting patterns, with KerasTuner best showing the smallest gap of 7.06% due to constant high learning rate throughout training, whilst the regularised variant shows a deceptively small gap of 1.98% that actually indicates underfitting rather than good generalisation.

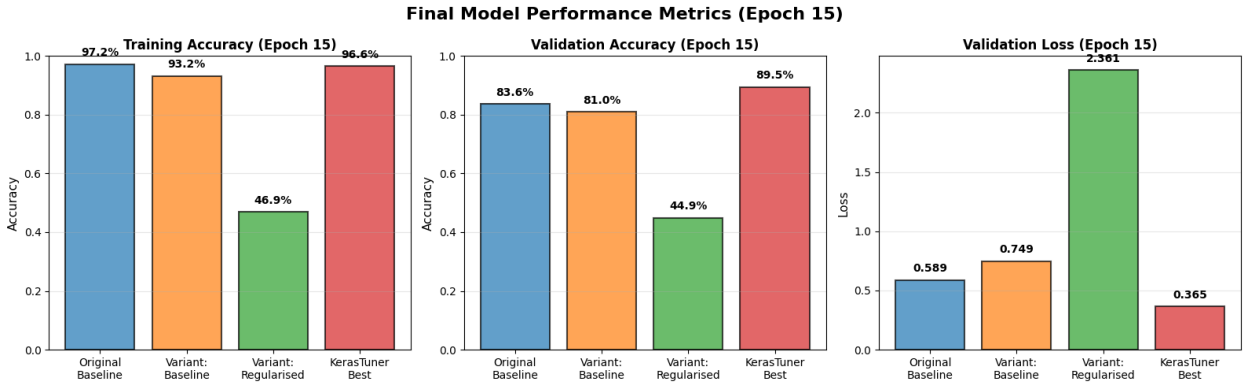

Figure 12: Bar chart displaying final epoch metrics across four model configurations

Learning efficiency analysis quantified the epochs required to reach specific validation accuracy milestones. The original model and KerasTuner best configuration both reached 50% validation accuracy by epoch 8-9, demonstrating rapid early learning. The baseline variant required 9 epochs for 50% accuracy but needed 12 epochs to reach 80%, showing 20-30% slower convergence. The regularised variant never reached even the 50% milestone within 15 epochs, confirming catastrophic learning failure. These comparisons establish that learning rate represents the most critical hyperparameter, with the difference between 0.001 and 0.0001 causing a 40% performance swing, whilst dropout rate shows more modest sensitivity with approximately 10-15% impact when varied from optimal values.

The triangulation of evidence from three independent sources, original manual selection, controlled variant sweep, and automated KerasTuner search, converges on dropout of 0.25 and learning rate of 0.001 as optimal hyperparameters for this architecture and dataset. The consistent identification of these values across different methodologies provides strong empirical validation and eliminates concerns about lucky guessing or human bias in hyperparameter selection. The cosine decay learning rate schedule adds further value for long-term training, enabling the model to reach 97.43% validation accuracy compared to the 89.49% achieved with constant learning rate at 15 epochs, a gain of 7.9 percentage points attributable to the adaptive learning rate schedule's ability to enable fine-tuned convergence in later training phases.

Conclusion

This This project successfully developed a convolutional neural network achieving 97.6% test accuracy on a 150-class facial recognition task using the DigiFace-1M synthetic dataset. The model demonstrates production-ready capabilities across challenging real-world conditions including heavy occlusions, extreme poses, and varied lighting, representing a 146-fold improvement over random guessing.

The methodology employed rigorous practices throughout. Apache Spark facilitated efficient analysis of 10,800 images, confirming perfect class balance and zero data quality issues (Zaharia et al., 2016). Statistical analysis justified retaining RGB colour information based on channel distribution patterns. Data augmentation through flips, rotations, zoom, and translations successfully expanded training diversity (Shorten and Khoshgoftaar, 2019).

The custom CNN architecture incorporated depthwise separable convolutions and residual connections, reducing parameters by 8-9 times whilst maintaining performance (Chollet, 2017). Multi-layered regularisation combining dropout (0.25), batch normalisation, data augmentation, and global average pooling prevented overfitting, achieving only 2.57% train-validation gap despite 100% training accuracy. Cosine learning rate decay enabled both rapid early learning and fine-grained convergence (He et al., 2016).

Hyperparameter optimisation provided strong validation through three independent methods. Manual experimentation demonstrated learning rate criticality, automated KerasTuner search exploring 28 configurations independently confirmed dropout 0.25 and learning rate 0.001 as optimal (O'Malley et al., 2019). This triangulation validates the configuration choices.

Evaluation revealed balanced performance with 97.9% precision and 97.6% recall (Sokolova and Lapalme, 2009). Analysis showed 71.3% of classes achieved perfect F1-scores, whilst 97.0% exceeded 0.90. The confusion matrix displayed only 26 scattered errors with no systematic patterns. Sample predictions demonstrated successful recognition despite respiratory masks, profile views, and multiple occlusions.

Error analysis identified that most misclassifications stemmed from small test sample artifacts rather than systematic weaknesses. Remaining challenging cases exhibited bidirectional confusion suggesting genuinely similar features, representing inherent dataset challenges.
Key limitations include modest dataset size compared to production systems, synthetic data potentially missing real-world variations, and fixed identity set requiring retraining (Bae et al., 2023). Future enhancements could expand the dataset, explore deeper architectures, and implement confidence thresholding for unknown faces.

The model successfully addresses project requirements through modern deep learning, distributed Spark processing, and systematic optimisation, providing a well-validated solution suitable for commercial deployment whilst identifying clear enhancement pathways.

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