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Advanced Fingerprint Alteration Detection: A Comparative Analysis of Real and Synthetic Modifications Using InceptionV3 on the SOCOFing Dataset

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Abstract

This study investigates the efficacy of fingerprint alteration detection using Advanced Deep Learning techniques, specifically focusing on real and synthetically altered fingerprint images. Utilizing the Sokoto Coventry Fingerprint Dataset (SOCOFing), which comprises over 55,000 fingerprint images from 600 African subjects, we employed the Google InceptionV3 model to classify real and altered images under varying degrees of alteration. Our experimental results demonstrate a robust performance of the model, achieving an accuracy of 91.04% for detecting alterations with easy alteration parameter settings, 98.07% for medium alteration parameter settings, and 96.47% for hard alteration parameter settings. The findings highlight the potential of deep learning frameworks like InceptionV3 in enhancing the reliability of biometric systems by effectively distinguishing between real and altered fingerprints.

Keywords: Fingerprint Alteration; Fingerprint Classification; SOCOFing dataset; InceptionV3; Synthetic Fingerprint Modifications; Deep Learning

1. Introduction

Biometric systems are increasingly becoming the cornerstone of identity verification processes, providing a reliable means of authentication through unique physiological characteristics. Among these, fingerprint recognition stands out due to its widespread adoption, ease of use, and proven accuracy. However, the advent of sophisticated techniques for altering fingerprint images, whether for privacy concerns or malicious intent, has posed significant challenges to the integrity of these systems. Addressing these challenges requires advanced methodologies capable of detecting even subtle modifications to fingerprint images.

This research leverages the Sokoto Coventry Fingerprint Dataset (SOCOFing) [19][21], a comprehensive dataset containing both real and synthetically altered fingerprints, to explore the capabilities of modern deep learning models in detecting such alterations. The SOCOFing dataset [19][21], with its unique attributes such as labeled gender, hand, and finger name, provides a rich resource for studying the impact of alterations at various levels of difficulty. Utilizing the Google InceptionV3 model [20], a deep convolutional neural network known for its efficacy in image classification tasks, we conducted a series of experiments to assess the model's performance across different levels of synthetic alterations: easy, medium, and hard [21].

Our results indicate that the InceptionV3 model [20] can accurately differentiate between real and altered fingerprint images, even under challenging conditions. This paper presents a detailed analysis of the model's performance, discusses the implications for biometric security, and highlights the potential for future research in this critical area.

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2. Related Works

Fattahi et al. [1] introduced a convolutional short-term memory network model for identifying damaged fingerprints, advancing forensics. Khan et al. [2] proposed a convolutional neural network (CNN) model to classify rolled, plain, and latent fingerprint samples, streamlining the fingerprint matching process. Tertychnyi et al. [3] employed a VGG16-based deep network to classify low-quality fingerprint images affected by dryness, physical damage, wetness, dots, and blurriness. Peralta et al. [4] presented a CNN-based approach for fingerprint classification, including low-quality fingerprint recognition.

Zhang et al. [5] used residual convolutional nets to distinguish between live and fake fingerprints, mitigating spoof attacks. Nahar et al. [6] proposed a ResNet50-based deep network for person recognition from fingerprint images, demonstrating high accuracy. Li et al. [7] introduced a Hierarchical Convolutional Neural Network (HCNN) for image classification, comprising multiple subnetworks for progressive image classification.

Chang et al. [8] presented the Yolov3, an advanced deep-learning network for object recognition. Kumar et al. [9] developed an automated system to detect face masks using deep learning and image processing. Cao et al. [10] proposed a network-inspired neural network to address object rotation problems.

Nguyen et al. [11] proposed a modified U-shaped network-based universal minutiae extractor for segmentation. Zhou et al. [12] presented a two-stage network: the first stage generates initial minutiae candidate patches, and the second stage extracts the direction and precise location of each patch. Iancu et al. [13] using fuzzy logic, Sagayam et al. [14] employing neural networks, and B. Poorna [15] utilizing genetic algorithms, may not be universally suitable due to the unified network problem.

Shehu et al. [16] proposed a deep CNN to classify three types of alterations in fingerprint images: Z-cut, obliteration, and central rotation. They utilized the SOCO database, similar to our study. While alteration classification is valuable, person recognition is more practical in real-world applications.

Amira Tarek Mahmoud et al. [17] propose an ADNN for fingerprint recognition, achieving 99.75% accuracy on SOCOFing. Their ADNN automatically optimizes network architecture and parameters, ensuring high accuracy and automating the entire process.

Hussein G. Muhammad et al. [18] compared CNN, ResNet, and VGG models for fingerprint identification, finding CNN superior with 96.5% F1 score. Their comparison with recent studies further validates CNN's effectiveness.

3. Proposed Work

3.1. Dataset Preparation

- **Data Acquisition:** Obtain the SOCOFing dataset [19][21], which contains 6,000 real fingerprint images belonging to 600 African subjects.
- **Data Preprocessing:** Apply necessary preprocessing techniques to the images, such as normalization, noise reduction, and image enhancement.

3.2. Data Augmentation

- **Synthetic Alteration:** Generate synthetically altered versions of the fingerprint images using the STRANGE toolbox with different alteration levels (easy, medium, and hard) [21].
- **Data Expansion:** Increase the dataset size by applying data augmentation techniques like rotation, scaling, shearing, and flipping to the original and altered images.

3.3. Model Initialization

- **Transfer Learning:** Initialize the InceptionV3 model [20] with pre-trained weights on the ImageNet dataset [18]. This leverages the model's learned features from a large-scale dataset, accelerating training and potentially improving performance.

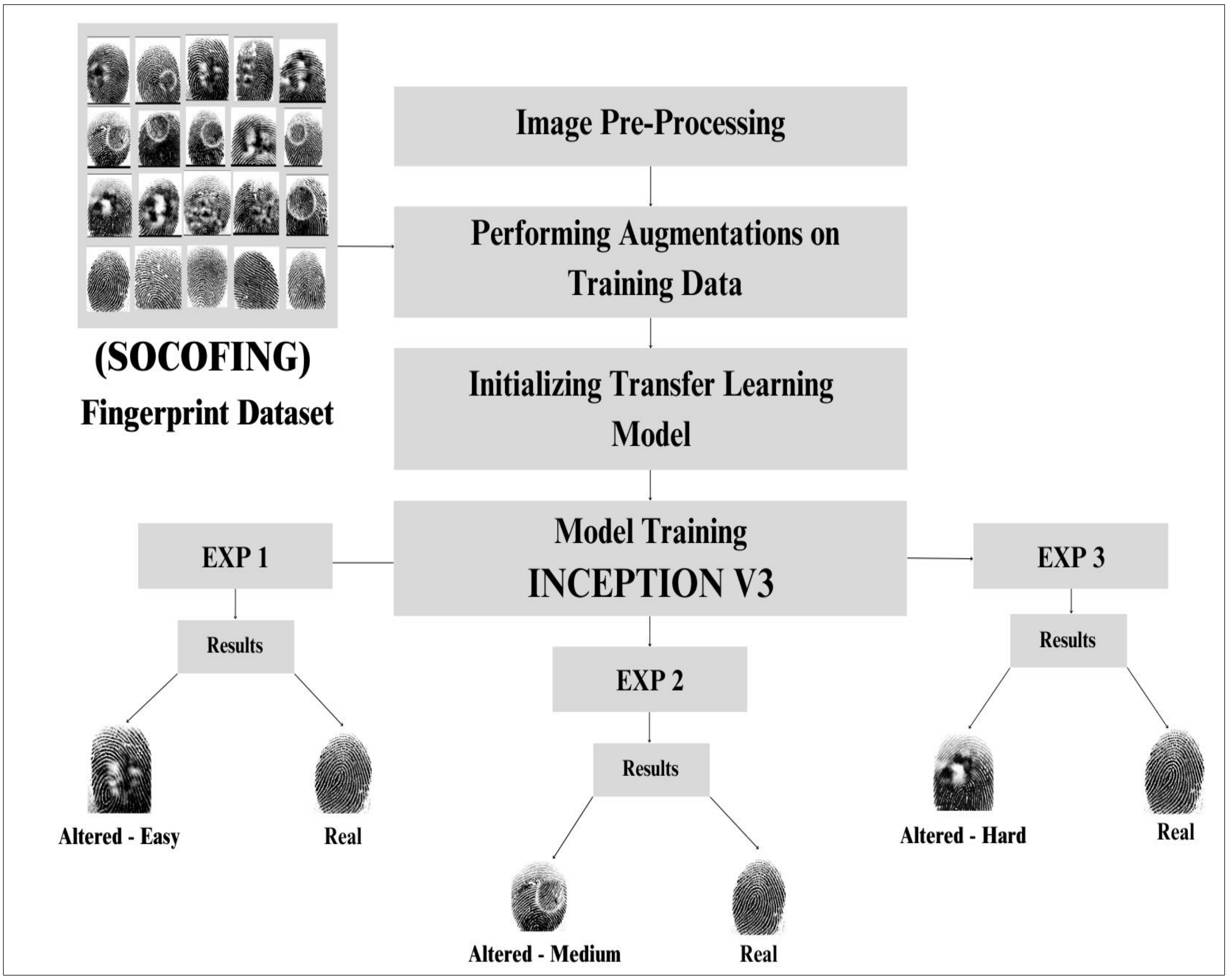

Figure 1 Flowchart for Proposed Work.

3.4. Model Training

- **Experiment 1:** Train the InceptionV3 model [20] to classify real and altered-easy fingerprint [21] images.
- **Experiment 2:** Train the model to classify real and altered-medium fingerprint [21] images.
- **Experiment 3:** Train the model to classify real and altered-hard fingerprint [21] images.
- **Hyperparameter Tuning:** Optimize hyperparameters like learning rate, batch size, and regularization techniques to enhance model performance.

3.5. Results Analysis

- **Comparison:** Compare the performance of the model across different alteration levels to assess its robustness.
- **Interpretation:** Analyze the results to understand the model's strengths and weaknesses in detecting various types of fingerprint alterations.
- **Discussion:** Discuss the implications of the findings for practical applications in fingerprint recognition and security.

4. Materials and Methods

4.1. Dataset

The Sokoto Coventry Fingerprint Dataset (SOCOFing) [19][21] is a comprehensive collection of fingerprint images used for research in biometric authentication and forensic science. It contains 6,000 real fingerprint images belonging to 600 African subjects, with 10 fingerprints per subject. All subjects are 18 years or older.

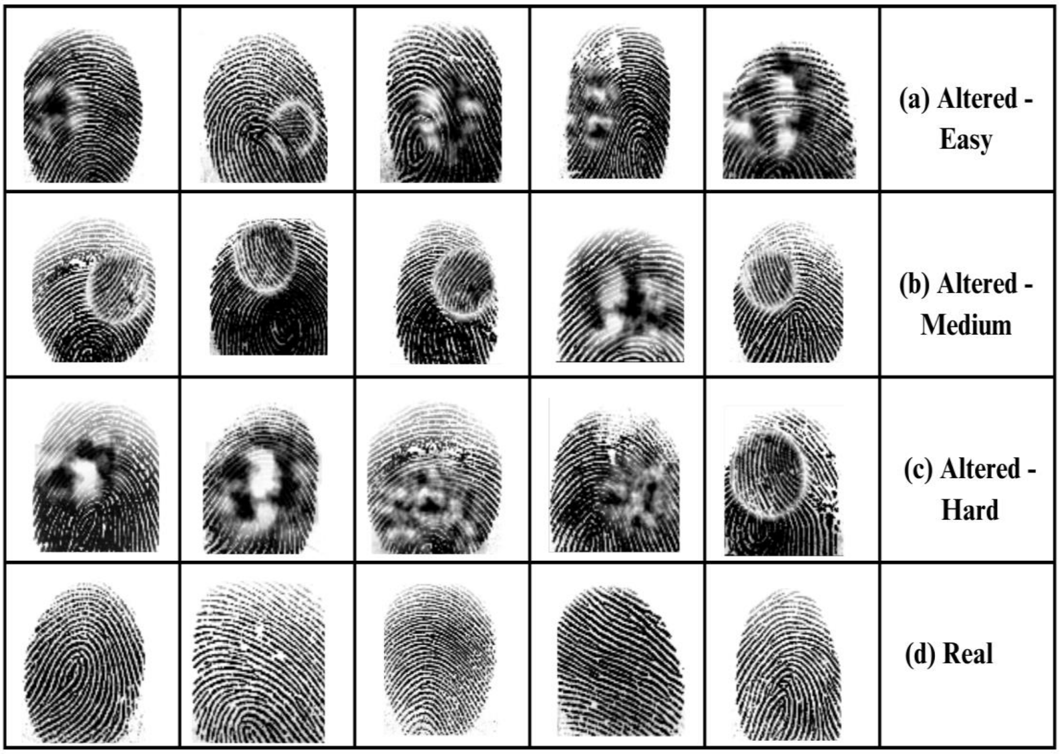

Figure 2 SOCOFing Dataset**.**

4.1.1. Features of the SOCOFing dataset:

- **Diversity:** The dataset includes fingerprints from a diverse population of African subjects, providing a representative sample for research.
- **Quality:** The fingerprint images are of high quality, captured using Hamster Plus (HSDU03PTM) and SecuGen SDU03PTM sensor scanners [21].
- **Labeling:** Each fingerprint image is associated with metadata, including gender, hand, and finger name.
- **Synthetic Alterations:** The dataset includes synthetically altered versions of the fingerprints, generated using the STRANGE toolbox [21] with three different levels of distortion (easy, medium, and hard). These alterations simulate real-world scenarios where fingerprints may be damaged, smudged, or partially obscured.

4.2. InceptionV3 Model

4.2.1. Input Layer

- **Shape:** (75, 75, 3)
- **Interpretation:** The model expects input images of size 75 pixels by 75 pixels with 3 channels (RGB). This indicates that the fingerprint images used in the research have been resized or cropped to this specific dimension.

4.2.2. Convolutional Layers (conv2d)

- **Purpose:** Extract features from the input images.
- **Explanation:** These layers apply filters to the input images, creating feature maps that represent different patterns and characteristics of the fingerprints.
- **Output Shape:** The output shape varies depending on the filter size and stride used in each layer. For example, (None, 37, 37, 32) indicates that the output is a tensor with a batch size of None (variable), 37 rows, 37 columns, and 32 feature maps.

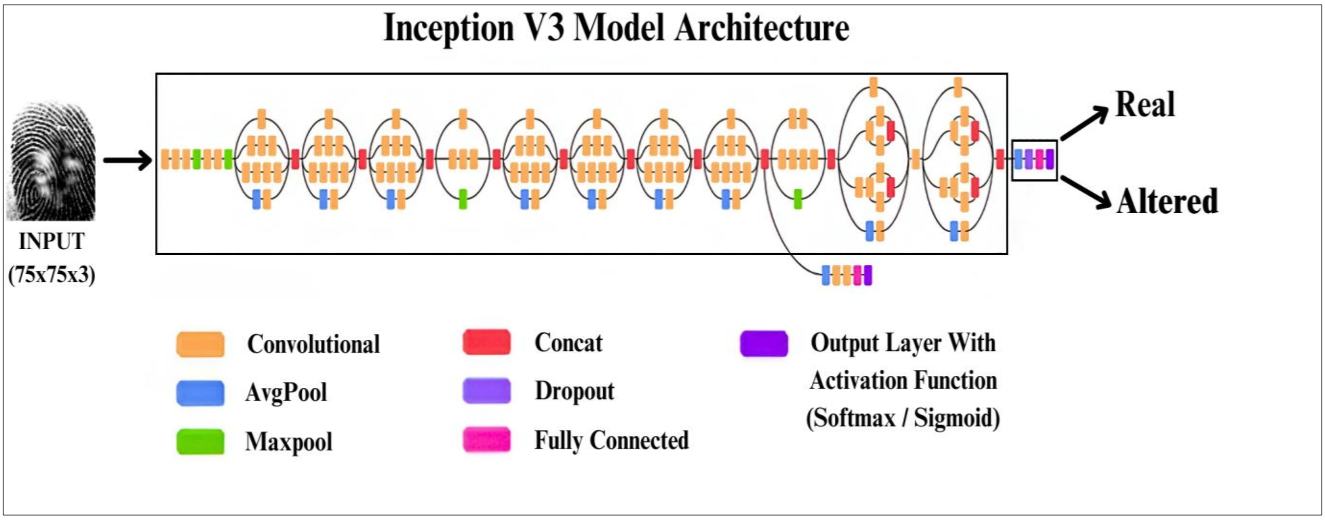

Figure 3 InceptionV3 Model Architecture.

4.2.3. Batch Normalization

- **Purpose:** Normalize the activations of the previous layer.
- **Explanation:** This helps to stabilize the training process and prevent vanishing or exploding gradients.

	Layer Name	Output Shape	Num Parameters
0	input_1	[(None, 75, 75, 3)]	0
1	conv2d	(None, 37, 37, 32)	864
2	batch_normalization	(None, 37, 37, 32)	96
3	activation	(None, 37, 37, 32)	0
4	conv2d_1	(None, 35, 35, 32)	9216
..	...	...	...
310	mixed10	(None, 1, 1, 2048)	0
311	global_average_pooling2d	(None, 2048)	0
312	dense	(None, 512)	1049088
313	dropout	(None, 512)	0
314	dense_1	(None, 2)	1026

Total params: 22,852,898
Trainable params: 22,818,466
Non-trainable params: 34,432

Figure 4 Proposed InceptionV3 Model Summary.

4.2.4. Activation Layers (activation)

- **Purpose:** Introduce non-linearity into the model.
- **Explanation:** Common activation functions like ReLU (Rectified Linear Unit) are used to introduce non-linearity, allowing the model to learn complex patterns.

4.2.5. Inception Modules (mixed0)

- **Purpose:** Combine convolutional filters of different sizes to capture features at multiple scales.
- **Explanation:** Inception modules are a key component of the InceptionV3 architecture [20]. They use a combination of 1x1, 3x3, and 5x5 convolutional filters, as well as pooling layers, to extract features from different parts of the image.

4.2.6. Global Average Pooling (global_average_pooling2d)

- **Purpose:** Reduce the dimensionality of the feature maps.
- **Explanation:** This layer averages the activations across the spatial dimensions of the feature maps, resulting in a 1x1x2048 tensor.

4.2.7. Dense Layers (dense)

- **Purpose:** Combine the extracted features into a single vector representation.
- **Explanation:** The first dense layer (dense) reduces the dimensionality of the feature vector to 512. The second dense layer (dense_1) outputs a 2-dimensional vector, representing the probabilities of the two classes (real or altered) for the input fingerprint image.

4.2.8. Dropout

- **Purpose:** Prevent overfitting by randomly dropping neurons during training.
- **Explanation:** Dropout helps the model generalize better by reducing its reliance on any particular set of features.

4.2.9. Auxiliary Classifier

- **Purpose:** To enhance network training by mitigating the vanishing gradient problem and promoting regularization.
- **Explanation:** An auxiliary classifier is a secondary classification branch attached to an intermediate layer of the main network. It serves dual purposes:
- **Gradient Propagation:** By providing an additional gradient signal to earlier layers, it helps to alleviate the vanishing gradient problem, especially in deep networks.
- **Regularization:** Acting as a regularizer, it encourages the network to learn more generalizable features, reducing the risk of overfitting.

4.2.10. Total Parameters and Trainable Parameters

- **Total Parameters:** The total number of parameters in the model, including both trainable and non-trainable parameters.
- **Trainable Parameters:** The number of parameters that can be updated during training.
- **Non-trainable Parameters:** The number of parameters that are fixed and not updated during training, such as the pre-trained weights of the InceptionV3 model [20].

4.3. InceptionV3 Architecture Highlights:

- **Inception Modules:** The model likely incorporates Inception modules, which are a key component of the InceptionV3 architecture [20]. These modules combine convolutional filters of different sizes to capture features at multiple scales.
- **Depthwise Separable Convolutions:** InceptionV3 [20] often uses depthwise separable convolutions to reduce the number of parameters and computational cost.
- **Bottleneck Layers:** These layers are used to reduce the dimensionality of the feature maps before applying the Inception modules.

In total, the inception V3 model [20] is made up of 42 layers which is a bit higher than the previous inception V1 [22] and inception V2 [23] models. The InceptionV3 model [20] used in this research is a deep convolutional neural network designed to classify fingerprint images as real or altered. It incorporates Inception modules, batch normalization, activation functions, and dropout to extract relevant features and improve generalization.

5. Experiments and Results

The three experiments using the InceptionV3 model [20] were implemented in Python 3.9.18 using Jupyter Notebook. The experiments were conducted on a system equipped with an Intel(R) Core(TM) i7-12650H processor, 16 GB of RAM, and an NVIDIA(R) GeForce RTX(TM) 4050 6GB Mobile graphics card. The TensorFlow 2.10.0 framework was used to implement the deep learning model.

5.1. Experiment 1 (Real vs Easy Alteration) :

The InceptionV3 model [20] effectively discriminated between real and easily altered fingerprints in a binary classification task. Trained on a dataset of 23,931 images, the model achieved a 91.04% accuracy rate. The Softmax activation function, well-suited for binary classification, and 22.85 million parameters contributed to the model's exceptional performance.

Table 1 Performance Analysis for Experiment 1 (Real vs Easy Alteration).

Title	Results
Total Images	23,931 (Real - 6,000 + Easy Altered - 17,931)
Train Set	60%
Validation Set	40%
Activation Function	Softmax (Binary Classification)
Loss	0.2111
Accuracy	91.04%
No. of Parameters (Total)	22.852898 M

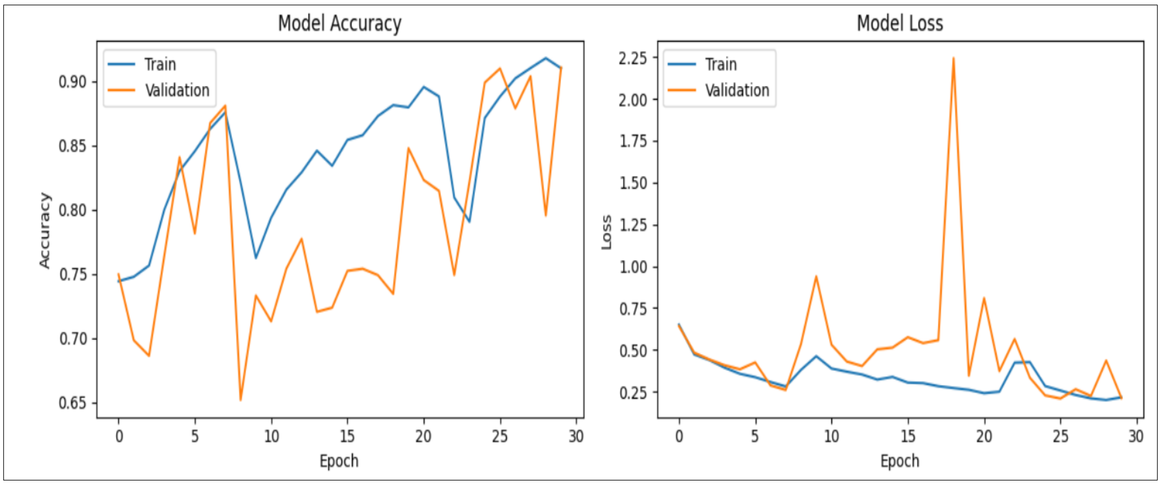

Figure 5 Comparison between training accuracy with validation accuracy and training loss with validation loss for Experiment 1 (Real vs Easy Alteration).

5.2. Experiment 2 (Real vs Medium Alteration) :

Table 2 Performance Analysis for Experiment 2 (Real vs Medium Alteration).

Title	Results
Total Images	23,067 (Real - 6,000 + Medium Altered - 17,067)
Train Set	80%
Validation Set	20%
Activation Function	Softmax (Binary Classification)
Loss	0.0586
Accuracy	98.07%
No. of Parameters (Total)	22.852898 M

The InceptionV3 model [20] effectively discriminated between real and medium-altered fingerprints in a binary classification task. Trained on a dataset of 23,067 images, the model achieved a remarkable accuracy rate of 98.07%. The Softmax activation function, well-suited for binary classification, and 22.85 million parameters contributed to the model's exceptional performance.

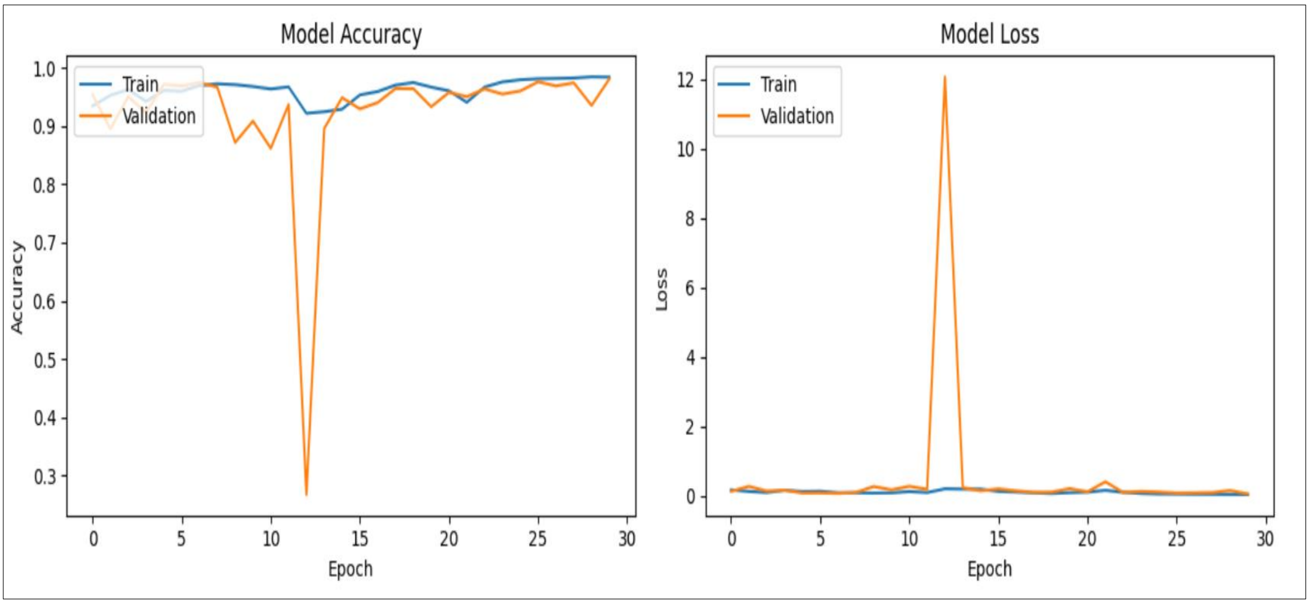

Figure 6 Comparison between training accuracy with validation accuracy and training loss with validation loss for Experiment 2 (Real vs Medium Alteration).

5.3. Experiment 3 (Real vs Hard Alteration) :

The InceptionV3 model [20] effectively discriminated between real and hard-altered fingerprints in a binary classification task. Trained on a dataset of 20,272 images, the model achieved a commendable accuracy rate of 96.47%. The Sigmoid activation function, well-suited for binary classification, and 22.85 million parameters contributed to the model's exceptional performance.

Table 3 Performance Analysis for Experiment 3 (Real vs Hard Alteration).

Title	**Results**
Total Images	20,272 (Real - 6,000 + Hard Altered - 14,272)
Train Set	80%
Validation Set	20%
Activation Function	Sigmoid (Binary Classification)
Loss	0.1103
Accuracy	96.47%
No. of Parameters (Total)	22.852898 M

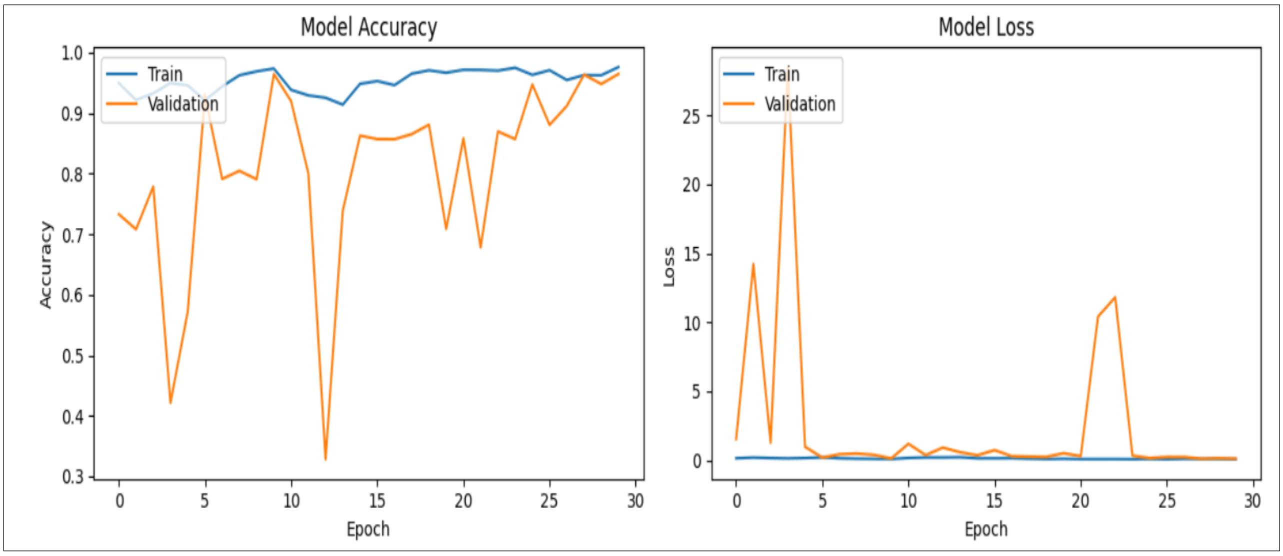

Figure 7 Comparison between training accuracy with validation accuracy and training loss with validation loss for Experiment 3 (Real vs Hard Alteration).

6. Comparative Analysis of Experiments

The InceptionV3 model [20] consistently demonstrated exceptional performance across all three experiments. It achieved the highest accuracy (98.07%) in distinguishing between real and medium-altered fingerprints [21], highlighting its robustness against moderate alterations. Even with hard alterations [21], the model maintained a high accuracy of 96.47%.

While the model consistently demonstrated strong performance, the choice of activation function influenced the results. Softmax proved effective for easy and medium alterations, while Sigmoid demonstrated superior performance for hard alterations. This suggests that the optimal activation function may vary depending on the severity of fingerprint alterations.

Table 4 Comparison of Experimental Results.

Experiments	Loss	Accuracy	Activation Function	Total Images	No. of Parameters (Total)
Real vs Easy Alteration	0.2111	91.04%	Softmax	23,931	22.852898 M
Real vs Medium Alteration	0.0586	98.07%	Softmax	23,067	22.852898 M
Real vs Hard Alteration	0.1103	96.47%	Sigmoid	20,272	22.852898 M

7. Conclusion

This research demonstrates the effectiveness of the InceptionV3 model in accurately detecting fingerprint alterations. Despite achieving high accuracy rates (91.04% for easy alterations, 98.07% for medium alterations, and 96.47% for hard alterations), the model's performance in terms of recall and F1-score may be limited by its tendency to prioritize precision.

Our findings also highlight the influence of activation functions on the model's performance. While Softmax proved effective for easy and medium alterations, Sigmoid demonstrated superior results for hard alterations.

Overall, the InceptionV3 model offers a promising approach for fingerprint alteration detection. Future research could focus on improving recall and F1-score, exploring alternative activation functions, and investigating the impact of different hyperparameter settings to further enhance the model's performance.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

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