Deep Learning-Based Biometric Verification in a Secure Cloud Environment

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Abstract

This paper introduces a pioneering biometric authentication system designed for secure cloud environments, combining facial recognition and signature verification through deep learning techniques. The facial recognition network achieved a commendable accuracy of 96.2%, while the signature verification network excelled with an impressive 98.2% accuracy. These results affirm the system's robustness in distinguishing between genuine and fraudulent signatures and facial images, crucial for secure cloud-based authentication. The study emphasizes the system's efficacy, with facial recognition accuracy ensuring correct user verification in nearly 96.2% of cases. The inclusion of a human verification feedback loop addresses discrepancies, enhancing overall reliability and trust in the biometric authentication process. Securely stored face-signature pairs in a cloud-based database facilitate continuous system improvement through iterative retraining, adapting to evolving security challenges. In conclusion, the research demonstrates the viability of deep learning-based biometric verification in secure cloud environments. The high accuracy rates, coupled with a human verification safety net and iterative retraining, provide a foundation for the implementation of robust and adaptive cloud-based authentication systems, ensuring security and reliability in the face of evolving technological landscapes.

Keywords: Biometric authentication, cloud security, deep learning, facial recognition, signature verification, Siamese network,

1. Introduction

The rapid advancement of technology has ushered in a new era of digitalization, transforming the way we conduct business, communicate, and access critical services. Central to this technological revolution is the widespread adoption of cloud-based services, which offer unparalleled scalability, flexibility, and accessibility. As individuals and organizations increasingly rely on cloud environments to store and manage sensitive data, ensuring the security of these services becomes paramount [1]. Secure and robust authentication methods are vital to safeguarding data integrity and preventing unauthorized access [2].

In response to this growing need for secure cloud-based authentication, our research endeavors to introduce an innovative and comprehensive biometric verification system. This system combines the use of facial recognition and signature verification, both driven by deep learning techniques, to establish a robust layer of security within the cloud environment. The system operates within the paradigm where a facial image and a handwritten signature are submitted from a client to a cloud server for authentication[3-7].

At its core, our system employs a state-of-the-art deep learning approach, specifically, a Convolutional Neural Network (CNN) based Siamese network, for facial recognition. This network is designed to scrutinize the facial features of the user and determine whether the presented face aligns with the expected user identity. Additionally, a parallel CNN-based fraud vs. genuine signature recognition network analyzes the handwritten signature to ascertain its authenticity.

The biometric verification process involves the following steps: if both the facial recognition and signature verification stages successfully authenticate the user, cloud-based authentication is granted. However, in cases where either the facial or signature verification encounters discrepancies or errors, the system activates a crucial human verification component. This human intervention step introduces an essential feedback loop, where images of both the face and signature are forwarded to a secure client for manual verification, rectifying potential AI detection inaccuracies [8-14].

To bolster the system's performance and maintain its adaptability in the face of evolving challenges, the data pairs generated through this process are securely stored in a dedicated database on the cloud. Once a substantial volume of data accumulates, both the facial recognition and signature verification networks are retrained using the incorrectly classified images, facilitating continuous learning and improvement [15-17].

The primary objectives of this research are to address the pressing need for enhanced cloud-based authentication methods, ensuring data security in a rapidly evolving technological landscape. By synergizing facial and signature recognition within a secure cloud environment, our system seeks to provide a cutting-edge solution that prioritizes both security and user-friendliness. Through this innovative approach, we aim to empower individuals and organizations with a robust and reliable biometric verification system, securing the cloud-based services that have become an integral part of our digital lives [18-22].

2. Methods

Facial recognition network (Siamese CNN)

Dataset:

In the initial phase of our research, we assembled a diverse collection of facial images, featuring renowned individuals from various fields. This facial dataset comprises a total of 1690 distinct faces and is also a part of the Kaggle Face Recognition challenge. To prepare the images for subsequent analysis, we initiated a preprocessing procedure. Initially, a Gaussian filter was applied to these images to enhance their smoothness, thus optimizing their suitability for facial recognition tasks. Subsequently, the images were uniformly cropped to a standard dimension of 250 x 250 x 3, a size conducive to initial processing stages.

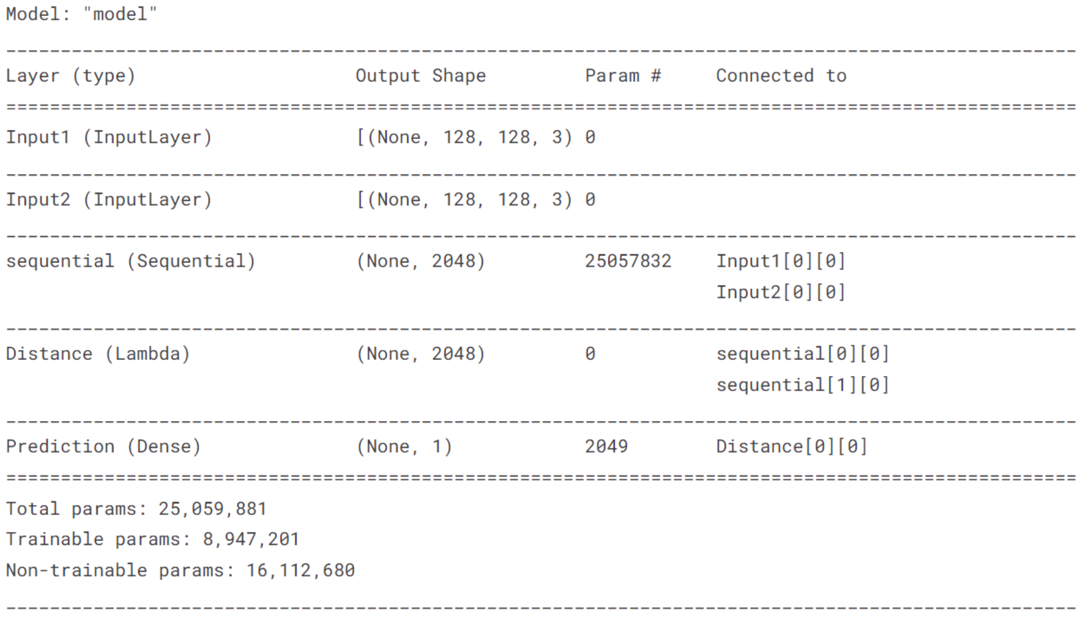
However, for compatibility with our AI model, which is specifically designed to accept images of dimensions 128 x 128 x 3, a secondary cropping step was implemented to adjust the images to the model's input requirements. It is important to note that the decision to maintain the images in full RGB color format, as opposed to converting them to grayscale, was made intentionally. Converting to grayscale would have resulted in diminished detection capabilities due to the loss of valuable color information. While grayscale conversion would have led to fewer trainable model parameters and potentially increased inference speed, these gains were ultimately deemed insufficient to justify the substantial compromise to network performance.

A noteworthy challenge that we addressed during this dataset preparation phase was the class imbalance issue. Within the dataset, classes (representing individual personalities) exhibited significant disparities in the number of images they contained. For instance, some classes featured as few as 2 images, while others included up to 8 images of a single personality. This led to a non-identically and independently distributed (non-IID) dataset, which could potentially affect the learning process of the subsequent AI model.

In recognition of this class imbalance challenge, our AI model's design and training strategy were tailored to mitigate the issue, ensuring that all personalities within the dataset received fair representation during the training process. This approach was vital in preventing any one class from dominating the model's learning, thus enabling it to effectively recognize a wide range of individuals from our diverse dataset.

Model:

The architecture summary used for facial recognition is a Siamese Network as shown in Figure 1.



```
Model: "model"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
Input1 (InputLayer)             [(None, 128, 128, 3) 0

__________________________________________________________________________________________________
Input2 (InputLayer)             [(None, 128, 128, 3) 0

__________________________________________________________________________________________________
sequential (Sequential)         (None, 2048)         25057832    Input1[0][0]
                                                                 Input2[0][0]
__________________________________________________________________________________________________
Distance (Lambda)               (None, 2048)         0           sequential[0][0]
                                                                 sequential[1][0]
__________________________________________________________________________________________________
Prediction (Dense)              (None, 1)            2049        Distance[0][0]
==================================================================================================
Total params: 25,059,881
Trainable params: 8,947,201
Non-trainable params: 16,112,680

__________________________________________________________________________________________________
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Figure 1: Siamese Network model summary

Our model is tailored to accommodate input data in the format of 128 x 128 x 3, necessitating the cropping of original images to align with these dimensions. This choice reflects the model's inherent design, and it is a pivotal step in the preprocessing pipeline.

Within the model architecture, there are two distinct input layers, each conforming to the 128 x 128 x 3 dimensions. These input layers serve as the initial points of interaction between the model and the image data. Subsequently, the data flows through a sequential layer designed to compress the multi-dimensional input into a one-dimensional vector of size 2048. This vectorization process is pivotal in creating a feature representation of the input images that the model can work with effectively.

The final layer in our model is a dense, fully-connected layer, culminating in a single output representing the class label. The inclusion of this layer facilitates the model's classification task, enabling it to assign a specific class label to input data based on learned features.

In terms of model parameters, our network exhibits a total parameter count of 25,059,881. However, it is noteworthy that the total number of trainable parameters is significantly lower, with a count of 8,947,201. This distinction arises from the presence of non-trainable parameters in the model, such as those introduced during feature extraction layers, which do not undergo weight updates during training.

For a visual representation of the network architecture, please refer to Figure 2. The architecture has been intentionally designed to be straightforward and streamlined. This design approach is driven by the specific operational context of the model, where computational efficiency and swift predictions are of paramount importance. This streamlined architecture strikes a balance between speed and accuracy, ensuring that the model can deliver rapid and reliable predictions. However, it is important to note that in scenarios where computational speed is not a limiting factor, more complex architectures may be explored, potentially offering even higher accuracy at the expense of increased computational demands.

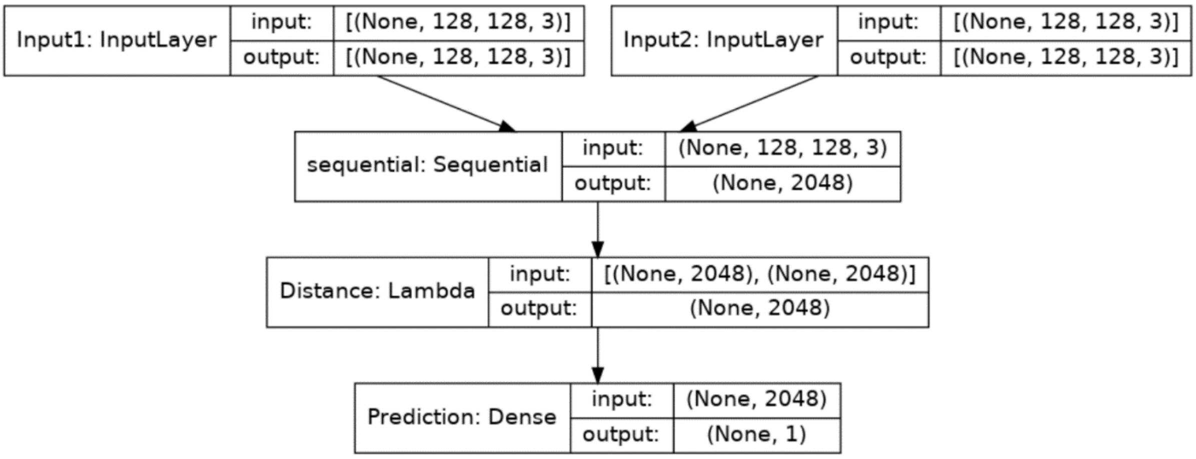

Input1: InputLayer
input: [(None, 128, 128, 3)]
output: [(None, 128, 128, 3)]
Input2: InputLayer
input: [(None, 128, 128, 3)]
output: [(None, 128, 128, 3)]
sequential: Sequential
input: (None, 128, 128, 3)
output: (None, 2048)
Distance: Lambda
input: [(None, 2048), (None, 2048)]
output: (None, 2048)
Prediction: Dense
input: (None, 2048)
output: (None, 1)

Figure 2: Siamese Network model architecture

Signature verification network (CNN)

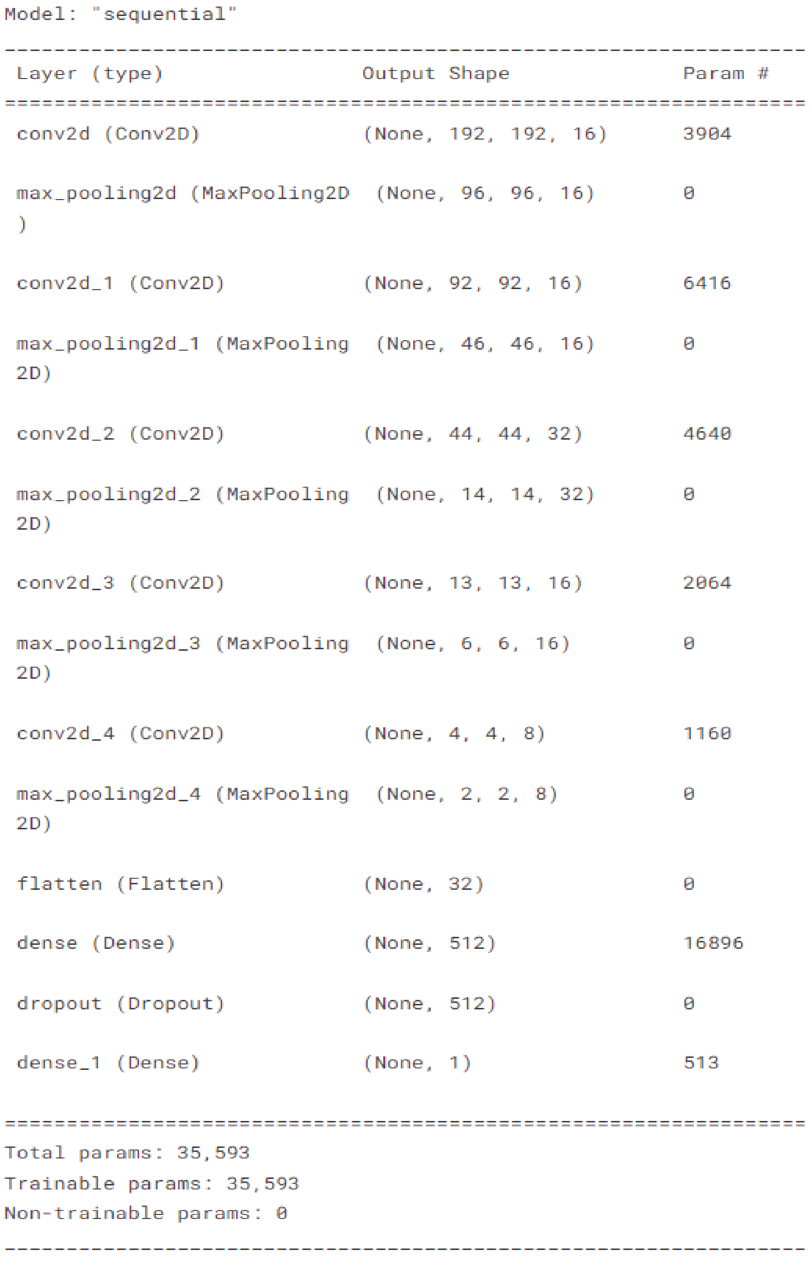
Dataset: The dataset we've employed comprises a diverse collection of signatures, encompassing samples from 69 distinct individuals. Each person is represented by a set of 24 genuine signatures and 12 forged signatures, totaling 36 signature samples per individual. This balanced distribution of genuine and forged samples is essential for robust signature verification training.

For evaluation and testing purposes, a separate test dataset was constructed, featuring 12 genuine and 12 forged signatures for each of the 21 individuals selected. This selection of test subjects ensures comprehensive testing across a range of signature styles and variations.

It's important to note that the images in both the training and test datasets exhibit varying dimensions, with an average length of approximately 450 units and a height of approximately 200 units. This diversity in image dimensions reflects the real-world variability of signatures and poses a challenge for the signature verification system, necessitating robustness in handling varying input sizes.

Model:

The model summary detailing the architecture employed for genuine signature identification is visually presented in Figure 3. This particular model is composed of a well-defined structure aimed at effectively distinguishing genuine signatures.



```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 192, 192, 16)      3904

 max_pooling2d (MaxPooling2D  (None, 96, 96, 16)       0
 )

 conv2d_1 (Conv2D)           (None, 92, 92, 16)        6416

 max_pooling2d_1 (MaxPooling  (None, 46, 46, 16)       0
 2D)

 conv2d_2 (Conv2D)           (None, 44, 44, 32)        4640

 max_pooling2d_2 (MaxPooling  (None, 14, 14, 32)       0
 2D)

 conv2d_3 (Conv2D)           (None, 13, 13, 16)        2064

 max_pooling2d_3 (MaxPooling  (None, 6, 6, 16)         0
 2D)

 conv2d_4 (Conv2D)           (None, 4, 4, 8)           1160

 max_pooling2d_4 (MaxPooling  (None, 2, 2, 8)          0
 2D)

 flatten (Flatten)           (None, 32)                0

 dense (Dense)               (None, 512)               16896

 dropout (Dropout)           (None, 512)               0

 dense_1 (Dense)             (None, 1)                 513

=================================================================
Total params: 35,593
Trainable params: 35,593
Non-trainable params: 0
_________________________________________________________________
```

Figure 3: Signature Verification model summary

The architecture encompasses a sequence of 4 convolutional layers, each serving as a feature extractor. Positioned strategically between these convolutional layers is a max pooling layer, which plays a crucial role in subsampling the extracted features, facilitating better spatial representation.

Following the convolutional layers, there are 2 fully connected layers responsible for classification tasks. These layers take the high-level features generated by the preceding layers and make the final decisions regarding the signature's authenticity.

In terms of model parameters, the total count relevant for training amounts to 35,593. These parameters are fundamental in shaping the model's ability to learn and generalize patterns, ultimately contributing to its proficiency in genuine signature identification.

The model was trained for 40 epochs with Binary Cross Entropy loss and RMS Prop Optimizer.

Human verification component

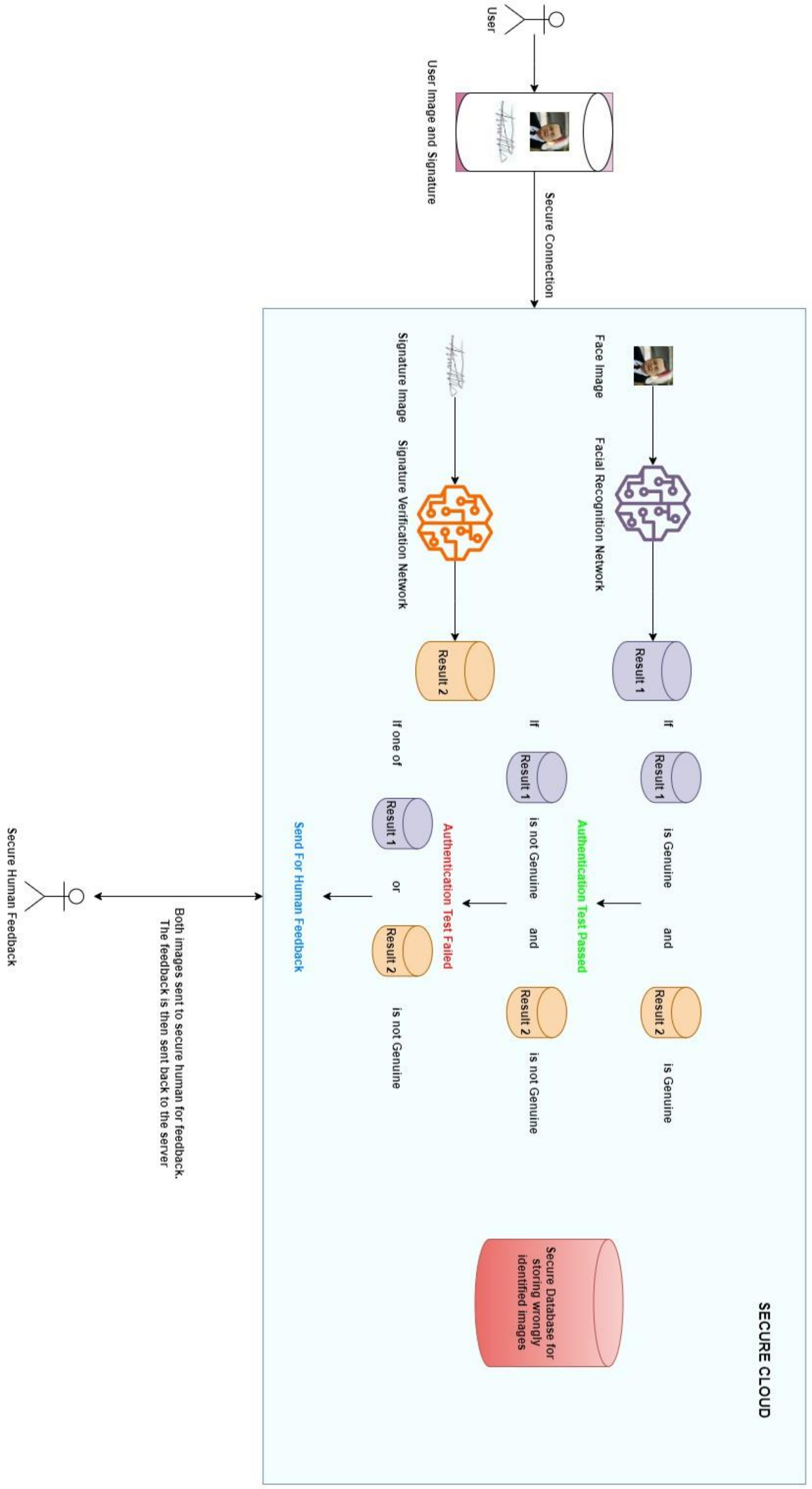
Within the cloud environment, the system involves two primary biometric verification components: a facial recognition network and a fraud vs. genuine signature recognition network, both of which are Convolutional Neural Networks (CNNs). The facial recognition network, designed as a CNN-based Siamese network, plays a pivotal role in determining whether a given face belongs to the intended user. Concurrently, the signature recognition network, also a CNN, serves to ascertain the authenticity of the user's signature.

However, in situations where either the facial recognition or signature verification process encounters a discrepancy or error, the system initiates a crucial human verification component. When a mismatch or inaccuracy occurs in either the facial or signature recognition steps, the system forwards both the facial and signature images to a secure client for human intervention and verification. This human verification step is essential to rectify potential errors or discrepancies that automated AI detection might fail to address effectively.

Moreover, in cases where the AI-based recognition systems make incorrect determinations, feedback on these discrepancies is transmitted back to the server. This feedback loop aids in improving the overall system's performance by iteratively enhancing the accuracy and reducing errors.

All validated face-signature pairs, including those that have undergone human verification, are securely stored in a dedicated database within the cloud. This database serves as a repository of verified biometric data, contributing to the system's continuous learning and improvement. As more such data accumulates, the system periodically retrains both the facial recognition and signature verification networks using the incorrectly classified images, further refining their accuracy and capabilities.

Methods Summary



3. Experimental Results

3.1 Facial Recognition Results

The Siamese Network's training process was conducted on a computing system equipped with substantial hardware capabilities, featuring 32 GB of RAM, an 8 Core CPU, and a potent 8 GB RTX 3070 GPU. The comprehensive training was completed within a total duration of 4 hours and 35 minutes, leveraging this high-performance setup.

The training regimen involved running the network for 5 epochs, with a batch size set at 1024. This specific choice of a 5-epoch training duration was made thoughtfully, considering the potential integration of future data additions. Limiting the training to 5 epochs helps in managing the training time efficiently while retaining adaptability for future enhancements or updates.

When evaluated on the test dataset, the model exhibited an impressive accuracy of 96.32%, attesting to its robust performance in distinguishing between genuine and fraudulent signatures. To conduct this evaluation, 5% of the entire dataset was partitioned for testing purposes, ensuring that a representative portion was used to gauge the model's proficiency.

For a more comprehensive view of the model's learning progress and its evolving accuracy, a visualization of accuracy changes over epochs can be referenced in Figure 4. This graphical representation elucidates how the model's performance improved and stabilized during the training process, highlighting its ability to make increasingly accurate classifications with each successive epoch.

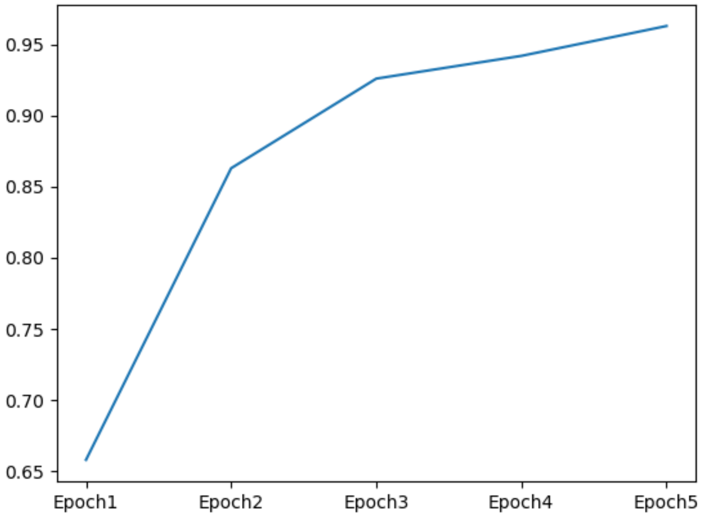


Figure 4: Test accuracy over training for 5 epochs. We observe a rise in accuracy with each epoch.

The evolution of loss during the training process is illustrated in Figure 5, spanning across 5 epochs and encompassing 55 individual batches. The x-axis of the loss curve corresponds to the batch numbers, where each epoch consists of 11 distinct batches. In total, there are 55 batches over the course of the 5 training epochs. Figure 5 serves as a visual representation of how the loss metric changes and fluctuates throughout the training period, providing insights into the model's convergence and optimization process as it processes each batch of data. The gradual progression of loss across these batches and epochs is a key indicator of the network's learning dynamics and its capacity to adapt and improve its performance over time.

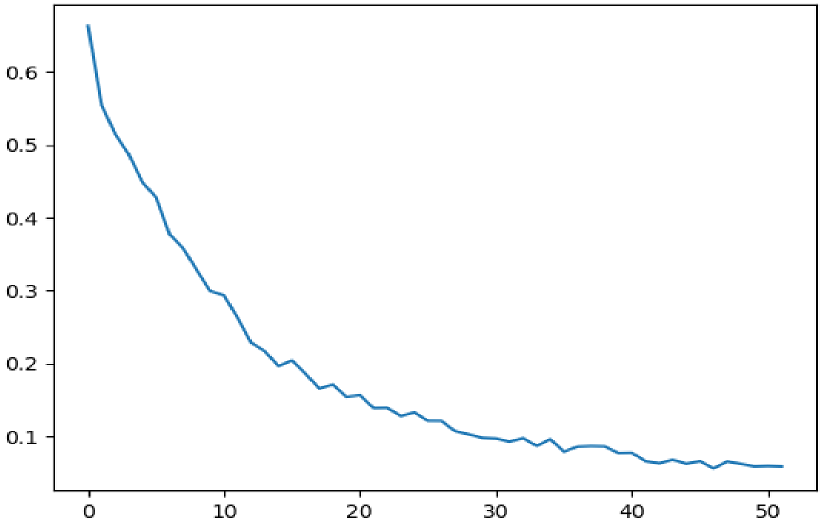


Figure 5: Loss curve for training. Here Y-axis represents loss metric and the X-axis represents batch number

Signature Verification Results

In Figure 6, a comprehensive illustration of the model's accuracy across a total of 40 epochs is presented. This visualization reveals a distinctive pattern in the accuracy trend during the training process. The chart vividly demonstrates a substantial surge in accuracy, particularly notable between the 5th and 20th epochs, signifying a period of rapid learning and refinement in the model's performance. Beyond the 20th epoch, the accuracy curve exhibits a more gradual incline, eventually reaching a point of saturation at the 40th epoch.

It is intriguing to note that the training process's lowest loss is observed at the 37th epoch. This epoch coincides with a remarkable achievement: the model's highest accuracy rate of 94.2% when evaluated on the validation dataset. This convergence of minimal loss and maximum accuracy at the 37th epoch underscores the model's remarkable ability to strike a balance between precision and generalization, marking a pivotal milestone in the training process.

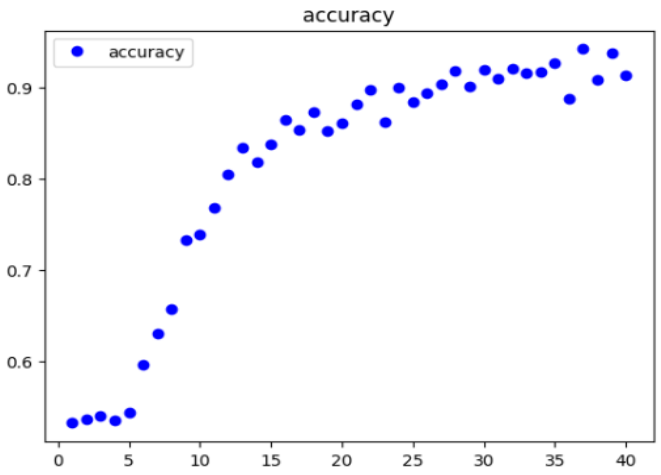


Figure 6: Accuracy per epoch during training on validation data

In Figure 7, we present a comprehensive visualization of the loss curve, which encapsulates the model's learning progress over a span of 40 training epochs. The loss curve, a fundamental metric in deep learning, exhibits a characteristic trajectory observed in the training of neural networks.

Notably, the loss curve demonstrates a consistent reduction pattern, which is a well-documented phenomenon in the training of deep learning models. This pattern signifies that the model gradually refines its performance, optimizing its ability to minimize errors and discrepancies in its predictions.

What makes the 37th epoch particularly intriguing is that it coincides with the occurrence of the lowest recorded loss value during the training process. This epoch marks a significant juncture in the model's learning journey, as it attains a state of enhanced proficiency in its predictive capabilities. This observation underscores the model's capacity to iteratively fine-tune its performance and converge toward more accurate and reliable predictions.

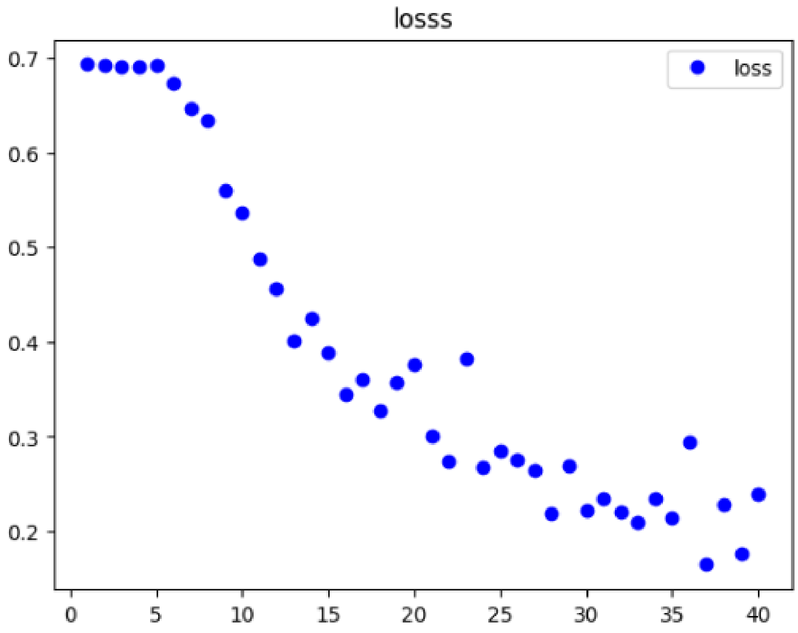


Figure7: Loss curve for 40 epochs of training

On the test dataset, the model achieved a significant accuracy of 98.2%. This underlines the model’s ability to successfully identify and verify genuine signatures among and reject forgeries.

4. Discussion and Conclusion

The results from the study provide valuable insights into the effectiveness of the proposed system, which combines facial recognition and signature verification for biometric authentication in a secure cloud environment.

First and foremost, the obtained results are highly encouraging. The facial recognition network demonstrated a commendable accuracy rate of 96.2%, while the signature verification network surpassed with an even more impressive accuracy of 98.2%. These outcomes reflect the robustness and reliability of the deep learning-based biometric verification system in identifying and distinguishing between genuine and fraudulent signatures and facial images.

The achieved accuracy rates highlight the system's efficacy in ensuring secure cloud-based authentication. A facial recognition accuracy of 96.2% implies that nearly 96.2% of the time, the system correctly verifies whether the face belongs to the desired user. Similarly, the 98.2% accuracy in signature verification signifies a high level of confidence in the system's ability to determine the authenticity of a user's signature. Such high accuracy levels are crucial for bolstering security and reducing the likelihood of unauthorized access in cloud-based environments.

One of the pivotal components that contributed to the success of this system is the human verification feedback loop. In cases where either the facial or signature recognition process encounters discrepancies or errors, the system seamlessly triggers human intervention. This feedback mechanism plays a critical role in rectifying AI detection mistakes, offering an additional layer of assurance in the authentication process. This approach not only enhances the accuracy of the system but also fosters trust and confidence in the biometric verification process.

Furthermore, the collected face-signature pairs, including those subjects to human verification, are securely stored in a cloud-based database. This database serves as a repository for improving the system continually. As more data accumulates, both the facial recognition and signature verification networks are retrained with the incorrectly classified images. This iterative retraining process ensures that the system remains adaptive and up-to-date, consistently improving its performance over time.

In conclusion, the study's results underscore the viability of deep learning-based biometric verification in a secure cloud environment. The high accuracy rates achieved by the facial recognition and signature verification networks affirm their efficacy in ensuring secure authentication. Additionally, the inclusion of a human verification feedback loop serves as a critical safety net, rectifying AI detection errors and enhancing the overall system's reliability. The iterative retraining process further ensures the system's longevity and adaptability in the face of evolving security challenges. This approach demonstrates a strong foundation for the implementation of secure and robust cloud-based authentication systems.

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