Volume 21 Issue 2: KUS: 1180: 03032024: 2024

KHULNA UNIVERSITY
STUDIES

journal homepage: www.kus.ku.ac.bd

Research article

INCV: An Inception Network Based Deep Learning Framework for Signature Recognition

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ABSTRACT

The signature of an individual is a handwritten sign or mark that resembles an individual's name, is often stylized and unique, and indicates the person's identity, intent, and consent. There are many cases where the signature may be forged by an anonymous person, which is one of the most complicated real-world problems and has significant social and commercial impacts. Given the widespread use of handwritten signatures in legal and financial transactions, it is imperative for researchers to carefully choose an effective method to verify these signatures and prevent forgeries, which can result in significant financial losses for customers. Although there has been a lot of study done on forgery detection and signature verification, the difficulty of detecting competent forgeries remains a major problem for both scholars and practitioners. This paper developed a strategy called Inception Network Customized Version (INCV) for signature recognition based on the two latest inception network architectures: Inception Network v3 and Inception ResNet v2. We have collected the signature images of individuals and worked with these pre-trained models to apply transfer learning to create our customized models. We have employed our customized versions to recognize the images of the individual's signature. Comparative analysis between the two customized versions of the inception network gives a better approach for recognizing individuals' signatures than the traditional approaches for recognizing signatures, where INCV I (based on Inception Network V3) gives 97% accuracy on the train set and 92% accuracy on the test set, however, INCV II (based on Inception ResNet V2) produced 98% accuracy on the train set and 96% accuracy on the test set.

ARTICLE INFO

Article timeline:
Date of Submission:
03 March, 2024
Date of Acceptance:
19 November, 2024
Article available online:
18 December, 2024

Keywords:
Signature Recognition
Convolutional Neural Networks (CNN)
Inception Network V3
Inception-ResNet V2

Introduction

Signature verification systems can be broadly classified into two distinct categories: online and offline. These categories are based on how the signatures are captured and processed, and they serve different purposes and have unique characteristics. In online signature verification systems (Bhowal, Banerjee, 2022), individuals provide their signatures using a digital device, such as a stylus and a digitizing tablet or a touchscreen interface. In offline signature verification systems (Sharma, 2022), signatures are recorded in a static format, generally as scanned pictures or photographs of handwritten signatures on paper documents.

The use of a person's handwritten signature to authenticate the legitimacy of documents such as certificates, cheques, drafts, letters, approvals, visas, and

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DOI: https://doi.org/10.53808/KUS.2024.21.02.1180-se

passports is commonplace. Sometimes human eyes can't catch smaller details of an image say an image of a signature of an individual where a well-trained detection model can easily catch very small details of that particular image as there is a use of feature extractor to be trained on (Zhu, Zheng, 2008). Feature extractor depends on how efficient the CNN architecture is, generally classical CNN's like inception network architectures are better feature extractor than traditional CNN architectures (Kao Wen, 2020).

Typical image detection is recognizing and categorizing features, patterns, or objects—like faces, animals, or commonplace objects—that are present in a picture. It makes use of deep learning algorithms, segmentation, and edge detection as broad image detection approaches (Li, Feng, Liu Han, 2021]. On the other hand, signature detection is a particular type of image analysis used to recognize electronic or handwritten signatures. It involves determining the distinctive characteristics of a signature, such as curves, pressure points, and stroke patterns. To verify authenticity, methods like pattern matching, feature extraction, and occasionally biometric verification are frequently used (Alajrami, 2020).

The purpose of this research is to utilize the best deep learning model among inception network v3 and inception Resnet v2 to classify 15 users' signatures. A total of 200 valid signatures are available to each user and a total of 3000 signature images are collected from 15 individuals 2400 train images and 600 test images are included in our training-testing set. We evaluated the performance between two inception networks (Inception Network V3 and Inception ResNet V2) customized versions and suggested the best approach for recognizing signature images. Based on our field of interest, we've tried to build a standard dataset which is the first and foremost task to achieve our targeted insight. Besides that, we preprocessed our collected signature images to give better inputs to the models.

We studied and observed the architectural design of inception network v3 and inception Resnet v2 deeply to create our own customized versions; hyperparameter tuning was one of the most complicated tasks. This was achieved by continuous observation and analysis of the results of the models and eventually we proposed a better model between inception network v3 and inception Resnet v2 for signature recognition which can recognize the signatures of fifteen individuals. We tried to find which deep learning approach is better for our multi-class image classification task (Szegedy, 2015), signature recognition by this research. Moreover, there were historically slight difference in performance between inception network models because even the first version of inception network gave better performance on image classification task than many deep learning models, version by version authors improved the inception networks by made subtle changes in its architecture. In this research, we also tried to show the performance evaluation between two latest versions of inception network, and we found that latest version of inception network is more stable in image classification task where inception Resnet v2 has improved because of more stable residual connection in the network.

We employed the same dataset for our two customized models of inception network, and we made some baselines based on our gained insights from the performance of the models where we took the precision, recall and F1 score as its performance metrics. We found that our customized inception Resnet v2 worked better on our signature image dataset and it has more architectural stability than inception network v3.

Literature Review

Neha Sharma at el.[Sharma, 2022] presents an automatic signature verification method based on deep learning, utilizing the Grupo de Procesado Digital de Seales and a synthetic signature dataset. Their improved Inception V3 model outperforms six previously trained models and achieves a remarkable accuracy of 88%. This study not only shows how well CNN-based models work for offline signature verification, but also shows how deep learning has the potential to increase security and productivity in businesses and financial divisions. Dimitrios Tsourounis at el. (Tsourounis, 2022) enhances Offline Signature Verification (OSV) using Deep Convolutional Neural Networks (CNNs), by utilizing prior knowledge from a comparable task. The study achieves state-of-the-art performance with fewer training samples by pre-training the CNN on handwritten text-based writer identification and fine-tuning it for OSV. In order to improve signature verification systems, knowledge transfer across domains has shown outstanding results on difficult signature datasets.

Teressa Longjam at el. (Longjam, Kisku, 2023) presents a writer-independent offline signature verification system using Convolutional Neural Networks (CNN) for multi-scripted signatures in India.The model outperforms existing models and delivers outstanding verification accuracy, up to 98.33% for combined scripts. The difficulty of successfully authenticating different signatures in a multi-cultural setting is addressed in this study. Duth P Sudharshan at el. (Sudharshan Vismaya, 2022) focuses on offline handwritten signatures and assesses three deep convolutional neural networks for feature extraction using transfer learning (VGG16, VGG19, and ResNet50). On the SigComp2009 dataset, the study finds that VGG19 performs the best, with an astounding 97.83% accuracy. Keiron O'Shea at el. (O'Shea NashO, 2015) broadly described the concept of convolutional neural networks. This paper explained how basic CNN works and also described about different types of layers in CNN which are the basic building block of classical CNN architectures like LeNet, ResNet, Inception networks etc. Szegedy at el. (Saha, 2018) discovered the new way of learning deeper features by a convolutional neural network which was way more efficient than traditional CNN. This paper was revolutionary in the field of image classification and they named it as inception network v1 and this was the first version; later other versions were released on top of it. Authors focused on to create wider version of CNN rather than highly increasing layers. Ioffe at el. (Ioffe Szegedy, 2015) improved the efficiency of previous network by offering the batch normalization on top of the previous version and named it inception network v2 and simultaneously rediscovered the whole architecture by modifying inception modules and some other architectural changes and named it inception network v3 which was more advanced version than previous one. Szegedy at el. (Szegedy, Ioffe, .2017) observed the previous versions of inception network and discovered improved inception modules which drastically improved the performance of the basic version of inception network. In this paper, researchers proposed modified previous inception modules and three different types of network which were inception v4 core version and besides inception Resnet v1 and v2, which involves resnet concept with the inception modules. Connor at el. (Shorten Khoshgoftaar, 2019) showed the importance of data augmentation in deep learning field by proper statistics where authors analyzed on various CNN architectures like AlexNet and ResNet which are the classical CNN and working better on image classification task rather than traditional approaches. Sinno at el. (Pan Yang, 2009) broadly researchers on transfer learning how it was going on the field of classification, regression and clustering problems. It was very helpful for understand the importance and guidance of transfer learning. In this paper, authors described about the statistics which helps to understand the importance of different settings of transfer learning approach and this transfer learning. Ali Karounia at el. (Karouni, Daya Bahla, 2011) proposes artificial neural network approaches for recognizing signatures of individuals; ANN performs better in image classification than other machine learning approaches that time. They used various data preprocessing steps; feature extraction was one of the main step they did but their ANN was too shallow than now. Alex Krizhevsky at el. (Krizhevsky, Sutskever Hinton, 2012) , this revolutionary paper shows the way of big improvement in the traditional convolutional neural networks where authors focuses on depth of the architecture of network as well as to train deeper network by a big dataset which is also important to build a good deep learning model. Authors develop the idea of memory-efficient model where they clearly address the importance of GPU and it was the break-through for the deep learning community to develop any idea faster than before. Here, authors also try to make improvement in the idea of the application of proper activation function and try to clearly address the overfitting issue which can be a problem as they used big dataset for training their model and they proposed good solutions to technically avoid overfitting problem of the model. Fadi Mohammad Alsuhimat at el. (Alsuhimat Mohamad, 2023) proposed a method utilizing the Histogram of Oriented Gradients (HOG) for feature extraction and coupled it with a Long Short-Term Memory (LSTM) neural network for improved performance in OSV. Managing the variation in signatures created by the same person was one of the main issues with signature verification that their method tackled. They used HOG to extract reliable features from signature photos, which they then fed into the LSTM model. Teressa Longjam at el. (Longjam, Kisku Gupta, 2023) presents a hybrid deep learning approach for offline signature verification, combining a Convolutional Neural Network (CNN) with a

Bidirectional Long Short-Term Memory (BiLSTM) network. The system excels at detecting subtle differences between genuine signatures and skilled forgeries by using CNNs to extract intricate features and BiLSTM for classification. Israa Bashir Mohammed at el. (Mohammed, Mahdi Kadhm, 2023) proposes a handwritten signature identification system using MobileNets and a Support Vector Machine (SVM) classifier. After preprocessing signature images, MobileNets extracts features, and SVM handles classification. S. Kevin Joe Harris at el. (Harris Anitha, 2023) proposes an enhanced signature forgery detection technique using a Siamese Network based on an improved Convolutional Neural Network (CNN) architecture. By incorporating additional feature maps from intermediate layers and extra convolutional layers, the method strengthens signature verification.

The current works have clearly provided the groundwork for understanding signature verification and its difficulties after this literature review. To address the complexities and subtleties of signature verification, this research study adopts a novel strategy by employing an Inception-based network architecture. As we examine the distinctive capabilities of Inception networks in signature identification and verification, this divergence from conventional approaches holds the possibility of delivering greater accuracy and efficiency in the field.

Methodology

In the methodology section, we explore the technical details of how our research was conducted. This section serves as the roadmap to understanding the practical steps and processes undertaken to implement our Inception-based signature verification system. This research work is divided into two major segments; in the first segment, we used traditional ten layers deep CNN to extract features from images and recognize individual's signature images. In the second segment, two transfer learning models were developed from inception network v3 and inception Resnet v2 and we named these two models as INCV I and INCV II respectively. We illustrated the performance of traditional CNN on our signature dataset in first segment to prove the fact that classical CNN's architectures like INCV I and INCV II always outperformed traditional architecture. The second segment is the major part where the main purpose of our research lies there. To achieve the overall purposes of our research, we needed to go through the following steps which are data collection, pre-processing of the collected data, development of conventional cnn model and transfer learning-based INCV models, and here is a workflow diagram to gain a preliminary insight of our total procedures. Figure 1 shows the workflow diagram of the proposed methodology.

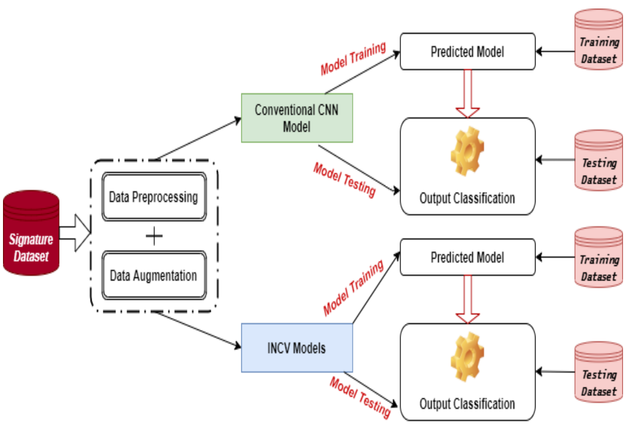


Figure 1. Workflow diagram of the applied system.

Data Collection

We collected genuine sample images of signatures from fifteen individual persons, there are fifteen separate classes for fifteen individuals. Collected images were taken on high quality camera to grab clearer details of the signatures. Total 3000 signature images were taken from 15 individual persons, images were distributed into two separate datasets which are training set and test set according to exact classes and there we skipped the validation dataset for lack of a good amount of data. We strictly maintained the sequence in the directory as it is more important to maintain the sequence for recognizing proper class by the model.

Data Preprocessing

In this step, at first images were randomly shuffled to avoid the skewness in dataset. We distribute the images by maintaining portions - 80% for training set and 20% for test set; which means our training dataset was built with 2400 signature images where fifteen individuals has 160 signature images each, and the testing dataset has 40 signature images each. After properly setting up the collected images, all images were resized into a specific size to maintain the consistency with the models, we cropped unnecessary portions by keeping the region of interest and we used the binary threshold of the open-cv library to extract necessary details from signature images and thus re-generate the pre-processed images in this way. Figure 2 shows sample of two original and re-generated images for our dataset images. For the limitation of our dataset, we used data augmentation technique to increase the variation in the training dataset and to train our models more efficiently where data augmentation making copies of existing images and making minor changes to them to bring variety in the training dataset; we didn't use data augmentation for testing dataset for technical purposes.

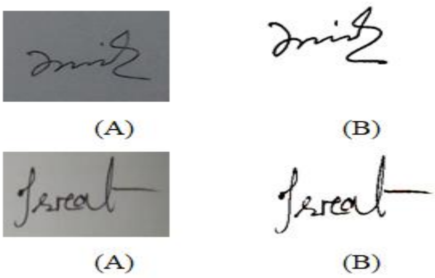


Figure 2. (A) Original image, (B) Re-generated image

Conventional CNN Model Development

CNN's main applications are in the field of image processing due to the secret potential to use the geometric of the images. It combines three architectural ideas: local receptive fields, shared weights, and spatial or temporal subsampling (Krizhevsky, 2012). In this step, custom-defined CNN architecture used in the conventional approach for feature extraction and for our image classification task. The models were developed using Keras API of tensorflow 2.0, which is a python-based framework for deep learning (Ribeiro, Gonçalves, Santos Kovacec, 2011). Our proposed CNN structure holds a total of eight layers which are shown in figure 3.

The proposed conventional CNN structure holds a total of ten layers which are as follows. First, the input layer: signature image features are given as input in this layer. Secondly, convolutional layer: 32 filters were used while having a 3×3 size kernel and batch normalization used there. Basically, in a convolutional layer, a filter is applied to the images and unnecessary details are removed while keeping the relevant information. Third, max pooling layer: max pooling operation was performed in this layer with a pool size of 4×4. Fourthly, we used a convolutional layer with 3×3 filter size and batch normalization was performed. Fifth, max pooling layer used with 4×4 pool size. Then, another two conv-max-pooling layer combinations used with 64 convolution filters and 4×4 pool size respectively. Then, flatten layer is used which is the function that converts the pooled feature map to a single column that is passed to the fully connected layer. So, the eighth layer was a dense layer which is a fully connected layer where the features from the previous layer are given as input. A sigmoid function was used as an activation function for these all layers. Finally, output layer used which gives the prediction probability from the given signature images to recognize signature of any of fifteen individuals; SoftMax activation function used as it was a multi-class classification task.

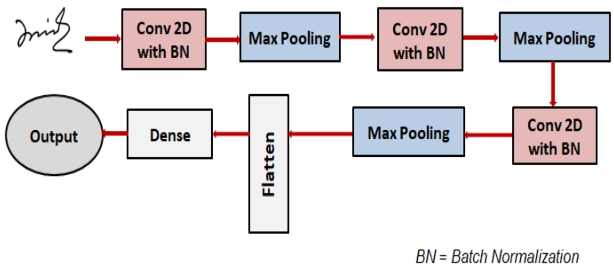


Figure 3. Architecture of the proposed CNN Model.

INCV Model Development

In this section, two different pre-trained models are used to build two different transfer learning models, we codenamed them INCV I and INCV II where first one was based on Inception Network V3 and second one was based on Inception ResNet V2; both of them are the latest version of Inception Network which is one of the efficient classical deep convolutional neural network (Ioffe Szegedy, 2015). We used the idea of transfer learning to build our customized inception network models; transfer learning is a machine learning technique in which a model created for one job is utilized as the basis for a model on a different task. We discussed the pre-trained inception networks in the following before jump into the creation of our transfer learning models.

Inception Network V3

By rethinking the inception network architecture, computational efficiency and fewer parameters are realized. With fewer parameters, a 42-layer classical deep convolutional neural network, with similar complexity as VGGNet, can be achieved. With 42 layers, a lower error rate is obtained and make it become the 1st Runner Up for image classification in ILSVRC (ImageNet Large Scale Visual Recognition Competition) 2015 (Szegedy, Vanhoucke, Ioffe, 2016). Figure 4 shows architecture of Inception Network V3.

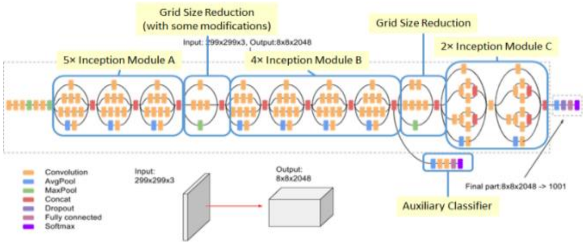


Figure 4. Architecture of Inception Network V3

Inception ResNet V2

Inception ResNet V2 was one of the classical CNN architecture proposed within inception-v4, which evolved from Google-Net / Inception-v1, has a more consistent and streamlined architecture than Inception-v3, as well as additional inception modules. The Microsoft ResNet-proposed Inception network with residual connections beats the comparably priced Inception network without residual connections. In the ILSVRC (ImageNet Large Scale Visual Recognition Competition) classification challenge, 3.08 percent error may be obtained using an ensemble of 1 Inception-v4 and 3 residual networks (Szegedy, Ioffe, 2017).Figure 5 shows architecture of Inception ResNet V2.

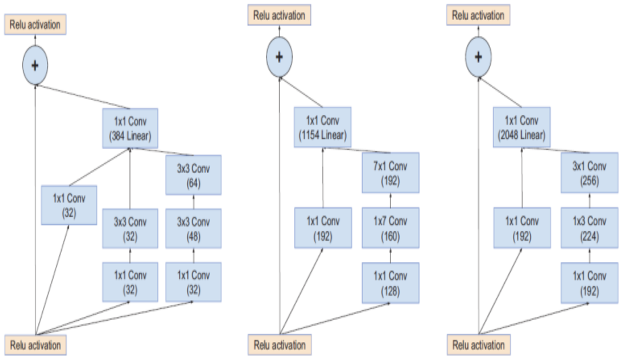


Figure 5. Architecture of Inception ResNet V2

We'll discuss INCV model now: as we used the idea of transfer learning, we collected the pre-trained weights of inception network v3 and inception Resnet v2 for INCV I and INCV II respectively. We declared the input shape (which were identical to the size of the images we trained on) and remove the top layer of the network as we would define this layer by ourselves by number of classes we want to train the model. Then, we freeze all the layers as we apply transfer learning method to build our own customized model. For creating INCV I, We took all the layers before the 'mixed9_0' named layer in inception network v3 architecture and we removed other layers after 'mixed9_0' from our consideration; this would be the exact place in the network where we would apply transfer learning method and from that layer, we would define our own customized layers. Similarly, For creating INCV II, We took all the layers before the 'block8_6mixed' named layer in inception Resnet v2 architecture and we remove other layers after 'block8_6mixed' from our consideration; this would be the exact place in network where we would apply transfer learning method and from that layer, we would define our own customized layers. By followed these steps, we defined our own customized models based on inception network v3 and inception Resnet v2; we codenamed these models INCV I and INCV II respectively. There were subtle parameter changes in comparison to the collected pre-trained weights of both the models. For INCV I and INCV II, after flattening the 'mixed9_0' and the 'block8_6mixed' respectively, we created a new layer with 1024 nodes and applied ReLu(Rectified Linear Unit) activation function. The rectifier function has the ability to produce a real zero value. To avoid overfitting in this network, we implemented dropout regularization. Several layer outputs are arbitrarily dropped out throughout our training. Then, we finally added 11 classes for final classification as we expect from our model to correctly classify 10 individual signature classes and one class for non-recognizable class. Here we use SoftMax activation for our multi-class classification.

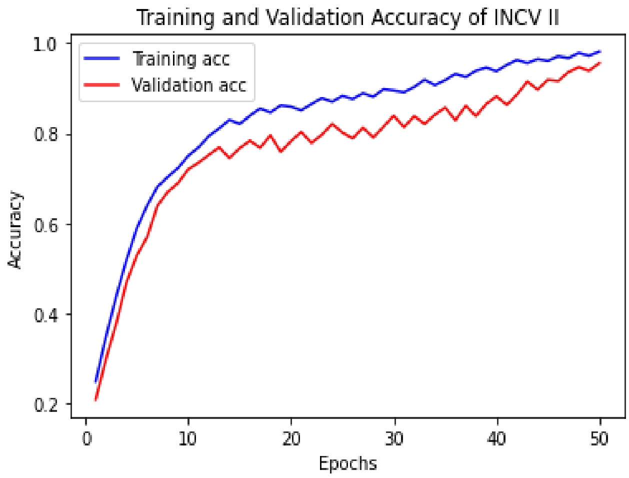
Hyperparameter tuning was an essential part of optimizing our signature recognition models. We focused on critical hyperparameters such as learning rate, batch size, number of epochs, and dropout rate, employing grid search and random search techniques to evaluate different configurations. By continuously monitoring performance metrics like accuracy and F1 score, we were able to identify the most effective settings

Results

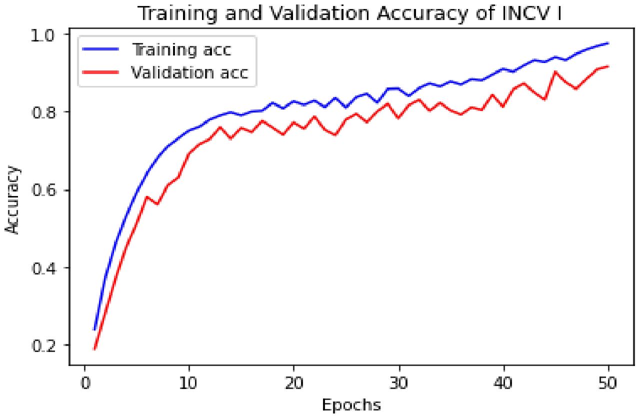
To evaluate the performance of each prediction model, a separate test set was used where all of the signature images of the test set, were completely un-used in train set. The test set contains a total of 600 images where 40 images were under each class. The performance of each prediction model was measured in terms of its accuracy, precision, recall, and F1 scores. Each of the evaluation parameters used for evaluation purpose, was obtained by performing macro averaging on the actual and model-predicted class labels, which calculated parameters for each class label and found their un-weighted means. Test dataset is the main concern to test which model performs better for a particular task like our signature recognition task. The best training performance was obtained by INCV II which were derived from inception Resnet V2 by transfer learning technique, though INCV I which were derived from inception network V3, had almost nearly performance to INCV II. INCV II obtained 98%, INCV I obtained 97%, and Conventional CNN obtained 88% train performances for different performance metrics including accuracy, precision, recall, and f1-score. However, INCV II outperformed INCV I in the test performance where INCV II obtained 96%, INCV I obtained 92%, and Conventional CNN obtained 86% accuracy, precision, recall, and f1-score: for each in analyzing the performance on the test dataset.

This research yielded three clearly defined outcomes. First, the best performing deep learning model was identified for classifying signatures from individuals signature images by applying conventional CNN approach and two classical CNN architectures on the labeled signature dataset and it was found that the transfer learning-based INCV II model gives better performance (98% F1 Score on training dataset and 96% F1 Score on test dataset) than rest of the approaches. Table 1 shows precision, recall and F1 score for Conventional CNN, INCV I and INCV II models both in training and testing.

Second, Inception Resnet v2 based transfer learning-based model INCV II has better performance on extracting features from signature images than inception network v3 based transfer learning model INCV I. Third, as INCV II outperformed the other two models on test dataset, so we can say that inception Resnet v2 is the better approach for recognizing signatures of individuals. Fourth, architecture of inception Resnet v2 is more stable to apply transfer learning approach for image classification task. Figure 6 presents the accuracy curves of the INCVI and INCV II.



(a)



(b)

Figure 6. Training and testing Accuracy Graph for each epoch (a) INCV I, (b) INCV II

While carrying out this study, the following obstacles were identified: first, there was a lack of a massive amount of data and here we used fifteen individuals' signature images but there is a scope to work with more and more individual's signatures and get more versatile data to establish our hypothesis. Second, extensive hyperparameter tuning can help to obtain even better performance for our CNN-based models in this study. Third, there was a trade-off between the algorithmic performance and the time complexity. Here in our training and testing procedure, we run the model with fifty epochs to compromise with the time complexity and to reduce the overfitting problem which is one of the vital problems faced by classical deep learning models.

Table 1: Results Obtained from proposed models

Models	**Models Based On**	**Training Performance**			**Testing Performance**		
		Precision	**Recall**	**F1 Score**	**Precision**	**Recall**	**F1 Score**
Conventional CNN	Traditional Deep CNN approach	0.881	0.876	0.878	0.864	0.857	0.860
INCV I	Inception Network V3	0.974	0.967	0.970	0.923	0.918	0.920
INCV II	Inception ResNet V2	0.981	0.976	0.978	0.963	0.957	0.960

Discussion

While digital signatures are more common in today's digital age, handwritten signatures continue to be very important in many different facets of society. For those responsible for making sure that documents are valid and secure, the problem of signature forgery continues to be of great concern. To successfully categorize people's signatures from signature photos, this research introduces the INCV II model, a cutting-edge transfer learning-based methodology. The proposed classifier's remarkable F1 score underlines its usefulness while also demonstrating the effectiveness and precision of the transfer learning strategy used in this work. Furthermore, the performance of two different Inception network versions is thoroughly explored in our research. With an emphasis on signature recognition tasks, this investigation aims to identify whether the version demonstrates superior stability and competency in the context of transfer learning and image classification. Our research not only suggests an improved approach for recognizing individual signatures but also sheds light on the architectural characteristics that affect performance discrepancies through a careful analysis of various deep learning models, including traditional CNN architectures and various iterations of the Inception network. Our research shows that Inception ResNet V2 has better stability and performance than Inception Network V3 because of its unique architectural layout. In essence, this research presents a transfer learning-based model that delivers improved accuracy and efficiency in identifying individual's signatures in order to address the ongoing difficulty of signature verification. In future work, we plan to apply our model alongside other signature detection models proposed by researchers on the same datasets. This comparative analysis will provide valuable insights into the relative performance of each model, allowing us to identify strengths and weaknesses and better understand advancements in the field.

Conclusion

In conclusion, this research introduces the INCV II model, a state-of-the-art transfer learning-based methodology, designed to address the persistent challenge of signature forgery in both digital and handwritten contexts. The proposed classifier demonstrates exceptional performance, as evidenced by its remarkable F1 score, highlighting its efficacy, precision, and utility in the realm of signature recognition. Through a comprehensive exploration of two different Inception network versions, namely Inception ResNet V2 and Inception Network V3, our investigation reveals that the former exhibits superior stability and competency in the context of transfer learning and image classification, owing to its unique architectural layout. The research further underscores the significance of exploring various transfer learning techniques, which are essential for enhancing the model's accuracy and efficiency. The findings indicate that the architectural design of the INCV II model not only boosts performance but also paves the way for future modifications and optimizations, potentially yielding even more effective signature detection solutions. Looking ahead, the future work outlined in this research encompasses refining transfer learning methodologies, expanding datasets to enhance model robustness, and addressing privacy concerns to ensure secure signature recognition. Furthermore, the incorporation of usability enhancements and benchmarking for real-world applications is crucial for validating the practical applicability of the proposed model. By advancing our understanding of effective methods for signature recognition tasks, this research lays a foundation for continued innovation in the field, offering a valuable contribution to the ongoing efforts in signature verification and document security.

Acknowledgement

We extend our heartfelt gratitude to the Department of Information and Communication Engineering, Noakhali Science and Technology University, Noakhali 3814, Bangladesh, for their invaluable support and contributions, which were instrumental in the successful completion of this research.

Conflict of Interest

The authors confirm that there is no conflict of interest with the publication of this article.

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