# NiohSign: A Siamese Neural Network Approach for Signature Authentication

MSc Research Project
Data Analytics


Anthony Effiok
x19108788

School of Computing
National College of Ireland


Supervisor: Dr. Hicham Rifai

**National College of Ireland**

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| **Student ID:** | X19108788 |
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| **Supervisor:** | Dr. Hicham Rifai |
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# NiohSign: A Siamese Neural Network Approach for Signature Authentication

Anthony Effiok
X19108788

**Abstract**

Signatures continuously play important roles as an accurate means of identification and also as a means to verify permissions given for tasks. The process of verifying if an appended signature for a task is forged or genuine plays a largely important role when trying to prevent acts relating to fraud or worse impersonation.
**Objective**- This project aims to create a network that is capable of identifying if a signature is forged or authentic through the use of Siamese neural networks which is essentially a twin neural network.
**Methodology**- The network to be used a s the base network is a model of the ResNet network known as InceptionResNetV2 model. The dataset used is a signature dataset that contains the signatures of 260 individuals with 100 in Bengali and 160 in Hindi.
**Results**- The Model is tested on the signatures appended in Hindi and is seen to perform well with an accuracy of 81.71%.
**Keywords -** ***Signature authentication, Siamese neural network, Artificial neural network***

# 1 Introduction

Signatures are basically pieces of text that an individual may use as a form of identification during a request or as a means of authorization. Many uses of signatures exist such as in a bank when an individual is signing off on a cheque, in the pharmacy when a doctor is issuing prescription drugs, or in places of work when an employee is signing into work and so much more. Considering the fact that signatures can be utilised to such a high degree, the task of signature authentication is of critical importance so as to control or better yet prevent the exploits that can arise in the case of forged signatures such as fraud along with other criminal acts.

Signatures can typically be appended online using digital pens and other applications or offline with a standard pen over paper approach. The main focus on this paper will be placed solely on offline signatures which have been converted to digital images through a scanner. The development of a signature verification system will help combat the uncertainty that exist in a manual method of authentication.

Numerous methods and techniques in the field of machine learning have been used in the past to help when determining if signatures are false or authentic. Such techniques include the discrete radon transform method used with a hidden markov model by Coetzer et al. (2004), also the use of geometric feature extraction using artificial neural networks by Chandra & Maheskar (2016) and the use of structural dynamic warping by Stauffer et al. (2019) just to name a few. Deep Learning techniques have popularly been used when performing image recognition tasks such as when it was used to recognize lung cancer in images by Jakimovski & Davcev (2018) an also when it was used to create the very popular Siamese neural network know as Signet by Dey et al. (2017) which was used for efficient signature verification.

A Siamese neural network represents a set of convolutional neural networks which are identical to each other as the same weights are applied to them both while they process two different inputs with the aim of producing an output that's based on comparison.

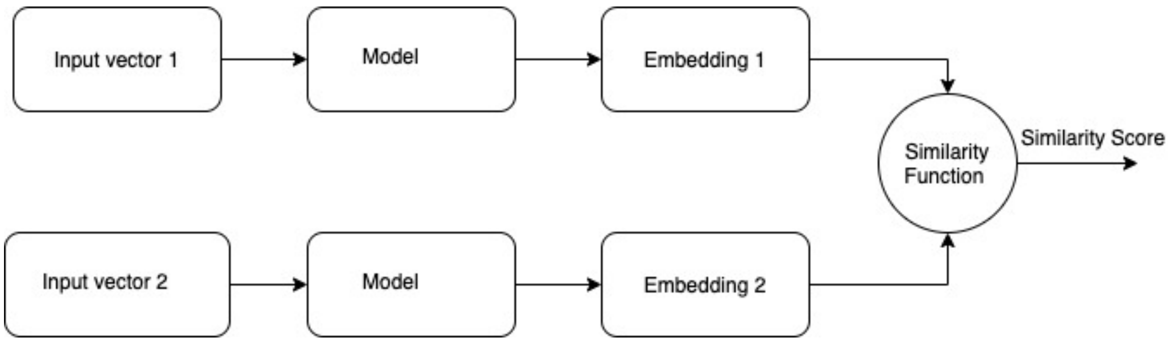


Fig 1: Approach to Siamese Neural Networks

The strength shown by this neural network is very apparent when there is limited data involved such as in tasks done using one shot learning. In the case of a normal singular neural network, more focus is placed on learning and making predictions over several classes typically with the use of large and complete datasets. The limitations that can exist in this is in the scenario where a new class is to be introduced into the model which in turn could lead to the whole model getting retrained with the new and updated dataset. An example which demonstrates this would be if a classification is to be made on a set of images to where a box, chair or bed would be the classes any of the images could belong to. Every image fed into the network is required to be categorised into any of these three classes. A large number of images is required for training for each class which also means the model is not expected to identify a whole different class that it is not trained for, so in order to identify a whole different class data has to be collected for that class and the whole model has to be retrained. Siamese neural networks on the other hand would not be constrained to the normal approach as it makes use of a similarity function which means the aim is to compute if two sets of images are the same. Using the example made above, the Siamese neural network would mainly require one training example for each class and a similarity score would be calculated for any input introduced into the model.

This paper serves the purpose of developing a Siamese neural network in order to further solve the problem of signature authentication. The Siamese neural network known as Signet already exists as a means for signature verification and authentication. This network is built on a set of standard convolutional networks but this paper aims to improve on this with addition of residual networks also known as ResNet. ResNets were introduced as another way to combat the vanishing gradient problems that exist form very deep networks and the ResNet network to be implemented in this paper is the InceptionResnetV2 model.

The research question then is how efficiently will the InceptionResnetV2 model as a Siamese neural network help in the prediction of an authentic signature.

The rest of the paper will have the following order. Section 2 will consist of the literature review of related works, Section 3 will consist of the methodology used in the paper, Section 4 will consist of the design specification, Section 5 will consist of the implementation of the project, Section 6 will contain the Evaluation and finally Section 7 will contain the conclusion.

# 2 Related Work

To carry out this project numerous pieces of literature have been reviewed in relation to neural networks and their many applications along with past research on signature authentication.

## 2.1 Deep Neural Networks

### 2.1.1 Application of deep neural networks

A deep convolutional neural network approach was taken by Almakky et al. (2019) to help solve the problem that exist in text extraction from biomedical figures. This model was developed to not only just extract text from their biomedical figures but also from images. The process involved the simplification of the text detection issue into more of a reconstruction problem where reconstruction was done on every image inputted into a single channel image. The image size was maintained so as to avoid any possible loss of necessary features during dimensionality reduction. Padding was also used as a means to maintain the image size as it passes through the layers. At the end of the model a sigmoid function was used which was used to convert the output into values that exist between 0 and 1 with each value representing how accurate a pixel belongs to a certain text region. The model performance displayed a precision of 62% and a recall of 91%.

### 2.1.2 Application of Siamese Neural Networks

The approach to solving the problem related to Gastric cancer detection in its early stages by Hsu et al. (2011) involved the development of a small-scale awareness Siamese neural network. The use of Siamese neural network greatly benefitted this problem due to the difficulty involved with attaining large amounts of training data for this problem, the training data used in problems like these are called magnifying narrow band imaging which is what doctors use when trying to diagnose gastric cancer patients and is usually difficult to obtain in large quantities. The Siamese neural network used in this problem was modelled towards learning discriminative features in the data based on image pairings with classification of these images done using a modified version of the popular network known as DenseNet. The Siamese neural network was seen to display a good performance with an accuracy of about 0.917 and a precision of about 0.93. The run time of this model was used as a measure of its efficiency which was about 15ms for the procession of one image. In an attempt to increase its efficiency, the use of less but more efficient parameters would help in its increase. In this paper more efficient parameters are used in its development.

Another application of Siamese neural networks is seen by Vizvary et al. (2019) where a Siamese neural network was developed to tackle the problem of image quality detection. The use of Siamese neural networks in this paper was essential considering they are a set of twin networks sharing the same weights and parameters which would highly suit the task of comparing two set of images in an attempt to determine which image is of a higher quality. Certain categories were established and furthermore used as features in an effort to determine the image of higher quality. For each category established, different accuracy scores were calculated with the inclusion of the overall quality. The accuracy attained by the overall quality was up to 81% with other categories such as brightness achieving 72.25%, sharpness achieving an accuracy of 81% and the neutrality of emotions achieving an accuracy of 71.75%.

Arabi et al. (2018) made use of a Siamese neural network in a change detection method for remote sensing images. The model employed here has the goal of learning important details present in images and then the comparison of the images with the use of a similarity score. The extraction of high discriminative features was done with the help of a constructive loss function used with a two stream Siamese network. This model shares some similarities to the model used in this paper as it makes use of the ResNet architecture which in turn helped the model achieve high levels of accuracy.

Another application of the Siamese neural network can be seen in Mueller & Thyagarajan (2016) where it was used to learn similarity present in different sentences. In the paper a Siamese recurrent architecture was developed as an adaption from a Long-term short memory (LSTM) network which consisted of labelled data. This data was comprised of variable length sequences in pairs. The network attempts to discover the semantic similarity that exist in different sentences. The paper was reliant on pre trained word vectors as inputs for the model and could be improved with more suitable word embedding methods.

All the related works discussed above are all examples of how Siamese neural networks have been used in various bodies of work.

## 2.2 Signature Authentication

### 2.2.1 Different Techniques used in Signature Authentication

Various techniques have been applied by different people in the task of signature authentication. Coetzer et al. (2004) made use of the discrete radon transform technique which was used with a hidden markov model in the classification of signatures into authentic or forged signatures. During the feature extraction process the features that were considered were mainly global features which work in describing the entire signature wholly. The name of the feature extraction technique used is the previously mentioned discrete radon transform which is calculated using the various static images of the signatures. The main role of the hidden markov model in the paper is to act as the pattern recognition technique while only considering each signature's spatial co-ordinates. Two popular signature datasets were used to test the model, this included 924 signatures that were obtained from 22 signees and also 4800 signatures that were obtained from 55 signees. After the model was tested on the first signature data set with 924 signatures an equal error rate of 18% was observed when looking at signatures made from very skilled forgers and when looking at signatures made from casual forgers it achieved an equal error rate of 4.5%. The second signature dataset when looking at signatures from skilled forgers achieved an equal error rate of 12.2%. The inclusion of local features along with the already used global features can be seen as an improvement to the model results.

Abuhaiba (2007) used a different technique when tackling the problem offline signature verification. The technique used was known as graph matching, this technique in an effort to avoid the usage of a complex feature set was solely dependent on raw binary pixel intensities. To solve the graph matching used in the paper, the Hungarian method was used. The dataset used to test this technique consisted of signatures both forged and authentic that were appended by five different individuals.

Another technique that has been used in the problem of signature authentication is a technique known as dynamic time warping done by Stauffer et al. (2019) which helps in the combination of results derived from matching of underlying graphs in the authentication of signatures. Through various perspectives graph matching was derived from graphs, this was done using a sliding window to help extract the many sub graphs form the original graphs. Dissimilarity measures are then used to match the sub graphs after extraction is done, the dissimilarity measure used in the paper is known as polar graph embedding distance. Two popular signature datasets were used to test the performance of the model which are the GPDS-75 signature dataset and the MCYT-75 signature dataset. The model was seen to perform a lot better than some already developed graph matching algorithms when considering their runtime and accuracy.

The technique for feature extraction known as the grid and tree-based extraction technique was used by Shukla et al. (2014) in the development of their signature authentication model. The authentication of signatures was determined with the use of particular features such as the Delaunay triangulation of any signature under consideration along with the Euclidian distance. The signatures used to test the model were provided by 11 persons with each appending 10 signatures. In consideration of the Delaunay triangulation feature three tests were carried out, one for the false acceptance which resulted to 15.32%, the second for the false rejection which resulted to 16.32% and the last was the ability to detect forgeries (accuracy) which was 46.8%.

Matsuda et al. (2017) combined a technique known as the verifier fusion technique with random forest classifier in the classification of multilingual signatures. The proposal of this technique served purpose of improving on a method that made use of combined segmentation authentication while authenticating signatures in multiscript. Each vector feature extracted from the offline signatures are calculated using the Mahalanobis distance. The SVM was also used as a classifier to make comparisons to the already used random forest classifier used for the paper. When the model was tested on a dataset that contained both Chinese and Dutch signatures it was seen to achieve and equal error rate of 3.92% and 4.37% respectively while using the standard random forest classifier and while using the SVM it achieved 4.10% and 3.10% respectively.

The works reviewed above all discuss different techniques that have been used already when determining the authentication of signatures but none of them discuss the application of deep neural networks in them. The next review discusses how deep neural networks have benefitted the task.

### 2.2.2 Application of Deep Neural Networks in Signature Authentication

A major application in deep neural networks in the task of signature authentication can be seen by Chandra & Maheskar (2016) where the technique for feature extraction known as geometric feature extraction was used with an artificial neural network. The geometric features used in the modeling of the network in the paper involve features such as Skewness, Centroid, Area and Kurtosis. The backpropagation technique was used to properly train the network. The accuracy of the model resulted to 89.24%. A better pre- processing method might help increase the accuracy of the model.

Another application of deep neural networks in signature authentication can be seen by Odeh & Khalil (2011) with the use of a multi-layer perceptron neural network. The preprocessing of the images done in the paper involved image enhancement of the signatures along with noise reduction. The features of the signatures such as the eccentricity, the orientation and the kurtosis are then extracted and the network trained. After the model is tested on a signature dataset known as GDPsig300, it was seen to achieve an error rate of 21.2%.

The use of deep neural networks is seen to have better performance when compared to other techniques but with deep neural networks a deeper network does not always guarantee better results because of issues such as the vanishing gradient. The ResNet is a means of solving that problem.

## 2.3 Application of ResNet in Machine learning

An application of the ResNet architecture can be seen by Zhang et al. (2017) where the network was used in an effort to recognize Chinese hand written signatures with the help of a learning metric that was based on center loss. The use of the ResNet architecture helped achieve an accuracy of about 97.03%.

Another application of the ResNet architecture is present in Mahajan & Chaudhary (2019) where the architecture was used in developing a network for the classification of images with the SVM used as the main classifier. Different ResNet layers were used with each giving a different level of accuracy. The ResNet consisting of 18 layers gave an accuracy of 93.57%, for 34 layers an accuracy of 91.58% and for the 50-layer ResNet an accuracy of 92.67% was achieved.

The ResNet architecture is seen to have great performance in different works, with the presence of different ResNet models this project aims to make use of the InceptionResnetV2 model as a Siamese neural network to test how efficiently that model works in the task of signature authentication hence the research question of " How efficiently will the InceptionResnetV2 model as a Siamese neural network help in the prediction of an authentic signature".

# 3 Research Methodology

The processes involved in research work based on data mining techniques are usually complex and also require complex decision making. A certain framework is needed which outlines the steps that will be taken to efficiently carry out the research. These frameworks are not only responsible for helping with approaches towards the data mining research project but also help with the process of documentation. They are numerous frameworks to choose from that facilitate this process such as the SEMMA which stands for Sample Explore Modify Model Assess or the commonly known KDD which stands for Knowledge discovery database. For the purpose of this project the research methodology framework KDD will be used.

## 3.1 Data Selection

The data selection stage is the first stage of the methodology which involves the selection of dataset relevant to the domain of this research work. In this project a popularly used signature dataset known as BHSig260 is used. This dataset contains signatures appended by 260 people of which 100 is appended in Bengali and 160 is appended in Hindi. The signatures to be used in this project are the signatures appended in Hindi. For each of the 160 individuals which have appended their signatures they also have appended 24 genuine signatures and 30 forged signatures which totals to 3840 genuine signatures in Hindi and 4800 forged signatures in Hindi.

## 3.2 Data Pre-processing / Data Transformation

This process involves the preparation of the data for processing. In this project the image of the signatures in the dataset are already gray scaled so do not require any gray scaling to be done. The only main pre-processing to be done on the images is resizing them. The size required to be passed into the ResNet network is (299,299,3) so image resizing is done to fit the requirement.

## 3.3 Data Mining Technique

In this project a classification is done as to whether signatures are authentic or forged. This is done using deep neural networks and the type to be considered is a Siamese neural network which uses twin networks with similar weights along with parameters.

## 3.4 Evaluation

The evaluation method used in this project is Accuracy. The general accuracy of the model is calculated and compared against previous models

# 4 Design Specification

## 4.1 Convolutional Neural Networks

After the discovery of neural networks, a large amount of popularity and interest has shifted towards it especially due to the amazing ability to some extent simulate the abilities of the human brain. In terms of supervised learning they can be considered to be one of the most versatile black box approaches. The application of neural networks ranges from prediction, regression NLP (Natural language processing) and even image recognition. The most basic unit of a neural network is considered a perceptron. These perceptron's when combined into multiple layers build up a simple neural network. The output given by a perceptron is usually in the form of a +1 or a -1 which makes it more of a binary linear classifier but in cases they can act as non-linear classifier if they are arranged in a set of layers. Several layers of perceptron's as said earlier make up a neural network and the first layer is known as the input layer. This layer is responsible for receiving the input for the network which also has some weight attached to it and the last layer is known as the output layer and in between both layers exist a number of hidden layers.

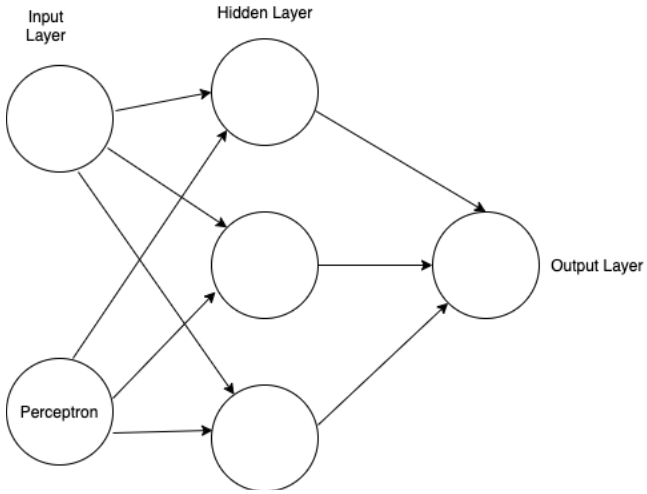


Fig 2: A Typical Neural Network

The type of neural used in this project is known as a convolutional neural network which contains one or a lot of convolutional layers. Before the result of one layer is passed to another layer, a convolutional operation is carried out on the result which leads to convolutional neural networks being much deeper with less parameters than other networks. As a result of this convolutional neural networks are seen to be extremely efficient when used tasks that involve image recognition.

## 4.2 Siamese Neural Networks

A Siamese neural network is also known as a twin network. These networks both share the same weights along with parameters. Since both networks are composed of the same weights, Siamese networks are mostly used when making comparisons between inputs. This project makes use of a Siamese neural network made of twin convolutional neural networks. Pairs of signatures are used as inputs and then a similarity score is calculated which then is the determinant as to whether the signature is authentic or forged. The Siamese neural network has been used in the past by Dey et al. (2017) to solve the problem of signature authentication but in this project the novelty is the use of the ResNet model known as InceptionResNetV2 as the base model for the Siamese network

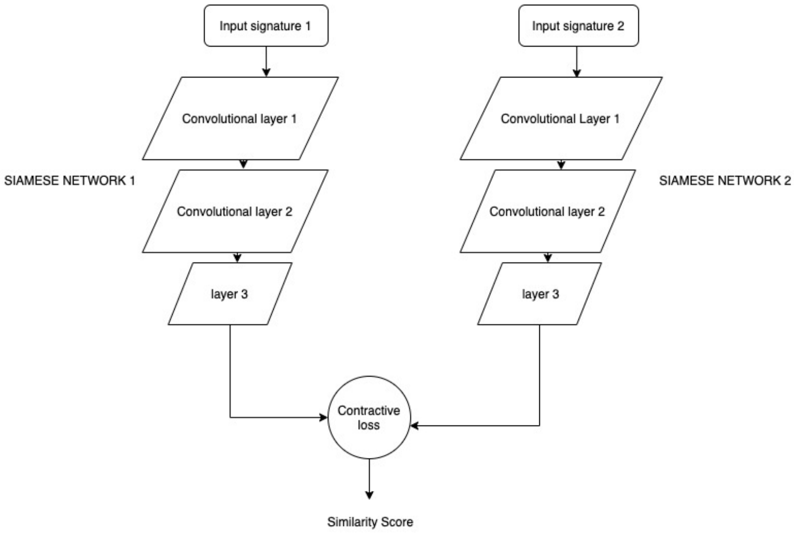


Fig 3: Siamese Neural Network

## 4.3 ResNet Architecture

The ResNet architecture is known as residual neural network. ResNets make use of skip connections that help to jump over some layers and this is way of solving the vanishing gradient problem by also making use of activations used in the previous layers only until the layers adjacent to the layer learns its weights. The ResNet architecture also makes use of residuals which means the output of a layer before getting passed onto the next layer is combined with output of that layer and activated using an activation function. The ResNet architecture has many variants such as the ResNet50 and ResNeXt just to name a few but for the purpose of this project the variation known as the InceptionResNetV2 model is used. This model combines the inception module with the ResNet architecture. In the inception module instead of the typical specification of one convolution such as a 3x3 or a 5x5, the inception module makes use of multiple convolutions of an input at once and ends up concatenating all the outputs before passing it on to the next layer.

## 4.4 Contrastive Loss

The contrastive loss function serves the purpose of calculating the distance between the two outputs of the Siamese neural network.

# 5 Implementation

## 5.1 Pre- Processing

This project was carried out on Jupyter Notebook using the python programming language along with the Keras and TensorFlow libraries. In this project the main pre-processing or transformation applied to the images is that. They were resized to fit the required sized for the ResNet network. An arrangement of the signatures into their groups of authentic and forged was done. After which a quick visualization which outputs two genuine signatures and one forged signature of an individual is done to visualize the data.

## 5.2 Modelling the Network

The Siamese network made up of the InceptionResNetV2 model. In the Stem of the network three convolution layers of (32,3,3) (32,3,3) and (64,3,3) are concatenated along with a max pooling layer (96,3,3) using Rleu as the activation function and a stride of 1. A shortcut to link the layers of the ResNet is then created. Next the A block of the ResNet is created where six different convolution layers are concatenated, three (32,1,1) layers, a (32,3,3), (48,3,3), and (64,3,3) layer along with the shortcut which links the output of the stem layer to the A block. A reduction of the A block is the created which is made up of a max pooling layer of (384,3,3) and strides of 2 and four other convolution layers of (384,3,3), (256,1,1), (256,3,3) and (384,3,3) of which they are all concatenated and passed unto the shortcut for the next B block. The B block follows a similar procedure with the concatenation of four convolution layers consisting of (192,1,1), (128,1,1), (160,1,7) and (192,7,1) with the shortcut passed from the previous block. A reduction block is also created for the B block with a max pooling layer of (256,3,3) and seven convolution layers of three (256,1,1) layers, three (288,3,3) layers and a (320,3,3) layer. The last block is the ResNet C block which involves the concatenation of four convolutions consisting of two (192,1,1) layers, a (224,1,3) layer and a (256,3,1) with the shortcut passed from the previous block. The total amount of parameters used in the network is 19,280 with all of them being trainable. The hyper parameters used in the model include an initial learning rate of 0.000001, batch size of 1, along with the reduction of the learning rate by 0.1 if the validation loss shows no sign of improvement for 5 epochs. After the network is created, the Siamese aspect of the network is introduced by creating two inputs and then these inputs are processed through the stem of the network simultaneously. The inputs of the network are a pair of signatures the first input being a pair of genuine- genuine signature and the other input a pair of genuine-forged signature.

The model is ran using a batch size of 1 for 100 epochs. The traditional batch size of 128 or 64 led to computational errors due to the ability of the GPU in use. An epoch due to a batch size of 1 ran for 10hrs per epoch and due to constraints of time only 10 epochs were left to run before a manual interruption. The weights gotten from the epochs are then loaded in to compute a threshold to be used to decide if the signatures are authentic or not. If the Euclidean distance calculated from the outputs of the network is greater than the given threshold then the signature is classified as forged otherwise the signature is a genuine signature.

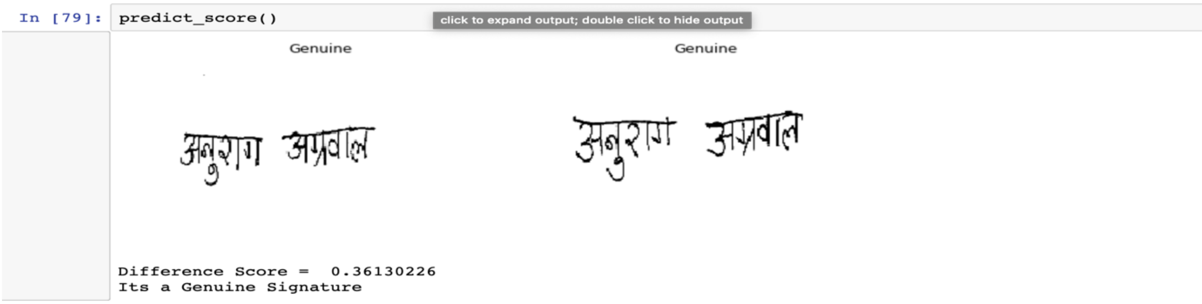


Fig 4: Classification Output (A Genuine Signature)


Fig 5: Classification Output (A Forged Signature)

The figures above show the output when a prediction is made to if a signature is forged or authentic. In the first figure fig 7 when the prediction is made, the difference score is seen to be less than the calculated threshold of 0.55 with a value of 0.36 which means the signature is authentic. In Fig 8 when the prediction is made, the difference score is seen to exceed the calculated threshold of 0.55 with a value of 1.5 which means the signature is forged.

# 6 Evaluation

## 6.1 Accuracy

The main evaluation method used in this project is the accuracy of the model. The table below shows the accuracy of the model with other state of the art models such as in Pal et al. (2016), Dutta et al. (2016) and Sounak et al. (2017) used on this dataset.

Table 1. Comparison of Accuracy between models

| Dataset | Models | Accuracy |
|---|---|---|
| Hindi | Pal et al. (2016) | 75.53 |

| | | |
|---|---|---|
| Hindi | Dutta et al. (2016) | 85.90 |
| Hindi | Dey et al. (2017 | 84.64 |
| Hindi | NiohSign | 81.71 |

As seen in the table above our NiohSign model is seen to perform relatively well in terms of accuracy with 81.71% when compared to other state of the art algorithms. This proves that the InceptionResNetv2 model performs efficiently when tasked with the problem of signature authentication. The model was seen to only outperform the model created by Pal et al. which had an accuracy of 75.53 but still behind the state-of-the-art models created by Dutta et al. (2016) and Dey et al. (2017).

# 7 Conclusion and Future Work

In this project a pretrained ResNet network known as InceptionResNetv2 was used as a Siamese network to help classify if signatures are forged or authentic. Experiments were conducted upon a signature dataset appended in Hindi which consisted of signatures appended by 160 individuals. The model was seen to perform relatively well when compared to other state of the art models already used in terms of its accuracy which completely answers the objective of the project which was to find out how efficiently the InceptionResNetV2 model would help classify signatures into authentic or forged. The drawbacks of the project can be seen in the inability to use a larger batch size which could be solved with a much more powerful GPU and the possibility of using other versions of ResNet is encouraged for future works.

# References

Abuhaiba, I.S., 2007. Offline signature verification using graph matching. *Turkish Journal of Electrical Engineering & Computer Sciences*, *15*(1), pp.89-104.

Almakky, I., Palade, V. and Ruiz-Garcia, A., 2019, July. Deep Convolutional Neural Networks for Text Localisation in Figures From Biomedical Literature. In *2019 International Joint Conference on Neural Networks (IJCNN)* (pp. 1-5). IEEE.

Arabi, M.E.A., Karoui, M.S. and Djerriri, K., 2018, July. Optical remote sensing change detection through deep siamese network. In *IGARSS 2018-2018 IEEE International Geoscience and Remote Sensing Symposium* (pp. 5041-5044). IEEE.

Chandra, S. and Maheskar, S., 2016, March. Offline signature verification based on geometric feature extraction using artificial neural network. In *2016 3rd International Conference on Recent Advances in Information Technology (RAIT)* (pp. 410-414). IEEE.

Coetzer, J., Herbst, B.M. and du Preez, J.A., 2004. Offline signature verification using the discrete radon transform and a hidden Markov model. *EURASIP Journal on Advances in Signal Processing*, *2004*(4), p.925026

Dey, S., Dutta, A., Toledo, J.I., Ghosh, S.K., Lladós, J. and Pal, U., 2017. Signet: Convolutional siamese network for writer independent offline signature verification. *arXiv preprint arXiv:1707.02131*.

Dutta, A., Pal, U. and Lladós, J., 2016, December. Compact correlated features for writer independent signature verification. In *2016 23Rd international conference on pattern recognition (ICPR)* (pp. 3422-3427). IEEE.

Hsu, C.C., Ma, H.T. and Lee, J.Y., 2019, September. SSSNet: Small-Scale-Aware Siamese Network for Gastric Cancer Detection. In *2019 16th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS)* (pp. 1-5). IEEE.

Jakimovski, G. and Davcev, D., 2018, September. Lung cancer medical image recognition using Deep Neural Networks. In *2018 Thirteenth International Conference on Digital Information Management (ICDIM)* (pp. 1-5). IEEE.

Mahajan, A. and Chaudhary, S., 2019, June. Categorical image classification based on representational deep network (RESNET). In *2019 3rd International Conference on Electronics, Communication and Aerospace Technology (ICECA)* (pp. 327-330). IEEE.

Matsuda, K., Ohyama, W. and Wakabayashi, T., 2017, November. Multilingual-signature verification by verifier fusion using random forests. In *2017 4th IAPR Asian Conference on Pattern Recognition (ACPR)* (pp. 941-946). IEEE

Mueller, J. and Thyagarajan, A., 2016, March. Siamese recurrent architectures for learning sentence similarity. In *thirtieth AAAI conference on artificial intelligence*.

Odeh, S.M. and Khalil, M., 2011, June. Off-line signature verification and recognition: Neural Network Approach. In *2011 International Symposium on Innovations in Intelligent Systems and Applications* (pp. 34-38). IEEE.

Pal, S., Alaei, A., Pal, U. and Blumenstein, M., 2016, April. Performance of an off-line signature verification method based on texture features on a large indic-script signature dataset. In *2016 12th IAPR Workshop on Document Analysis Systems (DAS)* (pp. 72-77). IEEE.

Shukla, A.K., Mohan, P., Ojha, G. and Wariya, M., 2014, February. Offline signature verification system using grid and tree based feature extraction. In *2014 International Conference on Issues and Challenges in Intelligent Computing Techniques (ICICT)* (pp. 784-789). IEEE.

Stauffer, M., Maergner, P., Fischer, A., Ingold, R. and Riesen, K., 2019, September. Offline signature verification using structural dynamic time warping. In *2019 International Conference on Document Analysis and Recognition (ICDAR)* (pp. 1117-1124). IEEE.

Vizváry, L., Sopiak, D., Oravec, M. and Bukovčiková, Z., 2019, September. Image Quality Detection Using The Siamese Convolutional Neural Network. In *2019 International Symposium ELMAR* (pp. 109-112). IEEE.

Zhang, R., Wang, Q. and Lu, Y., 2017, November. Combination of ResNet and center loss based metric learning for handwritten Chinese character recognition. In *2017 14th IAPR International Conference on Document Analysis and Recognition (ICDAR)* (Vol. 5, pp. 25-29). IEEE.