Handwritten Signature Detection using Deep Learning Approach

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JANUARY 2023

APPROVAL

This Project/internship titled **"Handwritten Signature Detection using Deep Learning Approach"**, submitted by M.H. Mobin Bhuiyan , ID No: 191-15-2715 and Sumi Akter, ID No: 191-15-2496 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on *23/01/2023.*

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ACKNOWLEDGEMENT

First we express our heartiest thanks and gratefulness to almighty God for His divine blessing makes us possible to complete the final year project/internship successfully.

We really grateful and wish our profound our indebtedness to **Md. Sabab Zulfiker**, **Lecturer (Senior Scale)**, Department of CSE Daffodil International University, Dhaka. Deep Knowledge & keen interest of our supervisor in the field of "*Deep Learning*" to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior draft and correcting them at all stage have made it possible to complete this project.

We would like to express our heartiest gratitude to Md. Sabab Zulfiker, Nadira Anjum Nipa and Head**,** Department of CSE, for his kind help to finish our project and also to other faculty member and the staff of CSE department of Daffodil International University.

We would like to thank our entire course mate in Daffodil International University, who took part in this discuss while completing the course work.

Finally, we must acknowledge with due respect the constant support and patients of our parents.

Abstract

Signature verification is a type of biometric technology that is widely used for personal identification. In many commercial circumstances, such as the payment of a bank check, the signature verification procedure is based on the human analysis of a single known sample. For verification purposes, the majority of organizations primarily focus on the signature's visual appearance. The signing of a signature is required for many documents, including forms, contracts, bank checks, and credit card transactions. Subsequently, it is of the highest significance to have the option to perceive marks precisely, easily, and as soon as possible. A manually written signature is normally rehearsed course for affirming the legitimacy of authoritative records. Because the signature varies on a regular basis and may alter in response to factors such as age, behavior, and the environment, its verification is crucial. To verify the signature, a deep learning model based on the CNN architecture is presented in this paper. We have data that has been gathered from volunteers who have consented to provide it. About 4200 photos, separated into 21 classifications, were used in this research. For each participant, we worked with a distinct class. After them, classes are named. 200 data are contained in each class. The dataset is classified using five different classification methods: CNN, VGG 16, VGG 19, Inception v3, and MobileNet v2. Here is separated the dataset into three sections for training, testing, and validation: 80%, 10%, and 10%, respectively. We have used multiple deep learning algorithms like Convolutional Neural Network it with image processing tools to form a better structure, leading to higher accuracy of 99.41% in VGG19.

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Chapter 1
Introduction

1.1 Introduction

Currently, one of the primary identity authentication methods is the handwritten signature: The majority of people are familiar with its application in everyday life, and signature acquisition is simple and non-invasive [1]. Signatures can be used as confirmation signs in a wide range of documents due to their ease of use, such as bank checks, identity cards, and various commercial contracts and certifications. A user's signature is a behavioral biometric that is acquired so that the user can declare their unique identity on printed documents. The requirement for signature-based authentication is growing across a variety of applications, including credit card authentication, security systems, banking systems, checks, agreements, and other legal documents. It is broadly utilized as evidence of character and a socially acknowledged confirmation technique in day-to-day existence. The framework partners are people, organizations,s or banks that need to confirm marks [2]. The stakeholders are the bank's customers, and before any required transaction can be executed on that account, bank staff must confirm that the test signatures match the actual signatures stored in the database. Customers of the business are also its employees: In any organization that still uses paper forms, workers are required to secure the supervisor's signature.[3]. Automated signature verification systems now face direct competition from the evaluation of alternatives, which is largely influenced by the verifier's background, disposition, and workplace environment. In addition, experts' eyes are unable to precisely compare the ratios between a genuine and fraudulent signature's lines and angles [4]. One explanation suggests that a sign is just a distinctive writing style with complex geometrical shapes and usually illegible plots [5]. There are two primary types of signature verification: static and dynamic verification. The most frequent method of verifying a document signing after it has been produced is static, or disconnected confirmation, whereas dynamic, or online, verification occurs as a person signs a document using a digital tablet or a similar device. The sign in question is then contrasted with earlier examples of that user's signature in the registry. While a human signature on documentation requires the computer to scan the samples for testing, an authentication that has already been saved in file formats can be utilized for verification and identification. [6]. The majority of businesses today use one of several offline signature verification methods. The accuracy of offline signatures is evaluated using image processing techniques and the fixed elements of the system. These are including the person's initial password-based identification. Other multimodal systems strictly authenticate a person's identity by utilizing the two distinct biometric features. A signature in a contract plays a crucial role in proving intent and informed consent as well as revealing the identity of the person in question. Any fraudulent or falsified signature could cause serious harm to a person's life and assets. For this reason, a methodical approach to verifying the signature is absolutely necessary. Traditionally, a person is required to authenticate a specimen signature: by evaluating and comparing the specimen to copies of genuine signature specimens that have been obtained in the past and with the assistance of some kind of witness. In the banking industry of Nepal, signature verification is an essential part of the approvals and transaction processes. Yet, this straightforward approach may not be adequate in that frame of mind as different high-level fabrication and distortion methods are arising. In order to assist and enhance the process of validating a person's handwritten signature, this study aims to employ deep learning. The data science field which also includes statistical data & predictive analysis includes deep learning as a key component. Deep learning expedites and makes this process much easier for data analysts, who are in charge of collecting, processing, and analyzing enormous volumes of data. This study aims to identify the most efficient method for extracting a written sign from photographs. The following are the research's overall contributions:

- This research has Collected different types of images
- Here has worked to pre-process the dataset through several procedures such as image labeling, managing unbalanced data, and zoom, flip, resize
- The method has predicted the Handwritten Signature using deep learning models.
- This study also carried out a comparison of all popular available methods for solving the same problem ((i.e., CNN, VGG16, VGG19, MobileNet v2, inceptionv3)

The balance of this study's material is as follows. Detailed and critical analyses of prior research are presented in Section 2. Section 3 offers the investigation's recommended strategy and a description of the investigation's dataset. The investigation's outcomes and analyses are described in Section 4. Section 5 covers the effects on society and the environment. The section's conclusion with some future scope is presented in Section 6.

1.2 Motivation

Signature is a method that is vulnerable to high-level attacks because it is the most socially and legally accepted method for person authentication. Forgery signatures and biometric applications can be identified through the use of signature verification. The purpose of biometrics is to determine an individual's identity by measuring their unique physical or behavioral characteristics. The iris, hand geometry, face, and fingerprints are examples of physical characteristics that make up a biometric attribute. Among these, fingerprints and iris do not change over time, resulting in very little intra-class variation; however, in order to capture the biometric image, these biometrics require specialized hardware that is relatively pricey. A bio-metric attribute's behavioral characteristics include a person's signature, voice, keystroke pattern, and gait [7]. The signature and voice technologies are the characteristics that have developed the most among these. A handwritten signature is a popular biometric characteristic. Written-by-hand signatures can only be utilized when the signer is aware and ready to write, unlike fingerprint technology, which may be used to collect prints even from unconscious people. This is a significant advantage over other identification verification technologies [8]. The recognition rate of a handwritten signature recognition system, on the other hand, is still in the middle of the range for other biometric systems. As a result, a lot of researchers are paying attention to improving accuracy by using a balance of machine learning and image processing techniques. So we decide to work on Handwritten Signature and collect different types of images and use different deep learning models to determine their accuracy. And from here we get motivated.

1.3 Rationale of the Study

To distinguish faculty in an association is basic and associations rely upon biometric frameworks for confirmation of people. One of the biometric technologies that is still acceptable for verification in society and the law is signature verification. The scanning of the iris and fingerprints are further biometric techniques. Signature-based detection is the act of validating or identifying depending on their signature because every person's handwriting is distinctive [9]. The first step in verifying a signature is scanning a person's handwritten signature onto a piece of paper to store it digitally. When the same individual has to be confirmed once again, a new signature is obtained, and it's compared to the previously preserved digital image. The following verification procedure does not utilize this dynamic information since the velocity, location, or pressure at the moment of obtaining the initial signing for the repository is not measured. The non-dynamic verification procedure is challenging, and it is known as offline biometric authentication [10]. In this research, the Deep learning model's classification layer was retrained using 21 classes of signature image data set, each with 200 signatures.

1.4. Research Questions

- What are the key features of this database?
- How does the algorithm work in this research?
- How can you detect a Handwritten Signature?
- What will the success rate of accuracy of image detection be?

1.5 Expected Output

The goal of this study is to apply deep learning to the issue of handwritten signature recognition in order to improve recognition performance. When a man is writing his signature, they gave more information like hand speed and pressure management and there are many things that we can take as the key points to identify real or forged images. This project will help to solve the problem of forged signatures and get the highest accuracy.

1.6 Project Management and Finance

To better understand emerging patterns of roles and responsibilities, data from the survey of project management roles and responsibilities was acquired. Project management includes scheduling and planning meetings, facilitating the entire study, and entering data into databases. Study progress was recorded via the timely release of meeting agendas and minutes outlining progress and action items. These resources accumulated throughout time to create an archive that is centrally accessible via the Madcaps communication platform. To produce high-quality data that can be signature recognized and verified as well as policy requirements, taking Competent project management is essential for executing signature-related research.

1.7 Report Layout

- The essential ideas of "Handwritten Signature detection using deep learning approach" were covered in chapter 1, along with the purpose, goal, and results of our study.
- The major subjects of the related works section in Chapter 2 include a quick summary of the assessment, the seriousness of the situation, and the obstacles. The research technique is covered in Chapter 3.
- The details of experimental findings are detailed in Chapter 4.
- Chapter 5 describes our social impact on environmental effects, etc.
- Chapter 6 contains an overview of evaluation data as well as a few more insights that can support me in current study efforts for subsequent publications.

Chapter 2
Background

2.1 Preliminaries

The problem of signature verification has not been resolved despite years of intensive study in this area. [11] investigates a number of possible causes for offline signature verification. In offline signature verification, Hidden Markov models & template matching are frequently employed techniques. These methods are based on the signature's structure. In digital image processing, a technique called "template matching" is used to match specific parts of an image to a template image. Template matching can be done with metrics like the n-square error or the structural similarity index, or it can be done with a warping method that warps one curve onto another while keeping the original shape. The authors in [12] demonstrate how Deep CNNs can be used to determine whether a signature is genuine or not. This is accomplished in two steps: writer-dependent classification and writer-independent feature learning By treating the forgeries and the signatures as separate classes, this paper simplifies this method. It is a completely author-independent strategy. In the literature, various strategies for recognizing signatures have been presented. An approach that works by subdividing each image into a number of blocks was proposed by Sahms [13]. The algorithm determines how similar these segments' lines are to one another. Porwik in [14] suggested a unique approach based on three phases of signature recognition. The Hough transform technique and a histogram were employed by the system both for the vertical and horizontal signatures. This Wavelet transform is utilized to search for the straight path that occurs in a signature in order to establish its shape. Following the Hough transform, a straight-line selection technique is employed to limit the number of the horizontal plane shown by the Hough transform. Zgündüz and others outlined a novel strategy that makes use of the signature's direction and grid features in [15]. They verified and categorized the signatures using a support vector machine in their strategy.

2.2 Related Works

Currently recognized as popular technologies, deep learning and artificial intelligence are widely utilized to identify a variety of issues. While several other pre-trained models have also been utilized by researchers, the deep learning method is the best model for detecting handwritten signatures.

Pre-processing and pattern classification methods that have been applied in the research were employed by AL-Saffar et al. [16], and several development avenues were recommended. We discuss existing deep learning techniques and tools for Arabic handwriting recognition (AHWR), point out roadblocks, and make several recommendations, of which is a conceptual model (DL) approach that is particularly effective for handling language families with a cursive character. In addition, due to the restriction on the Arabic language, special consideration had been paid to the status of handwritten recognition.

This Takagi-Sugeno fuzzy model was used by Madasu, V. K. et al. [17] to identify the signature picture. Their approach makes utilization of the Sugeno fuzzy model, which has a number of guidelines and evaluates a parameter to maximize the input.

A neural network-based offline signature verification system was proposed by Karouni, A. et al. [18]. The authors offer a method for offline signature verification using a collection of simple shape-based geometric characteristics. The highlights that are utilized are region, the focus of gravity, capriciousness, kurtosis, and skewness. Before extracting the features from a scanned picture, it is required to identify the signature section of the image and remove any extraneous noise that could be present. The framework is at first prepared to utilize a data set of marks gotten from those people whose marks must be confirmed by the framework.

A brand-new Caps-Net-based signature verification method was put out by Yapc, M. M. et al. [19]. We evaluate the suggested data augmentation approach using the four often mentioned convolutional neural network (CNN) approaches VGG16, VGG19, ResNet50, and DenseNet121. The method has significantly contributed to the success of all of the CNN strategies mentioned. The proposed method augmentation approach is especially advantageous for DenseNet121. We also evaluated our data augmentation technique using the suggested signature verification methodology on two popular databases, MCYT and GPDS. Our verification approach produced the best findings of any research on the MCYT database, and it produced the second-best verification results on the GPDS.

Hirunyawanakul, A. et al. [20] proposed in this paper to improve handwritten signature recognition accuracy. DCNN is utilized in two distinct signature recognition methods: 1) Applying leveraged features from a previously trained model to transfer learning on a larger dataset and 2) Building a CNN model from scratch Our considered dataset comprises 600 pictures of written by hand marks gathered from 30 individuals. To assess the adequacy of the proposed strategy, the precision is contrasted and the outcomes got from different machine learning strategies. The examination uncovers extremely fulfilled acknowledgment and brings about the feeling that the two proposed methodologies accomplish 100 percent of the acknowledgment rate. In terms of training time, the strategy of starting from scratch with the DCNN model is significantly faster than the transfer learning strategy.

Jarad, M. et al. [21] employed a well-known Back-propagation-based artificial neural network. To assess the effectiveness of the system, three metrics are calculated: the Similar False Positive rate (EER), the False Negative Rate, as well as the False Match Rate. The system was assessed using 400 experimental signature samples, 20 real and 20 fake signatures. By adding a label that indicates the degree of similarity between the signing authors want to understand and the original signature, this task aims to lessen the computer's unique feature in determining whether the sign has been modified and to enable signature verification personnel to participate in the process. Using this method, you can evaluate the accuracy of the signature and get better results.

Mautner, P. et al. [22] ART-2 the neural network model has been suggested for use in signature verification. A special digital pen was used to collect the signatures. Following that, the authors performed feature extraction and rapid wavelet processing. The findings demonstrated that, given the training set's size set, the proposed method could be utilized to verify signatures and produced outstanding results.

Basavaraj, L. et al. [23] applied an offline method for verifying signatures. The authors separated a static signature from a dynamic feature by utilizing the stroke speed. The stroke strength is taken into consideration while determining the stroke speed. This is due to the direct relationship between intensity and stroke speed. The intensity value is higher the faster the stroke speed.

In order to create instances that are completely built, Galbally, J. et al. [24] developed a model-based technique that integrates the Motion detection Hypothesis of fast human growth with the Virtual Analysis of actual marks. The employment of two different techniques for the synthesis of cloned items from the synthesis master signatures allows the create a whole new whole to generate massive synthetic databases entirely automatically.

In order to assess the online signature, Radhika, K. R. et al. [25] suggested using a shape analysis approach for the excitation plot with decreased Zernike moments. The temporal features of the signing process are used by the online signature. The reduced Zernike moments serve as a representation of a pattern's overall shape. Through sample signatures, which also include online pixels, the feature that results, in an accelerated vector, is produced. The acceleration plot's shape is represented by the Zernike moment. One may calculate the Zernike moment accumulation ratio for a signature sample using normalized acceleration data.

2.3 Comparative Analysis and Summary

Madasu, V. K. et at. [26] proposed, a robust recognition system has been developed using fuzzy modeling in this study. The knowledge base is made up of distinct aspect features that were retrieved using the box approach. These features are conflated by such an exponential classifier having two structural responses, intended to monitor even the smallest alterations in a person's signature. The membership functions within Takagi-Sugeno (TS) framework are in turn the weights. The output of the TS model is optimized in terms of structural parameters to get the parameter solution. The suggested method was put to the test using a sizable database with over 1200 signature photos provided by 40 volunteers, with a detection accuracy of over 99%.

Sam, S. M. et al. [27] used to categorize the signatures of 1000 individuals, we used the GPDS Synthesis User Profile, the broadest handwritten signature collection currently accessible. Each user had 30 fraudulent signatures and 24 real original autographs. In addition, two well-known CNN versions based on the GoogLeNet architecture, Inception-v1 and Inception-v3, were utilized. First, 20 user samples were used to train the algorithms, which were validated with an accuracy of 75% and 83% for Inception-v3. For 20 users, Inception-vl was able to achieve an EER of just 17 in terms of Equal Error Rates (EER); while EER for Beginning v3 with 20 clients got 24, which is a decent measure contrasted with earlier works in the writing. Even though Inception-v3 did better in the ImageNet image classification challenge, Inception-v1 did better in the classification task for 2D images of signatures than Inception-v3. This study also accepts that Inception-v1 required less training time than Inception-v3 due to fewer operations.

Porwal, U. et al. [28] suggested Deep Belief Networks learn the intricate data structure sequentially. There entered the algorithm's results, as well as proposed improvements. Here used an AMA Arabic PAW dataset with an accuracy of 75.05%.

Tamen, Z. et al. [29] it was suggested that many classifiers be combined and merged somewhere at the decision level during the classification step. There entered the algorithm's results, as well as proposed improvements. Here, the classifiers multilayer perceptron (MLP), support machine (SVM), & extreme learning machine (ELM) were utilized on the FN/ENIT dataset. Here is 96.82%accuracy.

Ashiquzzaman, A. et al. [30] Various convolution layers and dropouts are used in the proposed CNN model to reduce overfitting. Here used the CMATERDB dataset has an accuracy of 97.4%.

Rabi, M. et al. [31] presented a method founded upon Hidden Markov Models for offline identification of Arabic handwritten text in cursive (HMMs). Here used IFN/ENIT dataset has an accuracy of 87.93%. Table 1 demonstrates a comparison of the analysis of data works.

Table 2.3.1: Comparative analysis of previous research works

SL No	Literature	Dataset/ Num of dataset	Model	Highest accuracy
1	Madasu, V. K. et at. [26]	1200 signature images from 40 volunteers	TakagiSugeno fuzzy model	99%(TS)
2	Sam, S. M. et al. [27]	GPDS Synthetic Signature Database	Inception-v1 and Inception-v3	83% (Inception-v3)
3	Porwal, U. et al. [28]	AMA Arabic PAW dataset	Deep Belief Networks(DBNs)	75.05%(DBNs)
4	Tamen, Z. et al. [29]	FN/ENIT dataset	Multilayer perceptron(MLP), support vector machine (SVM),	96.82%(MLP)

			Extreme Learning Machine (ELM)	
5	Ashiquzzaman, A. et al. [30]	CMATERDB dataset	MLP, CNN	97.4%(CNN)
6	Rabi, M. et al. [31]	IFN/ENIT dataset	Hidden Markov Models (HMMs)	87.93%(HMMs)
7	This study	4200 images, separated into 21 classifications	CNN, VGG16, VGG19, inception v3, mobilenet v2	99.41%(VGG19)

2.4 Scope of the Problem

For signature verification, pressure-sensitive tablets that capture signatures also extract the dynamic characteristics of the signature in addition to its shape. Dynamic aspects include things like the quantity and sequence of strokes. Text is considered the main apparatus for safeguarding and imparting data. The modern world is made to interpret and communicate through the use of textual clues, labels, texts, and other means. found in the vicinity. In our social and legal lives, handwritten signatures are very important for verification and authentication. If a signature is not from the intended party, it cannot be accepted. There is very little chance that two signatures from the same person will be the same. Even when two signatures are made by the same person, many of the signature's properties may differ. As a result, it becomes challenging to identify a forgery.

2.5 Challenges

There are some challenging issuess to detect handwritten signatures.

1. As the lack of a proper dataset, need to assess the findings and make them implemented.

2. By taking live pictures of nearby people and friends signatures with high-resolution picture quality, the data has been collected.

3. Some of the data has been blurred and lower in pixels during the collection of data that are not selected due to insufficient quality of data.

4. Doing preprocessing data to resize the collection of data.

5. Splitting dataset is a challenging fact to get better accuracy. The more data get trained, the more accuracy will gain.

6. Classifying the data, doing deep learning algorithm to figure out the most efficient data to detect the following classes.

Chapter 3
Research Methodology

3.1 Research Subject and Instrumentation

Signature recognition is our project's main application. In essence, we worked on it. The project was implemented using the Python programming language with Keras, and we used Google Collab's Python notebook for this work. Today, it is quite well known. because it is easily accessible and is always accessible via the internet. As a result, Google Collaboratory's own machine does not require a separate GPU or TPU support. Through its own servers, Google offers the user GPU support. It can only be viewed on a computer with a browser and a Google account. The user may so simply finish the task using the notebook. Anyone may use Google sign-in to view their Python code on other machines if they so like. Convolutional Neural Network, also known as CNN, vgg16, vgg19, inception v3, mobilenet v2, and other models have all been employed in this implementation. I choose the one with the highest accuracy. The best accuracy was 99.41% in vgg19.

3.2 Data Collection Procedure/Dataset Utilized

We obtained the dataset from our friends and family members. Additionally, we have data that has been gathered from volunteers who have consented to provide it. About 4200 photos, separated into 21 classifications, were used in this research. For each participant, we worked with a distinct class. After them, classes are named. 200 data are contained in each class. Every piece of information is an image, and they are all in the jpg format. the following class names: Anik, Charity, Eyashin, Jahangir, Liton, Lubna, M.H.MOBIN BHUYAN, Mahima, Mizan, Mobin, Moshiur, Natasha, Nokshi, Riya, Sadia Sultana Mitu, Shihab, Taibur, Tanvir, Touhid, Shamsul, Sumi.

Figure 3.2.1: Data Sample

Table 3.2.1: Detailed image collection statistics

Class name	No of images	Image Format	Image size
Anik	200	JPG	256*256
Charity	200	JPG	256*256
Eyashin	200	JPG	256*256
Jahangir	200	JPG	256*256
Liton	200	JPG	256*256
Lubna	200	JPG	256*256
M.H.MOBIN BHUYAN	200	JPG	256*256
Mahima	200	JPG	256*256
Mizan	200	JPG	256*256
Mobin	200	JPG	256*256
Moshiur	200	JPG	256*256

Natasha	200	JPG	256*256
Nokshi	200	JPG	256*256
Riya	200	JPG	256*256
Sadia Sultana Mitu	200	JPG	256*256
Shihab	200	JPG	256*256
Taibur	200	JPG	256*256
Tanvir	200	JPG	256*256
Touhid	200	JPG	256*256
Shamsul	200	JPG	256*256
Sumi	200	JPG	256*256

Here table 3.2.1 shows the images of every class and the format of the images and the size of the image.

3.3 Statistical Analysis

Fig 2 illustrates the total number of pictures of all classes and Fig.3 reflects the quantity of train, test, and validation pictures.

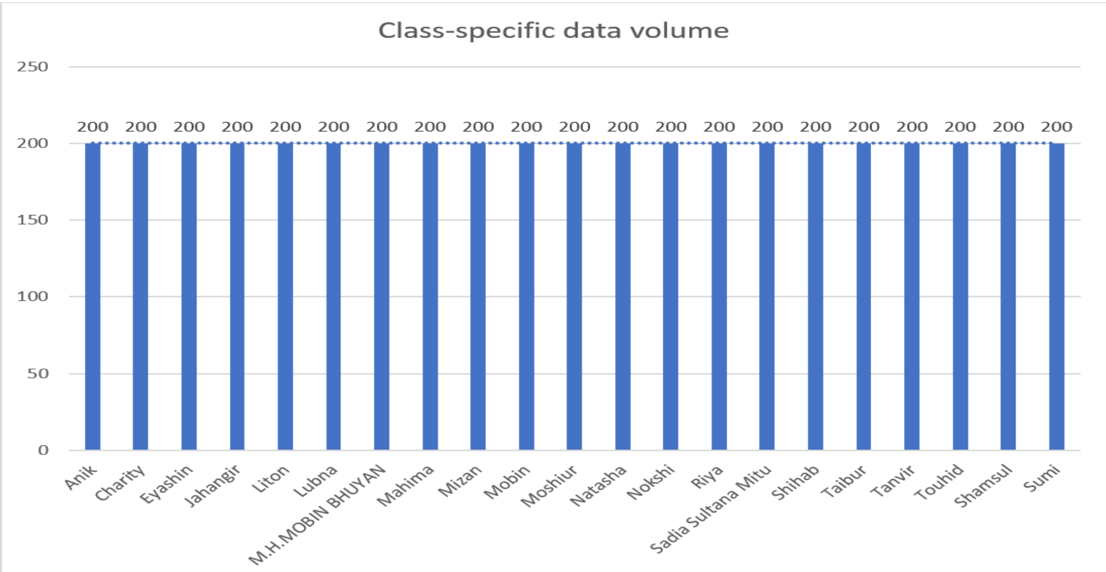

Fig. 3.3.1: Class-specific data volume

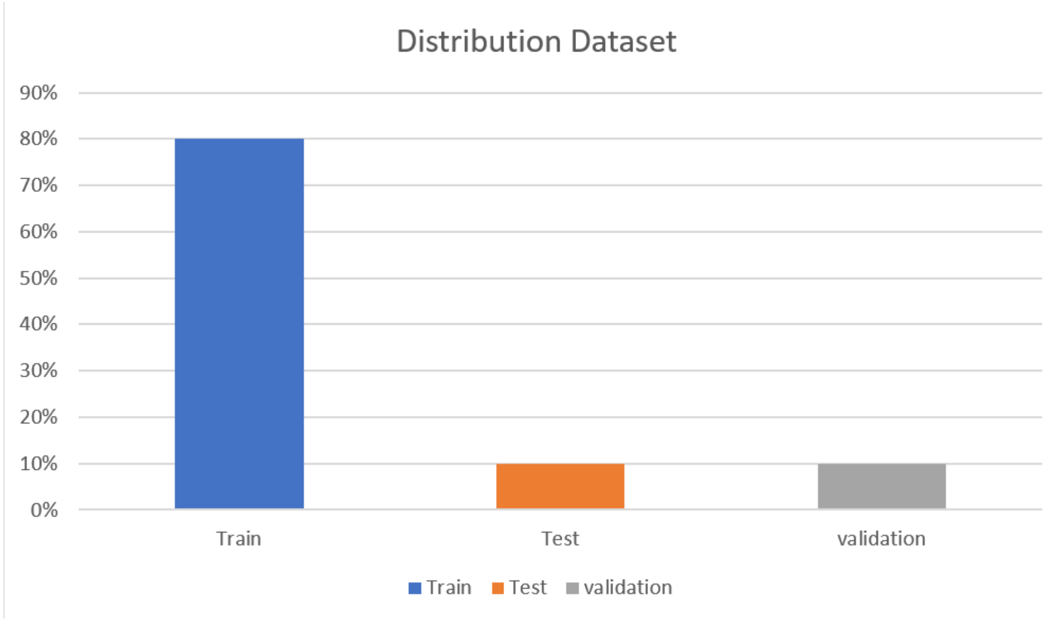

Fig. 3.3.2: Distribution dataset

There are 4200 photos and twenty-one different class groups in our dataset. We separated the dataset into three sections for training, testing, and validation: 80%, 10%, and 10%, respectively.

3.4 Proposed Methodology/Applied Mechanism

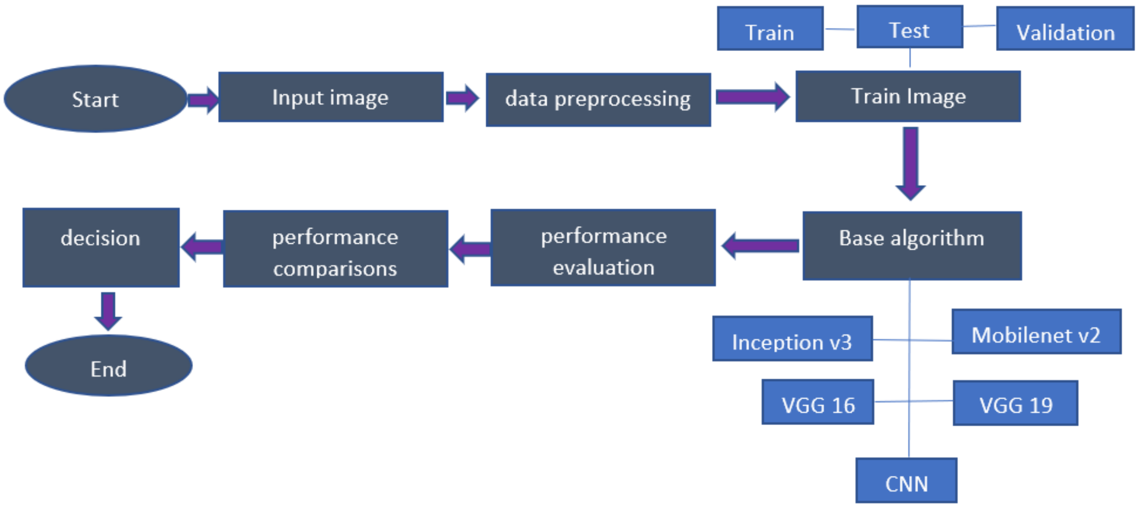

Fig. 3.4.1: Shows the system's execution process for this research.

This study's key goal is to recognize signatures. For that, we have gathered signature photos from various people. Various approaches must be used to complete this task.

Input data, pre-processed data, split data into trains, testing, and validation are notable examples. Use the most accurate method for performance evaluation, performance comparison, and debate.

3.4.1 Preprocessing

Pre-sole processing's purpose is to improve the picture's grade such that we are able to analyze it even more successfully. Preprocessing allows us to remove unwanted distortions and improve specific characteristics that are essential for such a project we're engaged in. Those characteristics could change depending on the application. "Image pre-processing" describes operations carried out on images at the most fundamental level of abstraction. These operations lessen rather than increase the information of the picture if volatility would be a measure of information. Preprocessing seeks to enhance the picture data by minimizing undesirable distortions or increasing particular visual characteristics that are crucial for later processing and analysis tasks. there are Different kinds of image pre-processing methods exist. such as Architectural changes, image filtering, and segmentation, as well as pixel intensity transformations and brightness adjustments Image restoration and the Fourier transform. In this work, the train picture data was preprocessed into 256*256 size. Additionally, the test and validation data sizes are the same. the data was also rescaled here. We apply random rotation, horizontal and vertical flips, and roughly 30%. The split uses 80% of the train data, 10% of the test data, and 10% of the validation data.

3.4.2 Performance Measures

Overall precision, recall, and F1-score, which serve as indicators of the architecture's effectiveness and accuracy, have been calculated using our datasets.

TP stands for True Positive and Fp for False Positive in this study. Once more, FN stands for false negative and TN for true negative. Our datasets show that the best accuracy is around 99.41%.

Recall = $\frac{TP}{TP+FN}$

Precision = $\frac{TP}{TP+FP}$

F1- Score = $2\times \frac{Precision \times Recall}{Precision + Recall}$

3.5 Implementation Requirements

This project is implemented by using deep learning models, which are Convolutional Neural Network or CNN, VGG19, VGG16, Inceptionv3, and MobileNet v2.

3.5.1 CNN

Convolutional neural networks are one of the main types of neural networks used in picture recognition and classification. Convolutional neural networks (CNN) are frequently used in a range of applications, including face recognition, object recognition, and scene labeling.

A photo is submitted to CNN, which classifies and analyses it using phrases like "dog," "cat," "lion," "tiger," etc. The computer's interpretation of the image as a collection of pixels depends on the image's size. In accordance with the image resolution, it will appear as h * w * d, where h stands for height, w for width, and d for dimension. For instance, a grayscale image is a matrix array of 4 * 4 * 1, whereas an RGB image is a matrix array of 6 * 6 * 3.

In CNN, a number of convolution layers, pooling, convolution layers, and filtering are used to process each input image. Then, an object will be classified by applying stochastic values ranging from 0 to 1 using the Soft-max function.

Convolution Layer: The convolution layer is the initial level to extract data from an input image. Using a little square of input data, the convolutional layer learns visual features to maintain the connection between pixels. Using an image matrix and just kernels or filters as two inputs, it performs a mathematical action.

Max Pooling: A sample-based discretization technique is max pooling. Its major goal is to reduce the dimensionality of an input representation so that assumptions may be made about the characteristics existing in the semi-binned.

Max pooling is achieved by applying a max filter on the original representation's non-overlapping subregions.

Fully Connected Layer: The inputs from the other levels will be reduced into a vector and transmitted to the fully linked layer. The output will be changed by the network into the appropriate number of classes.

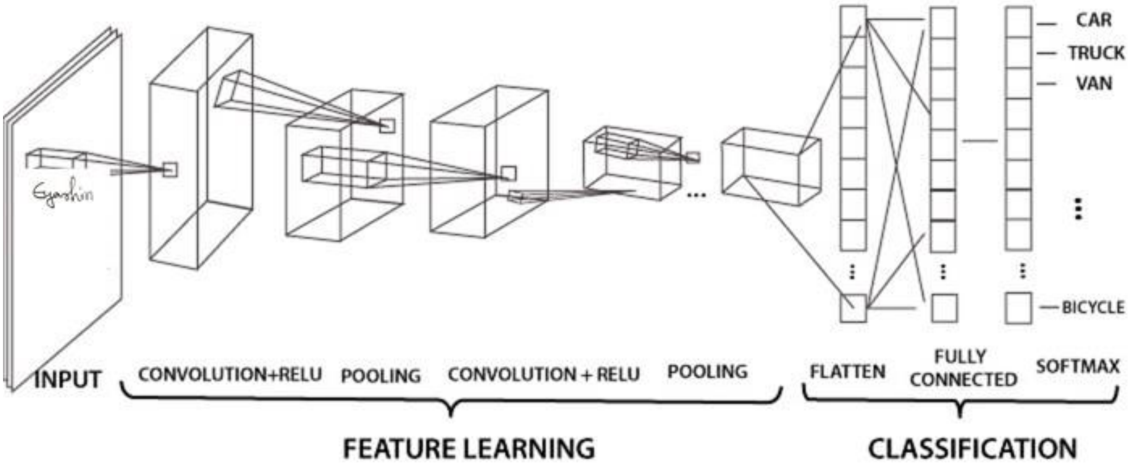

Fig. 3.5.1: Convolutional Neural Network

3.5.2 VGG 19

The VGG-19 design is comparable to the VGG-16 model. Simonyan and Zisserman developed the VGG model. And over a million photos from the ImageNet collection are used to train VGG-19. This model's deep neural network which consists of 19 layers, can categorize photos into 1000 different item categories.

A fixed-size (224 * 224) Color image was provided as input to this network, showing the matrix's form (224,224,3). Calculating the mean RGB value for each pixel across the entire training set was the sole pre-processing that was carried out. Using kernels with a size of (3 * 3) and a cycle duration of 1 pixel, the authors managed to cover the whole image. To maintain the image's spatial resolution, spatial padding was applied. Using side 2, a 2 * 2-pixel window was max-pooled over. This was supplemented by a Rectified linear unit (ReLu) with non-linearity to improve the model's capacity for data classification and accelerate processing. This model fared much better than prior models that used sigmoid functions. constructed three layers that are entirely connected, the first two of which were 4096 pixels wide. The third layer is a softmax function, and it has 1000 inputs for 1000-way ILSVRC classification. Below is a picture of VGG19 fig 6:

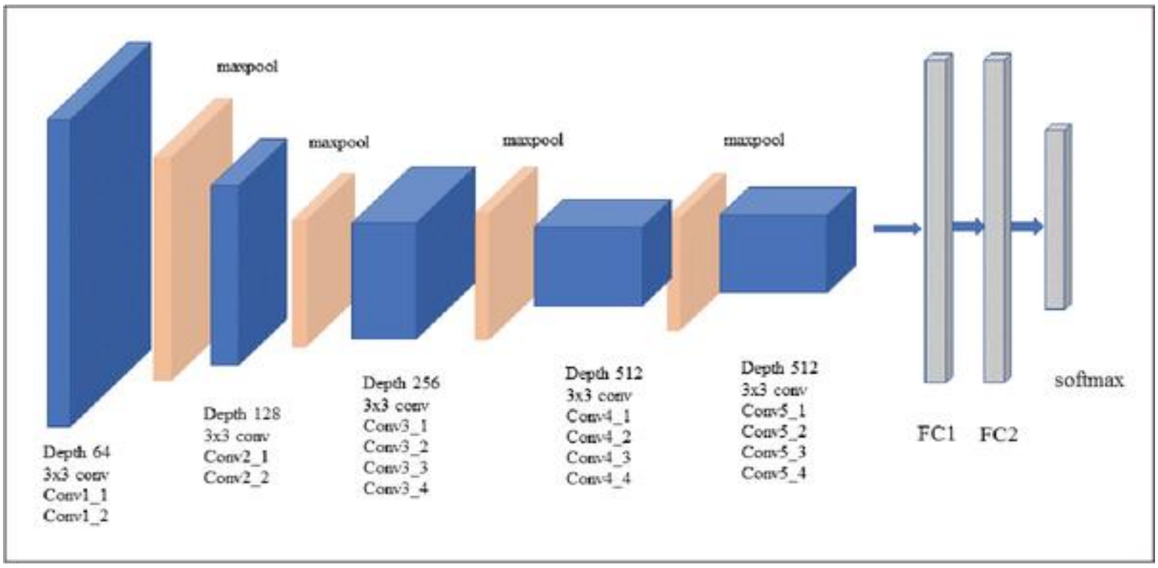

Fig. 3.5.2: VGG 19

3.5.3 MobileNetv2

MobileNet-v2 is a convolutional neural network with 53 layers. The ImageNet database has a pre-trained framework of such a system that has been trained more on than a million pictures [1]. The pre-trained model's network could categorize images into 1000 different item categories, including a set of animals, a keypad, a mouse, and even a pencil. The network has accumulated rich visual characteristics for a variety of photos as a consequence. Photos up to 224 by 224 can be uploaded to the network. Small, low-latency, low-power, parameterized MobileNet models are available to accommodate the various use cases' resource limitations. Like other widely used large-scale models, they may be applied to categorization, detection, embeddings, and segmentation. The figure of mobilenet v2 is :

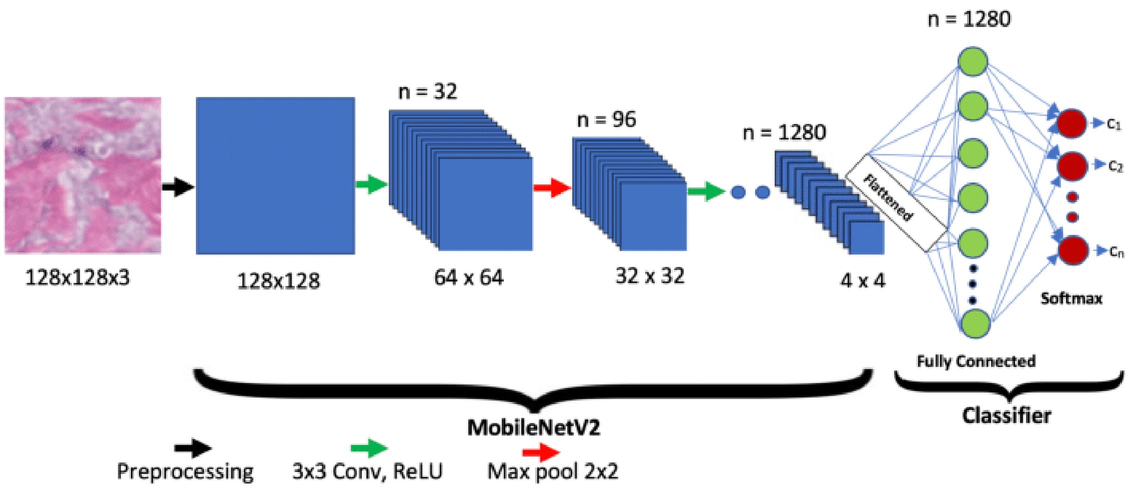

Fig. 3.5.3: Mobilenet v2

3.5.4 Inception v3

The model represents the confluence of several concepts created by numerous scholars over time. Convolution layers, average pools, pooling layers, sequence, dropouts, and fully connected layers are a few of the essential components that make up the framework itself. These elements can be either symmetric or asymmetric. Batch normalization, in addition to being used for the activation inputs, is heavily utilized by the model. Softmax is employed to compute loss. A convolutional neural system with 48 layers deep is called Inception-v3. The ImageNet database contains the pre-trained network model, which was developed using even more than a million images. The network of the pre-trained model can categorize photos into 1000 different object categories, including a group of animals, a touchpad, a mouse, and even a pencil. The network has accumulated rich visual characteristics for a variety of photos as a consequence.

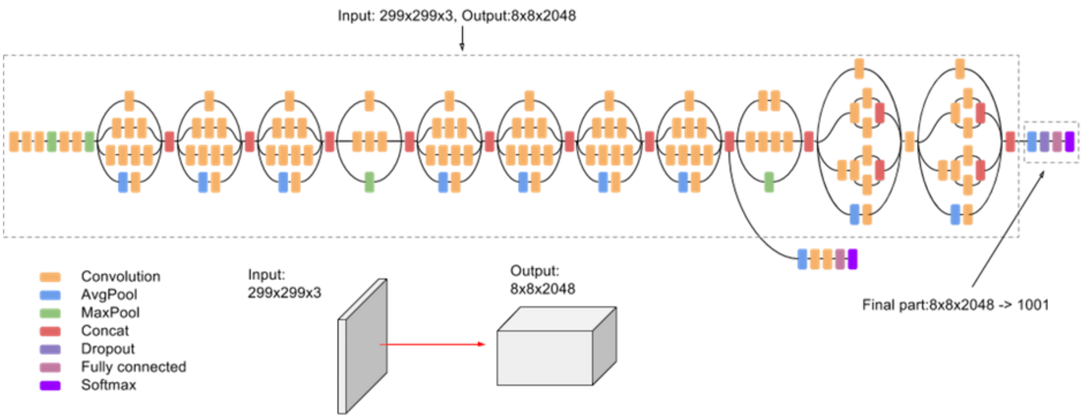

Fig. 3.5.4: Inception v3

3.5.5 VGG16

The VGG16 convolutional neural network model was presented by K. Simonyan & A. Zisserman from the University of Oxford in their article "Very Convolutional Neural Network for Picture Recognition." In the top five evaluations, ImageNet, which has information with over 14 million photos classified into 1000 classes, shows that the model executes 92.7% properly. The model that was presented to ILSVRC-2014 was well-known. It outperforms AlexNet by successively replacing multiple huge kernel-sized filtrations (11 and 5, accordingly, in the first and second convolution layer) with 33 kernel-sized filters.

VGG16 was trained for weeks using NVIDIA Titan Black GPUs.

The cov1 layer receives an RGB image with a predefined length of 224 by 224. Convolutional (Conv.) filters were used with a very narrow receptive field of 33 (the shortest available to capture the concepts of left/right, up/down, and center). The image is subsequently processed by stacking convolutional (Conv.) layers. This also uses 11 convolution filters in one of the settings, which may be thought of as a linear transformation of both data (followed by non-linearity). The convolution step is set at 1 pixel, and the geographic buffering of the convolution layer source is configured to maintain high precision after conversion, i.e. 1 pixel for 33 convolutions. Five max-pooling layers, some of which are convolutional layers, are used for spatial pooling (not all of the completely - connected. layers are represented by max-pooling). Max-pooling is performed throughout a 22-pixel frame using stride 2.

Three Fully-Connected (FC) stages are utilized after a convolution layer stacking (the depth of which varies between models); the first two contain 4096 connections each, while the third conducts 1000-way ILSVRC classification and hence 1000 units (one for each class). The soft-max layer is the last one. In every network, the fully linked layers have the same setup.

Rectification (ReLU) non-linearity is a property shared by all hidden layers. On the ILSVRC dataset, all of the networks do not apply Local Response Initialization (LRN), which significantly increases memory utilization and calculation time without improving performance. The vgg16 model architecture is shown in Fig 9

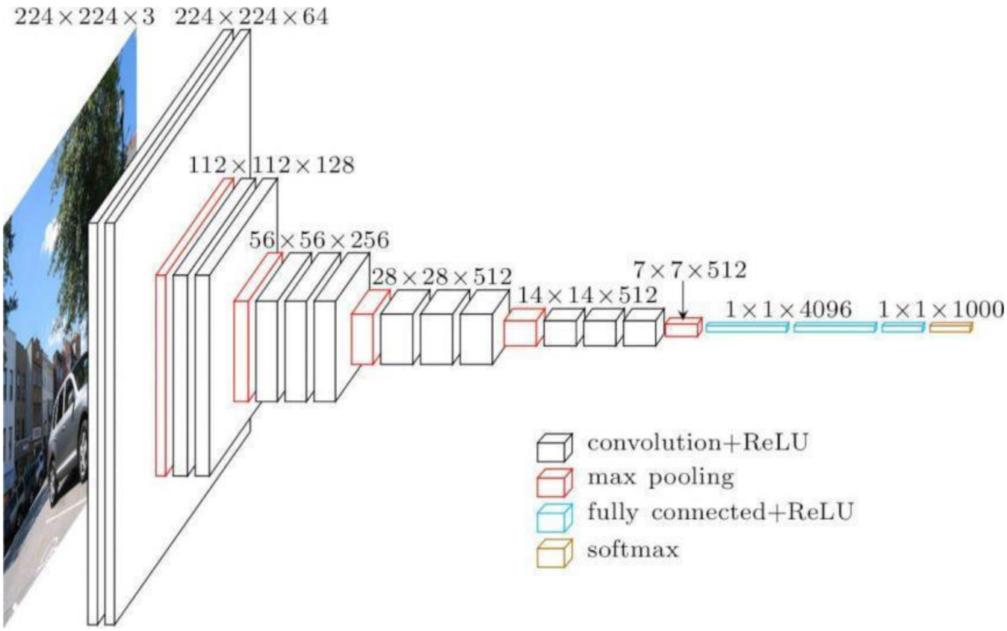

Fig. 3.5.5: VGG 16

Chapter 4
Experimental Results and Discussion

4.1 Experimental Setup

Here, we have gathered 200 signatures from 21 individuals. Following that, I made a fresh notepad in Google Collab. Google Drive must be used to build Google Collab. Through simply a browser, anybody, anyone may access the notebook.

4.2 Experimental Results & Analysis

Here, all of the models have been compared. Prior to that, we had to develop the model and select the best accuracy models. Additionally, we preprocessed the data to get a precise and uniform precision. For our best accuracy, we use CNN, VGG16, VGG19, inception v3, and mobilenetV2. However, we discovered that the vgg accuracy is 99.41%, which is our best accuracy. And this model loses 1.26% of the time. Table 4.2.1 displays the effectiveness of each model.

Table 4.2.1: Accuracy of Different Models and Loss Function

Model name	Accuracy score	Loss function
CNN	98.05%	0.0652
VGG16	98.82%	0.037
VGG19	99.41%	0.012
Inception V3	83.59%	0.417
MobileNet v2	82.42%	0.521

The vgg19 model has the best accuracy, as seen in the accompanying table. Its accuracy was 99.41%, and its loss function was 0.012. On the other hand, moblienet v2 has the lowest accuracy, with a loss function of 0.521 and an accuracy of 81.42%. To measure overall performance, the model's accuracy, recall, & f1 score are examined. Table 4.2.2 provides the model's performance results.

Table 4.2.2: The model's performance results

Catagories	Classes	Model				
		CNN	VGG16	VGG19	Inception V3	Mobilenet v2
Anik	Precision	1	1	1	1	1
	Recall	1	1	1	1	0.50
	F1 score	1	1	1	1	0.67
Chaity	Precision	1	1	1	1	1
	Recall	1	1	1	1	1
	F1 score	1	1	1	1	1
Eyashin	Precision		1	1	1	0
	Recall		1	1	1	0
	F1 score		1	1	1	0
Jahangir	Precision	1		1	1	1
	Recall	1		1	1	1
	F1 score	1		1	1	1
Liton	Precision				0.5	
	Recall				1	
	F1 score				0.67	
Lubna	Precision	1		1	1	1
	Recall	1		1	1	0.50
	F1 score	1		1	1	0.67
M.H.MOBIN BHUYAN	Precision		1	1		1
	Recall		1	1		1

	F1 score		1	1		1
Mahima	Precision	1	1	1	1	0.50
	Recall	1	1	1	1	1
	F1 score	1	1	1	1	0.67
Mizan	Precision	1	1			
	Recall	1	1			
	F1 score	1	1			
Mobin	Precision	1	1	1	1	1
	Recall	1	1	1	1	1
	F1 score	1	1	1	1	1
Moshiur	Precision	1	1		1	1
	Recall	1	1		1	1
	F1 score	1	1		1	1
Natasha	Precision	1	1	1	1	1
	Recall	1	1	1	0.75	1
	F1 score	1	1	1	0.86	1
Nokshi	Precision		1	1	1	0.67
	Recall		1	1	1	1
	F1 score		1	1	1	0.80
Riya	Precision		1		1	0.33
	Recall		1		0.50	1
	F1 score		1		0.67	0.50
Sadia sultana mitu	Precision	1	1	1	1	0
	Recall	1	1	1	1	0

	F1 score	1	1	1	1	0
Shihab	Precision	1	1	1		1
	Recall	1	1	1		1
	F1 score	1	1	1		1
Taibur	Precision	1	1	1	1	1
	Recall	1	1	1	1	1
	F1 score	1	1	1	1	1
Tanvir	Precision		1	1	0	0
	Recall		1	1	0	0
	F1 score		1	1	0	0
Touhid	Precision	1	1	1	0.86	0
	Recall	1	1	1	1	0
	F1 score	1	1	1	0.92	0
shamsul	Precision	1	1	1	1	1
	Recall	1		1	1	1
	F1 score	1		1	1	1
sumi	Precision			1		0
	Recall			1		0
	F1 score			1		0

Precision: Precision refers to how many of the positive classes we accurately predicted from all of the positive classes overall. The ratio between true positives over false positives is defined as precision.

Recall: It shows how much of all of the positive classifications we properly anticipated. The better the model's quality, the higher the values. Recall is defined as True Positive / (False Positive + True Positive).

F1-score: The F-score objectively assesses both retention and sharpness. It makes use of Waveform Mean rather than Geometric Mean. The ratio of (recall + precision)/(2*recall*precision) determines the F1-score.

In the aforementioned table, vgg 19 has the highest accuracy while mobilenet v2 has the lowest accuracy.

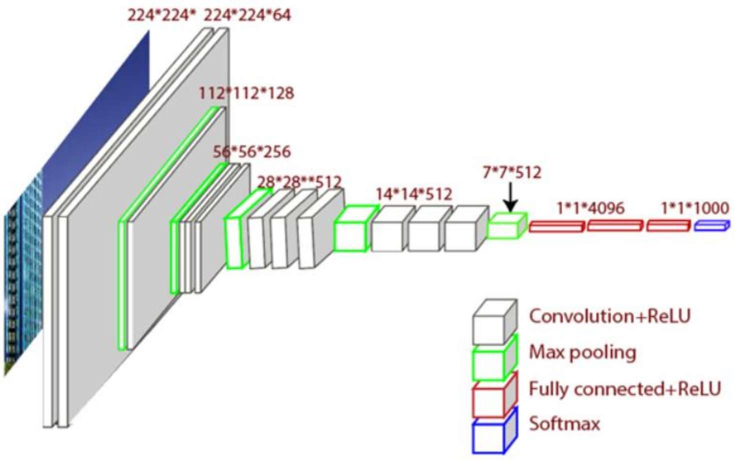

Fig. 4.2.1: Structure of vgg 19

4.3 Discussion

Here uses deep learning to recognize particular signatures from a variety of classes. To achieve this, we have employed a number of deep learning models. We used the CNN model, Inception V3, Vgg16, and Vgg19. The vgg 19 achieves the greatest accuracy among them, with a 99% accuracy rate.

A confusion matrix collects the projected results of a classification issue Count values are used to indicate the proportion of accurate to inaccurate forecasts for each class. The conundrum of the confusion matrix is this. A classification technique can nevertheless provide results despite being confused, as shown by the confusion matrix. More significant than just the mistakes your classifier is creating, it gives data on the kind of failures that are being generated. This breakdown avoids the disadvantage of depending entirely on classification accuracy. In Fig. 11, overall confusion matrix is shown.

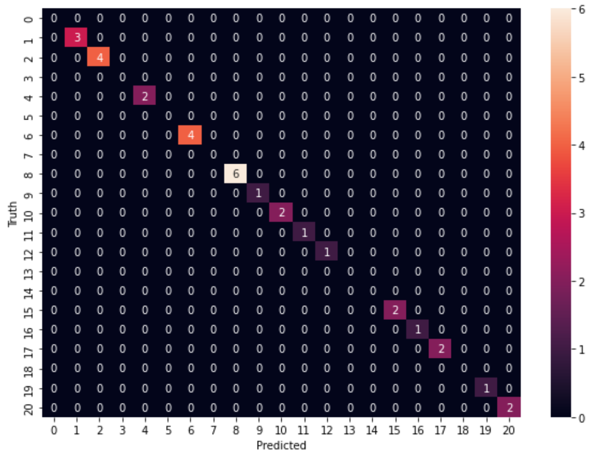

Fig. 4.3.1: Confusion Matrix of CNN

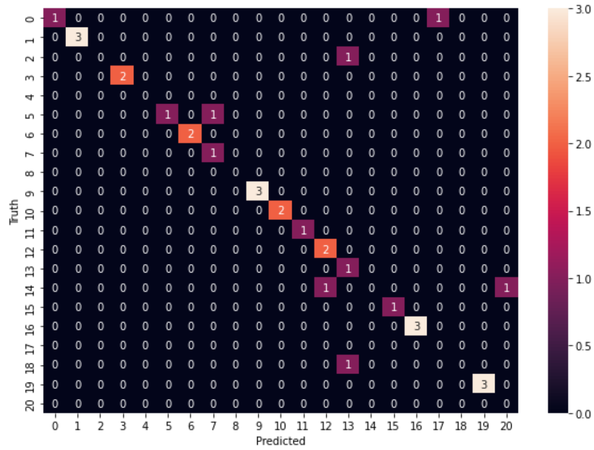

Fig. 4.3.2: Confusion Matrix of mobilenet v2

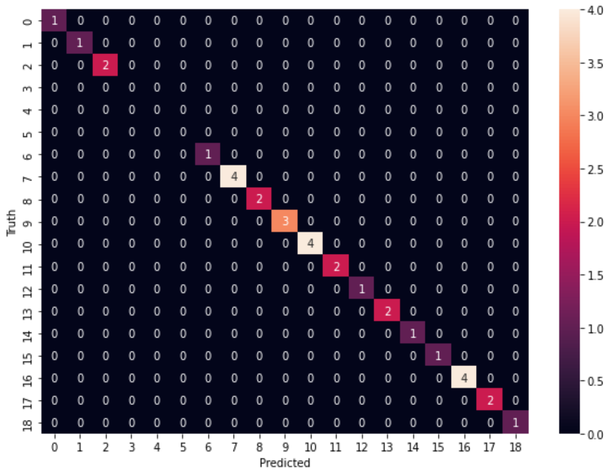

Fig. 4.3.3: Confusion Matrix of VGG16

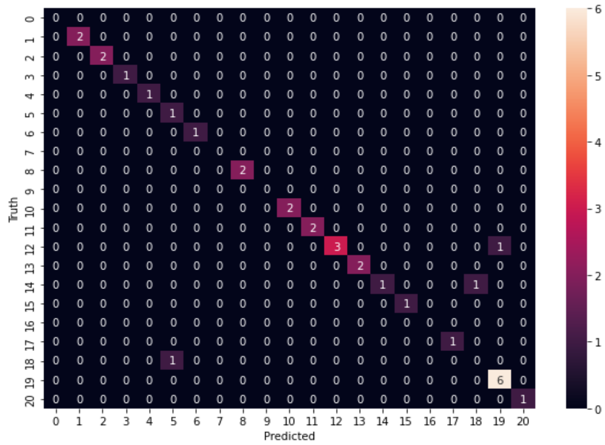

Fig. 4.3.4: Confusion Matrix of VGG19

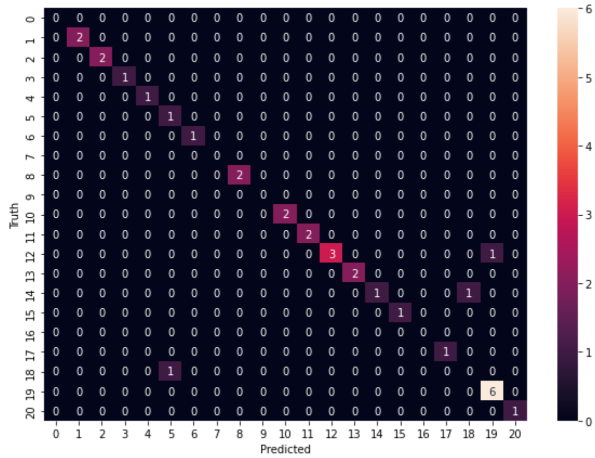

Fig. 4.3.5: Confusion Matrix of Inception v3

Chapter 5
Impact on Society, Ethical Aspects, and Sustainability

5.1 Impact on Society

Banks, government organizations, intelligence services, and prestigious institutions all employ signature verification to confirm a person's identification. In bank branches and other branch capture, the signature comparison is frequently employed. The signature verification program compares a direct signature or a picture of a signature to the recorded signature image.

Unexpected bank withdrawals by fraudsters and far more harm to victims can result from a tiny signature error. However, 99.4% of people can accurately see the outcome if the handwritten signature is confirmed using deep learning technology. As a result, there is a significantly lower likelihood of error during the signature verification. Because deep learning approaches provide accuracy after performing handwritten signatures, dishonest people and cheaters are unable to reproduce the signature. Therefore, common people won't suffer social harm or are less likely to suffer social harm. The propensity for forging signatures will then decline, resulting in a rise in societal values.

5.2 Ethical Aspects

In general, using a transfer learning model to identify handwriting signatures will produce accurate results, allowing the signature to be identified. The trained model will validate that accuracy if the signature matches. Deep learning is used in its implementation, hence there can be some mistakes and functionality loss. As a result, it occasionally may provide inaccurate results. Additionally, if someone is able to precisely duplicate the handwritten signature, the deep learning model will not be able to validate it, which might lead to inaccurate findings and even harm. This initiative was undertaken in order to prevent fraudsters from hurting anyone by forging handwritten signatures. Therefore, signatures must match correctly to prevent copying.

Hire professionals to assist you if necessary. Additionally, two or three levels of verification can be set up to prevent any unneeded occurrences.

5.3 Sustainability Plan

Without a signature, an agreement is open-ended, unclear, and very difficult to enforce. The handwritten signature grounds the agreement in a fact that is enforceable, enforceable, and actionable. Handwriting signature recognition is crucial for ensuring social, commercial, and individual safety. Deep learning may be used to identify handwriting signatures, which can be beneficial in many ways. This reduces the possibility of fraud during the authentication process, saves time and resources, and assists in preventing human mistakes during the signing process. People can occasionally be put at risk by signature forgery. because persons may be recognized by their signatures. The victim can lose financially and socially if someone copies it. Important papers also require signatures since handwriting is needed for financial operations. In this study, we use five alternative models to recognize handwritten signatures. This was mostly implemented using CNN, VGG16, VGG19, Inception version 3, and Mobilenet version 2. Here, using VGG19, we obtain the greatest accuracy of 99.41%.

Chapter 6

Summary, Conclusion, Recommendation, and Implication for Future Research

6.1 Summary of the Study

Organizations rely on biometric systems for individual verification because it is crucial for employees to be identified. The verification of signatures using one of these biometric techniques is still regarded as socially and legally acceptable. Two further biometric technologies are biometrics and iris scanning. Due to the uniqueness of each person's handwriting, signature verification involves verifying or identifying specific features on the handwritten signatures [1]. The first step in verifying a signature is scanning a person's handwritten signature onto a piece of paper to store it digitally. When the exact same individual is to be confirmed again, the mark is captured once again and opposed with and recently preserved advanced image of the mark. Because the velocity, location, or elevation at the moment of the initial database signature aren't really verified, this dynamic evidence is not utilized in the following verification procedure. This is known as offline verification and identification, and non-dynamic verification is challenging. Personal verification is widely done with signatures; This emphasizes the necessity of a system for automatic verification. Depending on the application, sign verification can either be done offline or online. Dynamic data captured during the creation of a signature is used by online systems. The scanned signature is what offline systems rely on. This study presents a way for leveraging the python deep-learning learning algorithm to verify signatures. An algorithm that really can learn from signings and determine whether a signature is forged or not has been successfully implemented. There are 21 classes that our model can predict. Our highest level of accuracy was 99.41%.

6.2 Conclusions

The idea of Deep Learning Algorithms, which are a subset of Artificial Neural Networks, has been put to use in this paper to verify signatures by employing twin Convolutional Neural Networks. This model contributes to the training of the dataset by learning the pattern of various signatures, which may be used to identify whether or not a particular signature is authentic. The dataset was provided to us by friends and family. Additionally, we have data from volunteers who have given their consent to provide it. This study used approximately 4200 photos, divided into 21 categories. We collaborated with a distinct class for each participant. Classes are named after them. Each class consists of 200 data. For signature identification, a convolutional neural network (CNN) depending on VGG 16, VGG 19, MobileNet v2, and Inception v3 is proposed to improve performance. While the training/testing/validation ratio remained constant (80/10/10), the images' pre-processing, which included cropping to a 256 x 256-pixel size, was also taken into consideration when developing the training and testing data. The experimental results give us an accuracy range of 82.42% to 99.41%, with VGG19 providing the highest accuracy.

6.3 Implication for Further Study

Using these concepts for predictions & evaluation does have a lot of future promise. This type of model promotes more competition and study in this field to enhance a neural network approach for training and evaluating datasets or real-time data, which aids in the solution of many real-world issues. Using deep learning, we will work on Handwritten Word Recognition for various languages in the future.

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Signature

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