Comprehensive Fingerprint Recognition Utilizing One Shot Learning with Siamese Network

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***Abstract*—Detailed Fingerprint investigation has been a dominant law enforcement tool which is utilized to distinguish suspects, settle crimes and violations for over 100 years. Moreover, gender classification from fingerprints is a vital step in forensic anthropology in order to identify a criminal's gender and reduce the list of suspects. A novel approach of machine learning (ML) which is One Shot Learning has been introduced in this report for identification of persons which will implement the Siamese learning approach for training fingerprint samples by using the triplet loss. One Shot Learning has shown to be efficient because it reliably performs with only one labeled training example and one or a few training sets. Moreover, by using Transfer Learning with EfficientNetV2S an accuracy of 99.80%, 99.73%, 97.09%, 99.66%, 98.61% for identification of person, gender, hand, finger and detection of forge fingerprints has been achieved on the Sokoto Coventry Fingerprint Dataset.**

***Index Terms*—Fingerprint, SOCOFing Dataset, One Shot Learning, Siamese learning; Machine Learning; Transfer Learning; Triplet loss Function; EfficientNetV2S.**

I. Introduction

Utilization of an individual's fingerprint in terms of unique identification is not a later technology, to the contrary, the method is being using for decades in various sectors. The grounds behind the strengths of fingerprint lie behind the physical structure of our fingers. For decades, through scientific investigation and microscopic visualization, the fact that each finger contains different pattern of ridges and furrows has been revealed. Moreover, the magnificence of each person has different patterns (actually, no two person in the entire world do not have similar fingerprints, even identical twins have different fingerprint patterns) can statistically identify any person and detect their identity [1] [2]. Using fingerprint identification, many criminals have been identified, or at least, the process of finding criminals has been easy. In police investigations, the ability to identify a person's gender can easily narrow down the elaborate process of narrowing down the identification process. methods for finding the data involves large data sets and complexity, which requires strong methods. In our paper we have shown methods used by other researchers throughout the years using deep convolutional neural network, RT method and so on, However, in our paper we will be proposing a method combining the technology of one shot machine learning as well as Siamese learning network. One shot learning method can extract data while eradicating the complexity of any form of data sets. Besides, even if the data sets lack in features, the algorithm will work fine. The implementation of Siamese learning model will help the data sets training phase. Using the one shot method, the the large data set, no matter how complex, can easily be incorporated since one shot simplifies the verification process. Moreover, the Siamese network will handle input similarities and make sure the output is accurate. By implementing mentioned procedures, we will try to validate, verify and ensure privacy through fingerprint recognition while proposing a cost effective system which can be implemented in various sectors. Thus, the main purpose of using Siamese Network is to address Neural networks for having a strong knowledge of similarity learning [3].Using the Siamese network, we will train our data set and for testing we will use a novel architecture which is one shot learning in order to do the fingerprint classification. The problems that will be addressed from this research paper are bio-metric validation, security, verification and cost-effectiveness. Here Chapter-II describes background study.Chapter-III describes Proposed method.Chapter-IV describes Dataset Processing.Chapter-V describes Result.Chapter-VI concludes the work.

II. Background Study

The authors of [4] in their research paper proposed CNN and Transfer learning in order to identify the fingers classification, hand and gender. Their proposed model because of the promising result was used in SOCOFing corpus. Their model learns the features for gender classification with CNN and by the incorporation of transfer learning the CNN classifier works faster [5]. With the implementation of both CNN and transfer function, the model learns the feature for classification by taking fingerprint image information into consideration to provide precise results [detailed identification]. Precisely, this paper utilizes ResNet model that is trained on ImageNet which acts like a source domain and then adjust the model to the domain of classification of fingerprints. The accuracy result for the identification of the hand is very high which is around 93.5%. In [6], few shot learning palm-print acknowledgment algorithms with the implementation of Meta-Siamese Network have upgraded the exactness and robustness of identification results to a better accuracy by implementing only few images for testing. Because of using few shot learning and testing few images for palm print recognition, investing huge amounts of time to label and train samples were resolved. To ensure personal security and for gathering individuals' palm print which will split the data set with the purpose of training and testing was also corrected by the utilization of few shot learning. Therefore, the authors of [6] proposed a few shot learning by implementing Meta-Siamese Network for palm-print recognition in a small sample of data.he whole experiment was conducted using the PyTorch framework. After the experiment, the results for different settings exceed around 99%. Alqahtani and Zagrouba [7] in their paper aimed to review different research papers which differentiate original and altered fingerprint images utilizing different ML algorithms and have also tried to scrutinize different schemes. In order to be able to differentiate between real and fake images, the most crucial thing is to understand the features of the image. Nevertheless each feature has different characteristics proposed by different studies [8]. The output of this research work have found that the SVM was extensively utilized as a classifier. Moreover, BFIF, LPQ are the extracted features in nearly all of the cases. Additionally the data-sets LivDet2013, LivDet 2011 were implemented in the training and testing phase.Arun and Sarath focused on the issue of gender classification through the use of fingerprint images in [9]. Following the success of an attempt to discover the differences between fingerprint scans using machine learning, the researchers decided to try the fingerprints at gender recognition.They are able to generate a reliable diversifying method for gender featured vector patterns by making use of SVM that was trained with a set of photos consisting of 150 males and 125 females [10]. The study [11] proposed a deep learning architecture for singular point detection using one shot learning from a fingerprint image. This proposed model comprised of three things for instance three stacked hour glass, Macro-Localization-Network along with Micro Regression.Using three distinct databases, the model has been run on with the goal of achieving a significant result. Therefore it has been found that this model achieves an optimistic result than most other state of the art models. Lothai and Bong [12] researched about the Bit-plane method of fingerprint identification. They paired bit-plane with POC to get a better result while occupying less storage space for the fingerprint extraction.The authors compared their method with other methods using FVC2002-Db1a and FingerDos dataset where they achieved 81.16

III. Proposed Method

A. Classification

For our thesis, we have utilized the Sokoto Coventry Fingerprint Dataset, in short SOCOFing , which is a specialized fingerprint based dataset useful for fingerprint recognition based works [13]. We have performed different data processing techniques on this dataset as well.We have implemented different models of transfer learning on our dataset [13] in order to identify the person and classify gender, hand, finger and also to identify types of alteration. We have performed ResNet34, ResNet50, ResNet152, InceptionV3, InceptionResNetV2 ,EfficientNetV2s. However after analyzing different Performance Indicators of these models, we have picked EfficientNetV2s for our classification of person's ID , gender , hand , finger and altered fingerprint.EfficientNet V2 is an improved version of the already existing EfficientV1 [14] family models(B0-B7). By improved it means that EfficientNetV2s can have better performance in terms of training agility as well as parameter efficiency [15]. The model solves the problem of accuracy drop during the increment of image size while trainng for the sake of boosting up the training. By proposing a method of adaptive regularization adjustment called progressive learning, the reduction of accuracy can be optimized. EfficientNetV2s uses

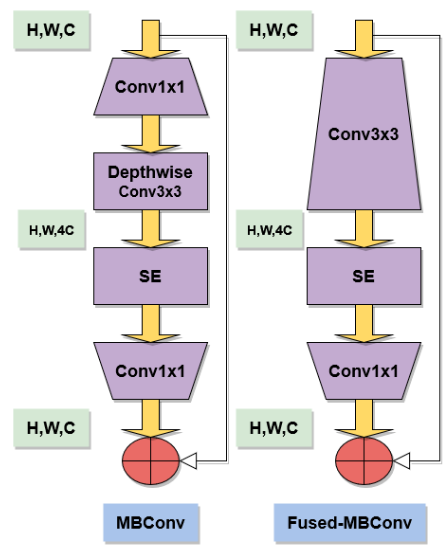

Fig. 1. EfficientNetV2s Architecture

both MBConv and Fused-MBConv [16] [15] [14]. Besides, the model manages less memory access overhead by utilizing a smaller expansion ratio. Moreover, 3*3 smaller kernel sizes are designated into this model. However, more layers are inserted to make up for the deducted receptive field due to the utilization of smaller sized kernels. Further, EfficientNetV2s optimizes the parameter size and the overhead by pruning the final stride-1 stage, existing in the V1 model [15].

B. One Shot Learning

We choose one shot learning where only one sample image is needed for learning new or unseen objects.Traditional convolutional network trains input images using softmax activation and produced output based on predicted probability distribution in a vector size in par with the number of classes. However, One shot learning does not do that. Instead the network take only one reference image, one test image and uses Siamese network to compare the two images and lastly generate a similarity output that shows how the test image is similar or dissimilar with the reference image.This turns the classification problem into a difference evaluation problem.

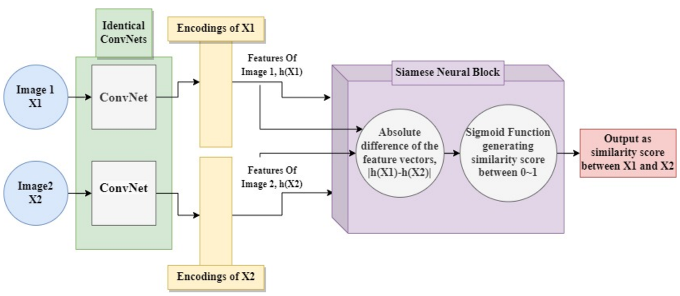

Fig. 2. One Shot Learning With Siamese Network

C. Siamese Network and Triplet Loss Function

Siamese neural network uses a triplet loss function where it is trained on three types of images. The network is trained on an anchor image, a positive image which is a slightly altered image of the reference or anchor image and lastly a negative image which is a completely different image. The network then compares the features of both images with respect to the reference image.The parameters for the neural network is tuned in such a way where the encoding values of the anchor and positive image is close .On the contrary the encoding values of the anchor and negative is very far apart.This is how Siamese neural network uses triplet loss function to evaluate the distance of the features of two input images , the reference image and the test image, provided into the one shot learning based network. Below Fig[3] shows the procedure of Triplet Loss function

The similarity then uses a threshold value to determine whether the reference image and test image belongs to the same person person on not Fig[4] . In our case, the threshold value is 0.75 meaning if the similarity score gives us a value lower than 0.75, our model will say that the test belongs to the reference fingerprint image and the person is matched. It

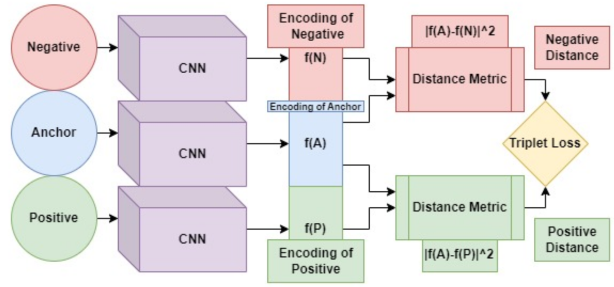

Fig. 3. Triplet Loss Function

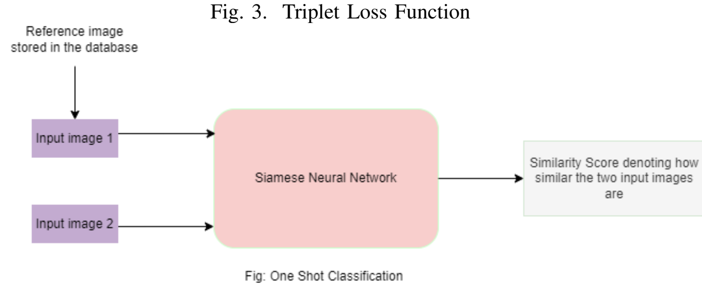

Fig. 4. One Shot Learning With Siamese Network

will otherwise not match. Lastly, the Siamese neural network uses the Sigmoid function to provide the output value between 1 and 0. If the output value is 1 or closer to 1 , then it denotes that the reference and the test image are of the same object. If it's 0 then it denotes that both the images have very little similarity Fig[2]. This is how using just a single reference image of an object we can generate similarity with other test objects and classify them. In this way the network does not need to train for dynamic classes as the network deals with the difference evaluation. Moreover, for an object or class to identify, the network only requires one reference image into it's database compared to traditional deep CNN. There in person identification issues, specially in terms of fingerprint recognition, to identify a person only one sample of his registered fingerprint is sufficient to identify him.

IV. Dataset details and processing

A. Dataset description

For our thesis, we have utilized the Sokoto Coventry Fingerprint Dataset, in short SOCOFing, which is a specialized fingerprint based dataset useful for fingerprint recognition based works [13]. The dataset is composed of the information taken from 600 different adult African individuals who are all aged over 18 years reportedly [13]. There are a total of 6000 fingerprints containing pairs of thumbs,forefingers,long fingers,ring fingers and little fingers of a single individual's left and right hands. Implementing STRANGE framework [17], realistically synthesized altered fingerprints pictures were generated which produces three different tiers of alterations in regards to obliteration, Z-cut and central rotation [13].

The altered images obtain a resolution of more than 500 dbi. Moreover, the numbers of altered images can be ranged from (with respect to parameter settings),Easy:17,934 images ; Medium:17,067 images ; 3.Hard:14,272 images.

B. Dataset division for training purpose

In order to prepare a dataset suitable for model training, a dataset has to be fragmented into three sets such as training set, validation set and testing set. This preparation can be visualized below Fig[5]

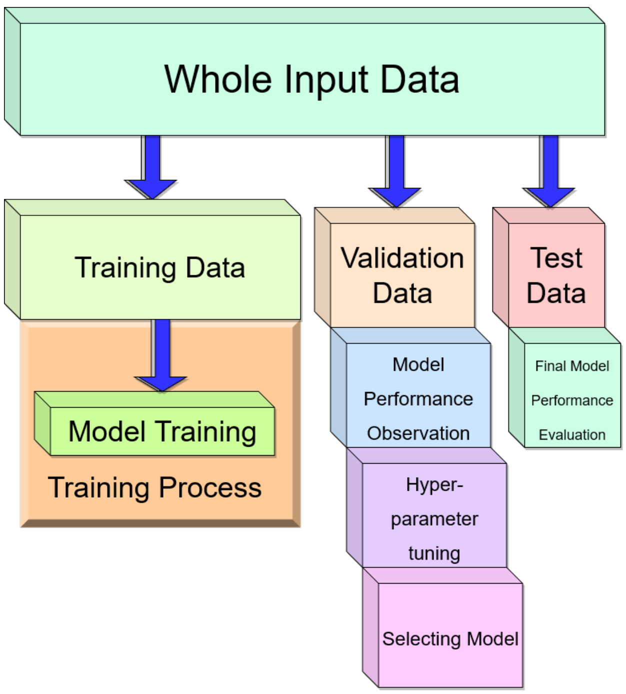

Fig. 5. Dataset division for training

C. Dataset pre-processing for model implementation

In order to implement the CNN models, data needed to be preprocessed. This will ensure that the data used for the models don't have any inconsistencies.

1) Data Segmentation: Inside the finger class the hand (Left/Right) and finger type (Thumb/ Index/ Little/ Middle/ Ring) are included. Therefore, the gender target class has 6000 images with Male Finger images consisting of 4770 images and Female Finger images consisting of 1230 images. Moreover, both the left and right thumb, index, middle, little, ring finger each class have 600 images.

2) Data Augmentation: Models tend to memorize the data instead of establishing relationship because of the overfitting nature. Thus the aim of the models is to increase the amount of data by creating new data points in order to mitigate the overfitting nature and form generalized relationship better.

3) Resize Pixels: In order to decrease the complexity of dealing with large sized pixels, the images were scaled down to 96×96 . Moreover, the models implemented in this research paper used 96×96 pixels.

4) Reflect and Random Crop: The reflection is used to ensure that the transition of outputs will occur smoothly to improve the performance of the implemented models. Since in the images our object of interest are not always entirely visible in the image, random crop creates random subset of original image to help the model learn and generalize better.

V. RESULT ANALYSIS OF IMPLEMENTED MODELS

1) Analysis of Pre-trained Models: To evaluate the performance of the implemented models, a comparison table is shown below based on the test accuracy, test loss, number of parameters, wall time. At first we tested on two target classes Gender and Hand so two different tables are shown below: From Fig[6] it can be seen that the test

Models	Number of parameters	Wall Time	Test Accuracy	Max Accuracy at Epoch Number
ResNet34	25567032	11min 23s	84.43%	23rd
ResNet50	21797672	22min 27s	82.50%	18th
RegNet_Y_3_2GF	19436338	48min 21s	82.19%	22nd

Fig. 6. Result analysis of hand and finger detection of the models

Models	Number of parameters	Wall Time	Test Accuracy	Max Accuracy at Epoch Number
ResNet34	25567032	12min	84.43%	16th
ResNet50	21797672	23min 56s	82.24%	18th
RegNet_Y_3_2GF	19436338	50min 15s	84.95%	21st

Fig. 7. Result analysis of gender identification of the models

accuracy of ResNet34 is highest of about 84.43% which depicts that this model can detect hand (Left/Right) and finger (Thumb/Index/Middle/Ring/Little) efficiently compared to other implemented models. However, RegNet-Y32GF has the least accuracy rate of 82.19% In Fig[7] Resnet50 has the least accuracy rate of 82.24% for gender identification compared to other models and RegNet-Y32GF has the highest accuracy for gender classification which is 84.95%.

2) Classification Report and Graphs of EfficientNetV2s: From the above section it can be seen that the implemented models have not given that much accuracy and also there are overfitting cases. In order to solve the problem, we have further implemented EfficientNetV2s and got high accuracy and the overfitting case has been solved too. Thus for classifying gender, hand, finger and identification of person we have used EfficientNetV2s. Here, in our main dataset there are a total 6000 images and for the alteration class there are more than 6000 images.Fig[8] shows the accuracy, precision, recall and epoch value have been shown at which we got the highest accuracy.

	Person	Gender	Hand	Finger	Alteration
Accuracy	99.80%	99.73%	97.09%	99.66%	98.61%
Precision	99.82%	99.73%	97.12%	99.66%	98.61%
Recall	99.80%	99.73%	97.07%	99.66%	98.61%
Epoch	28	49	22	31	36

Fig. 8. Result analysis of gender identification of the models

Fig[9],Fig[10],Fig[11],Fig[12],Fig[13] shows the respective graphs as well.

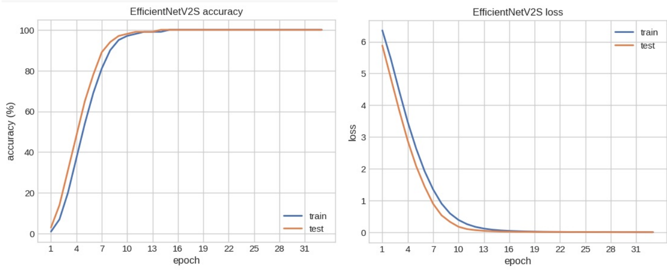

Fig. 9. Graph for Person class

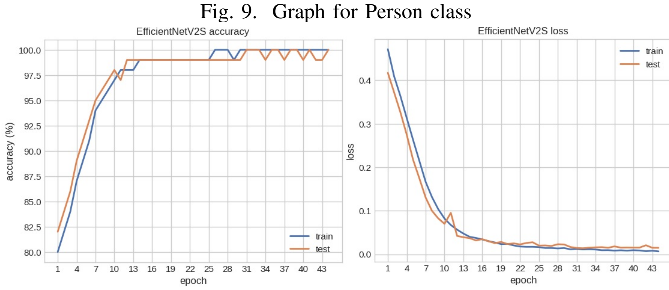

Fig. 10. Graph for Gender class

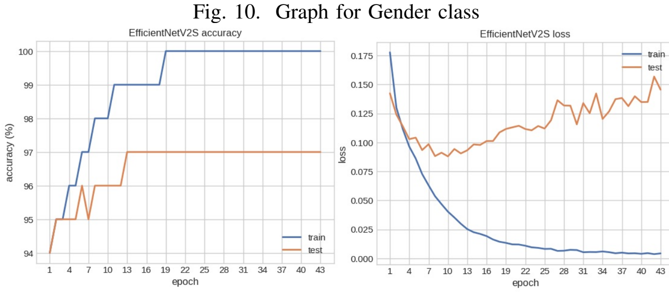

Fig. 11. Graph for Hand class

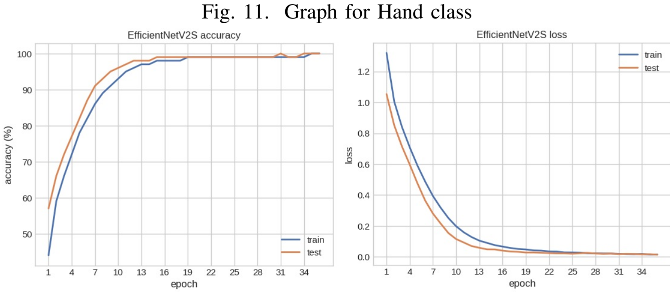

Fig. 12. Graph for Finger class

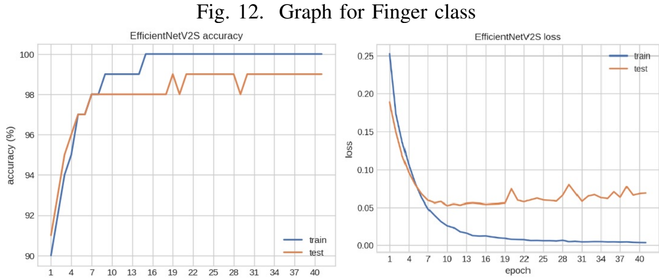

Fig. 13. Graph for Alteration class

3) Analysis of Result of One Shot Learning: The main purpose of using one shot learning is to get rid off the hassle of re-training the whole model again when a new entry has to be done in the database.That is why just for person identification, one shot learning has been implemented for training the dataset because new labels will be there if a new entry has to be done.For training the model, the triplet function has been used. However, for the case of gender, hand and finger classification there is no need to apply one shot learning as no new labels are there except for the already declared ones. The working principle of one shot learning is it measures the distance between the pixels and compare the result with the threshold value.After many trials, the threshold value is set to 0.75 for our work.For the main model InceptionV3 has been used here . To scrutinize the result of one shot application on the dataset, a comparison has been done with the images of same person and the image of different person.For the same person's fingerprints, the measured distance is 0.438806 which is less than the threshold value meaning the fingerprints belongs to the same person.For the different person's fingerprints, the measured distance is 1.0990736 which is more than the threshold value meaning the test fingerprint belongs to different person. Now to check

	precision	recall	f1-score	support
0	0.9608	0.8448	0.8991	58
1	0.8657	0.9667	0.9134	60
accuracy			0.9068	118
macro avg	0.9132	0.9057	0.9062	118
weighted avg	0.9124	0.9068	0.9064	118

Fig. 14. Classification report of One Shot Learning

the performance of one shot learning on the dataset, more than 100 random images have been picked and matched with the results of one shot learning in Fig[14]. Here 0 represents two different images and 1 represents the same images.

4) Comparison of works done on SOCOFing Dataset: Fig[15] can be helpful to illustrate the comparison of results of our works with the works of [18], [19], [20], [21], [22] and [4] on SOCOFing Dataset .

Title-Publication Year (Authors Last Name)	Accuracy				
	Person	Gender	Hand	Finger	Altered and/Or Fake Images
Detailed Identification of Fingerprints Using Convolutional Neural Networks-2018 (Shehu, Garcia , Palade & James)	N/A	75.2%	93.5%	76.72%	N/A
Fingerprint Identification using Modified Capsule Network-2021 (Sing, Bhisikar,Satakshi,Kumar)	N/A	99%	99%	99%	N/A
Fingerprint Classification Using Transfer Learning Technique-2021 (Aliweiwi)	N/A	N/A	N/A	N/A	1st Model: 99.4% 2nd Model: 97.5%
Integrated Different Fingerprint Identification and Classification Systems based Deep Learning-2022 (Oleiwi, Abood , Farhan)	N/A	99.96%	99.93%	99.9%	N/A

Single Architecture and Multiple task deep Neural Network for Altered Fingerprint Analysis-2020 (Giudice,Litrico,Battiato)	**N/A**	**92.52%**	**97.53%**	**92.18%**	**Fakeness : 98.21% Alteration : 98.46%**
Fingerprint Alterations Type Detection and Gender Recognition Using Convolutional Neural Networks and Transfer Learning-2021 (Kataria,Gupta,Kaushik,Chaudhury,Gupta)	**N/A**	**83.07%**	**N/A**	**N/A**	**Alteration : 98.50% Alteration Detection: 94.84%**
Comprehensive Fingerprint Recognition Utilizing One Shot Learning with Siamese Network (Our Model)	**99.8%**	**99.73%**	**97.09%**	**99.6%**	**98.61%**

Fig. 15. Classification report of One Shot Learning

VI. Conclusion and Future Directives

Utilization of fingerprints in terms of bio-metric validation, security and verification is ,as mentioned already, one of the most popular bio-metric systems. In our paper, we have depicted one shot learning that addresses several ongoing issues, if standard methodologies are followed. Through the implication of one shot learning using Inception V3, we demonstrated that our implication does not require additional retrain for each time the quantity of input images is changed. This is possible because One Shot Learning does not concern with the classification problem, rather our system proposes difference evaluation between the features of two input images, a reference image already stored and a new/altered/similar test image. Instead of inputting multiple images for a specific class , our implementation requires only one reference image stored into the database. It then compares another test image and lastly produces a similarity report.In our work, we have utilized a Triplet Loss function to train the Siamese Neural Network and allowed the network to tune the parameters to identify the correct images. Thus using Siamese Neural Network, our method is able to correctly identify the test fingerprint images. In our work, we have tested our designed system on a labeled dataset based on SOCOFing dataset. To measure the success of accurate classification based on the similarity report, we have generated an accuracy where our design showed above 90 percent accuracy. Besides the implementation of One Shot Learning we recognized Person's ID, Person's Gender, Person's Hand, Person's Finger and lastly Person's Altered fingerprint from a person's fingerprint with very high accuracy using EfficientNetV2s.To conclude, based on our work done , we can predict that using our one shot learning model will largely reduce the network complexity as our model requires only one sample fingerprint of a person. Moreover, our model is very cost-effective. Besides, our high classification accuracy can ensure a very accurate identification of an unknown person which is very crucial in forensic and medical environments. Especially in terms of criminal cases where getting lots of sample fingerprints is an issue, our system can very efficiently solve that problem with very limited resources. In the future, we want to implement our model on other biometric applications as well. We are looking forward to implement one shot learning to identify breathing of a person as breathing pattern is unique for each person. We also want to differentiate between healthy and unhealthy breathing based off that.

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