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FOOTPRINT RECOGNITION USING DEEP NEURAL NETWORKS

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Abstract

In this fast-paced technology-driven world, the blasting usage of the internet and the digital transformation have embarked great impacts across all possible domains viz. business, commerce, marketing, governance, defence, and what not? Digital operations entail easy, fast, and secure modes to reveal the user's identity. This led to the innovative emergence of Biometrics which refers to automated personal recognition based on intrinsic and unique features (biological and/or behavioural). Foot biometrics, like other prevailing biometrics, unleashes the distinguishing capability of human footprints to identify or authenticate a person. This article presents two tracks of the implementation of the latest technology of deep neural networks for personal recognition using human footprints. The first method uses a pre-trained VGG19 CNN model to drill down deep features followed by classification. This approach examines four classifiers namely, Gradient Booster, Random Forest, KNN, and ANN, to choose the best-suited classifier. The second approach employs transfer learning using RESNET-50 deep learning model to perform automatic feature extraction and classification both for footprint recognition. Experimental results reveal that the first method achieved an accuracy of 99.5% and 97.73% recognition accuracy was attained by implementing the second method, indicating the robustness of the proposed system for foot biometrics.

Keywords: Biometrics, Footprint Recognition, Convolutional neural network, Deep Feature Extraction, Classification, Deep learning, PCA, VGG19 and RESNET-50

1. INTRODUCTION

With the profound usage of the internet and the infusion of technology, the dominance of digitization and digitalization has brought a revolutionary transformation in various realms of human lives, society, trade, commerce, and governance, etc., which resulted in all operations being digitized. This scenario created a global nascent problem of identity theft, as digital operations require unveiling the user's identity automatically in an easy and secure way. This is where biometrics comes into play to serve the solution as compared to highly susceptible traditional identification systems, which are possession / knowledge-based systems. Each and every person carries unique God-gifted intrinsic characteristics (physiological/behavioural) which can't be forged or stolen, so are safe and secure to be used in Biometric systems. Among much prevalent biometrics like face, fingerprint, iris, ear, signature, ECG and gait, etc. foot biometrics has not gained a much wider reception. This very idea catalyzed us to move in this direction and contribute towards making it a global acceptance.

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This article presents a robust method of personal recognition using foot biometrics by implementing the latest deep learning techniques. It uses the pre-trained architectures of VGG19 and RESNET-50 with the principle of transfer learning. Using VGG19, deep foot features are extracted followed by classification and reveal the decision to be an authentic or spurious user while using RESNET-50, the second pre-trained deep model used, the identity of the genuine user is disclosed along with its ID. Both deep learning methods (VGG19 and RESNET-50) resulted in viable recognition accuracies of 99.5% and 97.73% respectively indicating towards computational competence and efficacy of the proposed footprint recognition system.

The remainder of the paper is structured as follows: Section 2 presents the related literature conducted on footprint recognition. Section 3 highlights brief insights of CNN preliminaries, namely, deep neural networks, transfer learning, VGG19 and RESNET-50. The proposed methodologies of current research work are explained in Section 4. The details of all experiments conducted, classification results, and their comparative analysis are discussed in Section 5.At last, and Section 6 concludes the paper with the indications of future directions.

2. RELATEDWORK

Among the numerous types of researches prevalent in foot biometrics, few of them are being analyzed. The history of foot biometry dates back to 1996 when **Robert Kennedy [1],** very first, recognized the powerfulness of human footprints and governed its uniqueness, strong enough to announce it as a new biometric trait for personal recognition in medical and forensic research domains. The database consisted of inked footprint impressions. By extracting 38 local geometrical features, their results showed recognition rates of 28.91% to1.35% FMR and 29.38% to 2.18% FNMR.

Nakajima et al. [2] presented a study on pressure distribution of human using positional and directional normalization of footprints based on Euclidean distance image matching. They claimed 85% recognition accuracy. **Uhl and Wild [3]** proposed shape and texture-based feature extraction methods for rotation-invariant footprint recognition systems with 97% recognition accuracy.

For protecting newborns and infants against child thefts **Kotzerke et al. [4]** and **Jia et al. [12, 13]** introduced newborn biometric systems using footprints with EERs of 22.22% and 97% recognition accuracy respectively. Many other traditional methods like SOM, HMM, PCA,LDA, SVD, NN, MHE, ART2, Fuzzy logic, correlation analysis, wavelet transformation,hidden spatiotemporal footstep information and ACO etc. were used for footprint-based personal recognition in **[5,6,7,8,9,10,11].**

Machine learning and deep learning, the advents of the latest technologies, have also been explored by very few foot researchers. **Omar et al. [14]** recommended a footstep-based identification system using CNN and SVM with EERs of 9.392% and 13.83% for validation and evaluation processes respectively. Implementation of deep analytics was conducted by **Nagvanshi and Dubey [15]** using 27 unique foot features of 220 people. They employed fuzzy rules, IBM Watson Analytics and BigML processes with 97%

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recognition accuracy. **Basheer et al. [16]**proposed a fuzzy logic-based algorithm using 3 classifiers - Fine KNN, Fine Gaussian SVM and FESD (Fuzzy Ensemble Subspace Discriminant) with the highest recognition accuracy of 98.89%(using FESD), FMR at 0.01% and FNMR at 0.093%. An induction of 5 deep transfer learning models (GoogleNet, AlexNet, Inception v3, Vgg16 and Vgg19) was done by **Abuqadumah et al. [17]** for footprint recognition. The results showed that the Inception v3 deep model achieved 98.52% as the highest accuracy. Following Figure 1 shows a brief diagrammatic representation of few researches done during the journey of foot biometry.

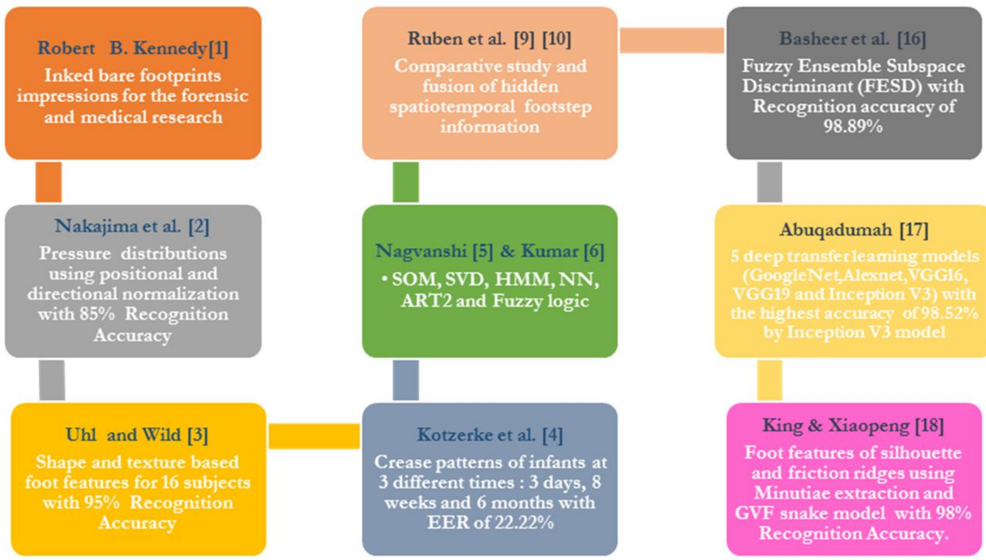

Figure 1: Pictorial representation of brief summary of related work on footprint Recognition

Basically, there are two approaches for implementing convolutional neural networks (CNNs). The first way is to develop a model from scratch and make it learn in accordance with the available dataset. The second technique employs transfer learning with pre-trained weights (ImageNet) to extract the features for classifiers. This paper proposes a deep transfer learning approach using two widely used pre-trained deep learning models, namely, VGG19 and RESNET-50 for feature extraction and classification.

3. CNNs PRELIMINARIES

Applications of deep learning techniques have brought revolutionary changes in the realms of image processing, computer vision and biometrics etc. More specifically, image classification, auto identification, medical image analysis and object recognition are the few example applications where deep CNNs are performing tremendously well with exceptionally better performances compared to other traditional approaches.

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3.1 Deep CNNs

Deep CNN is a feed-forward neural network implementing deep learning concepts, mainly utilized for visual data processing and image analysis in computer vision.CNN automatically performs two tasks: Image feature extraction and image classification. Deep neural networks employ deep architectures, where "Deep" refers to the functional complexity in terms of levels of layers and the count of computational units in a single layer. Basically, it comprises 3 types of layers namely, *input, hidden, and output layers* [19]. Further, the hidden layer is an amalgamation of three types of sub layers-

- *Convolution layer* consists of various filters that perform the convolution operation to generate a feature map.
- *ReLu (**Re**ctified **L**inear **U**nit) layer* implements a non-linear ReLu activation function on the convolved feature map pixel-wise to generate rectified feature map. It returns 0 for negative input values; otherwise, it acts as an identity function for positive inputs, i.e., f(x) = 0 if x < 0; else f(x) = x, where x is the input value. ReLUs accelerate training speed as they have a simple definition, rapid computation, and the absence of vanishing gradients.
- *Pooling layer* down-samples the convolved or rectified feature map to generate the feature map with reduced dimensions using max pool and average pool operations.
- *Fully Connected layer* multiplies the resulting value forwarded by pooled layers by adjustable weights and adds bias values to find input relationships and perform classification.

Following Figure 2 shows the basic architecture of CNN.

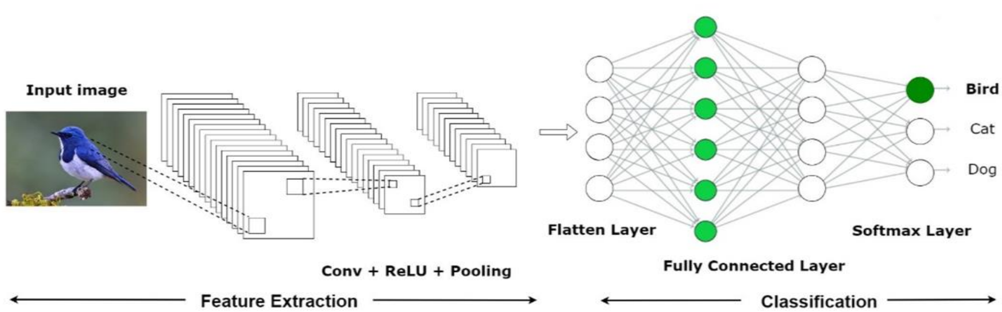

Figure 2: CNN Architecture Diagram

3.2 Transfer Learning

Usually, it is very difficult to train a deep learning model from scratch for image processing-related tasks due to higher computational requirements and overfitting problems. Also, deep learning models perform more accurately for applications having a huge amount of labeled image datasets. Transfer learning provides the solutions to solve the problems which have a small labeled dataset to start with. It refers to a machine learning technique to reuse a pre-trained model as a starting point for a target model to perform a similar new task, thereby, achieving significantly higher

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performance. In the proposed work, by utilizing the optimized transfer learning strategy two pre-trained models; VGG19 and RESNET-50; have been used for initializing the weights and feature extraction. Figure 3 illustrates the conceptualization of transfer learning.

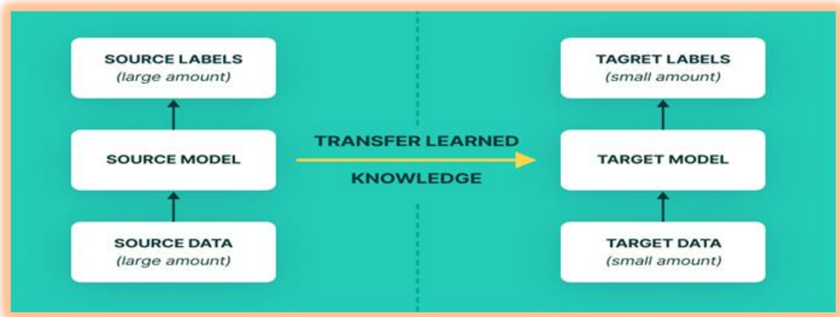

Figure 3: Transfer Learning

3.3 VGG19

Visual **G**eometry **G**roup created VGG19 as a pre-trained deep CNN model at Oxford University, widely used for image classification [28]. It is trained on the ImageNet database containing 14,197,122 images to classify the images into 1000 classes. The network accepts an input RBG image of size (224, 224, 3). It comprises of a stack of 19 layers (Figure 4):-

- ***16*** *Convolution layers* having filter size=3×3 and stride=1 pixel.
- *5 Pooling Layers* using MaxPool function with filter size=2×2 and stride=2 pixels
- ***3*** *Fully Connected layers* wherein the first two FCs have 4096 channels and the third FC has 1000 channels to predict 1000 classes**.**
- *1 SoftMax layer* to perform classification.

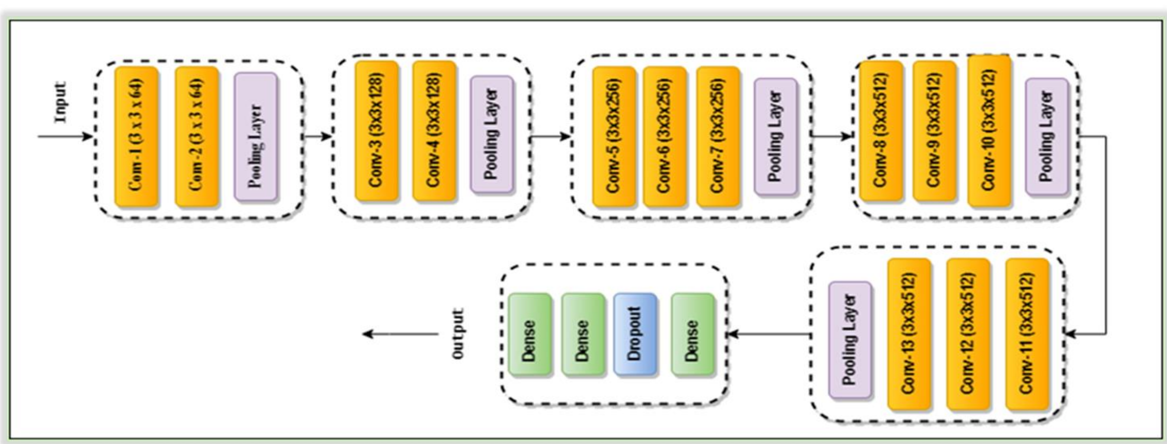

Figure 4: The architecture of VGG19 neural network model

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3.4 ResNet-50

ResNet or Residual Networks are archetypal deep CNNs used to power various computer vision applications. In 2016, K.He, X.Zhang, S.Ren, and J.Sun [23] introduced it for the first time. By and large, most deep CNNs have Vanishing Gradient Problem i.e., the gradient's value decreases a lot during back propagation, which makes bare changes in weights. To surmount this, ResNet uses "Skip/Shortcut Connections" which means linking the input of a layer directly to the output of a layer by omitting a few connections/layers and simply performing identity mappings [20]. ResNet-50 comprises 50 layers (including 48 convolutional layers, 1 MaxPool layer, and 1 Average Pool layer) formed by stacking residual blocks. The architecture of the RESNET-50 model is depicted in following Figure 5.

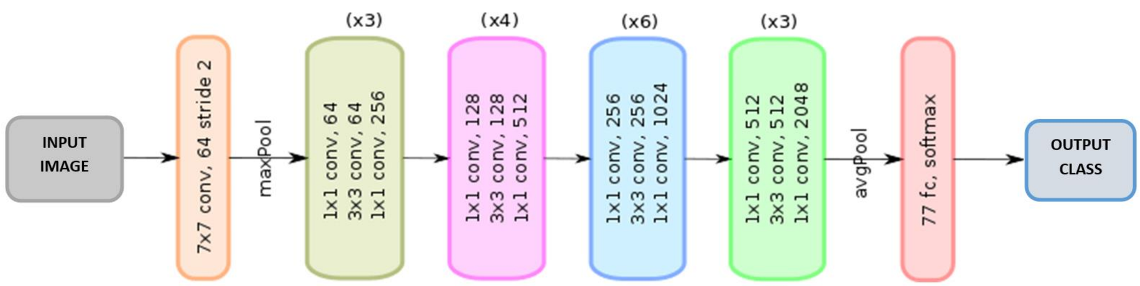

Figure 5: Architecture of ResNet-50 neural network

3.5 Performance Evaluation Metrics

For evaluating the accuracy and efficacy of a deep learning model, its performance is governed using different performance measures depending on the problem and methods used. In the proposed work, the performance analysis is done using various evaluation metrics like accuracy, recall, precision, specificity, and F1-score. These performance measures are computed using four primitive variables, namely, TP, FP, FN, and TN. They are defined as below:

- ***TP*** (True Positives) refers to the count when the system predicts correctly the actual true results.
- ***FP*** (False Positives) means the count of values when the system falsely predicts the true results.
- ***FN*** (False Negatives) measures the cases when the system falsely predicts the actual false values.
- ***TN*** (True Negatives) counts the cases when the system predicts correctly the actual false results.
- ***False Positive Rate (FPR or FAR)*** is the rate at which the system accepts unauthorized users.

$$FPR(or\ FAR) = \frac{(no.of\ False\ acceptances)}{(Total\ no.of\ false\ matching\ comparison\ attempts)} = \frac{FP}{FP+TN} \quad (1)$$

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•***False Negative Rate (FNR or FRR)*** is the rate at which the system rejects genuine users.

$$FNR(or\ FRR) = \frac{No.\ of\ false\ rejections}{Total\ no.of\ genuine\ matching\ comparison\ attempts} = \frac{FN}{FN+TP} \qquad (2)$$

•***Accuracy*** measures the degree of correctness of the Model.

$$Accuracy = \frac{TP+TN}{Total\ no.of\ attempts} \qquad (3)$$

•***Error Rate*** refers to the fraction of false predictions done.

$$Error\ rate = 1 - Accuracy = \frac{FP+FN}{Total\ no.of\ attempts} \qquad (4)$$

•***Precision*** measures the quality of positive predictions made by the model

$$Precision = \frac{TP}{Total\ predicted\ yes} = \frac{TP}{TP+FP} \qquad (5)$$

•***Recall (Sensitivity or TPR)*** quantifies the model's ability to detect positive results meaning a fraction of relevant instances among retrieved instances (positive or negative).

$$Recall(or\ sensitivity\ or\ TPR) = \frac{TP}{Total\ Actual\ yes} = \frac{TP}{TP+FN} \qquad (6)$$

• ***Specificity*** refers to the degree of identifying negative results correctly.

$$Specificity(or\ TNR) = \frac{TN}{Total\ Actual\ Negatives} = \frac{TN}{TN+FP} \qquad (7)$$

•***F1-score*** measures the harmonic mean of precision and recall.

$$F1 - score = \frac{2*(Precision*Recall)}{(Precision+Recall)} \qquad (8)$$

3.6 DATASET

Presently, there are only two publically available databases of human footprint images for biometric experimentation. The first database is uploaded by Nagwanshi and Dubey [21] in the IEEE Dataport open-access repository of scanned grayscale planter footprint images of the left feet of 220 volunteers. By varying the hue and saturation levels at different times, 6 diverse image samples are captured for each person, hence, adding up to a total of 1320 (= 6 × 220) images. The size of each image is 256 × 666. Another dataset has been uploaded by R. Kumar in the GitHub repository in 2019, now available on Kaggle. It is a database of 100 scanned footprint images of 21 persons and 100 dactyloscopic images (including left and right footprint) of 32 individuals with two to five images per subject [22]. The first database [21] of 1320 images is being used in this paper for experimentation. Following Figure 6 shows the sample footprint images of ten persons.

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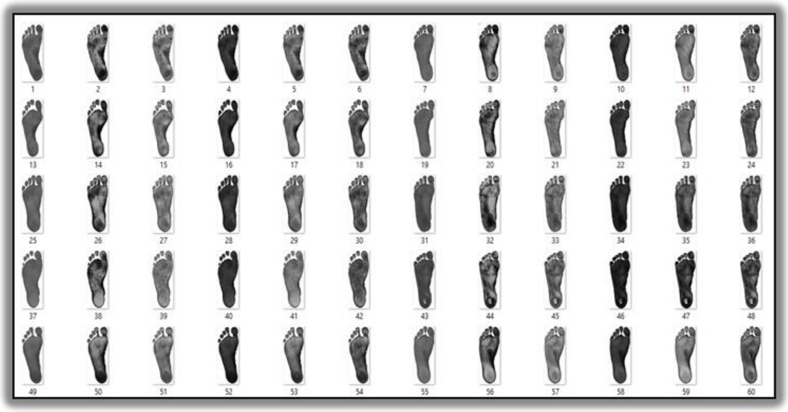

Figure 6: Sample footprint images of 10 subjects from Nagwanshi and Dubey [1] database

4. METHODOLOGY OF PROPOSED WORK

The major objective of our proposed work is to inspect the performance of the Footprint Recognition System using deep learning methods. For that purpose, the following two approaches are pursued:

- ***Method 1:*** Application of Pre-trained VGG19 deep CNN model for automatic foot feature extraction followed by classification using four machine learning classifiers: Gradient Booster, KNN, ANN, and Random Forest to seek out the best-suited classifier.
- ***Method 2:*** By using the transfer learning approach, implementation of ResNet-50 CNN model for performing automatic feature extraction and classification as well.

4.1 Method 1: Pre-Trained VGG19 deep CNN for feature extraction + ML classifiers

Method 1 of our proposed work uses VGG19 Model for automatic foot feature extraction and utilizes these foot features for the classification purpose using ML classifiers. This method uses four classifiers namely, KNN, ANN, Gradient Booster, and Random Forest to seek out the best-suited classifier for classifying the input footprint image as valid or invalid. Following figure 7 shows the schematic of method 1 followed to apply VGG 19 deep learning model for footprint recognition.

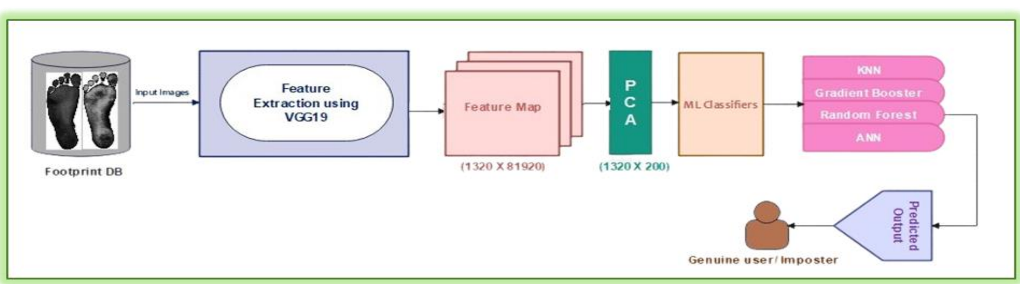

Figure 7: Method1: VGG 19 Model for feature extraction+ ML classifier

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The original dataset comprises of 1320 grayscale planter footprint images of the left feet of 220 volunteers. Since VGG19 works on RGB images, so, firstly, all grayscale images are converted to RGB images with each image size of 666×256×3. Also, the images are labelled as 1 or 0 to help them to classify them into genuine or imposter classes respectively. Using TensorFlow, the original data frame of features extracted by VGG19 was 1320 × 81920 showing 81920 foot features extracted from each image which can easily be visualized using feature importance score chart (Figure 8).

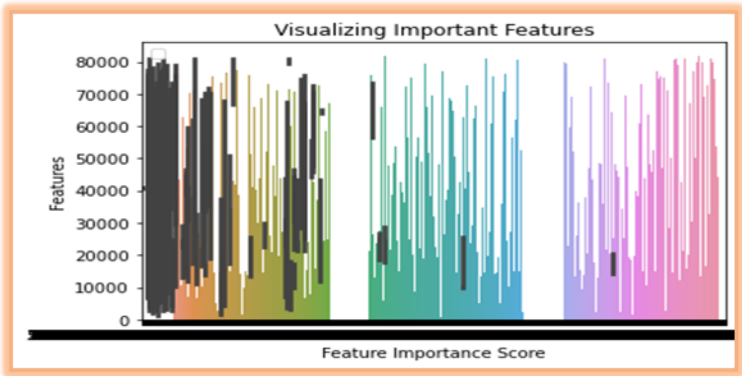

Figure 8: Feature Importance Score Chart

Since most of these extracted features have null space, so by applying PCA, extraction of essential features is performed to generate a 200-dimensional reduced feature vector which is evident from the variance chart of Figure 9. It shows the highest variability covered with 200 components. Hence, the reduced data size using PCA becomes 1320 × 200 from the original feature set of 1320 × 81920.

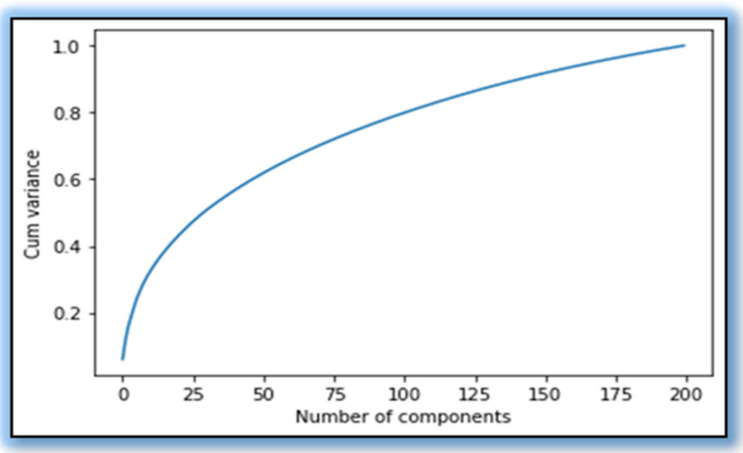

Figure 9: Variance chart with respect to number of Components

So, after feature extraction using VGG19 and feature selection using PCA, a classification task is performed. In this task, 4 classifiers – KNN, ANN, Gradient Booster, and Random Forest are utilized and tested on the basis of performance evaluation metrics to govern the best-tested classifier for footprint recognition.

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4.2 Method 2: ResNet-50 using transfer learning for feature extraction and classification

This method of our proposed work implements the concept of transfer learning on a pre-trained ResNet-50, deep CNN model. It performs both the operations of feature extraction as well as classification, that is, extracting deep foot features and classifying the user as genuine or imposter. If the user is legitimate then it also discloses its identity too else invalidates the illegitimate user. As discussed earlier Transfer learning is the repurposing of a pre-trained deep CNN model for another related work to have faster advancement rather than reinventing the wheel from scratch. It is helpful to achieve better performance in the cases where training dataset size is very small. Since our dataset is very small containing 1320 footprint images of 220 persons with 6 different instances per subject; data augmentation is performed prior to training using rotation transformations to generate 2640 images with 12 instances per subject(6 original left footprint images + 6 augmented right footprint images of each person).

Figure 10: Data Augmentation: *Upper row* - Original images; *Lower row*- Corresponding Augmented images

The ResNet model is a widely used pre-trained model on ImageNet-1k at a resolution of 224×224 having **48** Convolution layers, **1** MaxPool layer, and **1** Average Pool layer. It involves 3.8×10^9 Floating points operations. It is a Residual convolutional neural network that emulated the concepts of residual learning and skip connections to avoid the vanishing gradients problem. Given below is the visualization of method 2 to apply transfer learning using ResNet-50 depicted in Figure 11.

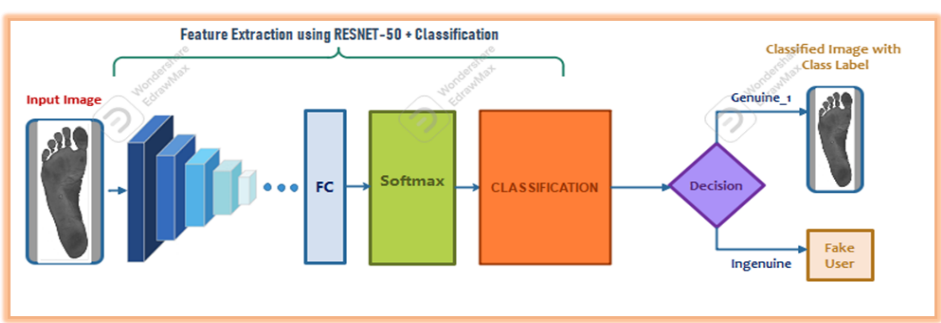

Figure 11: Method 2: Application of transfer learning using RESNET-50 for feature extraction and classification

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After performing the image augmentation process, the images are labeled using 220 labels for genuine as well as unauthenticated users as genuine_1, genuine_2, etc. for genuine users and unauthenticated_150, unauthenticated_218, etc. for imposters thereby generating 220 classes. This approach results in the output as a classified image with the corresponding class labels as identifiers for valid users else simply outputs as unauthenticated for fake users. With the use of transfer learning, only the footprint image of size 224×224 has to be provided to the ResNet-50 pre-trained model, all work means automatic feature extraction and classification is done by the ResNet-50 model. The last fully connected layer of ResNet-50 (fc1000) was changed to perform classification along with the Softmax layer to classify 220 classes. During implementation, the train-test split was 10% containing 2376 training images for 198 subjects and 264 testing images for 22 subjects.

5. EXPERIMENTAL RESULTS AND DISCUSSION

All the experiments are configured with CPU of Intel® Core™ i5-3110M @ 2.40 GHz with 16 GB RAM, NVIDIA® GeForce RTX™ 3060 graphics card and 64-bit operating system of Microsoft Windows 10 Pro. Our proposed work presents two approaches of using deep CNNs for footprint recognition; First method used pre-trained VGG19 CNN for extraction of deep foot features only and then classification using classifiers while second method used transfer learning on pre-trained ResNet-50 model for automatic extraction of deep foot features and classification both. Following is the analysis of experimental results and evaluation of efficacy of both proposed methods on the basis of performance metrics discussed under section 3.5.

5.1 Experiment1: Pre-Trained CNN VGG19 for feature extraction and 4 classifiers

During implementation following statistics was followed/ observed:-

- Total image dataset: 1320 footprint images
- Original feature map extracted: 1320 × 81920
- Reduced feature map using PCA: 1320 × 200
- Train Test Split: 15%
- Training Size: 1122 images
- Testing Size: 198 images
- Classes used: 2
- Class Labels : 1 - Genuine and 0 - Imposter

After the application of VGG19 automatic feature extraction takes place that generates a feature set of 81920 features containing essential and non-essential features. To dig out the most significant and relevant features PCA is applied that extracts 200 most essential foot features (examined through variance chart). This resultant reduced feature set is passed further to the classifier to perform classification. This experiment uses four classifiers-KNN, ANN, Gradient Booster and Random Forest, to look for the best performing classifier by analyzing the test results of performance metrics. The

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experiment was conducted four times to calculate and record the evaluation matrices for each classifier. Figure 12 shows the confusion matrices of all four classifiers. The comparison chart of performance matrices of all classifiers is listed below in the preceding Table 1.

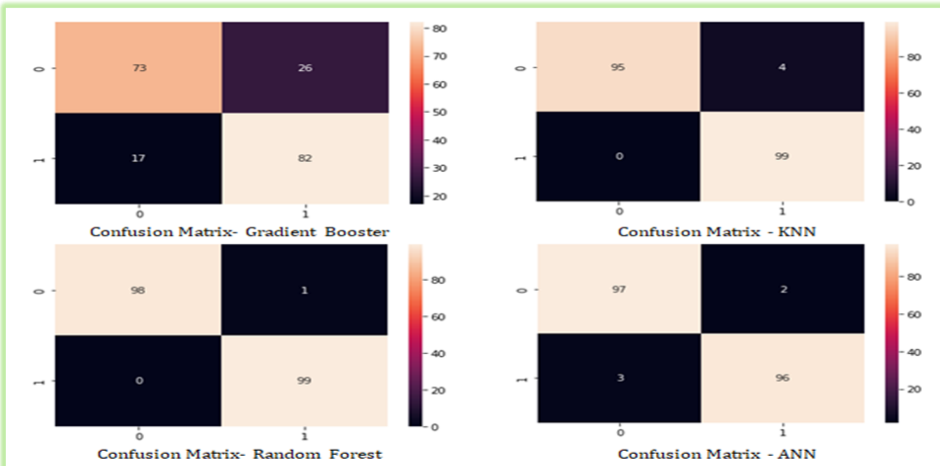

Figure 12: Confusion Matrices of different classifiers used

Table 1: Comparison chart of performance metrics of various classifiers used in the proposed work

Classifiers	*Accuracy*	*Precision*	*Recall*	*F1-scores*	*MAE*	*MSE*	*RMSE*	*ROC_AUC*
Gradient Booster	0.783	0.759	0.828	0.792	0.434343	0.868687	0.932034	0.728528
KNN	0.980	0.961	1.000	0.980	0.040404	0.080808	0.284268	0.987340
Random Forest	**0.995**	**0.990**	**1.000**	**0.995**	**0.010101**	**0.020202**	**0.142134**	**0.994682**
ANN	0.975	0.980	0.970	0.975	0.050505	0.101010	0.317821	0.974747

Experimental results of Table 1 show that **Random Forest classifier** is outperforming the other implemented classifiers with the **Recognition Accuracy = 99.5%**, Precision = 0.99, F1_score=0. 995 and Recall=1.00.Also, Figure 13illustratesthebar charts of Performance metrics of above mentioned classifiers i.e.KNN, ANN, Gradient Booster and Random Forest for comparing their performances towards footprint recognition.

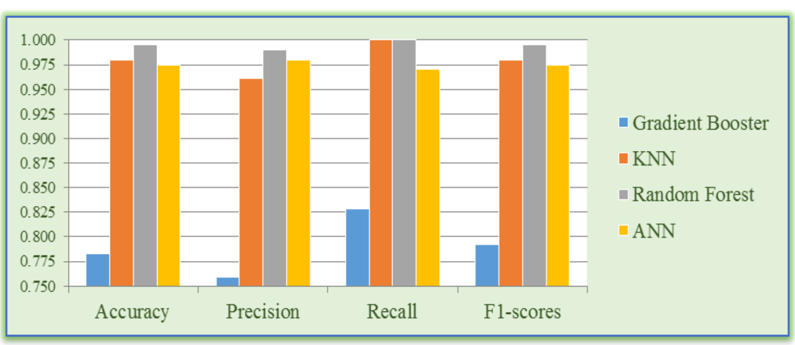

Figure 13: Performance Metrics of KNN, ANN, Gradient Booster and Random Forest classifiers

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It is evident from the above results that VGG19 in combination with Random Forest classifier is performing well and providing a robust solution for footprint biometrics.

5.2 Experiment 2: Transfer learning with ResNet-50 for feature extraction and classification

During implementation of second approach of applying transfer learning using ResNet-50 following statistics was followed/ observed:-

- Image augmentation: Generation of 2640 images with 12 instances per subject.
- Total subjects: 220
- Image Labelling: 220 labels: genuine_1, 2 –Genuine users and unauthenticated_150, 218 - Imposter
- Classes: 220
- Train Test split: 10%
- Training set: 198 subjects(2376 images)
- Testing set: 22 subjects (264 images)
- Total epochs: 10
- Iterations per epoch: 151
- Maximum iterations: 1510
- Learning Rate: 0.0001
- It outputs the results along with the person Id for genuine users else unauthenticated.

When a random test footprint image is inputted to the trained ResNet-50 deep CNN model, then using transfer learning it performs feature extraction and classification on its own and produces the result accordingly. For legitimate users it outputs the Id of the genuine users otherwise simply results as unauthenticated. Following Figure 14 shows the screenshots of outputs for both types of users.

a) Genuine User	**(b)Unauthenticated User**

Figure 14: Predicted Output Results

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The Confusion Matrix and corresponding ROC curves can be seen in the following Figure15 and Figure 16 respectively.

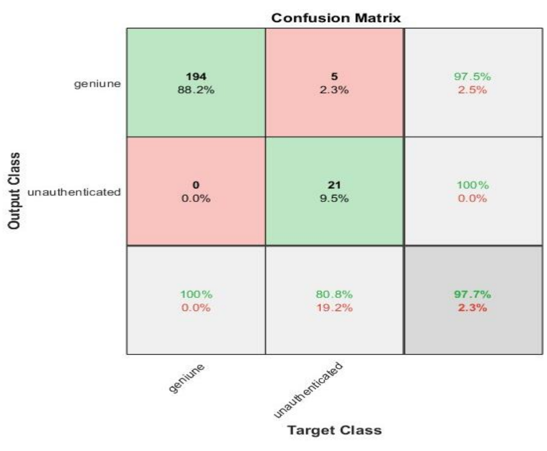

Figure 15: Confusion Matrix of ResNet-50

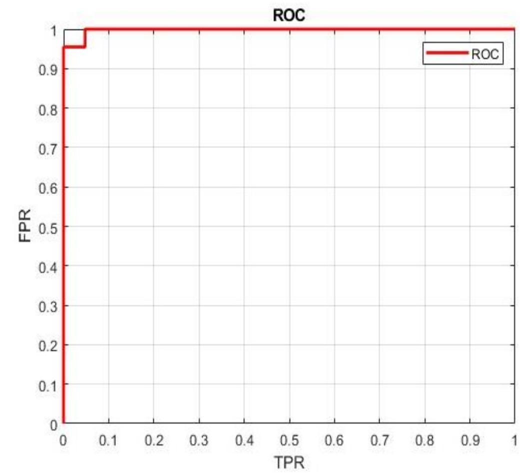

Figure 16: ROC Curve

The following Figure 17 shows the Training and Validation loss curves. The fitness of model on training data is indicated by training loss, while the validation loss refers to the fitness of model on new data. The horizontal axis marks the number of epochs for running the model while accuracy and loss of the model are represented by the vertical axis. From the figure it can be easily seen that at the end of epoch 10 and at iteration 1510 ResNet-50 attained the highest recognition accuracy of 97.73%.

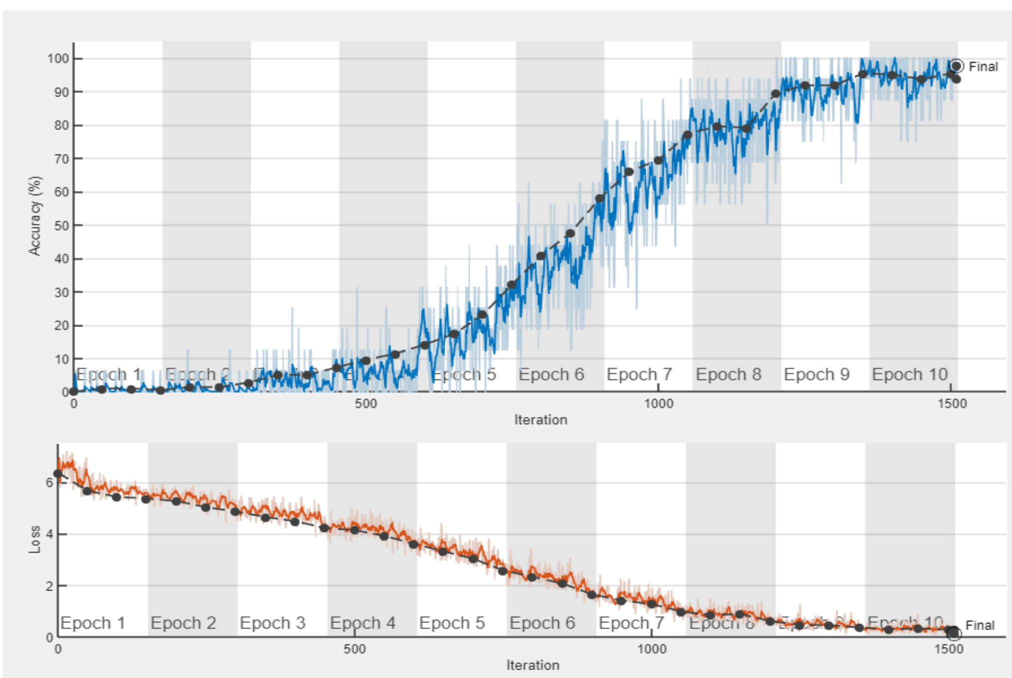

Figure 17: Training/Validation progress curves of ResNet-50

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Upon analyzing the results, it was found that the transfer learning using ResNet-50 deep CNN model scored striking Performance with the highest accuracy = **97.73%,** precision=99.8%, recall=97.49%, F1-Score=98.73% (Table 2).The resulting values of performance measures are clear indicators of high Performance of proposed work of employing transfer learning using ResNet-50 Model for footprint recognition.

Table 2: Performance Metrics of ResNet-50 Model

Performance Metric	Value
FAR (FPR)	0.0012
FRR (FNR)	0.0251
Accuracy	**0.9773**
Error Rate	0.0227
Precision	0.998
Recall (TPR)	0.9749
F1_Score	0.9873

Finally, Table 3 shows a comparison of evaluation results of both the deep learning methods of proposed work.

Table 3: Performance Comparison of VGG19 with Random Forest and Transfer learning on ResNet-50

Model	Accuracy	Precision	Recall / GAR	F1-scores	FAR
VGG19+Random Forest	**99.50%**	**99%**	**100%**	**99.50%**	**1.01%**
Transfer learning (ResNet-50)	97.73%	99.80%	97.49%	98.73%	0.12%

Through the outcomes of Table 3, it can be clearly seen that both the approaches are performing well towards the footprint recognition. To compare their performances, it is evident that the first scheme of using **VGG19 with Random Forest classifier** of proposed work is more performant with an accuracy of **99.5%** than the second method of implementing transfer learning on ResNet-50 with 97.73% recognition accuracy.

5.3 Experiment 3: Comparison with the other existing Models

An extensive literature study, on foot biometrics using deep learning, divulged that very limited work (hardly two or three) was found to apply deep CNNs for personal recognition using footprints. Probably, the reason is the availability of small footprint dataset while deep CNNs require huge dataset containing thousands to millions of images to achieve an optimal accuracy and provide a robust solution. Liu [24] presented an implementation of deep CNN with minutiae descriptor for newborn footprint recognition with FAR of 0.01 and GAR of up to 0.83. Abuqadumah et al. [25] explored the suitability and efficiency of 5 deep CNN models: AlexNet, GoogleNet, Inception v3, Vgg16 and Vgg19, for footprint recognition and conducted a comparative study to observe their accuracies. Their results showed that the Inception v3 model achieved the highest accuracy of 98.52%. Chen et al. [26] proposed transfer learning based ensemble deep neural network by incorporating VGG19, ResNet50 and DenseNet121 for footprint recognition. They evaluated the performance metrics of Fusion features with cosine distance metric as 83.63% Recall, 82.99% Precision and 83.31% F1-score. They used their own dataset of planter footprint images of the shoes instead of bare

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foots. Table 4 specifies the performance comparison of the proposed work with the state-of-the-art models.

Table 4: Comparison chart of performance of proposed work with state-of-the-art models

References	Model	Accuracy	Precision	Recall/ GAR	F1-scores	FAR
Chen et al. [26]	Fusion features(VGG19, ResNet50 & DenseNet121) + cosine distance metric	-	82.99%	83.63%	83.31%	-
Liu[24]	Minutiae descriptor based deep CNN	-	-	83%	-	1%
Abuqadumah et al. [25]	Inception v3	98.52%	-	-	-	-
Proposed Work	**VGG19+Random Forest**	**99.50%**	**99%**	**100%**	**99.50%**	**1.01%**
	Transfer learning (ResNet-50)	**97.73%**	**99.80%**	**97.49%**	**98.73%**	**0.12%**

The evaluation metrics results of Table 4 clearly indicate towards the improved performance of proposed work over the state-of-arts models for footprint recognition using deep learning approach.

6. CONCLUSION AND FUTURE SCOPE

This research study explores the application of pre-trained deep convolution neural network (CNN) models for foot biometric system. For the purpose, it has used two approaches. One using pre-trained VGG19 CNN model and another is the usage of transfer learning through ResNet-50 deep CNN model. In the first approach, VGG19 Model is used for extracting deep foot features and investigated the best suitability among four classifiers- KNN, ANN, Gradient Booster and Random Forest for classification task. Second method applies transfer learning with ResNet-50 pre-trained model for automatic feature extraction and classification both. The results of various experiments reveal that VGG19 Model along with Random Forest classifier achieved the highest accuracy of 99.5% among other classifiers used. While, ResNet-50 using transfer learning accomplished an accuracy of 97.73%.Though, both the methods of proposed work are performing well for footprint recognition, the first approach (VGG19+ Random Forest) is more performant with 99% precision, 100% recall and 99.5% F1-score. The results also showed that proposed work is performing in a more superior way than the existing models towards footprint biometry.

In near future, a more improved and efficient solution, demands the increased size of footprint database. Secondly, ensemble learning approach can be investigated for footprint recognition as it integrates the predictions from several models, thereby, trimming down the bias and variance, improving generalization, and achieving a better overall performance. Additionally Hybrid systems can be explored as another alternative for footprint recognition that combine the potent features of many approaches like machine learning, deep learning, image processing, computer vision and expert systems etc. for more accurate and robust solution in foot biometry. The new future dimensions of current research may be extended to unveil other personality traits like gender, individuality traits of any region, height, weight, age and health status of a person etc. Also, the present research work is done using plantar footprint images, its future direction can be extended by considering dorsal footprints to explore other innovative features and methodologies in foot biometry and contribute to make is global acceptance like other biometrics.

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