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MACHINE LEARNING BASED FOOTPRINT RECOGNITION

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Abstract

With the escalating digitization of the modern era and the infusion of technology into almost every aspect of human lives, biometric authentication systems have become the need of the hour to control the identity thefts. They are the automated systems that divulge individuals identify based on their unique biological or behavioral personality traits like fingerprints, face, iris etc. This article presents personal recognition using Foot biometrics by following machine learning approach. The implementation of three supervised machine learning methods namely, Regression, Classification and ANN (artificial neural network) has been done. The proposed method works in two stages: Geometric Feature Extraction and implementation of Machine Learning algorithms. Firstly, handcrafted foot features are extracted using geometrical methods which are instilled as input to three supervised machine learning algorithms to predict the identity of user. Experimental results reveal that the weighted KNN model is the most performant method among all the implemented classifiers with 99.5% validation accuracy and the overall training time of 0.29886 seconds. While other two utilized and tested supervised machine learning methods, also achieved a reasonable accuracy of 99.15% by Squared Exponential GPR model (Regression) and 97.47% by ANN (Feed Forward Neural Network with Back Propagation).

Keywords: Biometrics, Footprint Recognition, Feature Extraction, Geometrical Features, Machine learning, ANN, Regression, Classification

INTRODUCTION

In this technology driven era, the profusion of network security breaches and identity thefts, make a tremendous stipulation for sturdy and robust biometric authentication systems that truly rely on something that “you are” with unique God gifted physiological or behavioral characteristics as opposed to something “you know”(passwords, IDs etc.) or something “you have”(Identity cards, keys etc.). To have an easy and secure access to the digital world, many biometric systems like face, finger, iris, gait and ear, are prevalent. Unlike other biometrics, Foot Biometry has achieved limited global acceptance. This very idea is the catalyzation and motivation behind present research work to explore new potentials in foot biometrics comparable to state-of-the-art biometric techniques. Footprint identification can be applied in many areas like protection against child thefts, forensics, defense systems and legal capacitance etc. This paper proposes a novel archetype scheme for footprint recognition by amalgamating feature extraction and machine learning algorithms. The working proposal can be broadly divided into two parts; drilling down Geometrical foot Features followed by the application of supervised machine learning techniques. At first, 20 hand crafted geometric foot features are extracted from each sample footprint image which are fed into the machine learning algorithms as an

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input foot feature vectors in the second part of proposed technique. In this paper, three supervised machine learning methods namely regression, classification and ANNs have been applied for predicting the recognition outcomes. To measure the effectiveness of proposed algorithms, the biometric performance is tested by calculating False Accept Rate (FAR), False Reject Rate (FRR), Accuracy, Precision, Sensitivity, Specificity, F1-Score and training time. The experimental results of recommended approach demonstrate that the weighted KNN model (Classification) has achieved the highest recognition accuracy of 99.5% (with 0.29886 seconds as an average training time) compared to other two tested machine learning methods viz. Regression (99.15%) and ANN (97.47%).

The rest of the paper is structured as follows: Section 2 briefly presents the related work on footprint recognition. Section 3 presents the dataset used for experimentation. Section 4 introduces the proposed methodology of current work. Section 5 presents and analyzes the experimental results. At the end, Section 6 concludes the paper with the hints to future work.

2. RELATED WORK

This section provides a comprehensive literature available in the foot biometry

Robert B. Kennedy [1] can be awarded as the father of foot biometrics for exploring human footprints for the first time as biometric feature and used them for medical and forensic research by using inked bare footprints impressions. 38 local geometric features were extracted by proposing 6 different methods and achieving the minimum error recognition rates of 1.35% FMR and 2.18% FNMR. **Nakajima et al. [2]** performed a conscientious study of pressure distribution of footprints using positional and directional normalization and achieved recognition rate of 85% using Euclidean distance image matching. A rotation invariant footprint based authentication system was introduced by **Uhl and Wild [3]** who used geometry, shape and texture based foot features and achieved with 97% recognition accuracy for 16 subjects.

To protect against the child pilfering, **Jia et al. [4]** proposed an automated footprint based newborn personal recognition system by extracting 4 orientation based features (Ordinal Code, Binary Orientation Co-occurrence Vector, Competitive Code and Robust Line Orientation Code) and achieved 98% recognition accuracy. Also, **Jia et al. [5]** presented another scheme based on band-limited phase-only correlation (BLPOC) for extracting foot features using 101 footprint images of infants and claimed 97% recognition accuracy. Infant’s footprints were further explored by **Kotzerke et al. [6]** who developed a novel algorithm for feature extraction from crease patterns of infants at three diverse timestamps i.e. three days since birth, eight weeks and six months. With the implementation of morphological processing, directional filtering and block-wise crease line reconstruction, they observed an EER of 22.22%.

Nagvanshi [7] and Kumar [8] incorporated various prevalent techniques like PCA, SOM, SVD, HMM, NN, ART2 and Fuzzy logic etc. for footprint recognition. An extensive study

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on Correlation analysis of the scanned footprint images of 94 people (37 F and 37 M) of Northern Indian regions aged between 15-25 years, was carried out by **Khokher and Singh [9].** They observed a strong correlation between actual height and foot length, actual height and weight and actual height and toe lengths, and claimed a recognition accuracy of 93.1% for males and 94% for females. A variety of Neural Networks have also been utilized for footprint recognition like ANN by **Hashem and Ghali [10],** CNN by **Keatsamarn and Pintavirooj [11]** and fuzzy neural network and wavelets by **Wang et al.[12]** and **Kumar and Ramakrishnan [13]** with 92.5%, 92.69% and 92.80% and 96.32% recognition rates respectively. A novel method of Fuzzy Ensemble Subspace Discriminant (FESD) was proposed by **Basheer et al. [14]** for personal identification with the recognition accuracy of 98.89% and error rates of FMR at 0.01% and FNMR at 0.093%. **Ruben et al. [15]** presented a novel fusion scheme for personal recognition using spatiotemporal footstep information with respect to space, time and an amalgamation of both. They **[16]**, also, presented a prototype scheme of footsteps and gait for the same with an EER of 4.83% at score level. **King and Xiaopeng [17]** proposed an innovative approach for identification using static foot features of silhouette and friction ridges by implementing Minutiae extraction and GVF snake model with the verification accuracy of 98-99%. An analysis of footstep pressure signals was done by **Michael and Xianghua [18]** by integrating CWT (continuous wavelet transform) and RFC (Random forest classifier) with 16.7% ± 1.2% Predictive Error Rates.

Moorthy et al. [19] explored footprints of Indian Tamils to reveal their stature details. Later, a study on Malaysian Malays footprints using crease marks, corns and cracks, phalange marks and humps in the toe line, etc., was carried out **[20]** for personal recognition. **Ambeth et al. [21, 22]** followed an amalgamation technique to combine statistical computations of foot factors and Neural Networks with the recognition accuracy of 97.43%. **Khokher et al. [23]** proposed a novel texture and shape-oriented features based footprint biometric system using PCA and ICA with an accuracy of 97.23%.

An incisive classification method was proposed by **Costea et al. [24]** for elder persons by exploiting plantar foot features from middle area of footprints of 67 females aged 52-84 years. 5 types of foot categories were defined to help in designing age based customized prophylactic components, shoe lasts and foot wears. **Omar et al. [25]** presented a footstep identification system using CNN and SVM with an acquired EER of 9.392% for validation and evaluation processes. **Nagvanshi and Dubey [26]** conducted fuzzy logic based deep analytics (using IBM Watson Analytics and BigML tools) by utilizing 27 unique foot features of 220 people and claimed the recognition accuracy of 97%. In **[27] Nagvanshi** also investigated footprint and gait behaviour using statistical and morphological methods for personal recognition. **Abuqadumah et al. [28]** explored 5 deep transfer learning models (Googlenet, Inception v3, Alexnet, Vgg16 and Vgg19) for footprint recognition and observed the highest accuracy of 98.52% by Inception v3model. **Ibrahim et al. [29]** achieved 100% recognition accuracy by incorporating Image Processing feature extraction techniques (Binarization and Morphology) and AI based feature selection heuristics (ACO-Ant Colony Optimization) for Footprint Recognition. Later, **Kushwaha et al. [30]** investigated texture based feature extraction techniques (viz.

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HOG, GLCM and LBP) in conjunction with the classification methods (namely, LDA, SVM, KNN and ESD) using footprints and observed an accuracy of 97.9% for LBP + LDA as the most performant scheme for personal verification.The empirical studies on footprint biometrics done by **Khokher and Singh [31]** explored many footprint recognition techniques along with their impediments and future dimensions. They indicated footprints as a revealer of individuality information like age, height, gender, weight, health status and region specific personality traits etc. A multi-model rank-level fusion system was proposed by **Kumar and Shekhar [32]** by utilizing features from two modalities - palm and foot with the suggested accuracy of 92-99% using fusion. **Pataky [33]** presented correlation based approach by using 1040 dynamic plantar foot pressure images from 104 volunteers(40 males and 64 females)and obtained the classification rate of 99.6%. **Gupta and Raj [34-36]** proposed a novel method for footprint recognition using eigenfeet and a new distance metric for touch-less footprints with recognition accuracy of 97%.They further, presented a comparative analysis of texture based methods using LBP, LPQ, SIFT and SURF methods using footprints and claimed a 98% recognition accuracy. They also introduced an innovative approach for footprint biometrics using chronological implementation of LBP and SIFT with the recognition accuracy of 98.93%.

3. DATASET

Figure 1. Sample footprint images of 10 subjects from Nagwanshi and Dubey [37] database

Presently, there are only two publically available databases of human footprint images for biometric experimentation. The first database is uploaded by **Nagwanshi and Dubey [37]** in the IEEE Dataport open access repository of scanned grayscale planter footprint images of 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, add up to a total of 1320 (=6X220) images. The size of each image is 256 X 666.Another dataset has been uploaded by **R. Kumar [38]** in 2019 at GitHub repository, now available at kaggle. It is a database of 100 scanned plantar footprint images of 21 persons and 100 dactyloscopic images (including left and right footprints) of 32 individuals with two to five images per

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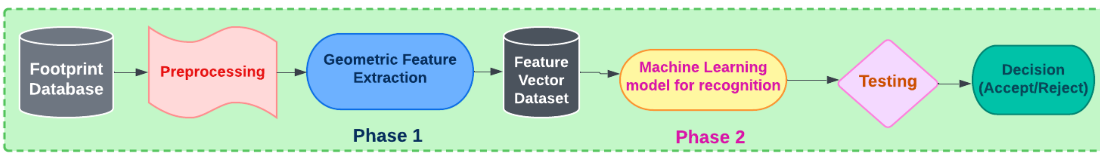
subject [37].The first database **[37]** of 1320 images is being used in this paper for experimentation. Following Figure 1 shows the sample footprint images of ten persons.

4. PROPOSED METHODOLOGY

In this section, the detailed description of proposed prototype scheme of foot biometrics is exhibited. Following Figure 2 shows the basic schematic diagram of proposed framework. Working methodology has been broadly divided into two phases:

1. Generation of Handcrafted Geometric foot features using feature extraction
2. Generation of Machine Learning model for foot recognition

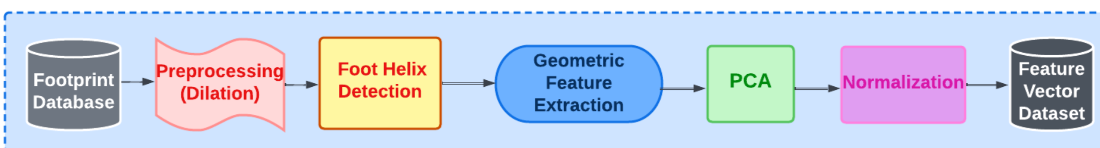
Figure 2. Proposed Framework



I. Phase 1

Phase 1 of the working methodology starts with the pre-processing steps followed by outer foot helix detection of registered plantar footprint images. Afterwards, geometric feature extraction followed by dimensionality reduction and normalization of feature vectors during enrollment and authentication process. The resulting dataset of extracted geometric feature vectors become the input vectors for the implementation of machine learning model in phase 2. Diagrammatically, various steps of phase 1 are shown below:

Figure 3. Phase 1 of proposed method



The detailed description of each step followed in phase 1 of the proposed scheme is explained as below. **Table 1** illustrates the listing of main abbreviations used in the following steps.

a) Pre-processing and the foot helix detection

The presence of noise in the scanned footprint images can hinder the results of obtaining outer helix of the footprint images. Hence, morphological operation-dilation is performed by using disc as structuring element resulting in the enlarged foot boundaries and small holes in objects are filled. After the application of dilation, outer helix of foot is detected using canny edge operator. **Figure 4** shows the typical edge detection results to extract the foot contours with/without dilation. It can easily be observed that by applying dilation

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followed by edge detection, improved results are obtained as cluttering edges and noise are suppressed and salient contours are enhanced.

Figure 4. Preprocessing and outer foot helix detection

a) Original Image   b)Canny_without_Dilation   c)Canny_with_Dilation

Table 1. Summary of main abbreviations used

Abbreviation	Full Name
FHL	Foot Height Line (as Feature vector FV1)
FWL	Foot Width Line (as Feature vector FV2)
U_t	Uppermost Toe end point on FHL
L_h	Lowermost Heel end point on FHL
L_w	Leftmost end point on FWL
R_w	Rightmost end point on FWL
$w_1,w_2,\ldots,w_5$	Five Equidistant Points on FWL
$ul_1,ul_2,\ldots,ul_7$	Seven Lengths from U_t to $L_w,w_1,\ldots..w_5,R_w$ (as Feature vectors FV3-FV9)
$ll_1,ll_2,\ldots,ll_7$	Seven Lengths from L_h to $L_w,w_1,\ldots..w_5,R_w$ (as Feature vectors FV10-FV16)
UPPER_Area	Area of triangle formed by points U_t, L_w and R_w (as Feature vector FV17)
LOWER_Area	Area of triangle formed by points L_h, L_w and R_w (as Feature vector FV18)
LEFT_Area	Area of triangle formed by points L_w, U_t and L_h (as Feature vector FV19)
RIGHT_Area	Area of triangle formed by points R_w, U_t and L_h (as Feature vector FV20)

b) Geometric Feature Extraction

After the smooth outer contour detection of foot by Canny edge detector, the next step is to extract the unique geometric features for unwavering description of outer helix of foot which, in turn, are helpful for the personal recognition. For the purpose, the first task is to find the boundary and boundary points lying on the contour of foot. Next step involves identification of 20 foot shape based geometric features that include maximum foot height, maximum foot width, 14 sub-lengths and 4 areas of triangles derived using maximum Foot height and maximum Foot width points. Following **Figure 5** portraits the visual view of all 20 features of a footprint image. Likewise, every footprint image in the database goes through the same process to extract their 20 geometric features to construct a feature set of 26,400 (=1320X20) features from1320 images.These features are strong

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enough to characterize the contour of outer helix of foot for personal identification and hence, achieve a better recognition performance.

Figure 5. All Feature vectors of a footprint image

The Feature extraction method involves three sub steps:

1. Finding the maximum Foot Height Line (FHL) and maximum Foot Width Line (FWL)
2. Calculation of sub-lengths ll_i and Ul_i where (i=1, 2,....,7) using uppermost toe point, lowest heel point, leftmost and rightmost point on maximum FWL.
3. Computation of four areas of triangles: Upper, Lower, Left and Right

i. Finding the maximum FHL and maximum FWL

The maximum Foot Height Line (FHL) refers to the longest length between any pair of foot boundary points. It is found by determining the two endpoints U_t and L_h, where U_t is the uppermost toe point and L_h is the lowermost heel point existing on the boundary of the foot helix.. Similarly, maximum Foot Width Line (FWL) denotes the largest width between any pair of points lying on the foot boundary. It is calculated by finding its endpoints L_w and R_w the leftmost end point and the rightmost end point respectively. So, maximum FHL and maximum FWL are considered as the first two geometric feature vectors, FV_1 and FV_2 respectively, of the proposed scheme. **Figure 6a** clearly shows these two feature vectors FHL and FWL and their respective endpoints,U_t and L_h ; Lw and Rw. **Algorithm 1** illustrates the detailed procedure of finding the maximum FHL and maximum FWL.

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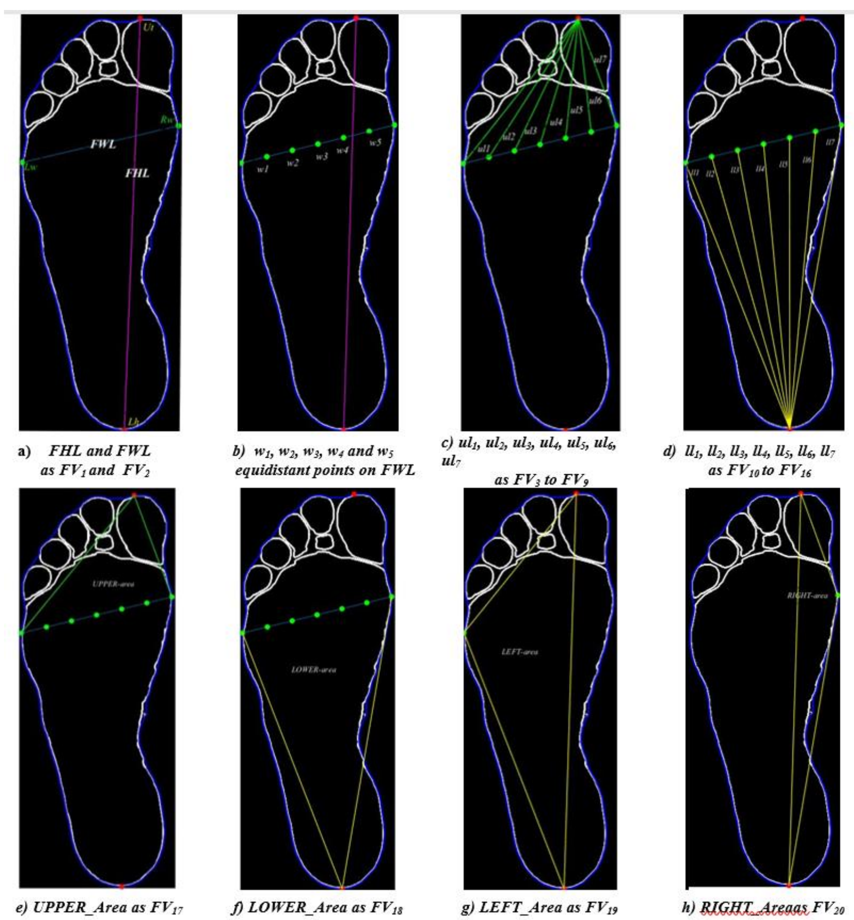
Algorithm 1
Input: Binary edge (boundary) of footprint image. **Output:** U_t and L_h , L_w and R_w, FHL_{max} and FWL_{max} as feature vectors FV_1 and FV_2 1. Search among the boundary points having minimum y value to get the uppermost toe point U_t. 2. Similarly, find L_h, the lowermost heel point, as the boundary point having maximum y value. 3. Also, find the boundary points L_w and $R_w$with the minimum and maximum x values respectively as the leftmost and rightmost endpoints of FWL. 4. Calculate FHL_{max} by finding the length of the line joining endpoints U_t and L_h. 5. In the same way, find FWL_{max} by computing the length of the line joining L_w and R

Figure 6. Individual feature vectors of a Footprint



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ii. Calculation of sub-lengths ll_i and Ul_i

After calculating the first two feature vectors, 14 more feature vectors are found using FWL, U_t and L_h. For the purpose, five equidistant points on FWL, as w_1, w_2, w_3, $w_4$and w_5, are determined. **Figure 6b** clearly shows these points. Afterwards, seven lines are constructed using one common end point U_t and L_w, w_1, w_2, w_3, w_4, w_5 and R_w as the other end points respectively. The lengths of these seven lines (referred as ul_1, ul_2, ul_3, ul_4, ul_5, ul_6, ul_7) are considered as feature vectors FV_3 to FV_9. Similarly, seven other feature vectors (FV_{10} to FV_{16}) are calculated by finding the lengths of the lines joining L_h as one common end point and the same above mentioned seven end points along FWL (namely ll_1, ll_2, ll_3, ll_4, ll_5, ll_6, ll_7). **Figure6c, d** display the feature vectors FV_3 to FV_9 and FV_{10} to FV_{16} of a sample footprint respectively. **Algorithm2** explains the pseudo code of finding sub-lengths ll_i and Ul_i.

Algorithm2
Input: U_t and L_h ; L_w and R_w **Output:** Fourteen feature vectors FV_3, FV_4 ,…………, FV_{16} 1. Find five equidistant points (w_1, w_2, w_3, $w_4$and w_5) on FWL. 2. Construct seven lines by joining U_t as one common end point and L_w, w_1, w_2, w_3, w_4, w_5 and R_w as the other end points respectively. 3. Calculate the lengths of above mentioned seven lines(ul_1, ul_2, ul_3, ul_4, ul_5, ul_6, ul_7) and refer them as next seven feature vectors i.e. $FV_3$to FV_9 4. In the same way, construct another seven lines by joining lowest heel point L_h as one common end point and L_w, w_1, w_2, w_3, w_4, w_5 and R_w as other end points respectively. 5. Compute their lengths as ll_1, ll_2, ll_3, ll_4, ll_5, ll_6, ll_7 and denote them as feature vectors $FV_{10}$to FV_{16}

iii. Computation of four areas of triangles

Furthermore, the remaining four feature vectors are extracted that comprise of the areas of triangles formed using U_t and L_h, L_w and R_w. in different combinations. We have considered four triangles namely: UPPER_TRI, LOWER_TRI, LEFT_TRI and RIGHT_TRI. UPPER_TRI is formed using uppermost toe point U_t and FWL as base(or L_w and R_w.as other vertices) **Figure 6e**. Similarly, LOWER_TRI is framed using lowest heel point L_h and FWL as base **Figure 6f**. L_w ,U_t and L_h form the LEFT_TRI **Figure 6g**.In the same way, RIGHT_TRI is formed from the points R_w, U_t and L_h **Figure 6h.** The areas of these four triangles, namely UPPER_ Area, LOWER_ Area, LEFT_ Area and RIGHT_ Area, are included as last four feature vectors FV17, FV18, FV19 and FV20. **Algorithm3** gives a quick glance of the procedure followed.

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Algorithm 3
Input: U_t and L_h ; L_w and R_w **Output:** UPPER_ Area, LOWER_ Area, LEFT_ Area and RIGHT_ Area **1** Consider four triangles namely: UPPER_TRI, LOWER_TRI, LEFT_TRI and RIGHT_TRI **where** Δ UPPER_TRI→ Triangle formed with U_t , L_w and R_w Δ LOWER_TRI→ Triangle formed with L_h, L_w and R_w Δ LEFT_TRI→ Triangle formed with L_w ,U_t and R_w Δ RIGHT_TRI→ Triangle formed with R_w**,** U_t and L_h **2** Find areas of step 1 four triangles as UPPER_ Area, LOWER_ Area, LEFT_ Area and RIGHT_ Area respectively. **3** Designate UPPER_ Area, LOWER_ Area, LEFT_ Area and RIGHT_ Area as feature vectors FV17, FV18, FV19 and FV20.

By following the above steps of algorithms 1, 2 and 3, a feature set FV= {FV_1, FV_2... FV_{19}, FV_{20}}, consisting of 20 geometric feature vectors, is extracted which characterizes the shape of outer helix of foot for personal recognition. Finally, feature vector set consisting of 26,400 features (=1320 ×20) from1320 plantar foot images gets generated. **Table 2** illustrates the listing of sample feature vectors of 12 footprint images of 2 subjects.

Table 2. Sample feature vectors of 12 footprint images.

S.N.	Max FHL	Max FWL	ll1	ll2	ll3	ll4	ll5	ll6	ll7	ul1	ul2	ul3	ul4	ul5	ul6	ul7	UP_ Area	LOW_ Area	LEFT_ Area	RIGHT_ Area
	FV1	FV2	FV3	FV4	FV5	FV6	FV7	FV8	FV9	FV10	FV11	FV12	FV13	FV14	FV15	FV16	FV17	FV18	FV19	FV20
1	621	247.8	375.1	409	442.4	475.4	508.1	540.6	572.8	104.1	46.58	115.3	150.3	173.2	188.5	198.1	10600	70451	63832	17219
2	651.4	249.5	406.8	440	473.2	506.2	539.2	572.1	605	129.9	48.03	100.7	143.1	169.5	186.6	197.1	11033	61425	52379	20079
3	622.8	247.8	378	411.7	444.9	477.8	510.3	542.7	574.8	104.1	46.58	115.3	150.3	173.2	188.5	198.1	10600	69902	63145	17357
4	621	247.8	375.1	409	442.4	475.4	508.1	540.6	572.8	104.1	46.58	115.3	150.3	173.2	188.5	198.1	10600	70451	63832	17219
5	622.4	247.5	374.6	408.8	442.5	475.9	508.9	541.8	574.4	84.68	78.81	132.9	164.9	186.6	201.3	210.4	9562	69479	65276	13765
6	622.8	247.8	378	411.7	444.9	477.8	510.3	542.7	574.8	104.1	46.58	115.3	150.3	173.2	188.5	198.1	10600	69902	63145	17357
7	628.8	167.7	386.7	397.6	408.5	419.4	430.2	440.9	451.7	129.3	110.8	89.7	63.3	12.99	58.91	83.12	22732	57067	57928	21871
8	651.8	168.5	649.7	618.6	587.4	556.2	524.8	493.4	461.8	3.317	32.91	63.54	94.09	124.6	155.1	185.6	525.5	71220	61126	70620
9	628.8	166.6	376.8	389.3	401.7	414	426.2	438.4	450.6	143.3	123.8	101.8	75.12	34.48	54.85	83.36	23069	56616	58044	21641
10	628.8	170.9	385.6	397.3	408.9	420.4	432	443.4	454.9	131.1	111.5	88.92	60.09	21.41	65.57	88.96	22485	57274	57918	21841
11	628.8	166.6	376.8	389.3	401.7	414	426.2	438.4	450.6	125.9	103	75.17	30.65	59.29	87.82	107.9	22661	56616	60522	18755
12	628.8	166.6	376.8	389.3	401.7	414	426.2	438.4	450.6	143.3	123.8	101.8	75.12	34.48	54.85	83.36	23069	56616	58044	21641

c) Feature Reduction using PCA and Normalization

After extracting 20 features per image, a feature set consisting of 26,400 (=1320×20) features from1320 plantar foot images gets generated. The larger dimension of feature set affects the recognition speed of the application. So, PCA method is applied on this feature set to reduce its dimensionality.PCA (Principal Component Analysis) is a well known widely used method of linear algebra to automatically perform dimensionality reduction. It finds maximum variance directions in high-dimensional data and projects it onto a new subspace with equal or lesser dimensions than the original one [39].So, to achieve a better recognition performance and smooth computation, 20 elements feature set of every image is reduced to 5 dominant feature vectors, by applying PCA, thereby, generating 6,600(=1320×5) features. Further, optimized results are obtained by performing normalization process that normalizes the values of reduced feature vectors

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in the range [0, 1] to achieve a normalized feature set. **Table 3** lists 5 dominant features of the corresponding 20 features of 12 footprint images of 2 subjects in **Table 2**.

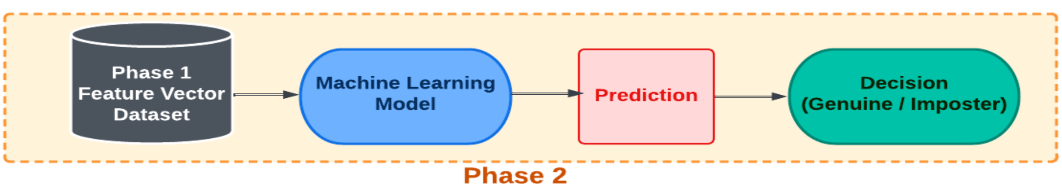
Table 3. Corresponding reduced feature vectors by applying PCA

S.N.	FV1	FV2	FV3	FV4	FV5
1	0.8105	0.1951	0.6266	0.6710	0.1968
2	0.6456	0.2729	0.6210	0.4752	0.1050
3	0.8026	0.1853	0.6287	0.6645	0.1860
4	0.7565	0.4517	0.6952	0.6139	0.3404
5	0.8649	0.4575	0.6405	0.7468	0.1179
6	0.7926	0.4546	0.6721	0.6410	0.2247
7	0.7189	0.4745	0.6527	0.6547	0.0806
8	0.7074	0.4629	0.6552	0.6535	0.0836
9	0.7183	0.4658	0.6539	0.6484	0.0711
10	0.7189	0.4745	0.6527	0.6547	0.0806
11	0.7130	0.4659	0.6543	0.6521	0.0790
12	0.7184	0.4680	0.6535	0.6503	0.0743

II. Phase 2

The normalized feature set of 6,600 features becomes the input for the application of machine learning algorithms in phase 2 of proposed methodology. On the basis of predicted output of machine learning algorithms, system decides that the claimed identity is a genuine user or an imposter. **Figure 7** shows diagrammatic representation of phase 2.

Figure 7. Phase 2 of proposed method



Basically, machine learning is the science of programming computers to learn from data to automatically predict the results for new set of data. It uses two types of techniques: supervised learning, which trains a model on known input and output data to generate predictions in response to new data and unsupervised learning, which finds hidden patterns or intrinsic structures in input data. Supervised learning uses classification and regression techniques to develop predictive models.

- Classification techniques predict categorical responses means Classification models classify input data into categories. Typical applications include medical imaging, image and speech recognition, and biometric identification etc.

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- Regression techniques predict a numerical value based on previously observed data. Their applications include stock price prediction and electricity load forecasting etc.

In machine learning, a classifier is a type of algorithm used to assign a class label to a given data input by employing sophisticated mathematical and statistical methods to generate predictions. So, a classifier refers to a set of rules used by machines to classify data. A classification model, on the other hand, is the end result of classifier's machine learning. The model is trained using the classifier, so that the model, ultimately, classifies the input data.

In the proposed work, 3 supervised machine learning techniques [40] namely; Classification, Regression and NNs (Neural Networks) have been explored and applied to recognize the footprints. Also, a comprehensive comparison among the above mentioned algorithms is carried out to find the best machine learning model based on recognizing accuracy and training time.

A brief description of the tested ML classifiers is as follows:

a) KNN (K-Nearest Neighbors) classifier

K-nearest neighbors (KNN) is a most frequently used supervised machine learning algorithm based on distance metrics used for classification and regression. It is a non-parametric algorithm, for it does not make any assumption on original data. It is also called a lazy learner algorithm because it does not learn from the training set instantly instead it stores the dataset (that is, it does not learn a discriminative function from the training data rather it "memorizes" the training dataset) and performs an action at the time of classification. The process starts by training data features with the assignment of label for each class. Afterwards, during classification, data is assigned to target classes according to their distances from query points. KNN uses all the available data and classifies the new data based on a similarity measure, or distance function. The new data is then assigned to the class to which most neighbors belong to. The basic idea of KNN is that similar data with the same classes are more likely to be closer to each other with respect to their distance. KNN uses many distance metrics like Euclidean, Mahalanobis, City block, Minkowski, Chebychev, Cosine, Correlation, Hamming, Jaccard and Spearman distances. Euclidean distance is the most common metric used by KNN which can be defined as follows:

$$EU\_d_{x,y}=\sqrt{\sum_{i=1}^{N}(x_i - y_i)^2} \quad (1)$$

Where $EU\_d_{x,y}$ refers to euclidean distance, x_i denotes input data, y_i represents training data, and N declares total number of features on the input data. Steps of K-NN can be summarized as below:

1. Select the value of K as the number of the neighbors
2. Calculate the Euclidean distances of K neighbors with respect to query point
3. Select the K nearest / closest neighbors as per the calculated Euclidean distance.

4. Among K neighbors, the number of the data points in each class is counted i.e. voting of neighbors
5. Assign the new data points to the class with the maximum number of the neighbors.

b) Gaussian Process Regression (GPR) classifier

Gaussian process regression (GPR) model is kernel-based, nonparametric probabilistic models. A GPR model is represented as:

$$y = h(x)^T \beta + f(x), \qquad (2)$$

where,

h(x) = Set of basis functions transforming the original feature vector x in R^d into a new feature
vector h(x) in R^p.
β = p × 1 vector of basis function coefficients.

f(x) = Gaussian Process with zero mean and covariance function, k (x, x′) i.e. GP (0, k (x, x′))

y = Observed response

The model of response y can be represented as:

$$P(y_i \mid f(x_i), x_i) \sim N(y_i \mid h(x_i)^T\beta + f(x_i), \sigma^2) \qquad (3)$$

In supervised learning method, the points with similar predictor values x_i are expected to have close response values y_i. In Gaussian processes, the similarity is expressed using covariance function which specifies the covariance between the two latent variables f (x_i) and f (x_j), where both x_i and x_j are d × 1 vectors. The covariance function k(x_i, x_j) is defined using various kernel functions based on kernel parameter vector θ. Hence, covariance function can also be expressed as k(x_i, x_j | θ). In general, the kernel parameters depend on two factors; signal standard deviation σ_f and the characteristic length scale σ_l which defines the minimum length between input values x_i and response values to be correlated.There are many built-in kernel (covariance) functions with same length scale for each predictor are: **Exponential Kernel, Squared Exponential Kernel, Matern 3/2, Matern 5/2 and Rational Quadratic Kernel. Among them,** squared exponential covariance function is most commonly used kernel and is defined as:

$$k(x_i, x_j, \mid \theta) = \sigma_f^2 \exp\left[-\frac{1}{2}\frac{(x_i - x_j)^T (x_i - x_j)}{\sigma_l^2}\right] \qquad (4)$$

c) Neural Networks (NNs)

Neural Network or neural net or artificial neural network is a computative learning system that uses a set of processing functions (activation functions)to learn and translate an input data set in one form into a desired output data, in another form. They, basically, represent a set of algorithms, modeled loosely after the human brain, and are designed to recognize patterns. They interpret sensory data through a kind of machine perception, labeling or

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clustering raw input. By varying layers and neurons, NNs are modeled for classification and recognition and many other applications [41]. In NNs , three types of layers are used: input layer, hidden layer, and output layer. Every network has one input and one output layer. All layers in between are referred to as hidden layers. The function that transforms the input into the output is known as activation function e.g. Sigmoid, RELU, Tanh, Step, Gaussian, Ramp and Linear etc.[42].The simplest mathematical representation for the NNs using Sigmoid Activation Function can be summarized as:

$$\hat{y} = \frac{1}{1+e^{-z}}, \text{ where } z=x.w+b \tag{5}$$

Where x represents the inputs vector, w refers to the weights vector, b is the bias and $\hat{y}$ denotes the predicted output.

Broadly, ANN is trained by using three approaches: Supervised Learning (Error based), Unsupervised Learning and Reinforcement Learning (output based). In supervised learning, there exists a mapping between input and target known output dataset and ANN model is trained with the labeled dataset to predict the output while in Unsupervised Learning, the target output is unknown, hence, ANN model learns on its own by discovering hidden patterns in the input data [43]. Reinforcement learning is based on rewarding desired behaviors and/or punishing undesired ones it enables to learn in an interactive environment by trial and error using feedback from its own actions and experiences. Our methodology uses supervised learning of ANN.

When ANN is trained using supervised learning, a known set of input data is presented to the network model along with the known set of desired output data, which produces a predicted output data. If there is a mismatch between predicted and desired output values, an error signal is spawned which causes the weights adjustments until zero error or minimum error value using back propagation Gradient Descent (GD) optimization method. GD method calculates the Error Gradient with respect to all weights in the network and is supplied to the optimization method to update the weights to minimize the error. So, Differentiable activation functions are required to be used by Back propagation.

Mathematically, if ΔW_{ij} is the weight update of link connecting the ith and jth neuron of two neighboring layers, then ΔW_{ij} is defined as:

$$\Delta W_{ij} = \eta \left(-\frac{\partial E}{\partial W_{ij}}\right) \tag{6}$$

where, η = Learning rate parameter

$\frac{\partial E}{\partial W_{ij}}$ =Error Gradient with respect to weight ΔW_{ij}

Weights are updated using:

$$W_{new}=W_{old} + \Delta W_{ij} \tag{7}$$

Since the error is not directly dependent on the weight matrix, so using chain rule Error gradient (using sigmoid activation function) is calculated i.e.

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$$\frac{\partial E}{\partial W_{ij}} = \frac{\partial E}{\partial \hat{y}} \times \frac{\partial \hat{y}}{\partial z} \times \frac{\partial z}{\partial W_{ij}} \tag{8}$$

$$\frac{\partial E}{\partial \hat{y}} = \frac{\partial}{\partial \hat{y}}\left(\frac{1}{2}[y-\hat{y}]^2\right) = -(y-\hat{y})$$

$$\frac{\partial \hat{y}}{\partial z} = \frac{\partial}{\partial z}\left(\frac{1}{1+e^{-z}}\right) = \left(\frac{1}{1+e^{-z}}\right)\left(1-\frac{1}{1+e^{-z}}\right) = \hat{y}(1-\hat{y})$$

$$\frac{\partial z}{\partial W_{ij}} = \frac{\partial}{\partial W_{ij}}\left(x.W_{ij} + b\right) = x$$

$$\Rightarrow \frac{\partial E}{\partial W_{ij}} = -(y-\hat{y}).\hat{y}(1-\hat{y}).x$$

$$\Rightarrow W_{new} = W_{old} + \eta(y-\hat{y}).\hat{y}(1-\hat{y}).x \tag{9}$$

So, the new weights are assigned / adjusted using equation 9 by propagating the error backward through network and the process continues until error is minimized to an acceptable low value or actual output is matched with the desired results.

5. RESULTS AND DISCUSSION

All the experiments are configured with Intel® Core™ i5-3110M CPU @ 2.40 GHz with 8 GB RAM, and NVIDIA® GeForce RTX™ 30 graphics card. Microsoft Windows 10 Pro 64-bit operating system and MATLAB R2019a (64-bit) has been used for the experimentation and evaluation of the proposed methodology.

5.1 Evaluation Metrics

To measure the effectiveness of proposed algorithm, the most widely adopted biometric performance indicators are considered such as False Accept Rate (FAR), False Reject Rate (FRR), Accuracy, Precision, Recall, Specificity and F1-score. These performance metrics are computed using four primitive variables of confusion matrix i.e.TP, FP, FN and TN. They are defined as below:

- **TP** (True Positives) refers to the count of cases when system predicted positive and it’s actually true.
- **FP** (False Positives) means count of values when system predicted positive and it’s actually false.
- **FN** (False Negatives) gives the number of cases when system falsely predicted the actual true values.
- **TN** (True Negatives) counts the cases when system predicted negative and it’s actually false.

It can be seen that actual results and predicted results contradict for FP and FN values. So, errors are calculated using these values. Other performance matrices are defined as:

- **False Positive Rate (FPR or FAR):** It is the rate at which system accepts unauthorized users.

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- **False Negative Rate (FNR or FRR):** It is the rate at which system rejects authorized/genuine users
- **Accuracy:** refers to the fraction of correct predictions made by the ML Model.
- **Error Rate:** It refers to the fraction of false predictions and equals to (1- Accuracy)
- **Precision:** It measures quality of positive predictions made by the model means fraction of relevant instances among positive retrieved instances
- **Recall (Sensitivity or TPR):** It quantifies the model's ability to detect positive results means fraction of relevant instances among retrieved instances (positive or negative).
- **F1-score:** It is defined as the harmonic mean of model's precision and recall.

5.2 Experimental Results and Analysis

In phase 1 of proposed methodology, the outer foot helix is generated after pre-processing steps. Afterwards, by implementing algorithms 1, 2 and 3 (discussed under section 4 b) proposed feature extraction scheme digs out 20 handcrafted geometric features and generates 20 element feature vector for each image **(Table 2)**. The resulting 20 elements feature set of every image is reduced to 5 dominant feature vectors by applying PCA, thereby, generating 6,600(=1320×5) features. Further, optimized results are obtained by performing normalization process that normalizes the values of reduced feature vectors in the range [0, 1] to achieve a normalized feature set **(Table 3)** which is injected further, as input feature vector (5×1320=6600 features set) to implement machine learning algorithms for personal recognition of Phase 2 of proposed methodology.

In Phase 2 proposed method utilizes 3 supervised machine learning techniques namely, Classification, Regression and NNs (Neural Networks) to recognize the footprints. All the experiments are conducted using training size of 6600 features set of 1308 images of 218 persons and 60 random images of 10 persons are kept for testing(genuine and imposter from seen and unseen data) with 5 features from each image sample. Through the experiments 1, 2 and 3, it was found that in classification approach KNN models for classification, GPR (Gaussian Process Regression) models for Regression and Feed forward Back propagation networks for ANN are the best performing ML models based on supervised learning. Following experiments are conducted individually by implementing Classification, Regression and ANN techniques and corresponding implementation outcomes of each applied ML algorithm are being presented in tabular as well as graphical notations to analyze the results.

A. Experiment 1

A comparison study between different classifications models has been performed by implementing 5-fold Cross-Validation. **Table 4** presents the results of this comparison study in terms of validation accuracy and training time.

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Table 4. Comparison of Validation Accuracies and Training Times of different classifier models

Classifiers	Accuracy	Training Time(Sec)
KNN MODELS		
FINE KNN	99.4	1.35800
MEDIUM KNN	98.9	0.37952
COARSE KNN	98.6	0.33961
COSINE KNN	98.8	0.41992
CUBIC KNN	98.9	0.50860
WEIGHTED KNN	**99.5**	**0.29886**
DECISION TREES MODELS		
FINE TREE	98.9	9.723900
MEDIUM TREE	98.6	9.382900
COARSE TREE	98.8	9.049600
SVM MODELS		
LINEAR SVM	98.6	4.123200
QUADRATIC SVM	88.6	0.609390
CUBIC SVM	99.2	0.537360
FINE GAUSSIAN SVM	79.3	0.365050
MEDIUM GAUSSIAN SVM	98.6	0.299560
COARSE GAUSSIAN SVM	98.6	0.299940
ENSEMBLE MODELS		
BOOSTED TREES	99	4.125115
BAGGED TREES	99.1	3.133600
RUSBOOSTED TREES	88.9	3.182300
SUBSPACE DISCRIMINANT	98.6	3.815700
SUBSPACE KNN	98.3	3.210000

From the above table, it is evident that **weighted KNN model** is outperforming among all the mentioned classification models with **99.5%** accuracy and overall training time of **0.29886 seconds.** The confusion matrix, scatter plot and the corresponding ROC curve of weighted KNN model are depicted in figure 8. It can be observed through the experimental results that all the applied classification models are performing well. But taking into consideration of training time, Decision Tree classifiers are the slowest ones in spite of having reasonable accuracy. Ensemble methods are also following the same scenario.

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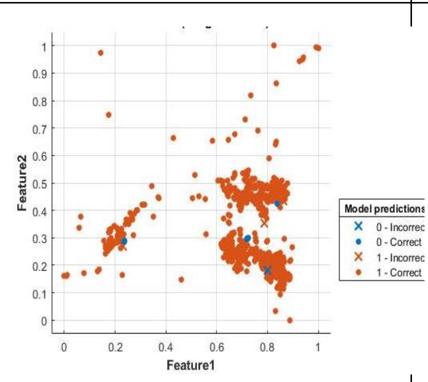
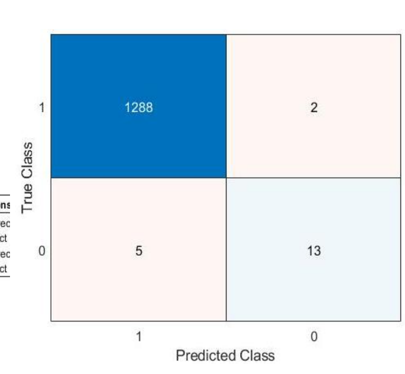
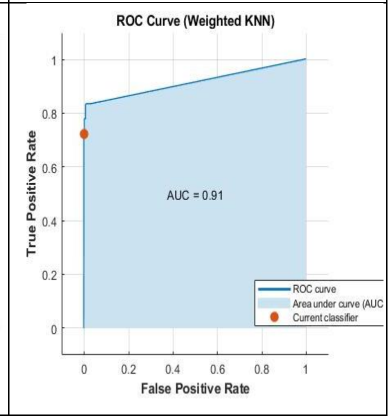
Figure 8a. Scatter Plot of Weighted KNN	Figure 8b. Confusion Matrix of Weighted KNN	Figure 8c. ROC curve of Weighted KNN
		

B. Experiment 2

A comparison analysis is done by applying different regression models with an implementation of 5-fold Cross-Validation strategy. **Table 5** outlines the results of this comparison study in terms of various performance metrics namely, RMSE (Root Mean Squared Error), MSE (Mean Squared Error), MAE (Mean Absolute Error) and Training Time in seconds.

Table 5. Comparison of various performance metrics of different classifiers for Regression models

Classifiers	RMSE	MSE	MAE	Training Time(Sec)
Linear Regression Models				
Linear	0.116680	0.013615	0.028470	4.55220
Interactions Linear	0.116480	0.013569	0.033448	0.66622
Robust Linear	0.117310	0.013761	0.013761	0.01376
Stepwise Linear	6.888500	0.013593	0.031128	6.88850
Decision Trees Models				
Fine Tree	0.097676	0.0095407	0.014709	2.9678
Medium Tree	0.107850	0.011633	0.020299	0.2129
Coarse Tree	0.110780	0.012271	0.024100	0.1630
Svm Models				
Linear Svm	0.131200	0.017213	0.085808	1.90210
Quadratic Svm	0.126420	0.015982	0.071229	9.48520
Cubic Svm	0.847730	0.718650	0.080368	122.790
Fine Gaussian Svm	0.093344	0.008713	0.071643	0.50894
Medium Gaussian Svm	0.117640	0.013839	0.053152	0.29717
Coarse Gaussian Svm	0.130460	0.017021	0.084494	0.31608
Ensemble Models				
Boosted Trees	0.095132	.00905.2	0.055900	3.5644
Bagged Trees	0.101770	0.010357	0.020115	2.2047
Gpr Models				
Squared Exponential	**0.064363**	**0.0041426**	**0.010850**	**41.329**
Matern 5/2 Gpr	0.070769	0.0050082	0.010556	36.105
Exponential Gpr	0.070477	0.004967	0.010260	36.055
Rational Quadratic Gpr	0.070377	0.004953	0.010726	92.984

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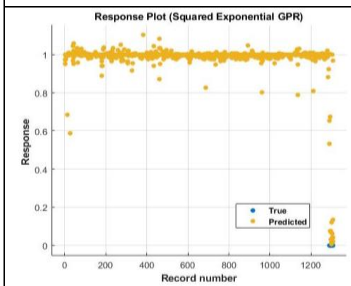
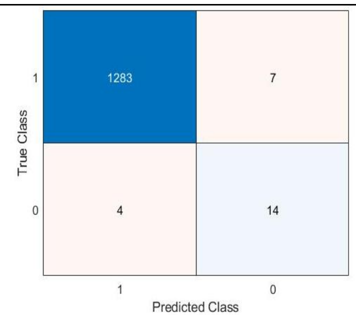
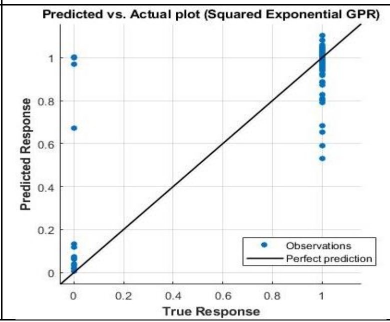
C. Experiment 3

It can be clearly seen that **Squared Exponential GPR model** is the best performing model among all implemented regression models with the least RMSE value of **0.064363** and overall training time of **41.329 seconds. Figure 9** shows the corresponding graphs of visualized results of Squared Exponential GPR model are shown below:

Figure 9a. Response Plot of Squared Exponential GPR	Figure 9b. Confusion Matrix of Squared Exponential GPR	Figure 9c. Predicted vs. Actual Plot of Squared Exponential GPR
		

This experiment seeks the efficacy of neural networks for footprint recognition. For the purpose, Feed-forward back propagation Neural network is implemented with 10 neurons at the hidden layer 1 with the Tansig as activation function and Purelin activation function at hidden layer 2 (**Figure 10a**). Other parameters used are: Data Division – Random; Adapting Learning Function- learnGDP; Network Training Function- Levenberg-Marquardt to update weight and bias values; Performance Function- MSE The experimental results show that the overall accuracy of **97.47%** and the training time of **3.4358 seconds** were achieved by applying ANN supervised learning approach. The resulting statistics of other performance metrics are as follows:

Error Rate: 0.0252
Precision: 0.2857
Recall: 0.2500
Specificity: 0.9883
F1-scores: 0.2667
FPR: 0.0117
FNR: 0.7500

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Following **Figure 10b, c** show the confusion matrix and performance plot of ANN:

Figure 10a. ANN Network View

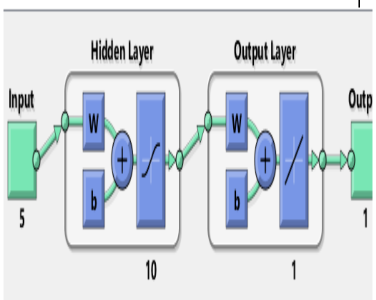


Figure 10b. Confusion Matrix of ANN

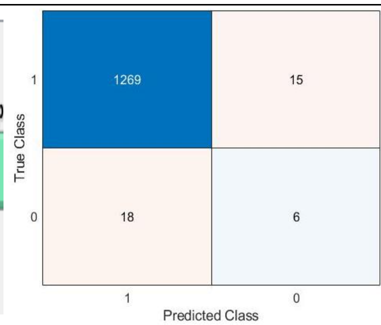
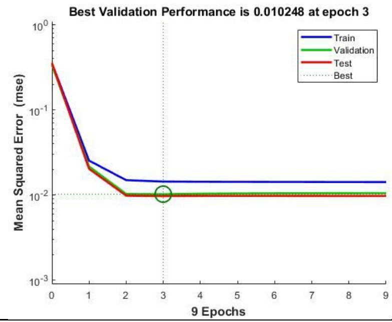


Figure 10c. Performance Plot of ANN



D. Experiment 4

From the results of previously discussed 3 supervised machine learning algorithms of classification, regression and ANN, it was concluded that the **weighted-KNN model** is the most performant method among all the mentioned methods with **99.5%** validation accuracy and the overall training time of **0.29886 seconds.** Following **Table 6** presents the comparison chart of performance metrics of various machine learning algorithms used in the proposed work. Also, **Figure 11a** and **Figure 11b** depict the bar charts of Performance metrics and Training Times of the best performing above mentioned ML algorithms i.e. Weighted-KNN, Squared Exponential GPR and ANN.

Table 6. Comparison of performance metrics of different classifiers

ML Algorithms	Accuracy	Error Rate	Precision	Recall	Specificity	F1-scores	FPR	FNR	Training Time
Weighted-KNN	**0.9946**	**0.0054**	**0.8667**	**0.7222**	**0.9984**	**0.7879**	**0.0016**	**0.2778**	**0.2989**
SQ- Exp-GPR	0.9916	0.0084	0.6667	0.7778	0.9946	0.7179	0.0054	0.2222	41.3290
ANN	0.9748	0.0252	0.2857	0.2500	0.9883	0.2667	0.0117	0.7500	3.4358

Figure 11a. Performance Metric Bar chart of KNN,GPR and ANN

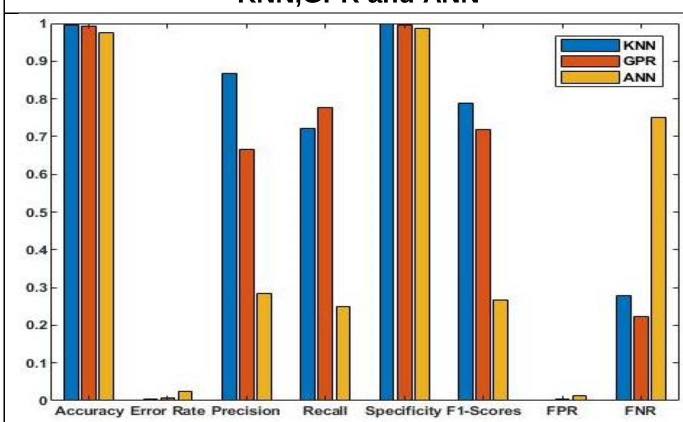
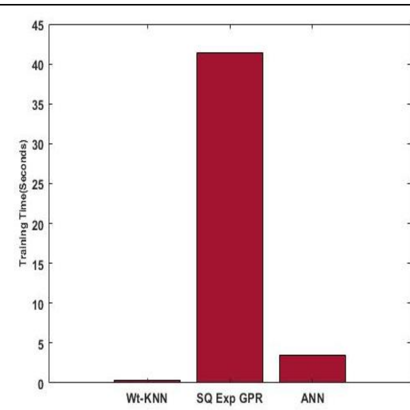


Figure 11b.Comparison of Training Time of KNN,GPR and ANN



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E. Experiment 5

Through the exhaustive literature study of foot biometry, it was revealed that only one work from Basheer et al. [14] is available for footprint recognition that applies Machine learning methods using fuzzy ensemble learning. They claimed the highest recognition accuracy of 98.88%, FPR at 0.01, FNR at 0.093 and the training time of 18.510 seconds. While, through the results of experiment 5 the proposed prototype scheme is outperforming the [14] approach **with 99.5% recognition accuracy, FPR at 0.00155039** and **FNR at 0.27777778** with overall training time of **0.299 seconds,** hence providing a better robust solution for footprint recognition **(Table 7 and Figure 12b).**

Table 7. Comparison of performance metrics of proposed method with the existing method [14]

Method	Accuracy	FPR	FNR	Training Time
Proposed Method	0.9946	0.0016	0.278	0.299
Basheer et al. [14]	0.989	0.010	0.093	18.510

Figure 12a.Comparison of performance metrics of proposed method and [14]

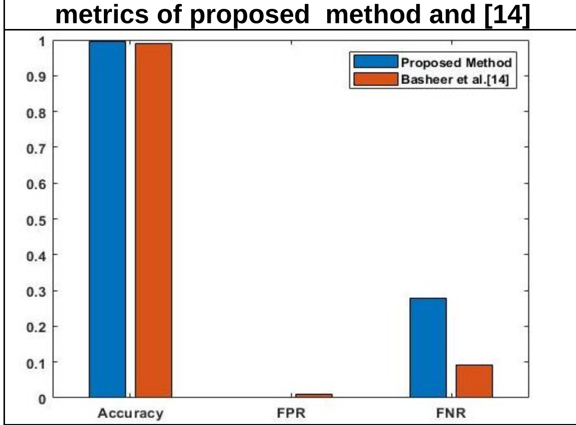
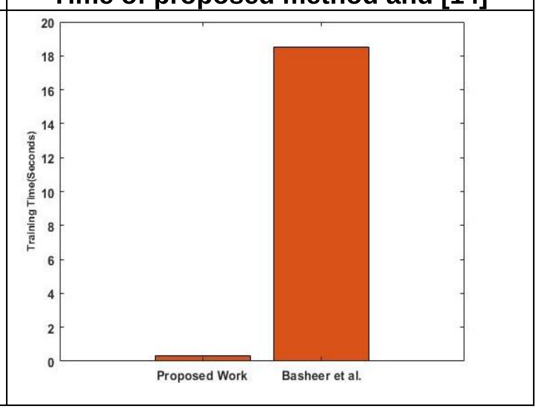


Figure 12b.Comparison of Training Time of proposed method and [14]



5. CONCLUSION AND FUTURE SCOPE

In this paper, an agile scheme of footprint recognition using supervised machine learning techniques has been proposed with an acceptable accuracy. For the purpose, 20 potent and salient handcrafted foot shape based geometrical features of footprints are extracted. Afterwards, feature reduction is performed to reduce the 20 foot features set per image into 5 dominant features followed by normalization. This normalized feature vector is induced as input vector for implementing Machine learning algorithms. The proposed methodology utilizes 3 supervised machine learning algorithms viz. classification, regression and ANN with different classifiers. Experimental results reveal that weighted KNN method is the outperforming method with the highest accuracy of 99.5% and training time of 0.29886 seconds in comparison to Regression and ANN with the greatest accuracy of 99.15% and 97.5% respectively. The application of optimized deep learning techniques for footprint recognition is the next target of our present work extension. Also, in near future, proposed scheme can be combined with other feature modalities to develop a multimodal biometric system.

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