Gender Classification from Behavioural Biometric Data using Convolutional Neural Network

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Abstract. Biometric modalities are used to identify the gender of an individual based upon their physiometrics or behaviometric data. Gender plays a crucial role in most applications like banking, security, document authorization, forensics, psychology, human-computer interventions, and many more. Gender classification using handwritten signatures is still considered to be a challenging task due to homogenous variations among male and female handwritten signatures. This paper monologues the gender classification from offline signature images using Convolutional Neural Network features. The results obtained are promising and competitive with state-of-art techniques.

Keywords: Biometrics · Convolutional Neural Network · Offline Handwritten Signature · Gender Classification

1 Introduction

Biometric security systems technologically rely on measurements of an individual's morphological (e.g. Face, Iris, Fingerprint, Hand geometry, etc.) and behavioral (e.g. Voice, Signature, Keystroke, etc.) attributes [1]. Soft biometrics are the demographic information-based biometric modality (e.g. Age, Gender, Ethnicity, Height, etc.) used to differentiate an individual. Recently, identification and authentication from ancillary information of biometric methods are extensively researched issues, whereas soft-biometrics and hard-biometrics work together to ensure best recognition rate for a specific environment [2]. Signatures are behavioural biometrics which is inconsistent and change due to an emotional and physical state like age, mood, and ecological conditions [3]. The word "signature" comes from the Latin word "signure", which means "to mark". It is a special type of person's handwriting, where everyone has their unique style of signature which is due to neuromuscular mechanical variance in the male and female signatures. It is a subconscious habitual act based on his/her habits and mannerism. Gender is one of the physical or social information of a person being male or female, which is used in many applications like forensic science, medical, video surveillance, etc. As a result, handwritten signatures are used to identify a person's various characteristics, such

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as gender [4], personality analysis [5], emotional state, neurological diseases, age, and also nationality. Handwritten Signatures made on document signifies approval, acceptance, and knowledge of an individual. These are broadly accepted biometric traits, legally and socially everywhere and also help in the court of law as evidence to find the culprit from the suspects [6]. In the past few decades gender classification from offline handwritten signature images is a hot research subject in the areas like health, security, pattern recognition, computer vision, and forensic document examination [7], and an adequate importance in banking agreement, cheque processing methods, official publications, and passport validation.

The biometric data contained in the handwritten signature can also be verified and used to improve the security authentication. In general Handwritten-Signature traits deeply reveal some of the gender-dependent aspects like the writing style, size, and shape of letters, decorativeness, pen pressure, slant/orientation, curvature, speed, irregular spaces, inconsistencies in writing and acceleration. The diversity in shapes of characters is the key challenges in writer identification. In this case, the features extracted from the signature samples may enhance the performance of gender classification. Many current technological studies have focused on the verification and recognition of handwritten signatures; whereas a small number of researchers are working on femininity. Therefore, we aim to propose a deep learning framework for the classification of male and female handwritten signatures using the convolutional neural network. The key contributions of the proposed study is to preprocess the offline scanned handwritten signature images, extract features using deep convolutional neural network and classification employed using state-of-the-art techniques.

The outline of this paper is organized as follows: Sect. 2 presents an overview of previous work done by the researchers. Section 3 is dedicated to the proposed method and feature extraction addresses the state-of-the-art. In Sect. 4 Experimental results are analyzed. Finally, the Comparative study, and the conclusion are presented in Sect. 5.

In the recent past, Biometric modalities like handwritten signatures are extensively accepted for authentication and authorization purpose. Several related studies showcased handwriting-based gender classification. Cavalante Bandeira et al. [8] have investigated the impact of keystrokes and handwritten signatures on gender prediction systems. A total of 100 participants were interviewed, and their handwritten signature images and keystroke information are collected from each participant. The dataset contains each participant's gender, emotion, and hand orientation information. Basic statistical and dynamic features were extracted and classified using the multilayer perceptron technique. An average accuracy of 68.03% is achieved. Pal et al. [9] have proposed work on gender classification using the Euler number as a feature for the offline 500 Hindi handwritten signature images. A backpropagation neural network is used for the classification and a recognition rate of 88.80% is obtained.

2 Related Work

In addition, to the handwritten signature-based gender classification, another aspect worth mentioning is that many works are carried out on handwriting-based independent writer identification and gender classification. In [10], the authors worked on 130 handwriting samples collected between the age group of 18–30 years where 65 males and 65 females. 27 different minute features are extracted and divided into two groups' macro and micro features using a magnifying lens, enlarger scale, and protector for the examination. Hypothesis testing (Z-test) is used to find the statistical significance level of the male and female handwriting and comparative results were obtained. Somaya Al Maadeed et al. [11] have proposed work on age, gender, and nationality prediction using offline handwriting. Several geometric features were extracted from the QUWI dataset and features are combined using random forest classifier and kernel discriminant analysis classification techniques. Recognition rate of 74.05%, 55.76%, and 53.66% for gender, age, and nationality is predicted. Angel Morera et al. [12] proposed a prediction system for Gender and Handedness using offline handwriting. IAM dataset of English texts and KHATT dataset of Arabic texts, two public databases are used for the experimentation. Deep learning and Convolutional Neural Network classification techniques used achieved comparative results. Gender using IAM dataset: accuracy 80.72% and Handedness using IAM dataset accuracy: 90.70%, for KHATT dataset accuracy of Gender, is 68.70% and Handedness is 70.91%. In [13] writer identification based on writer individuality using a combination of features has been proposed. Three types of features were selected namely word, line, and character-based features on English and Bengali handwritten text. Experiments were carried out on writings of both male and female volunteers with different age groups. Extracted features are classified using Multilayer Perceptron and K-Star algorithms. Best recognition results in 93.54% and 95.69% are obtained. Abdeljalil Gattal et al. [14] have proposed work on handwriting-based gender classification. The two new features were introduced in the work, Cloud of Line Distribution and Hinge features on the QUWI dataset. Two types of evaluation techniques were carried out on the database, Script-independent, and Script-dependent evaluations. The extracted features are classified using a Support Vector Machine classifier with an accuracy rate of 73.60% is obtained.

Many previous works have shown that texture features and shape features may enhance the performance of gender classification using offline handwritten signatures and handwriting. However, we observe that there are very little effort is done into gender identification using handwritten signatures that contain multilingual text. Therefore, we proposed a framework of deep convolutional neural network-based features from the offline handwritten signature, which are used to classify the different gender from signature images.

3 Proposed Methodology

In this section, we propose the general architecture of the proposed schema as shown in Fig. 1.

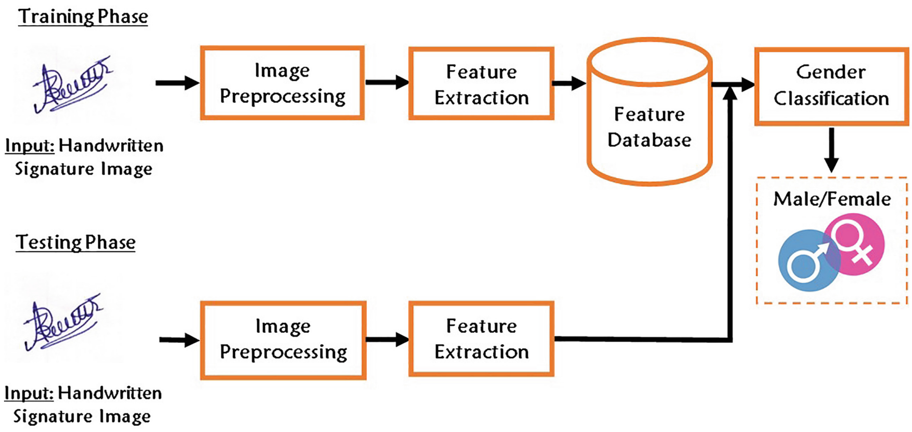

Fig. 1. General architecture for gender classification using handwritten signature

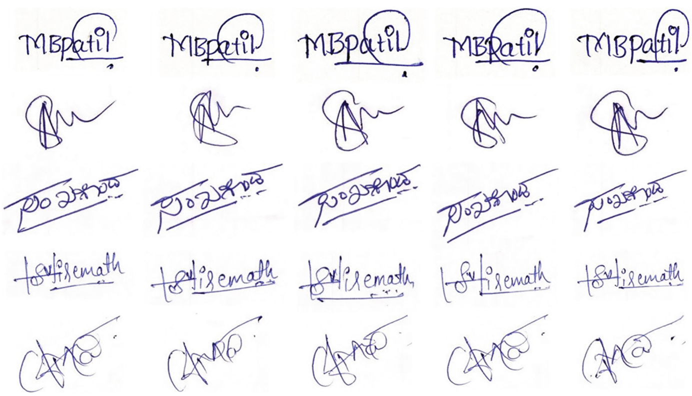

Fig. 2. Samples images from the Handwritten Signature Database

3.1 Dataset

The dataset used in this proposed work is retrieved from the Mendeley database, i.e., Offline Handwritten Signatures based on Gender Annotation [15]. The dataset contains 250 male and 229 female handwritten signatures, an in-house total of 4790 signature samples with different age groups. These samples consist of multilingual handwritten scripts of Kannada, Hindi, Marathi, and English. Signature samples from the dataset are shown in Fig. 2.

3.2 Pre-processing

The sequence of pre-processing steps is carried out to feed the neural network. Pre-processing module consists of enhancing the quality of the collected dataset such as Normalization and Resizing the signature. The neural network assumes that the input is

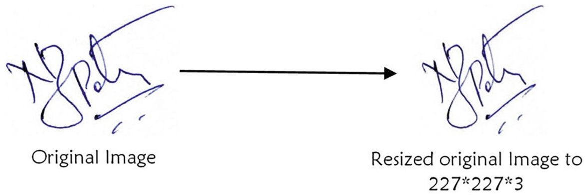

Fig. 3. Pre-processing of the signature image

a fixed size and the shape of the signature significantly varies. Our system consists of the following component: Normalization of the signature into 227*227*3 dimensions (Fig. 3).

Implementation Platform

MATLAB is high-performance language for technical computing and interactive environment for algorithm development. The GUI framework support many different predefined functions/objects in toolbox (https://in.mathworks.com/help/install/).

The proposed work was executed on the MATLAB 2018b with deep learning toolbox (https://in.mathworks.com/products/deep-learning/). A pre trained Convolutional Neural Network (AlexNet) is been trained to extract the features from the input image (Deep Learning Toolbox Model for AlexNet Network - File Exchange - MATLAB Central (mathworks.com)). Classification models trained using Classification Learner application.

3.3 Feature Extraction

Feature extraction is the process of locating or computing influencing and distinguishing qualities that may aid in classifying gender from a given dataset [17]. Feature Extraction converts input data into a set of features. The significant aspects of input data are called features, and they aid in identifying the input patterns. The proposed method exploits the features of a Signature image using a deep Convolutional neural network to differentiate between the two gender classes. A brief description of feature learning techniques is presented in the following.

3.3.1 CNN-Based Feature Extraction

Convolutional Neural Network was firstly introduced in 1980 by Fukushima [18] and developed in 1998 by Y.LeCun et al.[19]. In many computer-vision tasks, CNN is used to achieve better performance in state-of-the-art techniques. CNN architecture is typically composed of a Convolutional layer, a pooling layer, and a fully connected layer. The following Fig. 4 illustrates the general architecture of the CNN model.

The input layer of CNNs directly accepts raw images and convolves them using shared weights across several learning kernels. The number of maps and kernel sizes of the maps are the parameters that define a convolutional layer. Each layer contains M maps (M_x, M_y) of equal size, and (K_x,K_y) is the kernel size which is shifted to the valid region of the input image [16]. In layer l each map is connected to all maps of layer l -1.

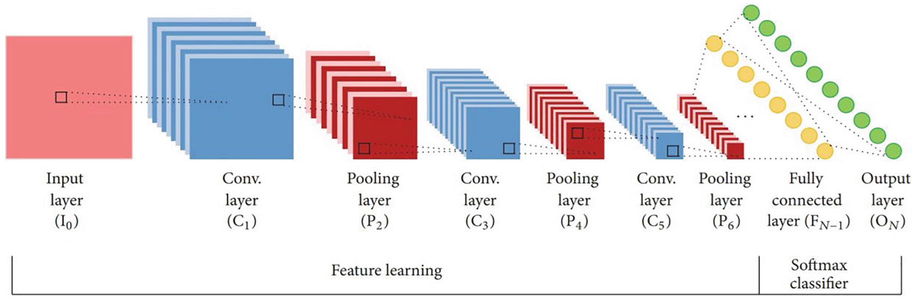

Fig. 4. A typical general architecture of the CNN model

The weights of neurons in a given map are shared but they have different input fields. Next, the pooling layer reduces the resolutions of the feature maps, the purpose is to achieve spatial invariance or to maintain the information contained in the image. The maximum, mean, or stochastic activation, corresponding to max-pooling, mean-pooling, or stochastic pooling, over non-overlapping rectangular sections of size (K_x, K_y), gives the output of the pooling layer. Feature learning is composed of a convolutional layer and a pooling layer, following which the extracted features are combined and weighted in multiple fully connected layers, and also classification part of the convolutional layer is represented in the fully connected layer. Each neuron in layer l is connected to outputs of all neurons in layer l-1 which corresponds to one character class. Table 1 list of operational modules performed in the above architecture of the CNN model.

Both convolutional layers and fully connected layers have learnable parameters that are optimized during training. After every learnable layer in the network, except for the last layer, the Batch normalization method is applied, followed by a non-linearity ReLU (rectified linear activation function) Layer. Finally, the last full Connected Layer uses the softmax layer of non-linearity, which interprets the assigned probability of each possible use by the network. The result of layer 'fc7' is the input of both output layers [20]. Table 2 describes the list of operations performed in the layers.

Where, $\mathbf{Z}^{l}$: Pre-activation output of layer l, $\mathbf{h}^{l}$: activation layer l, *: discrete convolution operator, W, γ, , β: learnable parameters, the mean ($E[z_i]$) and variance ($Var[z_i]$).

3.4 Classification

Classification techniques are used to systematically classify given data into one or more sets of classes [21].

3.4.1 Support Vector Machine (SVM)

SVM is one of the supervised and discriminative binary classifiers, which works on decision boundary in feature vector data of closest points using maximal margin hyperplane. It is used to maximize the difference between the two classes and also it gives a hyperplane as a result of classification [22]. SVMs training patterns select feature data

Table 1. Modules of CNN layers

Layer	Size	parameters
ImageInputLayer	227 × 227 × 3	Name: 'data'
Convolution2DLayer (C1)	96 × 11 × 11	Stride = 4, pad = 0, Name: 'conv1'
MaxPooling2DLayer	96 × 3 × 3	Stride = 2, Name: 'pool1'
Convolution2DLayer (C2)	256 × 5 × 5	Stride = 1, pad = 2, Name: 'conv2'
MaxPooling2DLayer	256 × 3 × 3	Stride = 2, Name: 'pool2'
Convolution2DLayer (C3)	384 × 3 × 3	Stride = 1, pad = 1, Name: 'conv3'
Convolution2DLayer (C4)	384 × 3 × 3	Stride = 1, pad = 1, Name: 'conv4'
Convolution2DLayer (C5)	256 × 3 × 3	Stride = 1, pad = 1, Name: 'conv5'
MaxPooling2DLayer	256 × 3 × 3	Stride = 2, Name: 'pool3'
FullyConnected2DLayer (FC6)	4096	Name: 'fc6'
FullyConnected2DLayer (FC7)	4096	Name: 'fc7'
FullyConnected2DLayer (FC8) + Softmax Layer	1000	Name: 'fc8', softmax
Classification Output Layer		Name: 'output', cross entropy

Table 2. Operations performed in the layer

Operation	Formula	
Convolution	$Z^l = h^{l-1} * W^l$	(1)
MaxPooling	$h_{xy}^l = max_{i=0,\ldots S, j=0,\ldots S} h_{(x+i)(y+j)}^{l-1}$	(2)
Fully-connected Layer	$Z^l = W^l h^{l-1}$	(3)
ReLU	$ReLU(Z_i) = \max(0, Z_i)$	(4)
Softmax	$Softmax(Z_i) = \frac{e^{z_i}}{\sum_j e^{z_i}}$	(5)
Batch Normalization	$BN(Z_i) = \gamma_i \widehat{Z}_i + \beta_i, \widehat{Z}_i = \frac{Z_i - E[Z_i]}{\sqrt{Var[Z_i]}}$	(6)

that lies on the hyperplane with maximum margin and the closest point distance in both the classes [23].

3.4.2 K-Nearest Neighbour (K-NN)

K-NN algorithm is firstly developed by Fix and Hodges [24] in the year 1950s. It is a machine learning classifier that is used for classification and also for regression analysis. K-NN classifiers classify data points into predefined classes based on different types of distances. This algorithm selects the feature space to predict the data points into k classes distance measurement as feature similarity. We used city-block distance to find out the shortest neighboring data points. It is calculated as:

$$D_{city-Block}(M, N) = \sum_{J=0}^{n} |M_J - N_J| \quad (7)$$

where M_J is the new point and N_J is the distribution for distance.

3.4.3 Ensemble Classifier

The ensemble classifier is the combination of multiple classifiers used to classify the number of samples by considering a vote on the predictions of its components to get output. Combining the classifiers generally has two types of methods i.e., classifier selection and classifier fusion [25]. Single classifier applied to get best accuracy for given sample is said to classifier selection, whereas in classifier fusion method different classifiers applied in parallel to get the final decision based on the groups consent [25]. In proposed study, bagging approach is applied for the computed features. The following Fig. 5 demonstrates the bagging the classifier.

The algorithm used for the proposed system is as follows:

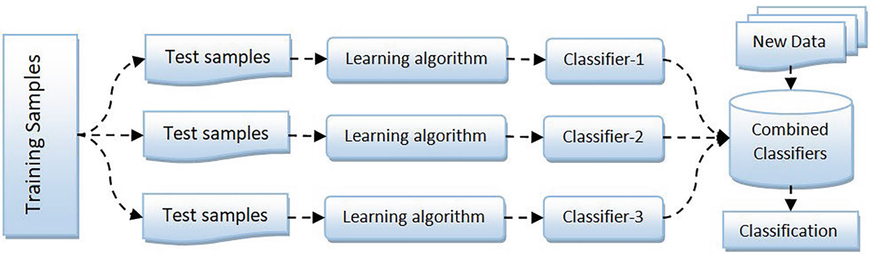

Fig. 5. General representation of bagging approach

Algorithm

Input: Offline Handwritten Signature Image.

Output: Gender Classification of the individual.

Step1: Input offline handwritten signature image

Step2: Pre-processing of the input image into 227x227 fixed sizes.

Step3: Compute Features using Convolutional Neural Network.

Step4: Classification of feature space using Support Vector Machine, K-Nearest Neighbor, and Ensemble Classifiers and output the gender class of individual.

End

4 Experimental Results

The experimental evaluation of the system carried on the Offline Handwritten Signatures based on Gender Annotation [15], which comprises 4790 offline handwritten signatures of a different gender. An in-house total of 479 writers contributed 10 signatures each, collected from 250 male writers and 229 female writers who belong to different age groups. Firstly, the signatures normalized to a fixed size 227×227. The entire dataset split into 70:30 ratios for training and testing the system shown in Table 3. The proposed work employ Convolutional Neural Network (alexnet) for feature extraction, the input layer accepts raw image followed by the convolution layer 'conv1' with 11×11 filters and 10 maps of size 24×24. Next the sub-sequential max-pooling layer 'pool2' reduces previous layer into 12×12 by 2×2 filters. Similarly 'conv3' also employs 5×5 filters but has 12 maps with dimensions of 8×8 pixels. 'pool4' with 2×2 pooling windows produces 4×4 feature maps that are fully connected to 100 hidden neurons. The 100 dimensional fully connected layer projected into the feature space. Lastly, the series of neurons used to cover these feature points class by class into feature vectors. These features were classified using CNN + KNN, CNN + SVM and CNN + Ensemble classification techniques are tested with 10 cross validation on the signature dataset. It is observed that 95.4% highest accuracy is achieved by the ensemble learning with bagging approach with number of learners = 30. Further, several experiments are carried on K-Nearest Neighbor algorithm with different distance 'k' which ranges from 1 to 20 values, directly impacts the accuracy rate. The proposed work is determines highest accuracy of the KNN model with k = 3 value, the resulted into better overall accuracy of 94.2%. Finally, the SVM algorithm yielded an enhanced accuracy of 84.4% which is less result rate compared to other classifiers. Table 4 represents the experimental results based on classification accuracy, performance analysis and confusion matrix, namely KNN, SVM and Ensemble classifier. In Table 3 Train_x (70% of 4790) indicates the 70% split from the original signature dataset for training, Test_x (30% of 4790) indicates the 30% split reserved for the model validation. The corresponding labels stored at the variable 'y' are again split into 70% for Train_y and the remaining 30% for the Test_y to test the model on the unseen data.

The performance evaluation of the proposed system analysed using performance metrics namely, Accuracy, Precision, Recall (True Positive Rate) and F_score which are defined in following Eqs. 8–11.

$$\mathbf{Accuracy} = \frac{\mathrm{TP}}{(\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN})} \tag{8}$$

$$\mathbf{Precision} = \frac{\mathrm{TP}}{(\mathrm{TP} + \mathrm{FP})} \tag{9}$$

$$\mathbf{Recall} = \frac{\mathrm{TP}}{(\mathrm{TP} + \mathrm{FN})} \tag{10}$$

$$\mathbf{F}_{\boldsymbol{score}} = \frac{2 * \mathrm{PRECISION} * \mathrm{RECALL}}{\mathrm{PRECISION} + \mathrm{RECALL}} \tag{11}$$

where, TP: True positive value, TN: True Negative value, FP: False Positive Value and FN: False Negative Value. Figure 6 is the graphical representation of classifiers and feature.

Comparative Analysis

Comparative analysis presented in Table 4 the results obtained by the proposed work is compared with similar state-of-the- art techniques used in the related work for gender classification. Pal et al. [9] have worked on gender classification using Euler number as a feature for 500 Hindi handwritten signature database. A Back Propagation Neural Network classification technique is used and obtained an accuracy of 88.80%. Somaya Al Maadeed et al. [11] proposed work on QUWI dataset, several geometric features are extracted and using random forest and kernel discriminant analysis classifiers for gender 74.05%, age 55.76% and for nationality 53.66% is obtained. In [12] authors proposed prediction system of gender and handedness using IAM dataset and KHATT dataset. CNN classification technique is used and achieved an accuracy of 80.72% for gender and 90.70% for handedness using IAM dataset, 68.70% for gender and 70.91% for handedness using KHATT dataset. Abdeljalil Gattal et al. [14] proposed novel feature

Table 3. Training and Test set Split into ratio as 70:20 for the given dataset

No. of Training Samples: 70%	Train_x	No. of Test Samples: 30%	Test_x	Total
	(3353,1000)		(1437,1000)	(4790,66)
	Train_y		Test_y	
	(3353,1)		(1437,1)	(4790,66)

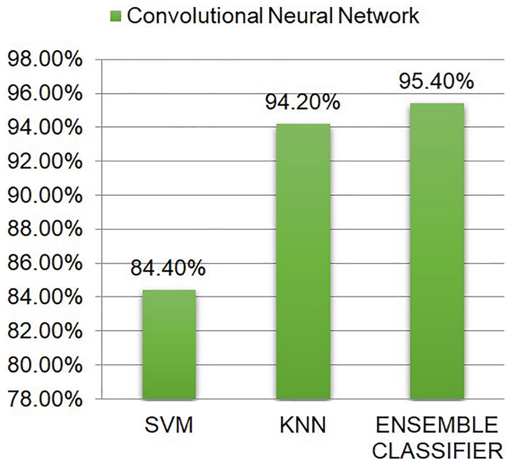

Fig. 6. Graphical illustrations of the obtained results from classifiers and feature

learning techniques such as Cloud of Line Distribution and Hinge features, for handwriting based gender classification using QUWI dataset. An accuracy of 73.60% is achieved using support vector machine classifier. Comparatively, the reported works have drawback of using limited size database for the experiments except the database used in [4]. It observed that the proposed method was able to outperform the other works by using Convolutional Neural Network as feature with Ensemble Classifier which yielded higher accuracy of 95.40%, which is an encouraging result.

Table 4. Summary of related methods in the literature, features, classifiers and datasets.

Authors	Features	Database	Classifiers	Results
Pal et. al [9]	Euler number and statistical features	500 Hindi handwritten signatures	Back Propagation Neural Network	84%
Somaya Al Maadeed et. al[11]	Geometric features	QUWI dataset	Random Forest and Kernel Discriminant analysis	74.05% for gender
Angel Morera et. al [12]	Deep features	IAM dataset and KHATT dataset	Deep CNN	80.72%, 68.70%
Abdeljalil Gattal et al. [14]	COLD features	QUWI dataset	Support Vector Machine	73.60%
Proposed method	**Convolutional Neural Network features**	**Offline Handwritten Signature based on Gender Annotation**	**K-NN classifier, Support Vector Machine, Ensemble Classifier**	**94.20% 84.40% 95.40%**

5 Conclusion

From recent past years the advancement of ML-based algorithms used for gender classification using handwritten signature and handwriting for better recognition. The proposed work presented a competent method to find out gender of the person using handwritten signature sample. The method mainly relies on the feature extraction of Signature samples of male and female writers. A pre-trained deep Convolutional Neural Network (AlexNet) was employed for feature extraction and for classification a number of standard classification techniques are used. Among this ensemble classifier has reported the highest classification result rate. In our further study, we will include study of feature selection and fine tuning of pre-trained models which are used to characterize the writing features, and other demographical biometric analysis such as age and handedness etc. will be studied.

Authors' Contributions. Sathish Kumar[1]: Conceptualization, Methodology, Software and Field study. Shivanand S. Gornale[2]: Data Curation, Writing-Original draft preparation, Software Validation and Field study. Rashmi Siddalingappa[3]: Visualization, Investigation, Writing-Reviewing and Editing.

Compliance with Ethical Standards. • Conflict of Interest: The authors state that they do not have any conflicts of interest.

• Research involving Human and Animal Rights: There are no animal trials by any of the authors in this paper.

• Ethical Standards: All procedures used in research involving human volunteers were compatible with the institution's ethical guidelines.

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