Fuzzy Systems and Soft Computing
ISSN : 1819-4362

IDENTIFICATION OF GENDER HANDWRITING IMAGE USING CONVOLUTIONAL NEURAL NETWORKS (CNN)

Murugan A, Associate Professor & Head, PG & Research, Department of Computer Science, Dr. Ambedkar Government Arts College (Autonomous) Affiliated to University of Madras, Chennai, India. Email id: amurugan1972@gmail.com
Umadevi T P, Assistant Professor, Department of Computer Science, JBAS College for Women (Autonomous), Chennai, India

Abstract
Handwriting can be characterized as archaeology, biometrics, psychology, forensics, and other subjects that have been employed in a wide range, handwriting recognition methods in the past relied on handmade characteristics and a lot of prior knowledge. It is difficult to train an Optical Character Recognition (OCR) system centered on these requirements. Advanced versions of Convolutional Neural Networks (CNNs) have a better capability for extracting relevant information than standard models. CNN is the supreme suited technique for tackling handwriting recognition issues, since it is highly good in understanding handwritten words or characters arrangement. In this paper, proposed CNN model based feature extraction technique showed better usage by minimizing human errors and identifying the gender handwriting images without any faults. This paper involves database segregation, pre-processing and classification that are implemented for distinguishing the gender handwriting images. In this research work involved in computation of extracting features from the input handwriting images using first-order statistics based histogram and spatial frequencies based co-occurrence matrix can be used for identifying a writer from his/her handwriting. Then, extract relevant handwriting features using CNN for gender categorization like female or male. The findings indicated that utilizing the IAM database, suggested CNNs architecture has a superior accuracy of 85% for gender handwriting image categorization.
Keywords: CNN, Handwriting Image, Gender, Male, Female, Conventional Recurrent Neural Network (CRNN), Features

1. Introduction
The manner in which images can be identified and categorized is one of the numerous computer related topics that are explored and investigated. As a human who identifies the image, how it is identified. In image processing, image recognition is a critical process. The image identification process is impacted by factors such as lighting environments, view angle and whether or not the recorded image is unblemished [1]. Owing to the fact that handwriting may assist people with tasks like analysis of bank cheques, processing handwritten form post-exposure, handwriting recognition is the paramount pursued after and investigated topics. Since every individual should possess a unique handwriting form, it is more difficult to recognize pictures of handwriting. Handwriting is much harder to identify as compared to computer writing that comprises of a fixed structure or arrangement, since it is not permanently straight and occasionally has a slanting up and down [2]. Handwriting detection has a lot more variables that impact how well handwriting is acknowledged. In the case of computer writing, this type will undoubtedly have a fixed structure hence misunderstanding will be a lot in handwritten.
Interpersonal and intrapersonal alterations in writing, employing diverse pen varieties, paper existence amidst a noisy backdrop, handwriting's cursive character, all contribute to overall handwriting identification difficulties [3]. The uniqueness of handwriting with scientific precision is examined and assessed by Srihari and team [4]. Online and offline recognition are the two approaches to the concerns of handwriting recognition. To identify handwritten text, which is originally inscribed in paper and subsequently digitized is the challenge of offline. To identify text produced with an electronic digitizer is the goal of online handwriting.
The writers in various languages have distinct handwriting styles and this has been a major problem in categorizing offline handwritten characters. Since characters produced by various authors is not equal in terms of similarity, font, shape and size, offline handwritten character identification is very challenging than other types of character recognition. Comprising numerous different writing styles

is the foremost perplexing issue in recognizing separate characters. As a result, recognizing the character identification issue in pattern recognition becomes more difficult. A well-researched deep learning structural design centered on natural visual perception devices is known as CNN or ConvNet. Applications such as digitalizing health documents, data processing of immigration, processing automatic cheques etc. are some of the applications of CNN in addition to a large variety of OCR utilizations. A multilayer network termed as LeNet-5 that could categorize handwritten numbers including the CNN architecture is introduced by LeCun and coworkers during the year 1990 [5]. The visual brain of animals stimulated CNN computing. A region of brain responsible for processing information through retina is visual cortex. It is sensitive to input’s tiny sub-regions of the input and visual information is carried out.

A receptive field that is a tiny portion of an input image capable of influencing a network’s certain area is computed likewise in a CNN. It aids in the selection of additional CNN characteristics and also a component of CNN architecture’s key design factors. A fully linked or thick layer, convolutional and pooling or subsampling is incorporated in this form of CNN. For the purpose of learning input feature depictions, convolutional layers are designed. It is utilized for generating various feature maps, as each one is made up of a number of convolution kernels. Every feature map neuron is linked to an area of neighbouring neurons from the preceding layer. To activate the resulting elements using an elementally nonlinear function, an original feature map is produced first by converting the input into a learning kernel preceding to it [6].

It is worth noting that kernel is mutual to entire input spatial locations, wherein numerous dissimilar kernels are used to create the full feature maps. While lowering feature map resolution, every pooling layer strives for shift invariance. It's generally positioned between two layers of convolutional neural networks. Finally, one or many completely linked layers arise after multiple convolutional stacks and pooling layers that execute the concluding classification mission. Like other multilayer networks, CNNs is trained using types of back propagation algorithms. CNNs are taught by back propagation techniques, similar to multilayer networks.

As a way of retrieving information, this study addressed feature extraction techniques based on mathematical procedures and models that define the spatial variations within handwriting images. The process of recognizing and choosing a collection of differentiating and adequate characteristics that may be used to characterize a texture is known as “Feature Extraction”. By calculating local features at each location in the image and deriving a set of statistics from the distributions of the local structures, statistical techniques evaluate the gray values three-dimensional dissemination. The CNN construction is prone to fluctuating and form initial characters deteriorations to some extent and is given for extracting trainable dataset features that are invariable.

The paper is structured in the following manner: Literature review including state-of-the-art job related to handwriting recognition is contained in Section 2. The Section 3 explains proposed CNN model with feature extraction for analyzing handwriting image. The experimental outcomes based upon performance evaluation are discussed in Section4, and the conclusion is presented in Section 5.

2. Literature Review

Shallow networks have previously shown excellent outcomes in handwriting recognition [7–11]. Recitation of novel approaches in classifying handwritten characters, numbers and words are printed in many research articles. In MNIST dataset, Deep Belief Networks (DBNs) having three layers and a covetous algorithm is examined, possessing 98.75 % precision. Pham and team stated that to enhance Recurrent Neural Networks (RNNs) capabilities in detecting unimpeded handwriting, a dropout regularization approach is deployed [12]. RNN performance has improved with considerable decline in Word Error Rate (WER) and Character Error Rate (CER) are stated by the writer. Providing high-tech results in this area is modernized by CNN in the arena of handwriting recognition [13–18].

Simard proposed that neural network training’s complicated technique is cleared, where common CNN design for visual document is processed [19]. Wang et al. demonstrated good performance on standard datasets such as Street View Text and ICDAR 2003 by developing a unique total integrated text recognition technique based on multi-layer CNNs [20]. Shi et al created the Conventional Recurrent Neural Network (CRNN) lately, wherein the benefits of both Recurrent Neural Network

(RNN) and Deep CNN (DCNN) are combined. It is discovered that, it outperformed standard techniques in scene text recognition by utilizing CRNN [21]. The suggested study by Ahlawat aims to investigate several design alternatives for CNN centered handwritten digit recognition such as size of strides, receptive field, layers quantity, size of kernel, dilution and padding. Furthermore, development in handwritten digit recognition outcome is assessed using numerous SGD optimization methods. For an MNIST dataset, the research yielded 99.87 percent recognition accuracy [21].
Ahmed et al. specified for the purpose of identifying Arabic handwritten digits, a deep learning approach is presented [22]. The approach that has been offered is on MADBase database comprising arabic handwritten digits, which contains 60,000 training and 10,000 testing pictures. A CNN having LeNet-5 is educated and evaluated. Several feature extraction approaches such as features of skeleton, contours quantity, the ratio of the top line to bottom line length of the supplied input image and features of water reservoir is employed by Ravi et al [23] by virtue of developing a Telugu printed number digits identification system. On a databank of 3,150 multi-font printed Telugu numbers, the suggested technique is taught and verified.
A method for developing a standalone digit recognition system is suggested by Vijay Kumar and team [24]. Hosts pot and geometrical features to extract characteristics from a digit image is used by the author of this research. The recommended technique is tested on the MNIST database, which has 60,000 training and 10,000 numerals testing samples, CENPARMI database has training set images of quantity 4,000 and testing test images of 2,000 Nos. A database of 18,468 training and 2,711 testing sets of digits is contained in the CEDAR and 7291 training and 2007 testing sets are comprised in USPS database. To categorize the numbers in separate databases, a SVM classifier or k-NN is utilized.
Dynamic Bayesian Network classification method for Arabic handwritten digit identification is suggested by AlKhateeb[25]. Discrete cosine transform coefficients are utilized as well to remove features in the classification. On MADBase, that includes 10,000 testing samples and 70,000 training Arabic digits, the suggested technique is tested. This study presents a proficient handwritten Hindi number digit identification structure centered on Root Mean Square Propagation (RMSProp) and CNN optimization approach as recommended by Reddy and team. The suggested technique CNN with RMSprop optimization obtained an identification rate of 99.85% in this trial, which is extremely encouraging [26].

3. Research Methodology

In this study, three phases are typically comprised in the suggested technique. Numerous handwriting samples including letters, digits, words and sentence format from IAM database are accumulated during primary phase. There is an online and an offline version comprised in this handwriting dataset. The selected words and letters consist of two categorizes of gender namely male and female subjects. In the first phase, extracting features from the handwritten images i.e. alphabets or words using first-order statistics based histogram features including spatial frequencies based co-occurrence matrix features, it can be used for identifying a writer from his/her handwriting. In second phase of research work, gender classification is done based on handwriting features using CNN. A superior handwriting feature extraction skills is demonstrated by CNN. Figure 1 illustrates the suggested technique block diagram

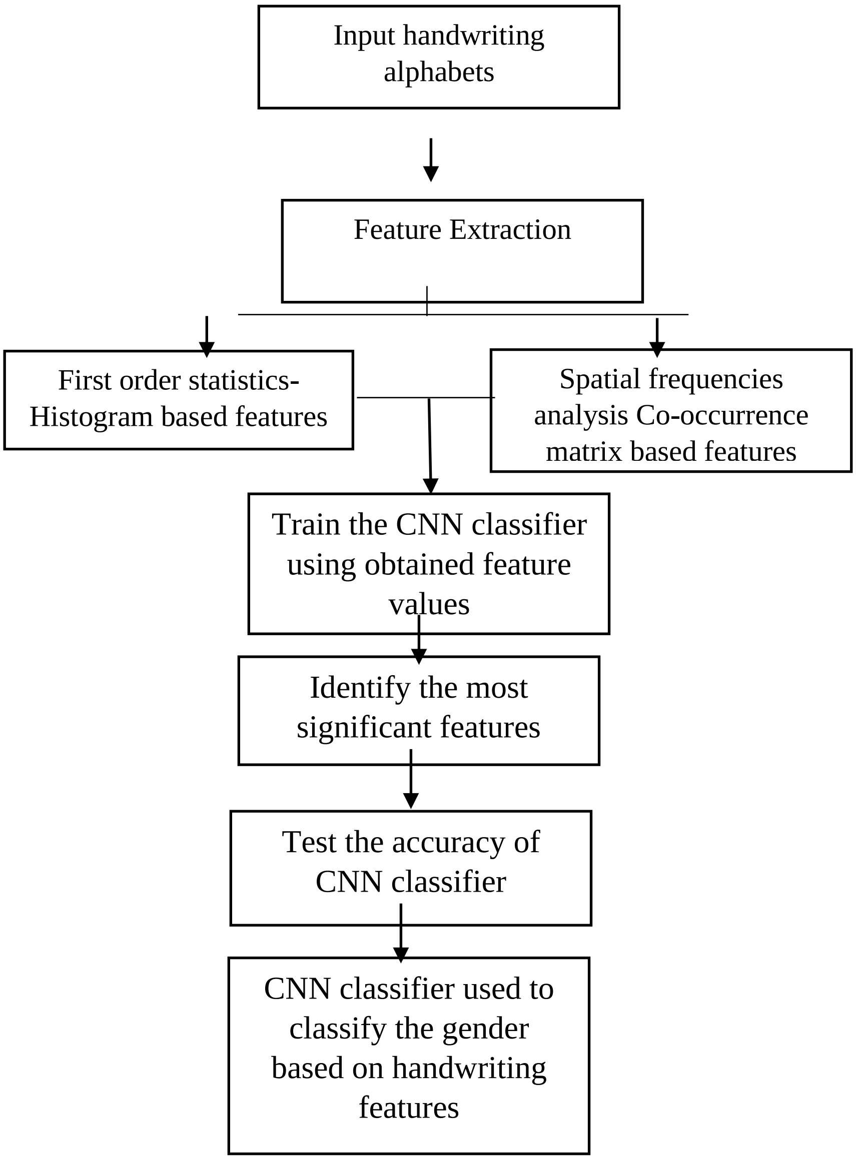

Figure 1: Recommended handwritten analysis block diagram

3.1 Handwritten image database assortment

The unimpeded handwritten forms of text included in this dataset is scanned at 300 DPI resolutions and with 256 grey levels, it is stored as PNG files. A padding of 2 pixels is applied on real character's entire four sides, when the character is centered inside 28x28 pixels. The grey level image is preprocessed to look for missing and null values. The illustration of alphabet related to male and female subjects are depicted in figures 2 and 3.

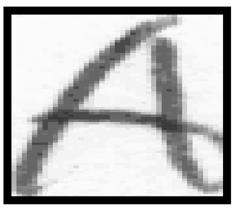

Figure.2 Alphabet from Male Subject Figure.3 Alphabet from Female Subject

3.2 Feature extraction of handwritten images by first order and second order statistics based analysis

In this phase, extraction of features determines and selects a collection of distinctive and appropriate characteristics to define a texture. This research has been initiated with first-order measures, which are calculated from real handwritten image values without taking into account pixel vicinity acquaintances and second order spatial frequency co-occurrence matrix related to the pixel pair's joint probability distributions.

First-order statistics based approach – Histogram based structures

Let P(I) represent the gray levels of the image area as a random variable.
P(I) = $\frac{number\ of\ pixels\ with\ gray\ level\ I}{total\ number\ of\ pixels\ in\ the\ region}$
According to the definition, P(I) represents first order histogram, 'M' represents Mean and $'\mu_k'$ represents central moments of I as given by
M = $\sum_{i=0}^{G-1} I\ P(I)$
$\mu_k = \sum_{i=0}^{G-1} (I - M)^k\ P(I)$
k = 2,3 and 4
Where G denotes gray level's potential value.
Variance, skewness and kurtosis are the most often used central moments and they are designated as μ2, μ3 and μ4 correspondingly. The indication of how far gray levels diverge from Mean is histogram thickness's dimension termed as "Variance". Kurtosis refers to histogram sharpness dimensions, whereas skewness pertains to asymmetry of histogram around the Mean measurement.

Spatial frequencies based Texture Analysis - Co-occurrence matrix based features

The information associated with the image of gray-level distribution from the features is produced by the statistics of first-order. Nevertheless, there are no details available about the corresponding location of several gray applied to the image. As a result, when the complete gray levels lesser value is combined together or swapped with the greater value, its characteristics are unable to modify. A matrix having relative frequencies P, d(I1, I2) may classify some phenomenon of any gray-level configuration. This explains about the frequency of two pixels existing over an opening divided through distance d towards the route of gray-levels I1 and I2. Moreover, the data may be derived from co-occurrence matrix which calculates the statistics of second-order images, whereas the pixels are represented in pairs. There are two parameters performed as a function of the co-occurrence matrix, wherein relative orientation 'θ' and pixel numbers (d) measurements are taken. Hence, an orientation θ computed by 135˚, 90˚, 45˚ and 0˚ are represented as anti-diagonal, vertical, diagonal and horizontal correspondingly. Simultaneously, there are different type of feature extractions namely Contrast, Correlation, Homogeneity and Energy as illustrated below.
Contrast = $\sum_{I_1 I_2} |I_1 - I_2|^2 \log P\ (I_1, I_2)$
Correlation = $\sum_{I_1 I_2} \frac{(I_1 - I_2)(I_2 - \mu_2)(I_1, I_2)}{\sigma_1\ \sigma_2}$
Homogeneity = $\sum_{I_1 I_2} \frac{P\ (I_1, I_2)}{1 + |I_1 - I_2|^2}$
Energy = $\sum_{I=0}^{G-1} [p(I)]^2$
These features have provided high discriminative power for distinguishing two dissimilar kinds of handwritten images.

3.3 Classification using Convolution Neural Network

Finally, classification is done by utilizing CNN. Using handwritten images of different alphabet metastases, features can be extracted using statistical and covariance analysis. Based on the features obtained, CNN classifier is capable to classify the alphabets of gender based on its type using properties of metastases. In this phase, CNN is trained using 19 chosen features at the time of extraction from each handwritten image. This is done to find out the most relevant features that could accurately classify the gender, based on handwriting features and thereby add to the reliability of the results. After training, CNN is tested for its accuracy. In post training and testing phases, CNN can be used for categorizing alphabets as two classes, namely female or male.
The order-3 tensors, i.e., a monophonic channel image having W columns and H rows are CNN's inputs to the issues. A c-dimensional vector as an output is yielded for c-class classification task, as entire network levels handle such inputs in progressive order. The value at location (i,j) in *k*-th feature map of *l*-th network layer is expressed in a mathematical scheme as depicted below

$$Z_{i,j,k}^{l} = w_k^{l^T}\ \ x_{i,j}^{l} + b_k^{l} \qquad \text{……………………(1)}$$

The indigenous input area for this layer and location is denoted as $x_{i,j}^{l}$, while w_k^l and b_k^l are the weight and bias vectors related to *k*-th filter at *l*-th layer respectively. The time taken for preparation is condensed since convolution kernels demarcated by network weight masks w_k^l is being pooled.

The value obtained by (1) is sent over Rectified Linear Unit (ReLU) activation equations, much as other forms of NN, to identify nonlinear structures:

$a^{l}_{i,j,k}$ = ReLU ($Z^{l}_{i,j,k}$) ………………………(2)

The activation function of CNN architecture is used to bring non-linearity into the method. Among the numerous activation functions used widely in deep learning simulations, Sigmoid function, Softmax and ReLu are some well-known examples. Owing to data misplaced in input data, sigmoid activation function is shown to degrade CNN type. The non-linear ReLu function that contains output 0 aimed at input less than 0 and raw output if not, is chosen as the activation function in this research. Resemblance to humanoid nervous system, ease of usage and capacity to train bigger networks quicker are few ReLu activation function's benefits.

In CNN construction, classification layer is the final of all layers. Classifier is embraced as the most commonly used entirely linked feed forward network. The neurons present in preceding layer are linked to neurons at fully linked layers. This layer computes predicted classes by recognizing an input image that is accomplished by combining its entire features learned by previous layers. The number of entire output classes is determined by quantum of classes present in target database. To categorize input image, produced structures obtained via previous layer to multiple classes data is utilized for training, wherein classification layer uses ‘Softmax' activation feature in this study.

Algorithm: Gender Classification Algorithm

Input: Handwritten Document Or Handwritten Documents

Output: Identifying male or Female

```
Begin
    Read the hand written documents
    doc=0
    While (doc = true)
conv_layer1 = Conv2D(num_filters1, filter_size1, activation='relu', input_shape=input_shape)
pool_layer1 = MaxPooling2D (pool_size=pool_size1)
conv_layer2 = Conv2D (num_filters2, filter_size2, activation='relu')
pool_layer2 = MaxPooling2D (pool_size=pool_size2)
flatten layer = Flatten()
dense_layer1 = Dense(num_hidden_units1, activation='relu')
dense_layer2 = Dense (num_classes, activation='softmax')
model = Sequential()
model. add(conv_layer1)
model. add(pool_layer1)
model. add(conv_layer2)
model. add(pool_layer2)
model. add(flatten layer)
model. add(dense_layer1)
model. add(dense_layer2)
model. compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
model.fit(x_train, y_train, epochs=num_epochs, validation_data=(x_val, y_val))
Endwhile
End
```

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4. Results

The tests and findings on Offline IAM databanks are explained in this segment. The selected words and letters are consist of two categorizes of gender namely male and female subjects. The proposed research work employs a subset of this dataset's offline sentences, as a total of 1,800 data samples are used for analysis. A test set and training set are two components present in the entire dataset, wherein 1440 and 360 images for training and testing set respectively is chosen arbitrarily.

Then feature extraction is performed from sample dataset of handwritten images. In this research work, the first order or central moment’s analysis is based on the intensity value to characterize the texture. The image intensity average levels are considered as mean that have been examined in which the description of variance is about intensity variation present in the mean. When the histogram is said to be symmetrical with mean, then the skewness is zero or else it may be positive or negative depending upon the skewness below or above the mean. Thus, μ_3 is the symmetry indication, whereas the kurtosis act as a histogram flatness measure and the component '3' gets integrated with equation of kurtosis normalizes μ_4 to zero at a gaussian-shaped histogram. In this research work, the second order GLCM spatial distribution is directly designed to quantify the textures of handwritten images and areas, instead of resolving the matrices by simplified scalar texture measurements. A metric for indigenous level differences that grosses large values for images with a lot of contrast is termed as "Contrast". A degree of how closely pixels in two distinct orientations are related is known as "Correlation". A metric which gives low-contrast images with high scores is termed as "Homogeneity". Image homogeneity may be determined using energy, it contains low values, while gray level pairings possibilities are identical, or else it has high values.

The first-order statistical feature set such as skewness and kurtosis features shows an outstanding difference for male and female handwritten images. The features like binary weight has been learned from handwritten image of training and these features are obtained by segregating 80% of train and 20% of test dataset that gets classified using CNN. Figure 4 has illustrated the detection of handwritten image from the extracted features based on proposed CNN model and are classified as male or female handwritten images.

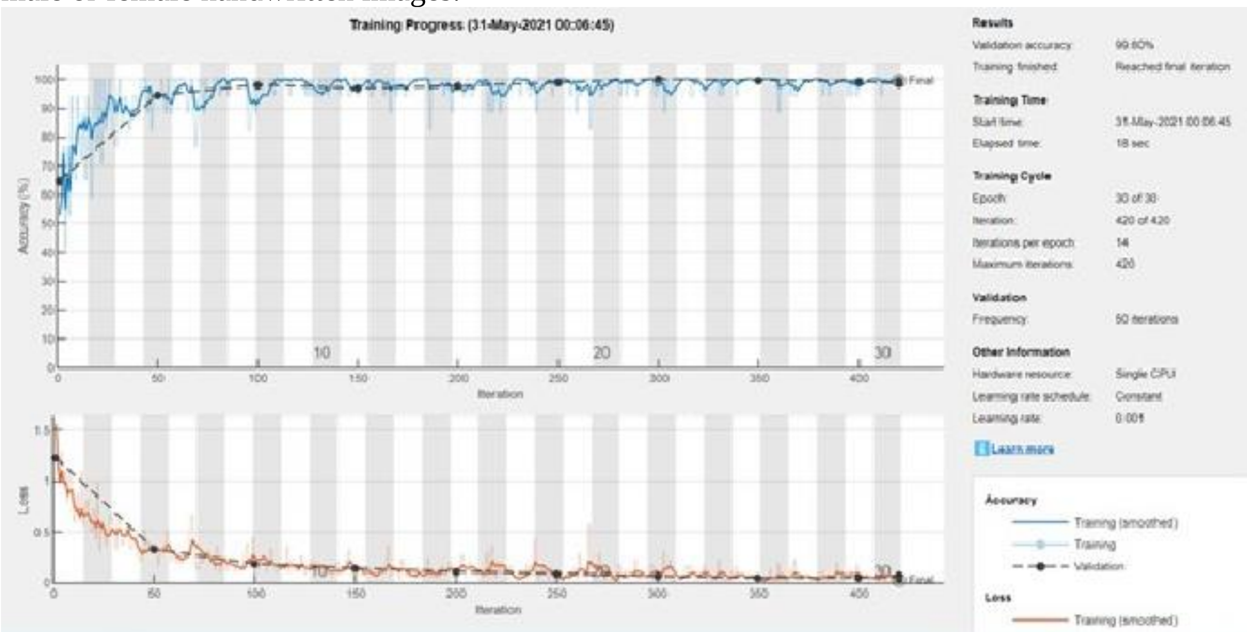

Figure 4 - Training and testing accuracy of Proposed CNN model

The most significant features of skewness and kurtosis are extracted out of all features from the input handwritten images showing outstanding difference between male and female based on classification accuracy 85% using proposed CNN model.

5. Conclusion

A deep learning technique utilized for gender handwritten image categorization is proposed in this study. The selected words and letters are consist of two categorizes of gender namely male and female subjects. There are overall 1440 training models in training data and 360 dissimilar characters comprised in testing data. However, the most significant features of skewness and kurtosis are extracted from input handwriting image have shown better results, whereas the textures are separable visually as simple as possible. Hence, the statistical approach is simple in implementing and has been illustrated to provide very good results over the region of large pixel. CNNs models have a higher capacity in extracting appropriate features compared to traditional models. In comparison to conventional models, CNNs models possess better capability for extracting relevant characteristics. The suggested approach yielded a great accuracy return having a recognition level of 85%.

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