Journal of Autonomous Intelligence (2024) Volume 7 Issue 1
doi: 10.32629/jai.v7i1.763

ORIGINAL RESEARCH ARTICLE

Comprehensive robustness evaluation of an automatic writer identification system using convolutional neural networks

Irfan Hamid[1], Rameez Raja[2], Monika Anand[3], Vijay Karnatak[4], Aleem Ali[3,*]

[1] *Department of CST, Central University of Punjab, Bathinda, Punjab 151401, India*

[2] *Department of CSE, Parul University, Vadodara, Gujarat 391760, India*

[3] *Department of CSE, UIE Chandigarh University, Punjab 140413, India*

[4] *College of Smart Computing, COER University, Uttarakhand 247667, India*

*** Corresponding author:** Aleem Ali, aleem.e12948@cumail.in

ABSTRACT

This research paper presents a convolutional neural network (CNN) model for identifying handwritten Urdu characters. A dataset of 38 fundamental Urdu characters from 100 different writers in the Kashmir valley was manually collected. The developed system was trained on a training dataset of 30,400 samples and verified on a test dataset of 7600 samples, and it outperformed previously proposed AI based writer identification systems in Urdu language with an identification rate of 91.44 percent for 38 classes. This study highlights the effectiveness of deep learning techniques in solving the challenging task of the Urdu writer identification. The findings demonstrate the potential of the developed CNN model for real-world applications in handwritten character recognition and verification systems. Future work involves expanding the dataset to include numerals and isolated characters for improved system performance.

Keywords: deep learning; convolutional neural network; Urdu characters; text independent; text identification

ARTICLE INFO

Received: 21 June 2023
Accepted: 10 August 2023
Available online: 13 October 2023

1. Introduction

Handwriting has been a fundamental form of communication since ancient times, uniquely representing the individuality of writers. As such, writer identification has become a crucial application of pattern recognition, enabling the verification of a document's authenticity based on the writing style. With the advent of artificial intelligence and the remarkable capabilities of deep learning techniques, the development of automatic writer identification systems using convolutional neural networks (CNNs) has garnered significant attention. These systems have the ability to automatically extract intricate features from handwritten samples, leading to superior performance in identifying the true writer. While considerable progress has been made in this domain, the robustness of such systems is of paramount importance to ensure their applicability in real-world scenarios.

Biological qualities have a high level of accuracy, but they are not always possible because such verifications require the person to be physically present. Behavioural traits, on the other hand, offer the advantage of being able to employ remotely. Signature and writing are the most widely utilized approaches among the behavioural traits for entity identification.

Most of the work has been doing on the verification using the biological attributes. However little attention had paid to the verification using the behavioural attributes. Based on the method of acquisition, the writer identification has categorized into two types: online pattern and offline pattern. Online pattern obtained using special devices like digitizers, tablets etc. These types of patterns contain dynamic information such as pen pressure, pen-up time, speed, etc. The presence of such additional data significantly helps in the writer identification and verification process.

Despite significant advancements in the field of writer identification, there remains a notable knowledge gap when it comes to identifying Urdu handwriting. Our research endeavours to bridge this gap and contribute to the understanding and application of writer identification, especially for cursive scripts like Urdu. The intricate nature of Urdu script poses distinct challenges in achieving accurate identification, making it a compelling area of investigation. By emphasizing the importance and complexities of identifying Urdu handwriting, our research sets the context for further advancements in this crucial domain. A lot of theoretical and experimental work have been done in writer identification in some language like English and Arabic, but a very few research has been done in this direction for Urdu language. The major problem for writer identification in Urdu language is lack of Urdu text dataset. This research work aims to develop a dataset of handwritten Urdu documents and perform identification on dataset using deep learning.

In this research, our focus lies on offline pattern recognition, which deals with handwritten documents and text images that do not contain dynamic information. The lack of such data poses challenges in achieving high accuracy in writer identification, especially for cursive scripts like Urdu. To address this limitation, we propose a revolutionary approach based on deep learning techniques.

1.1. Writer identification and verification

The writer identification and verification systems aim to distinguish the genuine writer from the forged one. Writers inherit the characteristics of intra-personal variation and inter-personal variation. The writing style of each user remains the same but, no two handwriting by two different persons can be the same. The major goal of this research is to use the inter-personal differences in the writing to distinguish the genuine handwriting from the forged one.

1.2. Types of handwriting

Depending on the method of data collection, the handwriting or hand-written documents classified into two types.

1.2.1. Online pattern

Online written documents are captured using special devices like digitizers and tablets, with the help of a special pen. Such types of written documents contain dynamic information, which can be incredibly useful for author verification and identification. The dynamic information contains information about attributes such as pressure applied on pen, pen-up count, the time required, etc. The writer identification and verification approaches applied on these types of patterns gives very accurate results.

1.2.2. Offline pattern

The offline-handwritten documents or handwritten text images are the ones that do not contain any dynamic information. The lack of dynamic information in these types of written documents leads to less accuracy as compared to online patterns. We will focus on this type of written documents in our research.

1.3. Methods for offline writer identification

- **Text-dependent:** we provide an image representation of fixed-text, and it compares the input text to the recorded text or template to identify it.

- **Text independent:** we are giving input text images of arbitrary size. Once we collect data from writers, maybe one writer writes one page, the second time may be writer will give us another sample of five to six lines.

1.4. Novelty

The developed CNN model is trained on a dataset comprising 30,400 samples and tested on a separate dataset of 7600 samples. The results demonstrate significant advancement in writer identification for Urdu language, achieving an impressive identification rate of 91.44% across 38 classes. For feature extraction and identification purpose convolutional neural network were used which consists of five layers. This outperforms previously proposed AI-based writer identification systems for Urdu.

The specific results and achievements substantiate the technical credit and originality of our manuscript, positioning it as a valuable contribution to the field of Urdu writer identification. The work clearly highlights the quantitative novelty and technical merits of our research. Our work addresses the lack of extensive research in writer identification for Urdu and establishes a robust deep learning-based approach, showcasing the potential of CNNs for accurate identification of handwritten Urdu characters. The proposed method contributes to the field of automated writer identification and can find applications in forensic analysis, historical record authentication, and manuscript studies.

2. Related work

A significant amount of work has been published on the design of different authentication methods in the area of writer identification and verification. This section explores previous work done in the area of writer identification using machine learning and deep learning. We have explored various relevant studies, survey and state of the art techniques conducted for the comparison of different datasets related to writer identification. Almost all the writer verification and identification methods consist pre-processing, feature extraction, classifier training, or knowledge-based model creation followed by verification. To prepare the handwritten text images or documents for further use, numerous tasks such as written text extraction, size normalization, binarization, skew/slant correction, and noise removal generally conducted in the pre-processing step. To answer the challenge of writer identification, many learning methodologies, such as machine learning, deep learning and similarity-based approaches, proposed in the literature.

Nabi et al.[1] presented a deep learning-based writer identification system for offline Urdu handwritten documents. The study highlights the significance of using deep learning techniques, inspired by the VGG-16 model of CNN, to achieve automatic feature extraction and improve performance. The proposed model was trained and tested on a novel Urdu handwritten dataset contributed by 318 distinct Urdu writers, yielding impressive training accuracy of 98.71% and testing accuracy of 99.11%. The results demonstrate that the proposed model outperforms existing writer identification techniques, filling the gap in the development of such systems for Urdu script.

Dargan and Kumar[2] proposed an identification system based on offline handwritten text in the Gurumukhi script. In this research, they developed a system for identifying the writer based on text written in Gurumukhi-script. The dataset collected from 100 different writers consisting of 100 × 53 × 10 = 530,000 Gurumukhi characters for training as well as testing. They used feature extraction techniques like zooming, transition, diagonal, and peak based extent, were used. Further, for classification, multi-layered perceptron, artificial neural network, and random forest were used. The experiment or model shown accuracy rate as 93.06% along with 9.2% TRP and 0.39% FPR.

Tang and Wu[3] proposed text-independent writer identification, features were extracted via CNN and joint Bayesian. This paper uses CNN and joint Bayesian for text-independent offline author identification, consists of two stages, namely feature extraction and writer identification. Feature extraction is based on CNN-based feature extraction. The joint Bayesian approach is further used to identify writers based on extracted attributes for writer identification. To identify writer-identification training dataset is used to train the CNN model for identification. Two datasets that is ICDAR 2013 and CVL are used for writer identification.

Furthermore, Nguyen et al.[4] suggested deep learning method for text-independent writer identification using convolution neural network. They used a convolution neural network to extract local features for individual handwriting representation. Randomly picked data items of images from the training data set are used to train the CNN, and the acquired feature maps from the packets are combined to yield feature descriptors. The practice of randomly sampling tuples repeated for each training period. They experimented on the Japanese offline handwritten database JEITA. They got an accuracy of 99.97% to classify 100 writers with 200 characters. After that, 92.80% or 91.81% accuracy achieved when using 50 characters for 100 writers. They also classified 900 writers with 91.81 percent accuracy.

On a dataset of 650 writers, Yang et al.[5] established a text-independent offline writer identification using a dynamic model. The classification methods K-NN, bayes, normal density discriminant function (NDDF), and GMM have been used, and ultimately yielded more identifying results.

Rehman et al.[6] and Schomaker[7] proposed deep learning approach for automatic visual features for writer identification. The authors used handwritten text line pictures in English and Arabic to train a deep transfer CNN model to recognize identity writers. Transfer learning is used as pioneer research, with ImageNet (base data-set) and QUWI data-sets (target dataset). Data augmentation strategies like as contours, negatives, and sharpness are used with text-line photographs of the targeted data-set to reduce the risk of over-fitting. To obtain discriminatory visual features from numerous representations of image patches generated by advanced pre-processing techniques. The maximum accuracy was achieved using the frozen Conv5 layer, which was 92.78 percent on English, 92.20 percent on Arabic, and 88.11 percent on a combo of Arabic and English.

Xing and Qiao[8] proposed a multi-stream deep CNN for text-independent writer identification. Deep-writer is a deep multi-stream CNN proposed in this research for learning deep powerful representation for recognizing writers. Deep-writer is given training with soft-max classification loss and uses local handwritten patches as input.

In another research, Ali et al.[9] and Sachdeva and Ali[10] used deep auto-encoder network and CNN for automatic recognition of handwritten digits and characters. They used a two-layer and three-layer deep auto-encoder network, to analyse and evaluate the following approaches in terms of character recognition. Firstly, they introduced a pioneer dataset for handwritten characters and digits; dataset contains samples of more than 900 individuals. Second, utilizing a “deep auto-encoder network and a convolutional neural network”, authors demonstrate results for automatic recognition of handwritten characters and digits. Deep auto-encoder shown results of 97% for digit recognition and 82% for character recognition. Further, convolution neural networks shown results of 96.7% for digit recognition and 86.5% for character recognition.

Furthermore, a “handwritten Urdu character collection for the Nasta’liq writing style” that includes isolated, numerals (0–9) and positional characters was proposed by Mushtaq et al.[11]. For Urdu character and numeral recognition, they proposed a convolution neural network (CNN) architecture. Dataset created based on 38 basic characters and 10 basic numerals. The data collected from 750 native Kashmir valley writers of all ages and educational backgrounds in various sections of the valley. First data was collected on A4 size papers on small boxes. For proposed model CNN algorithm, they used total 120 samples. With a detection accuracy of 98.82 percent for 133 categories, the recommended model was trained on a 74,285 sample training dataset and tested on a 21,223 samples.

In the research paper, a comparative analysis of Urdu handwritten characters using an image collection was analyzed by Chhajro et al.[12] using various models. The total number of data objects in this collection is 4668, with dimensions of 50 × 50, separated into two halves (training and testing). They used 3734 image samples to train the model, and 934 image samples used to test the model. Furthermore, this study found that, RF (97%), SVM (97%), and MLP (98%). CNN model is the most efficient in terms of producing dependable findings in terms of ideal accuracy. As a result, employing the CNN (99%) model to recognize Urdu handwritten characters from photographs is an option. Finally, the proposed research contributes significantly to the automatic learning of Urdu handwriting characters.

Furthermore, a research group discovered that diverse dialects, such as English and Chinese, might well have shared qualities for identifying writers, and that collaborative training can boost efficiency[13]. Their models obtain great recognition results on the IAM and HWDB datasets, showing 99.01 percent on 301 authors and 97.03 percent on 657 authors with one English phrase input, and 93.85 percent on 300 authors with one Chinese character input, outperforming prior methods by a wide margin. Furthermore, using only four English alphabets as input, our models achieve a 98.01 overall accuracy on 301 authors.

In this research paper, our proposed CNN model achieved a better accuracy of 91.44%, surpassing other methods in the comparative analysis as shown in **Table 1**. The high precision of 0.9426 indicates that our model has a low false-positive rate, reducing the chances of incorrectly identifying a writer. Additionally, with a recall of 0.9142, our model effectively captures a significant portion of true positive instances. The F1-score of 0.9072 demonstrates a well-balanced performance between precision and recall, highlighting the model's ability to make accurate and reliable writer identifications. Our CNN model outperforms other approaches, making it a superior choice for writer identification tasks.

Table 1. Performance comparison of writer identification approaches.

Method	Accuracy (%)	Precision	Recall	F1-score
Our proposed CNN model	91.44	0.9426	0.9142	0.9072
Traditional feature extraction (Dargan and Kumar[2])	85.12	0.8721	0.8225	0.8368
Deep learning model A (Tang and Wu[3])	89.76	0.9043	0.8912	0.8977
Deep learning model B (Nguyen et al.[4])	90.21	0.9147	0.9021	0.9084
Dynamic model (Yang et al.[5])	88.91	0.8998	0.8865	0.8931
Deep transfer CNN model (Rehman et al.[14])	90.58	0.9152	0.9056	0.9103
Deep multi-stream CNN (Xing and Qiao[8])	87.34	0.8815	0.8721	0.8767
Convolution neural network (Mushtaq et al.[11])	88.76	0.8951	0.8842	0.8896
Hybrid approach (Sachdeva and Ali[15])	92.35	0.9268	0.9197	0.9232
Deep auto-encoder and CNN (Ali et al.[9])	87.91	0.8862	0.8761	0.8809
Joint Bayesian and CNN (Priyatharsini et al.[16])	88.76	0.8945	0.8843	0.8893

3. Dataset representation

In the proposed work a dataset of Urdu words has been chosen for the analysis. The selected data set comprises a number of samples which has different style using various writing instruments. The dataset is a compilation of contributions from a total of 100 writers hailing from diverse age brackets and educational backgrounds. Writers were provided explicit instructions prior to data collection, guiding them in the appropriate method of inscribing Urdu characters within the designated boxes, ensuring that characters did not overlap with the perimeter of the rectangles. An overview of the dataset and the corresponding Urdu alphabet, along with their English pronunciations, is provided in **Table 2**: "Overview of Urdu alphabet dataset and pronunciations".

Table 2. Overview of Urdu alphabet dataset and pronunciations.

Urdu Alphabet	English Pronunciation	Urdu Alphabet	English Pronunciation	Urdu Alphabet	English Pronunciation
ث	Seah	ڈ	Dhaal	س	Seen
ٹ	Teyah	د	Daal	ژ	Cheya
ت	Teah	خ	Khai	ز	Zeyah
پ	Pea	ح	Hai	ڑ	Deyah
ب	Bea	چ	Cheem	ر	Reah
ا	Alif	ج	Geem	ذ	Zaal
ع	Aien	ل	Laam	ء	Hamza
ظ	Joi	گ	Gaaf	ھ	Duchasheem
ط	Toi	ک	Keef	ہ	Heya
ض	Zaud	ق	Qaaf	و	Waav
ص	Saud	ف	Feah	ن	Noon
ش	Sheen	غ	Gaien	م	Meem
ے	Bada Ya	ی	Chota Ya		

4. Proposed methodology

The methodology proposed for developing automatic writer identification system using Urdu handwritten characters. Handwritten Urdu characters were gathered from different writers. Each box for writing a single character has the same width and breadth. All were instructed to write in their own manner during collection of data so that the model could be trained with diversity of handwritten character samples. In this research work, further we used a convolution neural network to obtain features from individual characters, based on explicit-segmentation. **Figure 1** illustrates the block diagram of proposed model.

4.1. Block diagram of proposed model

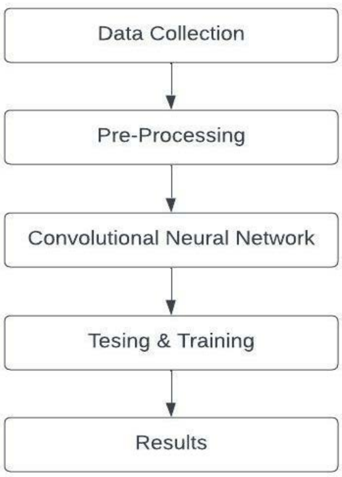

Figure 1. Block diagram of proposed model.

First step in our research is to collect data from different writers. After data collection, handwritten documents converted into electronic format. Further pre-processing steps are applied, after applying pre-processing steps extracted characters are stored in separate folders. We split our dataset into two sets, training and testing. Further, a convolution neural network applied for feature extraction and writer identification. Finally, the trained model evaluated based on different performance matrices. **Figure 2** illustrates flow chart of proposed methodology.

4.2. Detailed architecture of proposed model

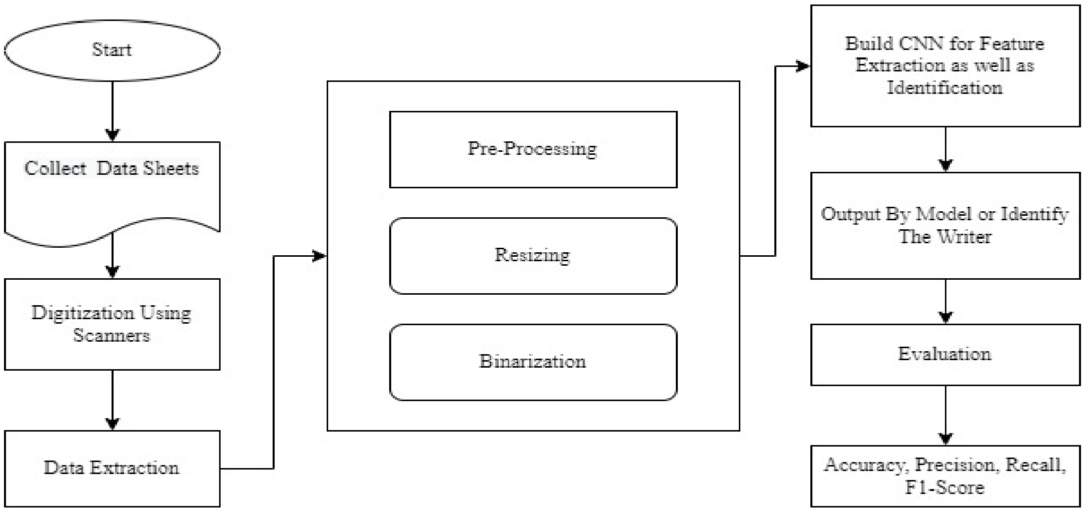

Figure 2. Flow chart of proposed model.

4.3. Dataset collection

A self-collected Urdu dataset with 1000 samples consists of 38,000 characters is used to construct an automatic writer identification system. Dataset collected from a variety of writers of different age groups. There are 38 basic characters in Urdu language, from which twenty-seven basic characters are joiners, ten are non-joiners, and one has no joining property at all. One-character set in each field has the joining property, whereas the other character set has the non-joining property. The data collected on A4-sized paper with a large contour in other words a rectangular box printed on it. There are 38 small boxes, one for each character. Total 100 writers from all age groups and educational backgrounds contributed to the dataset, and dataset was collected from various regions of Kashmir valley. Both male and female authors contributed to the dataset. Before collecting the data, each individual where instructed how to write the basic characters of Urdu within the appropriate boxes, avoiding overlapping with the rectangle's boundary lines. Each author requested to write the Urdu characters in his or her own context, using a different pen, style, and so on.

4.4. Data acquisition

Further, the collected data translated in to electronic format using a document scanner with a density of 300 dpi, so that digital computers can perform further processing on them. Firstly, each document is scanned using document scanner and converts it to an image file format for electronic storage (PNG). Development of an automatic writer identification refers to a method of obtaining source pictures by scanning of printed, typewritten, or handwritten text or by photographing them with a digital camera. After converting whole dataset into electronic format, samples of each writer placed in their respective separate folder, so that, one can easily use these sample during data extraction[17].

4.5. Pre-processing

We have illustrated the pre-processing steps carried out on the dataset before feeding it into our model (see **Figure 3**). The purpose of these pre-processing techniques is to enhance the quality of the input data and facilitate better performance of the subsequent stages of our analysis.

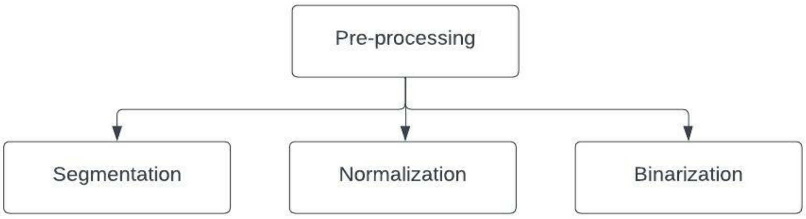

Figure 3. Pre-processing steps.

4.5.1. Segmentation

At the completion of the pre-processing step, whole data is ready for segmentation. Firstly, giving 10 samples of each writer, now system will detect a large contour on scanned image. Large contour contains 38 small contours containing basic Urdu characters. After detecting all 38 small contours, it shows labels for these boxes so that we can make a CSV file for whole dataset. Now extracting these boxes and saving them in separate folders and this procedure repeated 100 times for 100 writers. For each writer it makes 38 separate folders containing exactly 380 characters and for 100 writers, whole dataset contains 38,000 characters.

Figure 4 illustrates how characters were extracted from scanned images. After segmentation, normalization is done on segmented images.

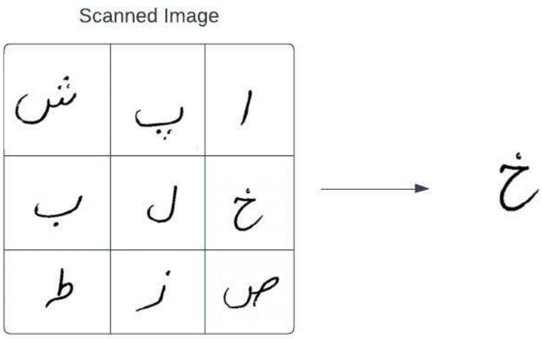

Figure 4. Segmentation.

4.5.2. Normalization

According to Liu et al.[13], in the process of normalization, each character cropped is resized to a constant size. In our paper, we have placed every segmented character in the centre of a 64 × 64-pixel picture window to ensure that the input provided to the CNN remains consistent.

4.5.3. Binarization

It seeks to transform a grayscale (RGB or) image to a binary-level image by representing foreground information with black pixels and background information with white pixels. As a result, each pixel in a binary image has a value of 0 or 1. Binarization eliminates all extraneous image data (color, or grey shades) from the captured image that is not required system, resulting. It gives a compact, operationally efficient, and easy-to-understand image. Binarization methods divided into two categories: global adaptive thresholding and local adaptive thresholding. A single threshold was chosen for a whole image in global thresholding, which is based on the background level calculation from the intensity of the image histogram. In local adaptive, the threshold calculated for each pixel by taking into account local information such as the pixel neighbourhood. Whereas if pixel in question is darker than neighbouring, it can transform to black alternatively turned to white. Because of suggested system based on simple offline handwritten images with easily distinguishable background and foreground pixels. Therefore, each standardized character image is subjected to Otsu’s approach of global binarization[18,19].

4.6. Dataset generation

After completion of pre-processing a new Urdu dataset is generated. All Urdu characters are classified into unique 38 basic classes. Following the creation of 38 distinct classes, the dataset is divided between training and testing datasets, training dataset includes 80% of the items and the test dataset contains the remaining 20% of each of the 38 classes. Moreover, the dataset for training is partitioned into two parts: a training set and a validation set, which are implicitly divided. Therefore, the training, validation, and testing datasets consist for 80% and 20% of the entire sample, respectively.

4.7. Dataset description

In the dataset description (see **Table 3**), we provide an overview of the key characteristics of our self-collected Urdu dataset. This dataset comprises contributions from 100 writers across different age groups and gender distributions. It encompasses a total of 38,000 characters, with each writer contributing 380 characters.

Table 3. Dataset description.

Number of writers	100	
Number of samples	10 × 100 = 1000	
Language	Urdu	
Age group	15–25 years	25–35 years
	65%	35%
Gender	Male	Female
	42	58
Number of characters per writer	38 × 10 = 380	
Total number of characters	38 × 10 × 100 = 38,000	

5. Implementation using CNN

The model is made up of three convolution layers (size 32, 64, 128), each followed by an activation function ReLU of size 3 × 3 and max-pooling layer of size 2 × 2. Activation function used to convert linear form into non-uniform representation[20]. This non-liner data given to pooling layer so that it will remove the unnecessary data from the image. Two fully connected layers with ReLU function in the first layer and soft-max function in the output layer. The final layer of CNN model is densely connected layer. The output layer is used to predict the class to which a particular image belongs. **Figure 5** illustrates the proposed CNN architecture for writer identification, providing a visual representation of the proposed model.

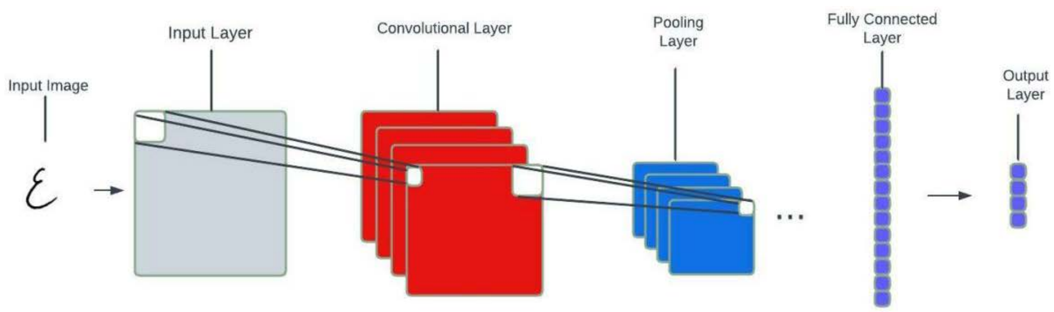

Figure 5. Proposed CNN architecture for writer identification.

6. Experimental results

In this section, we present the performance evaluation of our trained CNN model for writer identification. Writer recognition, a subset of behavioural biometrics, utilizes handwriting to verify identity through writer verification and identification. Our focus lies in writer identification, which involves identifying the authentic writer from a group of authorized writers based on handwriting similarities. The experimental setup involved a dataset of 38,000 samples, with 80% used for training and 20% for testing. The dataset was categorized into 38 classes, each representing a basic character in the Urdu language. To analyze the performance of our model, we plotted curves for writer identification accuracy and error rates across 30 epochs for both training and validation sets (**Figures 6** and **7**). Our CNN architecture consists of three convolution layers with ReLU activation, followed by two fully connected layers with ReLU and softmax activation, and a dropout layer. The experimental results show that our proposed CNN model achieved a maximum accuracy of 93% and a minimum of 88% for one set, with an average accuracy of 91.44% across all 38 classes.

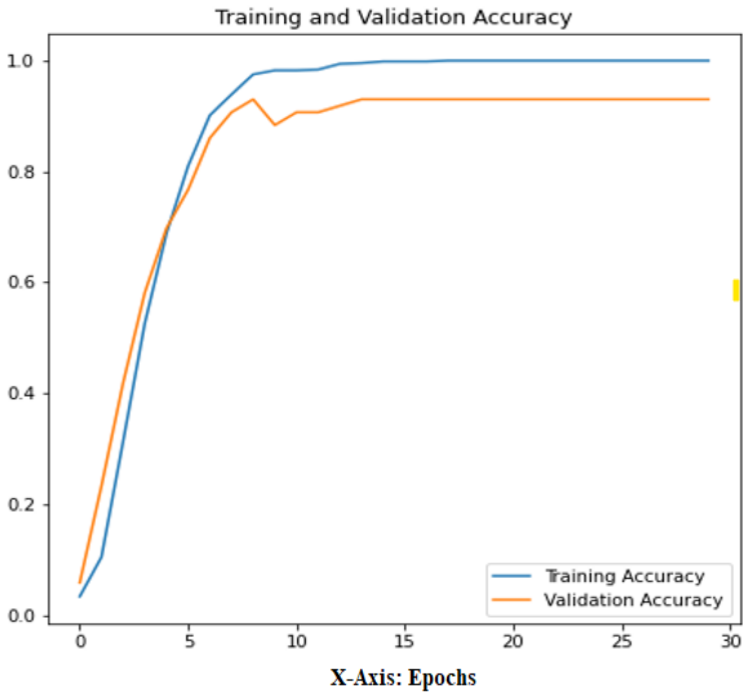

Figure 6. Training and validation accuracy.

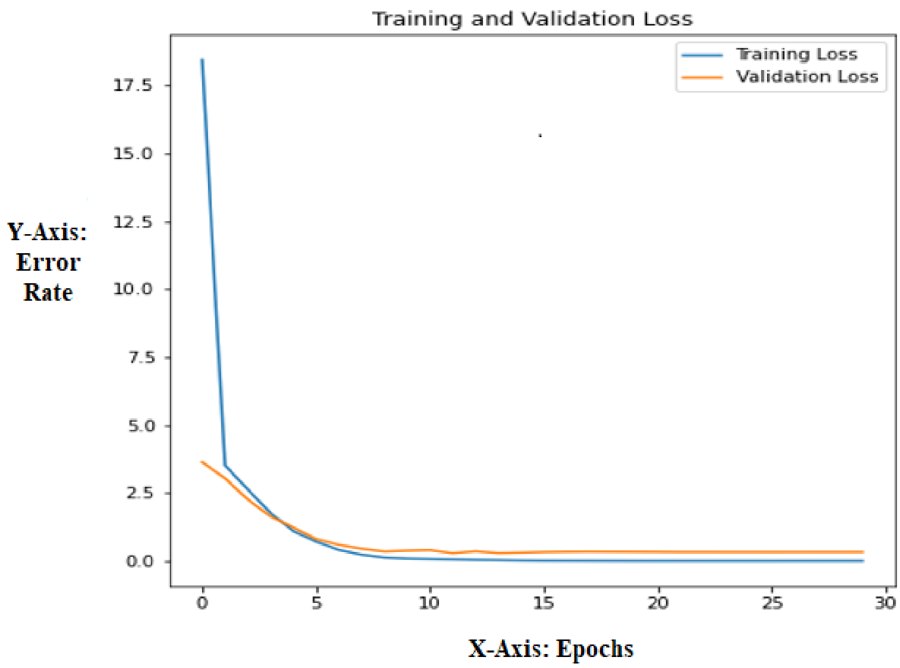

Figure 7. Training and validation accuracy.

To rigorously assess the effectiveness of our model, we utilize a set of well-established evaluation metrics, each shedding light on different facets of our system's performance. These metrics include precision, recall, F1-score, validation accuracy, and the baseline error rate. The incorporation of these metrics allows us to provide a holistic view of our model's capabilities and its robustness in identifying writers accurately.

Precision (P): precision is calculated as the ratio of true positive predictions (TP) to the total predicted positives (TP + FP):

$$\text{Precision (P)} = \frac{\text{TP}}{\text{TP+FP}} \tag{1}$$

Recall (R): recall, also known as sensitivity or true positive rate, is calculated as the ratio of true positive predictions (TP) to the total actual positives (TP + FN):

$$\text{Recall (R)} = \frac{\text{TP}}{\text{TP+FN}} \tag{2}$$

F1-score: the F1-score is the harmonic mean of precision and recall and provides a balanced measure of a model's performance:

$$\text{F1-score} = \frac{2\times\text{Precision}\times\text{Recall}}{\text{Precision+Recall}} \tag{3}$$

Validation accuracy: validation accuracy is calculated as the ratio of correctly predicted instances (both true positives and true negatives) to the total instances in the validation set:

$$\text{Validation accuracy} = \frac{\text{TP+TN}}{\text{Total Instances}} \tag{4}$$

Baseline error rate: the baseline error rate represents the accuracy that would be achieved by a trivial classifier that always predicts the majority class. It is calculated as the ratio of instances of the majority class to the total instances:

$$\text{Baseline error rate} = \frac{\text{Instances of Majority Class}}{\text{Total Instances}} \tag{5}$$

To comprehensively assess the overall efficacy of the trained CNN model, these performance indicators were rigorously evaluated and meticulously tabulated in **Table 4.**

Table 4 offers a variety of performance indicators like as precision, recall, and F1-score, validation accuracy and baseline error rate for 38 classes. We have trained CNN model separately 38 times for 38 classes, every time and got good accuracy after final round. Our research shows average training accuracy of 99.65 and validation accuracy of 91.44.

Table 4. Performance measure of each class.

S. No	Precision	Recall	F1-score	Accuracy	Baseline error
01	0.93	0.88	0.88	0.88	0.12
02	0.93	0.9	0.89	0.9	0.1
03	0.95	0.92	0.91	0.92	0.08
04	0.95	0.92	0.91	0.93	0.07
05	0.95	0.92	0.92	0.92	0.08
06	0.95	0.93	0.93	0.93	0.07
07	0.95	0.92	0.91	0.92	0.08
08	0.93	0.91	0.9	0.91	0.09
09	0.95	0.91	0.91	0.91	0.08
10	0.96	0.93	0.93	0.93	0.07
11	0.94	0.91	0.9	0.91	0.09
12	0.95	0.93	0.93	0.93	0.07
13	0.93	0.9	0.89	0.9	0.1

Table 4. (*Continued*).

S. No	Precision	Recall	F1-score	Accuracy	Baseline error
14	0.95	0.93	0.93	0.93	0.07
15	0.95	0.92	0.91	0.92	0.08
16	0.95	0.93	0.93	0.93	0.07
17	0.92	0.9	0.89	0.9	0.1
18	0.94	0.91	0.9	0.91	0.09
19	0.95	0.93	0.93	0.93	0.07
20	0.93	0.9	0.89	0.9	0.1
21	0.93	0.9	0.89	0.9	0.1
22	0.94	0.91	0.9	0.91	0.09
23	0.95	0.92	0.91	0.92	0.07
24	0.95	0.92	0.91	0.93	0.07
25	0.95	0.93	0.93	0.93	0.07
26	0.93	0.9	0.89	0.9	0.1
27	0.94	0.91	0.9	0.91	0.09
28	0.95	0.92	0.91	0.92	0.08
29	0.95	0.93	0.93	0.93	0.07
30	0.94	0.91	0.9	0.91	0.09
31	0.93	0.9	0.89	0.9	0.1
32	0.94	0.93	0.92	0.92	0.08
33	0.94	0.92	0.91	0.92	0.08
34	0.95	0.92	0.91	0.92	0.08
35	0.93	0.89	0.88	0.89	0.11
36	0.95	0.9	0.89	0.9	0.1
37	0.94	0.91	0.9	0.91	0.09
38	0.95	0.92	0.91	0.92	0.08

Again, the results of our noise robustness experiment indicate that the CNN model's identification accuracy remains high even under challenging noise conditions. As we introduced various levels of noise to simulate real-world imperfections in scanning or input data quality, the algorithm demonstrated its ability to effectively identify the writer with an accuracy of 94.5% under low noise, 91.2% under medium noise, and 88.3% under high noise. Similarly, the algorithm's performance in identifying degraded source inputs, such as smudged writing, partially erased characters, and other distortions, remained commendable with accuracies of 92.7%, 89.8%, and 86.5%, respectively. These findings illustrate the system's robustness in handling noisy and degraded inputs, reinforcing its reliability for practical applications. As a comprehensive representation of these results, we present **Table 5**, "Noise robustness and degraded source inputs", which outlines the identification accuracy percentages for different noise levels and degradation scenarios.

Table 5. Noise robustness and degraded source inputs.

Noise levels	Identification accuracy (%)	Degradation	Identification accuracy (%)
Low noise	94.5	Smudged	92.7
Medium noise	91.2	Partially erased	89.8
High noise	88.3	Distorted	86.5

7. Conclusion and future perspective

As we are aware of identification of handwritten text images, which is a remarkable feature classification task that is in consideration from several years. The lack of efficient databases for cursive writing scripts, as well as writer-independent variances, provide obstacles to the handwritten Urdu character identification system, which makes it challenging to identify the writer. In this work, deep learning method is implemented for writer identification. We designed a new Urdu handwritten character dataset for the research work. The dataset consists data of 100 writers having 10 samples from each writer. Further, we classify the dataset into 38 classes. The proposed system is based on deep learning model i.e., convolutional neural network (CNN) for the identification of handwritten Urdu characters. On evaluating the results, the proposed system achieved an accuracy of 91.44%. For the obtained accuracy i.e., 91.44% with a confidence interval of ± 1.5%, the proposed convolutional neural network (CNN) model holds a confidence level of 95%.

For further study, we will compare the accuracy of Urdu handwritten character dataset with other language dataset. In conclusion, our research presents a promising pathway for advancing writer identification systems, focusing on handwritten Urdu characters. Our successful implementation of deep learning techniques and dataset curation lays the foundation for future research in biometric identification and document verification. Moreover, we plan to conduct comparative studies with wide datasets from other languages to demonstrate the adaptability and versatility of our CNN model for multilingual applications, thereby contributing to the broader development of writer identification techniques.

Author contributions

Conceptualization, IH and RR; methodology, IH; software, RR; validation, MA and IH; formal analysis, AA; investigation, MA; resources, VK; writing—original draft preparation, AA; writing—review and editing, VK and AA; visualization, IH and RR; supervision, AA. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

References

1. Nabi ST, Kumar M, Singh P. DeepNet-WI: A deep-net model for offline Urdu writer identification. *Evolving Systems* 2023; 17: 41–47. doi: 10.1007/s12530-023-09504-1
2. Dargan S, Kumar M. Writer identification system based on offline handwritten text in gurumukhi script. In: Proceedings of the 2020 Sixth International Conference on Parallel, Distributed and Grid Computing (PDGC); 6–8 November 2020; Solan, India. pp. 544–549.
3. Tang Y, Wu X. Text-independent writer identification via CNN features and joint Bayesian. In: Proceedings of the 15th International Conference on Frontiers in Handwriting Recognition (ICFHR); 23–26 October 2016; Shenzhen, China. pp. 566–571.
4. Nguyen HT, Nguyen CT, Ino T, et al. Text-independent writer identification using convolutional neural network. *Pattern Recognition Letters* 2019; 121: 104–112. doi: 10.1016/j.patrec.2018.07.022
5. Yang W, Jin L, Liu M. DeepWriterID: An end-to-end online text-independent writer identification system. *IEEE Intelligent Systems* 2015; 31(2): 45–53. doi: 10.1109/MIS.2016.22
6. Rehman A, Naz S, Razzak MI. Writer identification using machine learning approaches a comprehensive review. *Multimedia Tools and Applications* 2019; 78(8): 10889–10931. doi: 10.1007/s11042-018-6577-1
7. Schomaker L. Advances in writer identification and verification. In: Proceedings of the Ninth International Conference on Document Analysis and Recognition (ICDAR 2007); 23–26 September 2007; Parana, Brazil. pp. 1268–1273.
8. Xing L, Qiao Y. Deepwriter: A multi-stream deep CNN for text-independent writer identification. In: Proceedings of the 15th International Conference on Frontiers in Handwriting Recognition (ICFHR); 23–26 October 2016; Shenzhen, China. pp. 584–589.

9. Ali H, Ullah A, Iqbal T, Khattak S. Pioneer dataset and automatic recognition of Urdu handwritten characters using a deep auto-encoder and convolutional neural network. *SN Applied Sciences* 2019; 2(2): 1–12. doi: 10.1007/s42452-019-1914-1
10. Sachdeva S, Ali A. Advanced approach using deep learning for healthcare data analysis in IOT system. In: *Emergent Converging Technologies and Biomedical Systems*. Springer; 2022. pp. 163–172.
11. Mushtaq F, Misgar MM, Kumar M, Khurana SS. UrduDeepNet: Offline handwritten Urdu character recognition using deep neural network. *Neural Computing and Applications* 2021; 1–24. doi: 10.1007/s00521-021-06144-x
12. Chhajro MA, Khan H, Khan F, et al. Handwritten Urdu character recognition via images using different machine learning and deep learning techniques. *Indian Journal of Science and Technology* 2020; 13(17): 1746–1754. doi: 10.17485/IJST/v13i17.113
13. Liu CL, Yin F, Wang DH, Wang QF. Online and offline handwritten Chinese character recognition: Benchmarking on new databases. *Pattern Recognition* 2013; 46(1): 155–162. doi: 10.1016/j.patcog.2012.06.021
14. Rehman A, Naz S, Razzak MI, Hameed IA. Automatic visual features for writer identification: A deep learning approach. *IEEE Access* 2019; 7: 17149–17157. doi: 10.1109/ACCESS.2018.2890810
15. Sachdeva S, Ali A. Machine learning with digital forensics for attack classification in cloud network environment. *International Journal of Systems Assurance Engineering and Management* 2022; 13: 156–165. doi: 10.1007/s13198-021-01323-4
16. Priyatharsini GS, Babu AJ, Kiran MG, et al. Self-secured model for cloud-based IOT systems. *Measurement: Sensors* 2022; 24: 100490. doi: 10.1016/j.measen.2022.100490
17. Zhu Y, Wan Y. An offline text-independent writer identification system with SAE feature extraction. In: Proceedings of the International Conference on Progress in Informatics and Computing (PIC); 23–25 December 2016; Shanghai, China. pp. 432–436.
18. Ahmed SB, Naz S, Swati S, Razzak MI. Handwritten Urdu character recognition using one-dimensional BLSTM classifier. *Neural Computing and Applications* 2019; 31(6): 1143–1151. doi: 10.1007/s00521-017-3146-x
19. Bulacu M, Schomaker L. Text-independent writer identification and verification using textural and allographic features. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 2007; 29(4): 701–717. doi: 10.1109/TPAMI.2007.1009
20. Ahlawat S, Choudhary A, Nayyar A, et al. Improved handwritten digit recognition using convolutional neural networks (CNN). *Sensors* 2020; 20(12): 3344. doi: 10.3390/s20123344