A novel personal identification method using Convolutional Neural Network and Long Short Term Memory: A hybrid method

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Abstract-

Iris, fingerprint and DNA are the most prominent technology specifically used for personal identification purposes. The iris recognition is not so efficient due to the wavering morphological variations of devices. It leads to a huge challenge for the conventional processing methods like cognitive and statistical learning during the identification process. The availability of dataset and classification approaches makes a barrier to fulfilling the learning requirements under the learning framework. This research considers multi-level feature fusion concept and three different datasets like iris, fingerprint, and DNA datasets are considered for validation thus, this research concentrates on modeling a hierarchical method to measure both the spatial and temporal features using Convolutional Neural Networks and Long Short Term Memory (CNN-LSTM) to predict the personal identification. The proposed hierarchical model works for processing the image at the initial stage and recognition/prediction model by transforming the image into a recognition label. The prediction module is based on a statistical learning process that includes ReLU, different input gates of LSTM, and Dense with ReLU. The dataset is collected from the online available Kaggle repository, and the experimentation is validated with various prevailing methods in terms of average training and validation accuracy. This hybrid model outperforms the prevailing methods and shows superiority to other models.

Keywords- Iris recognition, DNA recognition, morphological variation, spatial and temporal features, convolutional neural network, long short-term memory

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1. Introduction

Biometric identification technology is widely used in the personal recognition and commercial security fields wherein iris and fingerprint dataset are widely considered [1-5].Generally, the iris dataset is utilized for personal recognition [6] hence it does not provide efficient recognition results due to uncertain morphological variation of devices. Besides, fingerprint validation is a traditional method and has been widely used in forensic departments [7] and personal recognition [8]. The following pitfalls are the major problem in the identification process using fingerprints such as (i) if the fingerprint area is scratched or damaged, (ii) physically challenged persons, (iii) if the fingerprint area is covered by other artificial skins. Furthermore, nowadays deoxyribonucleic acid (DNA) sequences are also utilized to identify the person, bio-cyber security, bioinformatics software applications, advance scientific research [9], autonomous internet of think systems [10]. In biometrics and bioinformatics, utilization of DNA sequence has some issues such as storage of information is difficult due to infinite sequence of data, easy to hack, and DNA information is not 100% accurate. Therefore, a few pieces of literature

were proposed their recognition methods with the combinations of iris with fingerprint [11,12] and fingerprint with DNA [13,14].

Based on the works of literature, it is not enough to produce the accuracy of identification or recognition of the person with single or two dataset combinations therefore it is needed to propose a combination of three datasets like iris, fingerprint, and DNA sequence for personal identification tasks. In the view of technology part of the proposed methods, most of the early works implemented using image processing and machine learning techniques. For more than five decades, image processing techniques are playing a vital role in personal identification or recognition [15-18]. Similarly, machine learning-based personal identification methods were proposed in [11, 19-24]. However, still, the problem is unable to fix in terms of accuracy.

To overcome the above-mentioned issues, this paper proposed a hybrid method (Convolutional neural network with long short-term memory) named CNN-LSTM and tested on the combination of iris-fingerprint-DNA sequences. A detailed discussion of CNN and LSTM is presented in section 3. Additionally, this paper has been gathered useful information in the utilization of iris, fingerprint, and DNA sequence datasets.

This paper is organized as follows: Section 2 discusses the existing related works which include existing hybrid methods and other techniques approached in the existing methods. Section 3illustrates the introduction to techniques involved in the proposed method and the detailed discussion of the proposed method. In section 4, the implementation and results of the proposed method are discussed. Conclusion and future scope are presented in section 5.

2. Related works

Generally, most of the existing works of literature are focused on personal identification using any one of the techniques from artificial intelligence with datasets iris, fingerprint, and deoxyribonucleic acid (DNA)sequence. A few pieces of literature were proposed a hybrid technique. This literature survey is mainly focused to review the early published articles in terms of single and hybrid techniques involved in their proposed methods.

Most of the researchers incorporated the combination of CNN and LSTM in speech detection. Particularly, in hate speech detection, Ziqi Zhang et. al. [25] proposed a convolution-LSTM based deep neural network which handled an extensive evaluation of the large collection of publicly available speech datasets. Similarly, Jiarui Zhang et. al.[26] proposed a hybrid of LSTM and CNN to improve the performance of the relevance of context and complex abstraction of semantic information of the text. The historical information in long text preserved by LSTM and the local features were extracted by CNN. The analysis of secondary stock market done with CNN-LSTM proposed by Yu Wen et. al. [27] wherein the market changes have been analyzed.

To predict the ozone concentration, the combination of CNN and LSTM was proposed to extract the features of air quality data and process on time series data [28]. Y. Lu and H. Li [29] proposed an automatic lip-reading system using CNN with RNN and attention-based LSTM. The CNN with RNN was used for image feature extraction and LSTM was used to learn sequence information. Wenjie Lu et. al. [30] approached a hybrid model to predict the stock price. Initially, the CNN was used for feature extraction then LSTM was applied to predict the stock price with the extracted features. A hybrid of deep convolutional neural networks (DNN) and bidirectional long short term memory (BLSTM) was proposed for automatic speech recognition [31] where spatial and temporal properties were considered. This method was approached to improve the continuous speech recognition task.

Recently, the combined deep convolutional neural network with LSTM [32] was proposed to detect the COVID-19 on the x-ray images. The CNN and LSTM were used to extract features and predict the COVID-19 using extracted features, respectively. Omar Alharbi [33] approached a combined CNN and Bi-LSTM with Support Vector Machine (SVM) classifier for analysis and classification of Arabic sentiments where the linear SVM classifier was used for embedded vectors obtained from CNN and LSTM. Theautoencoder-based hybrid CNN-LSTM model [34] was proposed to predict COVID-19 from lung ultrasound. This method approached the severity estimation of the basic lung ultrasound (LUS). A fivefold validation has been done to improve the efficacy of the method.

The aforementioned literature is considered a dataset with hybrid techniques. However, the accuracy of the existing methods is still not up to the level. Therefore, in this current study, the hybrid method of CNN-LSTM is proposed, and it has experimented on three different datasets to prove the improvement of the accuracy.

3. Methodology

The proposed model is a hybrid method comprised of CNN and LSTM to perform spatial and temporal analysis on the three different datasets. As per the literature [35-37], the spatial-temporal features are well utilized by many existing works particularly in time series forecasting. Generally, the CNN can extract the spatial features of the data whereas the LSTM can acquire the temporal features of the data. Thus, the present work makes a hybrid CNN-LSTM method for personal identification using iris, fingerprint, and DNA datasets. Figure 1 shows the flow diagram of the proposed method.

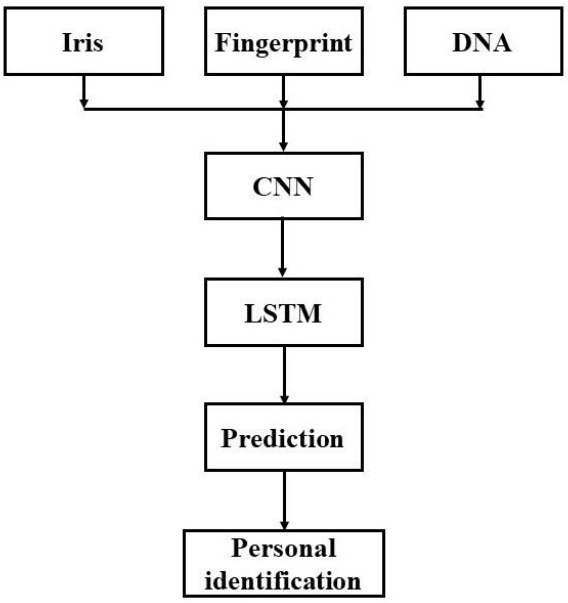

Figure 1: Flow diagram of the proposed method

3.1 Convolutional neural networks (CNN)

Convolutional Neural Networks (CNN) are derived from biological neural networks and involve multilayer perceptron [38].Furthermore, it is a well-known state-of-art technique in the field of image classification, face recognition, object identification, etc., [39-41]. Generally, CNN is used for feature extraction and classifications where different layers are involved such as input, output, and hidden layers. Multiple convolutional layers are included in the hidden layer which convolves with the dot product. Particularly, the pooling layer is utilized for reducing the number of constraints in the input. Additionally, the important features can be extracted from an image by CNNs using local spatial coherence which gives good performance on image classification problems. A simple CNN architecture is shown in Figure 2.

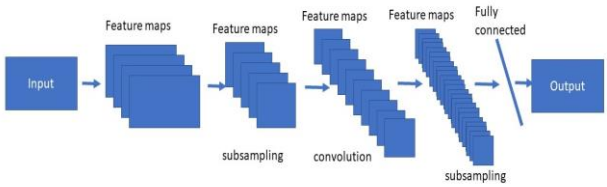

Figure 2: A simple CNN architecture

3.2 Long Short-Term Memory (LSTM)

Various sequential processing problems in language modeling, speech recognition, and others [42-44] have been solved by Long Short-Term Memory (LSTM) neural networks. Last two years, LSTMs have been used for covid-19 detection and forecasting fields. Based on the results obtained from the early works done by LSTM for the handling of time-series data, this study incorporated the LSTM. An LSTM cell consists of three gates such as input, forget and output gate. The LSTM cell is shown in Figure 3 and the mathematical representation is presented from equations 1 to 6 as follows:

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \quad (1)$$

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \quad (2)$$

$$\bar{C}_t = tanh(W_c.[h_{t-1}, x_t] + b_c) \quad (3)$$

$$C_t = f_t \times C_{t-1} + i_t \times \bar{C}_t \quad (4)$$

$$O_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \quad (5)$$

$$h_t = o_t \times \tanh(C_t) \quad (6)$$

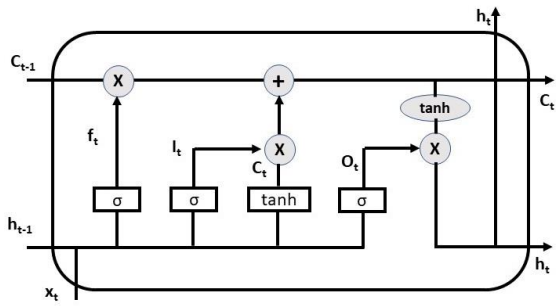

Figure 3: The LSTM cell

As shown in figure 3, C_{t-1}, h_{t-1}, and x_t are three inputs, respectively. The f_t, i_t, c_t, and o_t are the forget, input, memory cell, and output gate, respectively. In equations 1 to 6, W and b are representing the weight matrices and bias vector. σ indicates the sigmoid function.

In an LSTM cell, the main entry date, input fate is extracted with new data at time *t* and is capable of deciding or decision making on the information which processes. The processes of regulation and removing of information from the cell have been done with forget gate.

3.3 The proposed CNN-LSTM method

In this paper, the proposed method comprises the 1D convolutional layer in the CNN architecture which can be utilized for the extraction of important features. Then the extracted features will be input to the LSTM network which can be learned the information. Therefore, this hybrid of CNN-LSTM layers is lightweight, and it provides accurate results with less computation complexity.

The architecture of the proposed method is illustrated in Figure 4 which comprises CNN, LSTM, and dense layers. In the convolutional layer, a kernel is created to produce the outputs by convolving with a single spatial dimension. The ReLU (Rectified linear unit) is used as an activation function in this layer. The LSTM layers are playing a vital role in this architecture in terms of learning the sequences and patterns available in the data to make the correct decision.

Finally, two dense layersare used to predict the exact output. The structure of the proposed method is shown in Table 1.

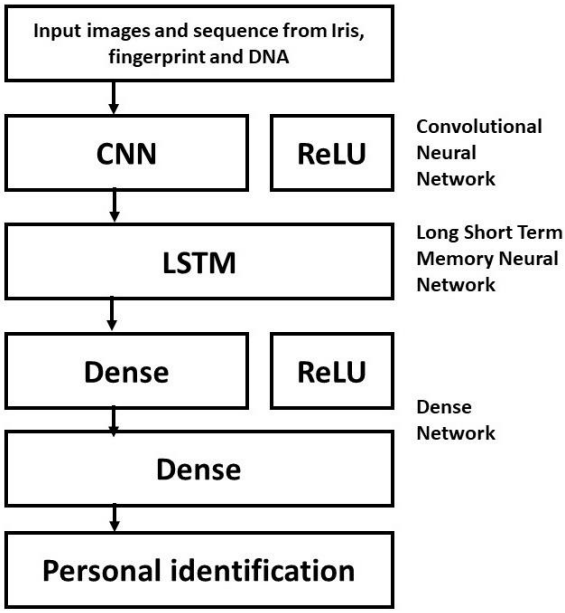

Figure 4: The architecture of the proposed hybrid method CNN-LSTM

Table 1:Structure of the proposed method

Type of layer	Shape of the output	Parameters
CON1D	32	182
LSTM	64	24632
Dense_1	30	850
Dense_2	10	190
Lambda	1	0

4. Experiment and Results

Many personal identifications have been done by researchers in the earlier articles using anyone among the dataset like iris, fingerprint, and DNA sequences. The present work not only focuses on the development of the hybrid method but also considers the experiment on the above-said datasets combinedly which might produce more accuracy than the individual applicability on the dataset. The proposed method is implemented on the following configured system:11th generation Intel Core i7 process with 16GB RAM.

4.1 Datasets

In this paper, various datasets like iris, fingerprint, and DNA sequence are collected from the Kaggle repository.

The iris eye images were collected from MMU-iris-database which consists of 460 eye images including a few empty images. The images include left and right eye images. The link to the dataset is as follows: https://www.kaggle.com/naureenmohammad/mmu-iris-dataset.

The fingerprint images werecollected from the following link: https://www.kaggle.com/peace1019/fingerprint-dataset-for-fvc2000-db4-b/discussion which contains 800 images.

The DNA human sequenceswere collected from the following link: https://www.kaggle.com/singhakash/dna-sequencing-with-machine-learning which contains approximately 6 billion letters of 'A', 'C', 'G', and 'T'.

Figure 5 illustrates the sample iris, fingerprint images, and DNA human sequence

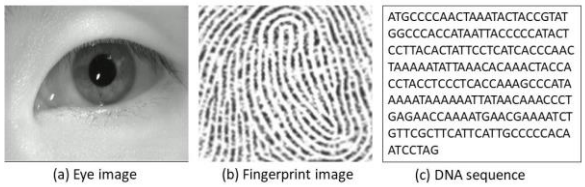

Figure 5: Sample images and DNA sequence from the chosen dataset

4.2 Results

The proposed hybrid model (CNN-LSTM) is applied to the publicly available image datasets as mentioned in the previous section. The proposed method is validated and compared against CNN and LSTM these are applied on each dataset and the average training accuracy and validation accuracyare calculated where the identical parameters were kept for all experiments.

Table 2 shows that the average training accuracy and average validation accuracy of the proposed method compared with other methods. The proposed hybrid method provides the average training accuracy of 89.567% and average validation accuracy of 90.256%, and other methods CNN and LSTM provide the average training accuracy of 85.167% and 86.628%, and the average validation accuracy and 86.983%, 85.587%, respectively. Based on the accuracy, the proposed hybrid method is significantly higher than the other compared methods.

Table 2: Average accuracy comparison over Iris, Fingerprint, and DNA datasets.

Method	Average training accuracy (%)	Average validation accuracy (%)
CNN-LSTM	**89.567**	**90.256**
CNN	85.167	86.983
LSTM	86.628	85.587

5. Conclusion

Personal identification is an important application in a wide variety of fields and needs effective performance with appropriate accuracy. While identifying or recognizing the person, the contribution of biometric data is important, and the accuracy is based on the taken data. In this article, the iris, fingerprint, and DNA sequence datasets are considered to obtain more accuracy in personal identification wherein a hybrid method using CNN-LSTM is proposed and experimented on three different datasets. The experiment with three different datasets shows that this proposed method has achieved better accuracy than the compared methods CNN and LSTM. The LSTM served as superior feature extraction, and it is supported to increase the accuracy of the CNN. Finally, the proposed method provides 89.567% of average training accuracy and 90.256% of average validation accuracy which were significantly higher than compared methods. Therefore, the hybrid method CNN-LSTM is outperforming in the personal identification using three different biometric datasets and this method will lead to the researchers in a new perception.

In the future, the CNN-LSTM will be optimized in terms of additional layers, and the number of dense increases. Furthermore, the filters in convolution also are modified. Additionally, the CNN-LSTM will be extended with RCNN-LSTM.

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