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ORIGINAL RESEARCH

Automatic attendance system based on CNN–LSTM and face recognition

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Abstract In the era of the Covid-19 pandemic, the education system has undergone a significant shift from traditional offline classes to online modes of learning for students. However, keeping track of student attendance, both in offline and online modes, has become a time-consuming task. To address this issue, various automated attendance systems have been proposed, utilizing technologies such as biometric recognition, barcodes, QR codes, and mobile devices. However, earlier algorithms used in these systems have shown poor accuracy and inefficient processing times. To overcome these limitations, this paper proposes a method that leverages face recognition technology, specifically a combination of convolutional neural network (CNN) and long short-term memory (LSTM) models, to track course attendance. The combination of CNN–LSTM in attendance system is novel concept. This proposed method can be applied in both the online and offline phases of education with minor modifications. The proposed method captures both spatial and temporal information, resulting in improved accuracy. The experimental findings reported in the paper demonstrate the effectiveness of the proposed attendance system. It achieves an impressive face recognition accuracy of 99.82%, surpassing the performance of state-of-the-art methods used in similar applications with faster runtime of 6.93 s. This high accuracy rate implies that the system can reliably identify and track student attendance, ensuring accountability and providing valuable data for academic institutions.

Keywords CNN–LSTM · Attendance · Face recognition

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1 Introduction

Evaluating student attendance is a crucial aspect of assessing their active participation and engagement in educational institutions [1]. However, measuring attendance manually can be a time-consuming and energy-intensive task [2]. The traditional manual methods of taking attendance often involve calling out students' names or using attendance sheets, which are prone to inefficiencies and can be susceptible to fraudulent practices [3]. To address these challenges, the development of an automatic attendance system has been proposed [4]. Such systems utilize both non-biometric and biometric techniques to monitor and track student attendance. Non-biometric identification systems are typically complex and offer advantages such as high accuracy and ease of implementation [5–7]. However, they also have drawbacks. For example, in non-biometric solutions, attendance can be recorded by anyone if they possess the object identification (OID) used for attendance tracking [8]. While non-biometric solutions provide precise results and are relatively easy to deploy, the reliance on objects or tokens for attendance verification introduces vulnerability. If a student fails to present their assigned OID, someone else can potentially use it on their behalf, leading to inaccuracies in attendance records and potential misuse of the system [8]. To overcome these limitations, biometric-based attendance systems have been developed. Biometric techniques, such as fingerprint recognition, iris scanning, or face recognition, uniquely identify individuals based on their biological or behavioral characteristics. These methods offer higher security and reduce the chances of proxy attendance. However, biometric systems may require more advanced infrastructure and may raise privacy concerns that need to be addressed in their implementation.

Various biometric features, such as face, palm, iris, and fingerprint recognition, are employed in different systems to track attendance [9–12]. The primary advantage of using biometrics is that an individual can be identified based on their unique physical characteristics. However, some of these approaches have certain limitations. The fingerprint recognition method is often compared to the traditional manual attendance system [13]. In this method, students are required to place their fingertips on a fingerprint scanner, and after a brief processing period, their attendance is recorded as present [14]. However, if each student takes a few seconds for scanning, the overall time required for the entire process can be significant. This time-consuming aspect is also applicable to iris scanning, which involves scanning the unique patterns of the iris [15]. As a result, applications that rely on fingerprint or iris scanners often face challenges related to time consumption [16].

While biometric systems offer high accuracy and reliable identification, the processing time required for each individual can impact the overall efficiency of the attendance tracking process. The time taken for scanning and processing multiple students' biometric data can accumulate and become a significant factor in the overall duration of the attendance process. It is important to consider these time constraints when implementing biometric-based attendance systems. Steps can be taken to optimize the scanning process, improve the speed of recognition algorithms, or utilize parallel scanning techniques to reduce the time required for each individual's identification. Additionally, proper planning and system design can help ensure that the overall attendance tracking process remains efficient, even with biometric-based methods.

The automatic attendance system operates according to the block diagram shown in Fig. 1. The process begins with capturing the image of the student, followed by the application of a face detection mechanism to identify the presence of a face in the image. Subsequently, a face recognition algorithm is employed to recognize the specific student, and if the recognition is successful, the attendance is updated in the database. Hence, the automatic attendance system can be viewed as a multi-step process.

Implementing face recognition in real-world scenarios poses significant challenges due to the vast diversity of facial images encountered [17]. Convolutional neural networks (CNN) have proven to be effective in addressing various computer vision problems. CNN-based face recognition algorithms have achieved remarkable performance, as they can adapt robust features to handle the variations encountered in real-life face images used for training [18]. The incorporation of CNN technology can help overcome the challenges associated with biometric identification-based approaches.

This research article introduces an attendance registration system that utilizes a CNN–LSTM face recognition method. Long short-term memory (LSTM) is a type of recurrent neural network (RNN) that can capture long-term dependencies in sequential data, thereby reducing complexity and enhancing performance [19]. Additionally, the proposed system employs data augmentation techniques to minimize over-fitting and handle issues related to limited sample sizes.

By combining the strengths of CNN for effective feature extraction and LSTM for handling temporal dependencies, the proposed attendance system aims to improve the accuracy and reliability of face recognition in the context of attendance tracking. Moreover, the inclusion of data augmentation techniques mitigates the limitations arising from a small number of available training samples.

The following is a summary of this article's objectives:

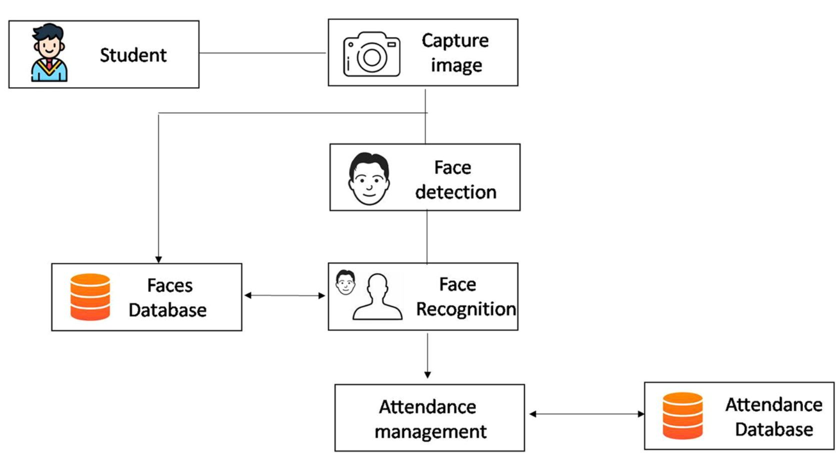

Fig. 1 Block diagram of automatic attendance system

1. By combining deep feature extraction with long short term memory (LSTM) classification, we can offer the simplest and most efficient automatic attendance system.
2. It has been demonstrated through experimentation that the CNN with LSTM classification achieves incredibly high image classifier accuracy.
3. Facial recognition and face counting are combined to increase system performance.
4. By taking pictures within the lecture hall with just one camera, the system's cost has been kept to a minimum.

The rest of the paper is organised as follows; in Sect. 2 of the paper, literature survey regarding the automatic attendance system is presented. The proposed automatic attendance system is detailed in the Sect. 3 of the paper. The results and discussion of the proposed automatic attendance system are presented in Sect. 4 of the paper. The major conclusions of the paper are discussed in the Sect. 5.

2 Literature review

Automatic attendance-taking systems have gained significant success in various research studies. Several approaches have been proposed to improve the accuracy and efficiency of these systems. Sanli and Ilgen [20] proposed a camera-based approach for self-recording attendance by capturing pictures of students. They utilized principal component analysis and local binary pattern histograms (LBPH) techniques for object recognition, specifically facial recognition. The system achieved a performance rate of 75% effectiveness. However, it is worth noting that modifying the employed algorithms could potentially enhance the facial recognition efficiency on these systems. Pei et al. [21] presented a Deep Learning-based method using the VGG-16 model for recording attendance. The model was trained on 3538 students' faces and evaluated on 372 photographs. However, the training process for this technique is time-consuming, taking approximately 8 h. Furthermore, the proposed method achieved a recognition accuracy of only 86.3%, which is considered relatively low. Indra et al. [22] developed a method based on Haar-like features for facial recognition patterns in attendance systems. Khan et al. [23] proposed a face recognition system using the YOLO V3 algorithm. However, the computational resource requirements for running these systems on the CPU are high, making them less suitable for real-time face identification. Setialana et al. [24] introduced a deep convolutional neural network (CNN) based attendance system. The system achieved an accuracy rating of 81.25% for recording student attendance. However, the study did not evaluate the system's accuracy under different lighting conditions or with various camera qualities, which may affect its performance. Shah et al. [25] developed a facial recognition-based automatic attendance system with an accuracy of 93.1%. However, the accuracy of this system is significantly influenced by image noise, making it impractical for real-time person identification. A summary of the literature survey is presented in Table 1.

To address the challenges and limitations of existing methods, a proposed system utilizes CNN and LSTM. This system aims to quickly and accurately identify student faces in real-time for the purpose of attendance-taking. CNN is employed to extract deep features from the facial images, while LSTM captures long-term dependencies, reducing complexity and enhancing accuracy. By combining these techniques, the proposed system aims to overcome the challenges related to recognition accuracy in attendance systems.

The application of attendance systems has proven to be useful in various scenarios. One such scenario is during the Covid-19 pandemic, where attendance systems have been employed to limit the total number of students in classes [26]. By tracking and monitoring attendance, educational institutions can ensure compliance with social distancing guidelines and maintain a safe learning environment.

In addition to physical attendance management, attendance systems also find application in online settings. Online

Table 1 Literature survey of the notable methods

Authors	Proposed method	Accuracy	Limitations
Sanli and Ilgen [20]	Camera-based approach with object recognition	75%	Facial recognition system can be improved with algorithm modifications
Pei et al. [21]	Deep learning-based method using VGG-16	86.3%	Lengthy training time (8 h), recognition accuracy could be further improved
Indra et al. [22]	Haar-like features method with facial patterns	–	Slower, not suitable for real-time face identification
Khan et al. [23]	Face recognition using YOLO V3 algorithm	–	Slower performance when running on CPU, not suitable for real-time face identification
Setialana et al. [24]	Deep convolutional neural network-based system	81.25%	System accuracy not evaluated under different lighting conditions or with varying camera qualities
Shah et al. [25]	Facial recognition-based attendance system	93.1%	Accuracy affected by image noise, impractical for real-time person identification

attendance systems enable the automatic storage of attendance data in the cloud, particularly in Internet of Things (IoT) applications [27]. With the integration of IoT technology, attendance data can be collected remotely and securely stored in cloud-based platforms. This eliminates the need for manual data entry and provides convenient access to attendance records for both administrators and students.

3 Proposed method

The various stages of the system deployment life cycle are shown in Fig. 2. The foremost step is student data collection. For this data acquisition interface is developed and data is acquainted and collected data is stored. In the second step is model development, in this stage input image is captured, and face is extracted, using face detection and transformation phases. Finally, CNN–LSTM model is applied and face is recognised. In the next phase, model is trained and tested. For this data is divided into three parts, i.e., training, validation and testing. The CNN–LSTM model is trained using training data and classifier is used classification. Once model is trained with minimum loss function, the model parameters are kept fixed. On the trained model testing is performed. Finally, the model evaluation is done in terms of precession, recall, F-score, accuracy and error.

3.1 Dataset creation

In the method proposed here, ten images are shot perpendicularly of each student. Each of these images is taken from a different angle, side view, distance and facial emotions. These images which are taken are all saved in PNG format in a dedicated folder for each student. During this phase, a data augmentation method was used to reduce model over-fitting and enhance the model's generalisability [28]. Each image undergoes a 20° range of rotation during the augmentation procedure. Moreover, the zoom and shear were both set to 20%, and eventually it is kept the blurring, noise, and actual horizontal flip. The data augmentation approach is used to enhance the uploaded photos and 45 modified variants of the original photos are produced for each image. To design a classifier for face recognition, 2800 images of faces were used to develop the face image data set.

3.2 Model creation

In the model creation there are various sub-processes which are detailed in next a few sub-section.

3.2.1 Face detection

In order to identify the faces in an image, one uses the Histograms of Oriented Gradient (HOG) approach. For extracting

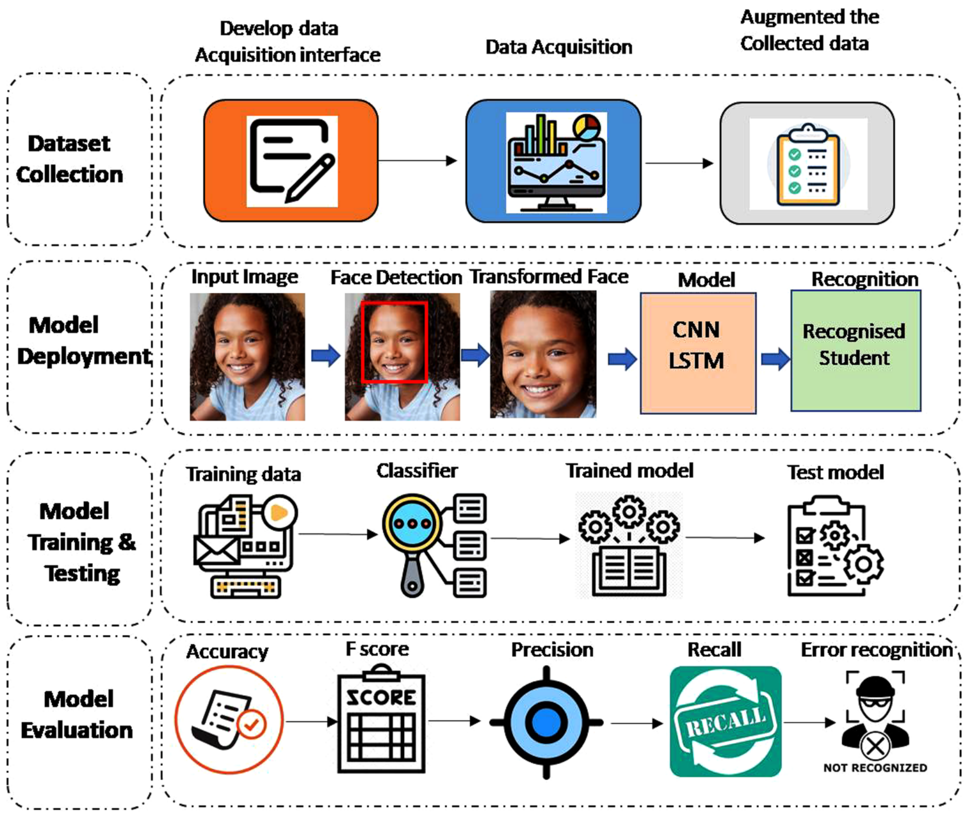

Fig. 2 Detailed diagram of automatic attendance system

data features from image, feature descriptors like HOG are frequently utilised. It is commonly used for object detection in computer vision tasks. HOG serves as a suitable descriptor for face and object identification particularly [29]. The HOG algorithm measures how dark a given pixel is in comparison to its immediate surroundings.

3.2.2 CNNs

Among the various DLTs, the most effective one is CNN, which can operate with multiple hidden layers. It can convolve these hidden layers and sub-sample for extracting features from input data. CNN basically have following layers: (i) Convolution layer (ii) sub-sampling/pooling, (iii) fully connected layers [30] (Fig. 3). CNNs are primarily used here for the purpose of extracting feature and classification. Many convolutional layers are applied for this and after that, max-pooling and activation functions are applied. Layers that are totally coupled together often make up classifiers.

(A) Convolution layer

In this research, the convolution layer acts as an important part CNNs and is quite useful in extracting features. In this layer, input features are convolved with a filtering kernel to produce n output features that are recognised from input images. The kernel and input feature maps of size $i * i$ are convolved to produce the output features.

There are a number of convolution layers in CNN, and the output features serve as the inputs for more convolution layers. Every convolution layer (CL) consists of set of filters that are convolved with inputs to produce feature maps. Keep in mind that every filter map is regarded as a well defined feature at a particular location in the inputs. The output obtained from the lth CL which is represented by $C_i^{(l)}$, include feature maps that were calculated using Eq. (1)

$$C_i^{(l)} = B_i^{(l)} + \sum_{j=1}^{a_i(l-1)} K_{i,j}^{(l-1)} * C_j^{(l)} \tag{1}$$

In the given equation, bias matrix is represented by $B_i^{(l)}$ and $K_{i,j}^{(l-1)}$ is convolution filter that establishes a connection between the ith feature map in the current layer and the jth feature map in the preceding layer. The feature maps is consisted by $C_i^{(l)}$. Feature map is generated by the kernel. For non-linear transformation of the outputs, the activation function is used after the convolution layer and can be written as

$$Y_i^{(l)} = Y\left(C_i^{(l)}\right) \tag{2}$$

Here, $Y_i^{(l)}$ represents activation function output. The used activation function is ReLUs and formulated in Eq. (3).

$$Y_i^{(l)} = \max\left(0, Y_i^{(l)}\right) \tag{3}$$

Because they lessen interactions and nonlinear effects, RELUs are utilised in DLTs. ReLUs transform outputs to 0 when the input is negative, but they leave positive values alone. The primary advantage of activation functions is that they facilitate faster training based on an error derivative, which shrinks significantly in the saturating region and results in almost total disappearance of weight updates, also known as the vanishing gradient problem.

(B) Pooling layer

This layer's primary goal is to decrease the dimensionality of incoming feature maps produced by earlier convolutions. The mathematical representation of the sub-sampling process between feature maps and masks is Eq. (4).

$$X_j^l = f\left(\beta_j^l \,\mathrm{down}\left(X_j^{l-1}\right) + b_j^l\right) \tag{4}$$

Here,down$(\cdot)$ is defined as a sub-sampling sums. The multiplicative bias and additive bias b of each output map are unique.

(C) Fully connected layer

The features extracted by the CLs and were sampled with the help of pooling layers that made up the final output of the network. The likelihood for each class in classification tasks are a subset of layers that are fully linked. The output is written as

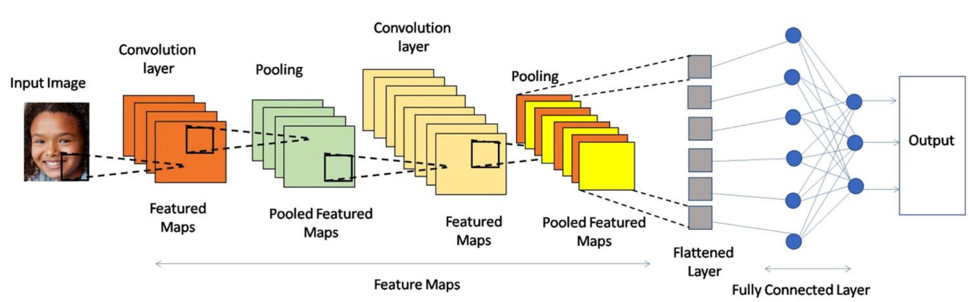

Fig. 3 CNN structure

$$Y_i^{(l)} = f\left(z_i^{(l)}\right) \tag{5}$$

where 'f' is softmax activation function.

$$z_i^{(l)} = \sum_{i=1}^{m_i(l-1)} w_{i,j}^{(l)} y_i^{(l-1)} \tag{6}$$

In the above equation,$w_{i,j}^{(l)}$ are the weights.

3.2.3 LSTMs

The LSTMs, a subclass of re-current neural networks (RNNs) is more effective than conventional RNNs as it can capture long term dependency [31, 32]. A conventional LSTM cell comprising input (i), forget (f), and output (o) gates as well as a cell activation component such as sigmoid and tanh is shown in Fig. 4. These devices use certain multipliers to control cell activations after receiving activation signals from various sources. In the preceding equations 'w' represents the weight and 'b' represents the bias of respective gates. The time stamp is denoted by 't'.

The definition of the LSTM's input gate (i) is

$$i_t = \sigma\left(W_{xi}x_t + W_{hi}h_{t-1} + b_i\right) \tag{7}$$

where 'σ' is sigmoid function.

The definition of the forget gate (f) is

$$f_t = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f\right) \tag{8}$$

The definition of the cell gate (c) is

$$c_t = f_t c_{t-1} + i_c \tanh\left(W_{xc}x_t + W_{hc}h_{t-1} + b_c\right) \tag{9}$$

The definition of the output gate (o) is

$$o_t = \sigma\left(W_{x0}x_t + W_{h0}h_{t-1} + W_{c0}c_t + b_0\right) \tag{10}$$

At last, the hidden state (h) can be computed as

$$h_t = o_t \tanh\left(c_t\right) \tag{11}$$

Using the above definitions data can be passed or forget depending on the usefulness of the data. The proposed

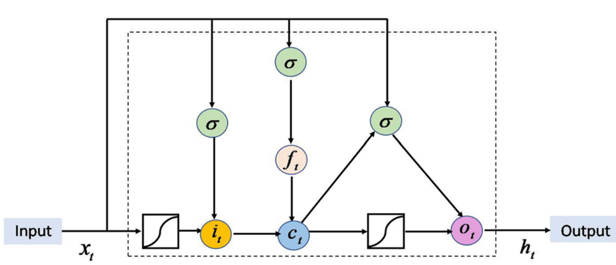

Fig. 4 LSTM structure

CNN–LSTMs method uses multiple layers of CNNs to reduce dimensionality after extracting features from a facial image as its input. When various filters recognise the same features in the actual image and convolve them, the outcome is a collection of activation maps, which are produced by the convolution layers using learnable filters. After being decreased in spatial dimensionality, these produced maps are fed into LSTMs.

Train and test data Here, the efficiency of the recognition system is assessed using the split data strategy. Various combination of original samples used to build the dataset. For training validation and testing, the face dataset was split into three portions, 50, 30 and 20%, respectively. The proposed model's efficiency was evaluated in this research article using the accuracy measure and confusion matrix.

3.3 Face counting

To get the number of persons in an image, a Haar feature-based cascade classifier is applied. Although numerous algorithms for counting items are quite effective, their slow processing durations preclude their application in real-time detection. The working principle of Haarcascade algorithm is based on ML technique [33]. The algorithm comprises four parts, which are: Haar feature selection, integral image generation, AdaBoost training, and cascade classifiers.

3.4 Application module

In the teacher application module teacher login for his/her course classes, and connects to the camera to obtain a photograph of the student using a mobile device, and uploads the photo to a server. In case of online classes this image is captured at random time during the class which is not known to the student to enable student presence during the complete class. The student enters his personal information, including name, ID, stage, and email, on the student application. Additionally, the student is informed of the outcome of each course's attendance check and is warned when the maximum permitted absence is surpassed. When a student is authenticated his/her attendance is marked, processed, and electronically stored. The SQL Server database is used in the reports section to generate reports on student attendance. Via email or SMS, this application is in charge of informing the student, family, and administration of notices and alarms.

4 Results

The LSTM parameters are detailed in Table 2. The number of hidden layers is set to be 100. The maximum number of epochs is 50. As discussed above form the datasets synthetic datasets are created using rotation, cropping and noise to

Table 2 LSTM parameters

LSTM parameters	
Input size	Feature vector
Hidden units (LSTM)	100
Maximum number of epochs	50
Minimum batch size	32
Drop out	0.1
Loss function	Cross entropy

		Correct Level	
		Positive	**Negative**
Predicted Level	**Positive**	True Positive (TP)	False Positive (FP)
	Negative	False Negative (FN)	True Negative (TN)

Performance Measure	Formula
Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{TP+FN}$
F-Score	$\frac{2TP}{2TP+FP+FN}$
Accuracy	$\frac{TP+TN}{TP+FP+TN+FN}$

Fig. 5 Confusion matrix

original images. In each synthetic datasets some unknown samples are also included to judge the accuracy of the proposed method.

In Fig. 5, correct and predicted levels are shown. In terms of confusion matrix parameters recall and precision are defined and further F-score and accuracy are defined as detailed in Fig. 5.

Cross entropy is plotted vs. epochs for train, test and validation process. Cross entropy for training is at 27 epochs is 9×10^{-8} while for testing it is 0.02 and for validation Cross entropy is 0.1452, which is minimum for validation process (Fig. 6).

In Fig. 7 gradient vs epochs are shown, here it is clear that gradient is falling with number of epochs and after 27 epochs gradient is 8.7×10^{-7} which is very small clearly indicating full learning of ANN. Cross validation vs epochs are also shown, at 27 epochs validation fail is 0, however the maximum value of fail validation is 1. Finally testing is performed, at various epochs accuracy varies, the minimum accuracy is 0.9975 and maximum accuracy is 0.9993.

In Table 3, performance evaluation of the proposed method is detailed in Table 2. Here number of samples is varied from 1200 to 2800 samples. The results are presented in terms of TP, TN, FP, FN, precession, recall, F-score and accuracy. The average precession is 0.999, average recall is 0.9986, average F-score is 0.9987 and average accuracy is 0.9982. It is also clear that the values of performance measure is nearly same and seems to be independent of number

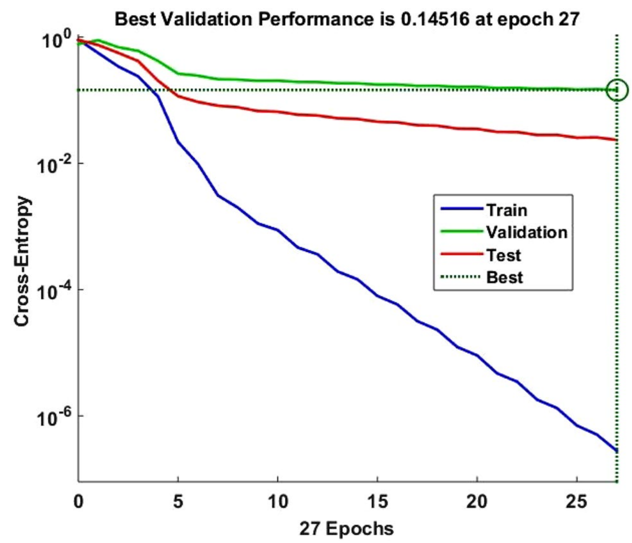

Fig. 6 Cross entropy vs. epochs

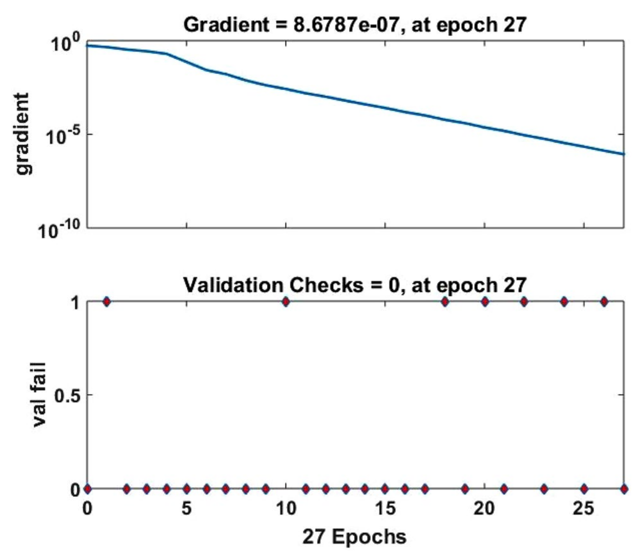

Fig. 7 Gradient and validity check vs. epochs

of samples. However, it must be remember that this is only true when the number of samples is large enough which can properly train the network.

4.1 Comparisons with cutting edge techniques

The Table 4 provides a comparison of different techniques for automatic attendance systems, including their reference numbers, the specific technique used, accuracy achieved, and runtime. Sanli and Ilgen [20] employed the combination of Local Binary Pattern (LBP) and Principal Component Analysis (PCA) techniques, achieving an accuracy of 75% with a runtime of 1.21 s. Pei et al. [21] utilized the VGG-16

Table 3 Performance evaluation of proposed method

# of samples	TP	TN	FP	FN	Pre	Rec	Fs	Acc
1200	1195	2	1	2	0.999	0.998	0.999	0.998
1600	1589	7	2	2	0.998	0.998	0.998	0.9975
2000	1988	8	1	3	0.9995	0.9985	0.998	0.998
2400	2386	10	2	2	0.9992	0.9992	0.9992	0.9983
2800	2791	7	1	1	0.9996	0.9996	0.9996	0.9993
Average					0.999	0.9986	0.9987	0.9982

Pre precession, *Rec* recall, *Fs* F-score, *Acc* accuracy

Table 4 Accuracy comparison of student attendance system

Reference no.	Technique	Accuracy (%)	Runtime (s)
Sanli and Ilgen [20]	local binary pattern + PCA	75	1.21
Pei et.al [21]	VGG-16	86.3	3.43
Indra et.al [22]	HAAR	78.90	2.67
Setialana et al. [24]	CNN	81.25	4.57
Shah et al. [25]	HAAR cascade	93.10	3.78
Ahmed et al. [33]	Deep CNN + SVM	99.75	11.94
Proposed	CNN–LSTM	99.82	6.93

deep learning model, achieving an accuracy of 86.3% with a runtime of 3.43 s. However, the training process for this method took a relatively long time (approximately 8 h). Indra et al. [22] used the HAAR-like features method with facial patterns, achieving an accuracy of 78.90% with a runtime of 2.67 s. Setialana et al. [24] employed a convolutional neural network (CNN) for their attendance system, achieving an accuracy of 81.25% with a runtime of 4.57 s. Shah et al. [25] developed a facial recognition-based attendance system using the HAAR Cascade method, achieving an accuracy of 93.10% with a runtime of 3.78 s.

However, the accuracy of this system was influenced by image noise, and it was not practical for real-time person identification. Ahmed et al. [33] utilized a combination of deep CNN and support vector machine (SVM) techniques, achieving an accuracy of 99.75% with a runtime of 11.94 s. The runtime of this method is comparatively higher due to the deep structure of the CNN. Finally, the proposed system in the table, labeled as "Proposed," employs a CNN–LSTM-based method for automatic attendance. It achieves an impressive accuracy of 99.82% with a runtime of 6.93 s. This proposed system aims to address the limitations of previous methods and provide quick and accurate face identification for attendance tracking.

5 Conclusion

In this paper, an automatic attendance system based on CNN–LSTM is proposed. The CNN is used for the feature capturing while LSTM is used for capturing the long term dependency. The detailed description of the various processes is also discussed. User faces were successfully confirmed as being those of students, and the associated student was then successfully identified and attendance is marked. In the proposed method the precession, recall, F-score and accuracy are around 0.999. Finally comparison of notable methods is made in terms of accuracy. The accuracy of the local binary pattern + PCA is around 75% which increases to 99.75% with deep CNN + SVM. The proposed method accuracy is 99.82% which is best among the chosen methods.

Data availability Not applicable.

Declarations

Conflict of interest No.

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