Automatic Attendance System Using Extreme Learning Machine

Ankit Dalal, Priyanka Dalal, Sahil Dalal

Abstract: ***Attendance is a way of knowing whether the person is present at the place or not. This is done manually i.e. by calling the names and using biometric systems. Both these methods are time-consuming and an individual face lots of waste in their time. Therefore, to prevent this loss, a novel technique is introduced, which is based on the recognition of face of an individual for the attendance. This is done by detecting the face of the individual in some event or in a classroom, in case of students and the detected face region is matched with the stored database.Here, this is done with the help of ViolaJones algorithm for the face region detection and extreme learning machine algorithm for the matching of the detected face with the stored database. The results are observed over self-made database of few students with quite promising performance.***

Index Terms: Deep learning; ELM; Automatic Attendance System, ViolaJones; Detection.

I. INTRODUCTION

Attendance is a very important part of any organization. There are so many employees, working over there, and so many visitors that visit the organization daily. Maintaining this record on the daily basis is a part of attendance. Now-a-days, this is either done manually i.e. by calling the names of the individual or with the help of biometric i.e. by thumb impressions. Both of these methods are time consuming and also requires lots of energy and patience because one have to wait for their turn to cum for their roll call. Similar, things are done in the classroom as well where a teacher takes attendance of so many students by calling their names one by one. Therefore, to save time and energy, an automatic system is needed which can record someone's attendance by identifying the face of an individual. This technique is similar to object detection [15].Since 1970s many methods have been utilized for face detection. Those methods are unadaptable to the required conditions and hence, some presumptions were considered to fulfil the achievements. These includesfrontal face images, proper lighting conditions should be there etc.

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Earlier these techniques were introduced on the standard available databases. But as the time passes and research is extended to the real time problems, real time face images were started using in the face detection. There are so many countries which are utilizing the face recognition and machine learning concept in cctv surveillance at the crowded places.They observe the movement of the pedestrians in those places and summed up the information for getting the information on some person that how often th person is moving in that area. This is done to keep an eye on the illegal activities occurring these days. Neural network is giving a great help in such activities as it worls similar to the human brain and learn from the previous activities. Therefore, it is very useful in tracking the facial characteristics [1]. In the facial characteristics, features such as eyes, nose, mouth, colour etc. are the key features or any face to be identified. Detecting these features can be very helpful in identifying the person in the image. These features can further be extended to eyebrows and lips. Shapes of eyebrows and lips make it easier to recognize a face.This characteristic can be utilized to differentiate the facial components. Dividing the face into these sub parts helps a lot in studying the divided facial regions in much simpler manner.

TABLE 1. Comparison of learning algorithms

Datasets	Learning Methods	Testing Accuracy
MNIST OCR	Deep Belief Networks (DBN) [18]	98.9%
	Stacked Denoising Auto Encoders (SDAE) [19]	98.70%
	ELM (multi hidden layers, ELM auto encoder) [20]	99.10%
	Stacked Auto Encoders (SAE) [21]	98.58%
	Deep Boltzman Machines (DBM) [22]	99.08%
	ELM (multi hidden layers, unpublished) [23]	~99.59%
3D Shape Classification	Convolutional Deep Belief Network [24]	77.35%
	ELM (multi hidden layers, local receptive fields) [25]	81.40%
Traffic sign recognition (GTSRB Dataset)	Multi-column deep neural network (MCDNN) [26]	99.50%
	HOG + ELM [27]	99.60%
	CNN + ELM [28]	99.50%

In this, contour of the face images is also playing a crucial role in identifying someone's face because contour of different persons

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varies from person to person.Based on these common features of the face images, Wong et al. introduced a method in which the calculation is done with the help of weighted human eye contours [2].Similarly, Hoogenboom and Lew focused on the facial spots such as nose tips and faces were recognized [3]. Huang et al. also made their contribution in this area in which he introduced a concept that the quality of the image is diminished because of averaging or sub-sampling. To overcome this, they introduced a rule projected schema.Resolution of the face image can be retained with this and results came out to be more accurate. This technique of Huang et al. was also incorporated in rotation invariant face recognition. This was done by lv et al. This concept of face recognition can be utilized in the places where attendance is noted down on the daily basis. Earlier method for this is by calling the roll numbers or some identity of the individual such as roll number of the students in the classroom. Such records are maintained by an organization for knowing the individual's regularity. This conventional method was time consuming and wastes very much time of the students as well as teachers.So, to utilize the time in studies and prevent the loss of time, an automatic attendance system is proposed using extreme learning machine through this paper. It is tested over self-made database of some pictures. The paper is organised as follows: Section II provides a brief overview of the preliminaries used. Section III provides details about the proposed method. Section IV provides the classification results followed by conclusion in Section V.

II. MATERIALS AND METHODS

A. ViolaJones general object detectionframework

The face detection has increases its popularity since last few years and shown a very good improvement in the face recognition [3,4]. Recent methods have reduced the latency of the process to a large extent of accuracy without being disturbed by any motion presence or colour in the image. [5,6].Such technique is ViolaJones which helps in detecting the object by utilizing the window approach as shown in Fig. 1. In ViolaJones algorithm, region of interest is detected by searching the pattern at various scales of resolution of the input image and detect the required image with the help of a classifier.

Fig.1. Shifting of matching window in an image for object detection technique at various resolutions

Using the window approach, remarkable results have been achieved in [6] so that a framework for the object detection can be designated [7]. Such framework combines the weak classifiers by cascading them and increases the possibility of detection.All of these cascaded classifiers act likea filter which uses the properties of haar wavelet transform.Regions detected in all the resolutions are detected as the target.In Fig. 2 shown is a separate sub classifier which is trained for each stage in the cascade so that most of the targets can be observed. With that, non objectsthat were incorrectly classified as objects can also be rejected.

B. Extreme Learning Machine

Over the past years, a technique is emerged and has become a topic of interest for research and analysis. This is extreme learning machine (ELM). Various researchers have contributed for ELM from all over the world. Among these, G.B. Huang [1, 2, 3] gave the important contribution. ELM works begin from our intuitive belief on biological learning and neural networks generalization performance theories [14].Recently, ELM is misinterpreted as similar with few earlier works and hence, differentiated from others in [8]. ELM is much better in terms of robustness and novelty as development compared to the designs of Frank Rosenblatt multilayer perceptron [9], SVM[10], LS-SVM [11], linear systems,matrix theories,Fourier series, numeral strategies, etc. [12].Rosenblatt experimented the perceptron networks and said that it can affect the computers by reproducing by itself but countering this, Minsky and Papert proved that perceptron learning can't even tackle the XOR problem because of not having any hidden layers [13].However, afeedforward neural network can act like a brain that has inputs and outputs. This is same as the humans in which eyes nose etc. act as inputs and motor sensors act as the outputs.Obviously, such a "brain is an empty shell and has no "learning and psychological feature capabilities in the slightest degree. However, Rosenblatt and Minskydifference additionally tells the reality that one little step of development in AI and machine learning might request one or many generations nice efforts. Their skilled difference might end up to indirectly inspire the invigorating of artificial neural network analysis within the finish. Thus, there's little doubt that neural networks analysis revives when hidden layers are emphasised in learning since 1980s. However, an on the spot quandary in neural network analysis is that since hidden layers are vital and necessary conditions of learning, by default expectation and understanding of neural network analysis community, hidden neurons of all networks have to be compelled to be tuned.

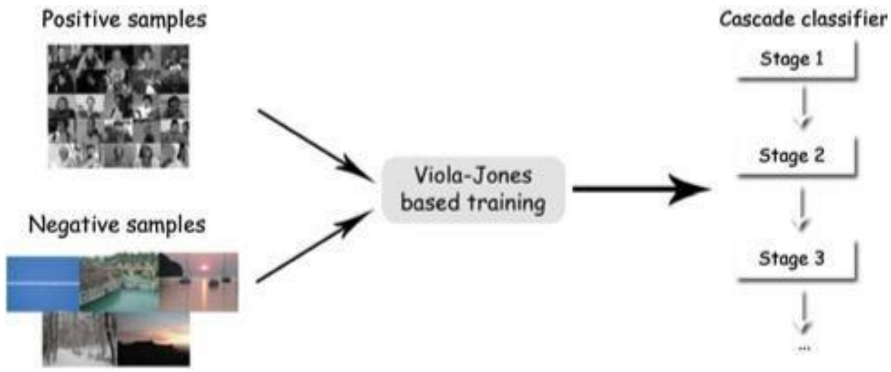

Fig.2. Block diagram of ViolaJones algorithm

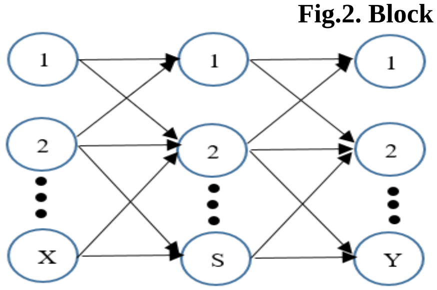

Fig. 3. Architecture of single layer FFNN

Thus,since1980stensofthousandsofresearchersfromalmosteverycorneroftheworldhavebeenworkinghardonlookingforlearningalgorithmstotrainvarioustypesofneural networks mainly by tuning hidden layers.The architecture for the single layer FFNN is shown in Fig. 3. It is having a hidden layer having *S* number of neurons. The input weights and bias are selected on random initialization of the parameters of the hidden layer. Compute the output φ for the hidden layer matrix[14] as follows:

$$Y=\sum_{m=1}^{M}\gamma_m\varphi(a_m,b_m,x)=\gamma.H(x) \qquad (1)$$

where $H(x) = [\varphi(a_1,b_1,x)\ldots,\ \varphi(a_M,b_M,x)]$ is the output matrix obtained from the hidden layer with respect to the input x. a_M and b_M are the input weight and bias respectively which are randomly generated. The output weight γ which connects output and hidden nodes is obtained analytically and can be obtained by:

$$\gamma = H^{-1}Y = H^T\left(\frac{I}{C}+HH^T\right)^{-1}T \qquad (2)$$

where T is the target class and C is user defined parameter for regularization. Therefore, ELM model can be formulated as:

$$Y_{ELM}(x)=H(x)H^T\left(\frac{I}{C}+HH^T\right)^{-1}T \qquad (3)$$

ELM is to minimize the training errors and the output weights norm i.e. $||\gamma||^2$. It also allows to reduce the computational time that is required in optimizing the parameters. Gradient-descent methods or global search method stake a much longer time as compared to ELM [16], [17].ELM not only achieves state-of-art results but also shortens the trainingtimefromdays(spentbydeeplearning)toseveralminutes(byELM)in MNISTOCRdataset,trafficsignrecognitionand3Dgraphicapplication,etc.Its difficulttoachievesuchperformancebyconventionallearningtechniques.

III. EXPERIMETAL RESULTS AND ANALYSIS

Schools and colleges record the regularity of the students with the help of class attendance. Attendance tells about the student that he/she is physically present or absent on that day or time. This maintenance of the record is very important aspect and hence, should be as fast as possible because the method of marking the attendance manually i.e. by calling name or roll number of the students during class hours is time consuming and a wastage of time and energy. Therefore, an automatic attendance system is introduced by recognizing the face of the person and that is utilized to mark the attendance.

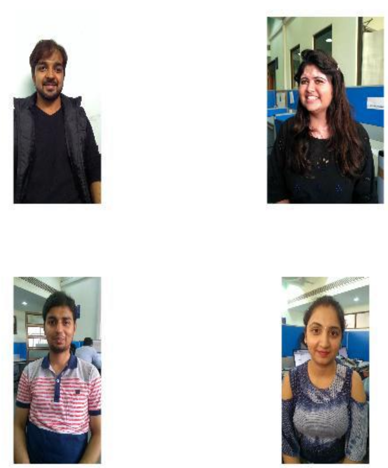

Fig. 4. Training Set Images

Therefore, the proposed method is experimented over a small database containing total of 32 images only. These images are of four subjects with eight images per subject. All these images are resized to 162 × 162 pixels of resolution and all are used as the training set.Sample image for each of the subjects is shown in Fig. 4. While testing is done with ELM, the test image set is taken from the live webcam, with a student appearing in the webcam. As the test images are taken live, so obviously, they are different from the images that are used for training purpose. Image taken from the webcam is larger in size and differentfrom the one that are taken for training in the database. Hence, it is resized to the standard size of 162 × 162 pixels of resolution and only face part is cut from the image. It is shown in the Fig. 5.Then,the best match of the image is the one which has lesser most Euclidean distance measure and therefore, that image is considered as the recognized image.

Fig.5. Webcam Image and Detected Image

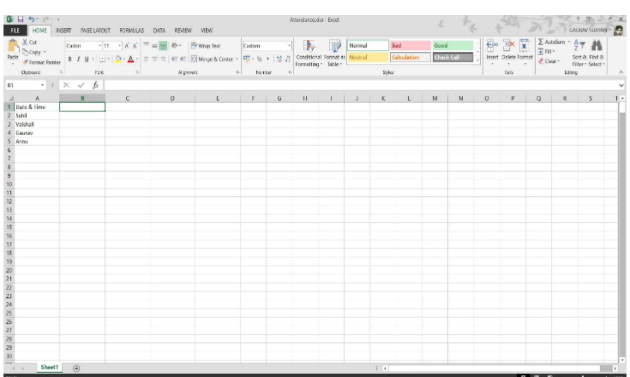

Fig.6. Representation of students names stored in the cells

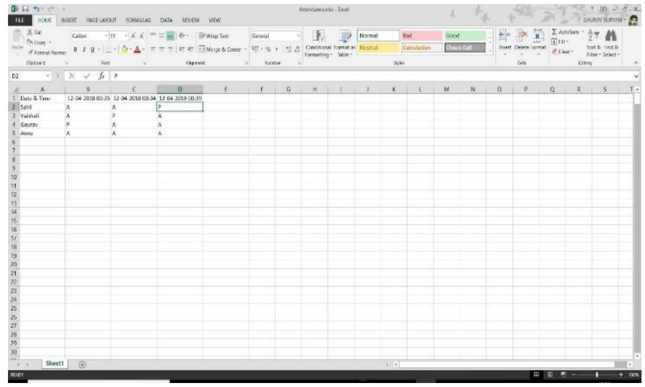

Fig.7.Record of the attendance of students

The attendance sheet for the database of four students is created. It will record the name of the students and correspondingly, date and time of the attendance is also noted down. Then ‘P’ for present and ‘A’ for absent denotes the attendance status of a student on that day. It is shown in the Fig. 6.Here, it is shown for students named as Sahil, Vaishali, Gaurav and Annu. In Fig. 7, attendance marked for the particular date at some particular time is showing the happening of the class. Say, for Gaurav, if he is present in the class then his attendance is marked with ‘P’ and rest are marked with ‘A’ representing their absence in the classroom.

IV. CONCLUSION

The attendance system based on face recognition is very well experimented through this paper. ViolaJones algorithm with extreme learning machine introduced a novel combination of taking attendance of the individuals and register them as a data in the attendance sheet.The proposed method is fast compared to the biometric based attendance system as biometric is time consuming and non-efficient. It is experimented over a small bunch of students and results are promising and hence, it can be established in a classroom. Further, it can be enhanced to operate online for the whole institute or some work place at large scale.SMS alerts can also be added in future so that individual can get the idea that their attendance is marked.

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