International Journal of Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281 Volume 1, Issue 4, June 2018
https://doi.org/10.31426/ijamsr.2018.1.4.224

International Journal of
Advanced Multidisciplinary Scientific Research (IJAMSR) ISSN:2581-4281

A Novel Face Recognition Using LBP For Attendance Management System

A. Renaldo Maximus
Assistant Professor, Department of Electronics and Communication Engineering, Government College of Engineering Tirunelveli.
Email: renaldo.ece@gmail.com

R. Bharathiraja
Assistant Professor, Department of Electronics and Communication Engineering, Thanthai Periyar Government Institute of Technology Vellore.
Email: rajaecegce@gmail.com

ABSTRACT

The main topic in the domain of verification is face recognition and identification. An aspect of administration that takes considerable time and administrative effort is the maintaining of student data and supervision of class attendance. Face detection and recognition technology has made significant advancements in security, identification, and attendance but still has difficulties that prevent its ability to be as exact as people's. These issues include variations in how a individual's face looks, including various lighting situations, noise in facial images, size, posture, etc. To solve some of the problems hindering face-recognition accuracy and enhance the LBP logic, improving the accuracy of entire face-recognition scheme. This research study provides a novel method employing LBP in combination with innovative imaging methods includes Bilateral Filter, image blending and Histogram Equalization. The outcomes of the tests depict that proposed system is highly accurate, predictable for facial identification systems that can be used in realistic settings as an automated attendance management structure.

Keywords: Bilateral Filter, Face Recognition, Local Binary Pattern (LBP), Attendance Management System.

1. INTRODUCTION

The automatic face recognition method uses geometric or statistical elements extracted from facial pictures to allow computers to recognize a person's identity. Face recognition is a complex, multidimensional structure that can communicate several details about a person, including emotions, feelings, and facial attributes [1]-[4]. It's a complex stage that takes a substantial amount of effort and time to analyze facial information characteristics effectively and quickly. As described in citations [5]– [8], various face recognition-based algorithms have since been created, enhanced, or integrated to build facial recognition systems or uses. These algorithms are proposed, successfully implemented, and used for automatic attendance management.

Even though there have been more advances in the system of face identification algorithms and design, certain issues with these algorithms and design need to be resolved or considerably minimized, as suggested [9], to develop an accurate and trustworthy automatic attendance system based on face recognition that might be very beneficial in the verification field.

The impacts of effective face recognition and identification designs are environmental conditions, posture, backgrounds, scale, emotions, occlusion, etc., since mentioned [10]. Convolutional neural networks are used for illumination-invariant face recognition to handle lighting concerns, while wavelet transform (CWT) and Fisher face are used to address shift and rotation problems [11]. Many algorithms and techniques have been created to overcome these difficulties. LBP, Dual Cross Pattern (DCP), and Support Vector Machine-based Robust Posture Invariant Face Recognition are proposed to overcome pose-related challenges (SVM).

CovNets are a specific class of neural networks used for analyzing the input with a predetermined, grid-like structure. Images can be represented as a 2-Dimensional grid of pixels, while time-series data can be seen as a 1-Dimensional grid that takes samples at predetermined intervals. have been successfully applied in practice using these networks [12]. CNN is an essential neural network that uses convolution rather than conventional matrix multiplication in, at minimum, one of its layers. An artificial neural network that executes the mathematical convolution operation is called a "convolutional neural network."

2. RELATED WORK

The developed ensemble system utilizes 3 classification methods: correlation coefficient, Chi-square, and K-nearest neighbor [13]. Also, the proposed methodology combines the conclusions generated from independent classifiers using the AND logic, bluk voting, and OR logic. UFI, LFW and AT&T face databases are used in the experiment to compare the outcomes of the ensemble system. The ensemble face recognition system has achieved an accuracy rate of 87.3372 percent on the LFW,100 percent on AT&T, and 99.3488 percent on the UFI face database by using an innovative dense local graph structure.

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They proposed an expression-EEG interactivity multimodal reactions identification technique employing a deep automated encoder to address this issue. Initially, decision trees are used as an objective approach to feature selection. The features are identified using sparse representation, training features are extracted using BDAE and Classification jobs are processed out using the LIBSVM. [14]. The discrete emotion state type and average emotion identification rate have been considerably enhanced, with the average facial expression rate being 85.71%. Overall, there has been a tremendous advancement in our ability to discern emotions.

The face method description and matching problems in face recognition are addressed in this work using a unique technique. The method is based on Deep Learning approaches and multi-level Gabor features. The Caltech, Yale, Yale B and ORL databases were utilized in the studies described in this study to determine the face recognition rate [15]. The findings demonstrate that, in terms of recognition rate, the novel face recognition algorithm beats more established techniques like global Gabor face recognition based on PCA. To jointly develop face representation utilizing multimodal data, this research offers a complete deep-learning architecture [16]. A group of intricately built convolutional neural networks (CNNs) plus a three-layer tiered auto-encoder make up the proposed deep learning framework (SAE). The collection of CNNs derives supplementary face characteristics from multimodal data. For the LFW database, a 98.43percent verification rate is attained using the proposed single CNN architecture and small amounts of training data.

The conventional Local Binary, Patterns Principal Component Analysis, and Fisherfaces have all been proposed as superior and more innovative methods for facial recognition than the Kohonen approach [17]. The LBP was particularly recommended because of its straightforward theory, computational simplicity, invariance to any monotonic modification of grey scale, efficient uniform rotation-invariant investigation, and superior textual discrimination.

In the proposed approach, the YOLO-Face method—a fast, real-time face detector created on YOLOv3—is used for the face detection job, while FaceNet and a supervised learning algorithm, for example the SVM, are combined for the identification step [18]. The face detector aimed to achieve 89.6 percent accuracy using the Honda/UCSD sample, which operates at 26 FPS with darknet-53 to VGA-resolution for classification jobs. According to the experimental findings, the FaceNet+SVM model employed the LFW dataset to obtain an accuracy of 99.7 percent. FaceNet+RF attain 85.1 percent and FaceNet+KNN attain 99.5 percent of accuracy on the same sample, respectively, whereas FaceNet only manages 99.6 percent. The final result of the proposed methodology is that when the face recognition and classification stages work together, the recognition accuracy is 99.1percent, and the runtime is 49 ms.

A new computer vision-based technique is suggested in this study using face detection and face recognition methodologies [19]. The OpenCV approach is mainly utilized to develop facial detection technologies. The

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YouTu and Seetaface approaches help face recognition technologies in applied requests. Comparing the detection and identification rates for the three different demands of side face detection, blocking detection, and exaggerated facial expression increases the accuracy of each technique simultaneously. The deep neural network mechanism, sparse autoencoders, and the denoising job are all combined in this face recognition system application called Deep Stacked Denoising Sparse Autoencoders (DSDSA) [20]. By using constraints to learn precise illustrations of the data, an autoencoder is to build a neural network that develops an estimation of an individuality role. Two classifiers—multi-class SVM and Softmax classifier—were employed for the classification challenge. Outcomes from experiments on well-known face datasets, such as ORL, Yale, Caltech, and a subset of PubFig, demonstrate that the proposed approach performs well and obtains equivalent accuracy.

The system is appearance-based, combining Gabor wavelets and General Discriminant Analysis to analyze characteristics from the complete face image. Subspace projection is next performed to the feature vectors. The outcomes were obtained using the BANCA face & FERET face databases. The research outcomes demonstrate that Gabor wavelets may suggestively boost system presentation, as GDN outperforms alternative subdomain prediction techniques like PCA, LDA, and KPCA. Using the FERET database, our approach had a 97.5% identification rate and the confirmation error rate 5.96% on the BANCA database [21]. It has been demonstrated that CNN, a subset of deep networks, are effective for FR. Prior to deploying CNN in real-time systems, sampling, and other preprocessing procedures are required. This is the cause of the occasionally difficult and drawn-out implementation of CNN. The research offers a novel face recognition method utilizing a deep neural network (another deep network type). With this method, just the extracted face characteristics are given as input, rather than the raw pixel data [22] [23]. With 97.05 percent of accuracy on the Yale faces dataset, this reduces complexity.

3. PROPOSED METHODOLOGY

In this research, we recognize the performance of LBP face recognition algorithms was subject to the feature extraction accuracy and contrast stage, which in turn was subject to the value close of the input face images and the training images employ in the face evaluation procedure. We consider advantage of the succeeding image value features of training set: denoising, lighting, sharpness, size, posture, and resolution, to acquire pictures of the highest quality possible, which will provide more information about image characteristics and allow for more precise feature comparison and extraction.

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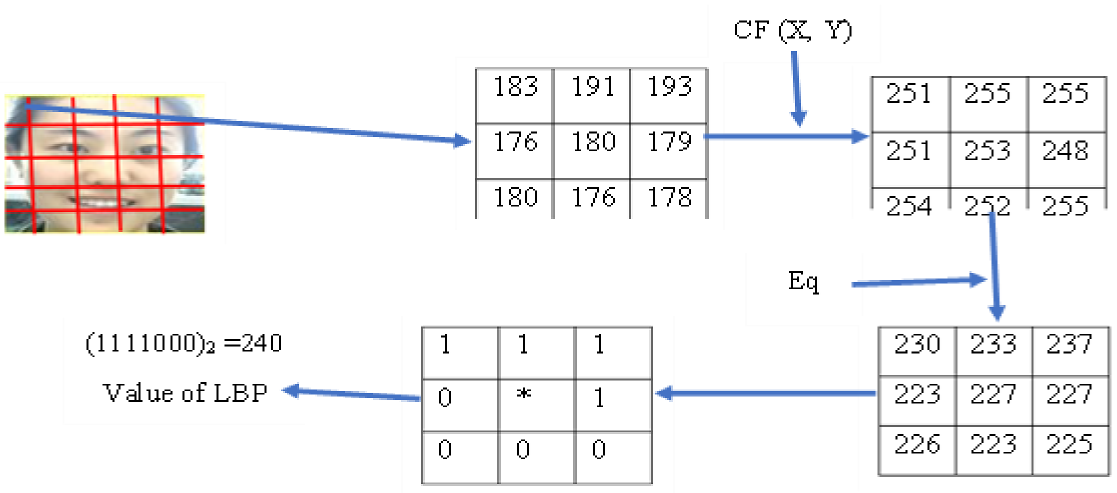

Figure 1: Enhanced LBP Operator

The two primary elements of our study project are as follows: The first part concentrated on enhancing the face recognition mechanism, and the second part concentrated on developing an attendance control management based on identified faces. firstly, high-end image processing methods are used to enhance the quality of the collected photos, includes contrast modification, noise dropping using a bilateral filter, and histogram equalization. Next, the Haar Algorithm is employed in the taken pictures to find individual faces and then used as source to the text recognition algorithm.

Applying the Contrast Adjustment technique to the input face photos as specified in the 1st equation is our initial enhanced strategy. We evaluated this strategy using a variety of alpha and beta values before settling on the 1.5 and 0.0 values, respectively, that result in the best detection and identification accuracy results.

$$G(x,y)= \alpha * f(x,y)+\beta \quad \rightarrow \quad (1)$$

In the second strategy, we choose the bilateral filter, which is specified in 2nd equation, since it provides the best outcome in our scenario.

$$F(x,y) = \frac{\sum_{x=-N}^{N}\sum_{y=-N}^{N} I(x,y)W(x,y)}{\sum_{x=-N}^{N}\sum_{y=-N}^{N} W(x,y)} \rightarrow (2)$$

Here, N is the normalized weighting function, W(x,y) is filter weighting function, F(x,y) is the outcome of the bilateral filter when applied to a 2N + 1 neighborhood and I(x,y) is a neighborhood pixel from the input face picture,. CF(x,y) is now described in 3rd equation as the function to regulate contrast effects and decrease noise in the source pictures, where g(x,y) is the compared image and F(x,y) is the functional filter.

$$CF(x,y)=g(x,y)*F(x,y) \quad \rightarrow \quad (3)$$

Finally, using histogram equalization method stated in the fourth equation, the result image pixels created by the previous equation are equalized to fix the overall lighting problems in the processed face photos.

$$Eq= H'\,(CF(x,y)) \quad \rightarrow \quad (4)$$

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Next, we used the LBP technique to our identified face pictures for feature extraction & comparison, where H' is the normalized cumulative distribution. LBP operator documented in prose employs a fixed 3 X 3 window:

$$\text{LBPp, r}\,(X_c, Y_c) = \sum_{p=0}^{p-1} 2^p S(i_p - i_c) \rightarrow (5)$$

S(X) is the sign function specified in the 6th equation where $(X_c, Y_c)$is the gray-level rate of the center intensity, with i_p and $i_c$being the near intensity value and p the adjacent pixels in the circular near with a radius r.

$$S(X) = \{1,\ if \quad x \geq 0\ 0,\ if \quad x < 0 \quad \rightarrow (6)$$

When the output pictures from equations 3rd and 4th were examined, it was clear that the problems with noise, lighting, sharpness, and resolution had been much reduced. After applying equations 1st through 4th to the original input images and attained threshold and best pixel values exposed in Figure 1. Shows that our technique enhances high-quality pictures, which indicates enhanced image quality, proposes better picture features, presents better image quality, and enables higher accurate images. The outcome was improved LBP codes, improving face recognition overall accuracy.

Using the proposed procedures described in equations 4th and 5th, and enhanced the quality of input face and training faces. Now, the techniques in conjunction with the LBP algorithm to extract added distinct and observable facial characteristics to improve evaluation certainty for many accurate face identifications.

i. face identification using Haar classifiers

ii. Face identification using enhanced LBP

Figure 2: identify the faces using Haar and LBP cascade classifiers with our proposed approaches [24]

The Haar classifier technique, as seen in Figure. 2, is utilised in this experiment to identify faces in a picture (i). Four (4) steps make up the Haar classification algorithm: combined image, Haar, AdaBoost with Cascading Classifier, where the face images are first denoted as combined images for analyzing Haar features which is used for feature selection for optimization reasons, and the certain features are then accepted through a cascading classifier to categorize faces in picture. As illustrated in Figure. 2, our enhanced LBP approach is utilised in addition

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to the Haar-based Classifier is used to find faces in images (ii). It can be seen from a comparison of the two methods in Figure. 2 that our proposed approach outclassed the Haar-based Classifier for face identification in terms of both detected faces count and the number of FP or FN faces that were not correctly identified as faces in picture.

Attendance System: Based on recognized face images along with date and time calculated. Also, extraction each identified face image from our attendance system and mark each person's presence.

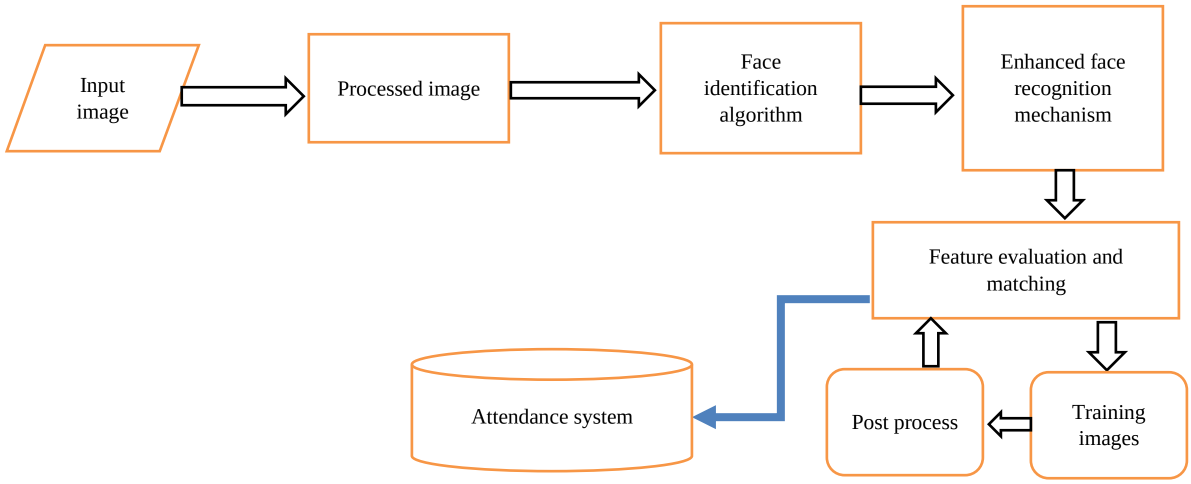

Figure 3: Face identification algorithm

The algorithm's flowchart is displayed in Figure 3The flow chart shows how the recorded input image are handled using our recommended imaging methods before the face detection procedure is used to find faces. After faces have been identified, the face recognition algorithm used in the proposed technique to recognize faces. Following face recognition, the retrieved metadata are used to record attendance using the attendance system.

4. RESULT AND DISCUSSION

In our study, we developed three separate samples: sample[I], sample [II], and sample [III], and each one has various face positions and situations that are limited to 181x181 pixels. Samples [I] and [II] each had 1.0α linear blending, while Sample [III] had 0.5α linear blending. Sample [I] did not have any image blending done. These three samples were used to evaluate the enhanced

LBP face recognition algorithm, and Sample [III] was chosen since it produced excellent face recognition accuracy results for our system. Before limiting the training pictures to 181x181 pixels and analytically tested several pixels on the training samples to verify whether they would influence the face recognition accuracy. Though the impact isn't very significant, the best result—181x181 pixels—was chosen.

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International Journal of
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Table 1 compares the Haar, acutal LBP, and enhanced LBP created with our technique for face identification on face images of 230. This mechanism outperforms them all. With the help of our approach, we were able to decrease the number of FP and FN while simultaneously raising the accuracy rate of face detection, a crucial component of face recognition accuracy.

Table1: face identification evaluation result

	Total faces	Haar classifiers	LBP classifier	Proposed Approach
TP	230	210	208	218
FP	230	20	23	13
FN	230	55	42	35
Accuracy		92%	91%	97%

Table 2 compares the facial recognition accuracy of our proposed technique in a controlled setting with two other different current methods. The findings in Table 2 validate that our approach, when compared to other approaches, seems to be extremely resilient to be applied in a exact real-world setting. Our method is innovative because it couples the LBP algorithm with advanced strategies for image processing for input pictures and training images. These techniques include contrast correction, bilateral filtering, histogram equalization, and image blending. Figure 4 shows the comparison of other and proposed approaches.

Table 2: comparison of face recognition accuracy

Approaches	Accuracy (%)
Orginal LBS [17]	89.3
DCP+LBP+SVM [23]	97.5
Proposed approach	99.62

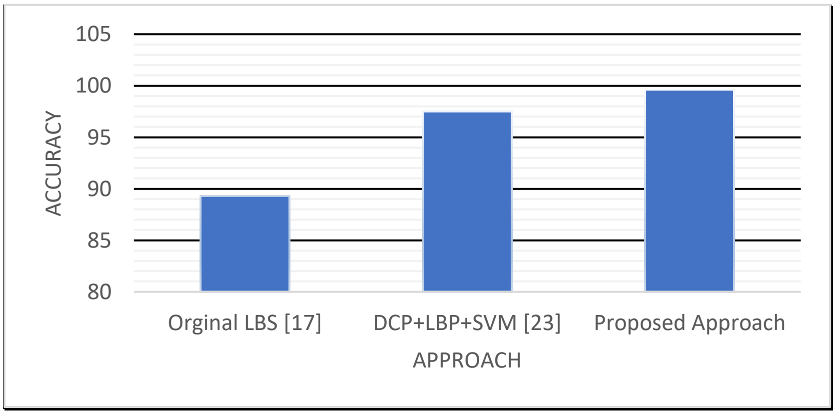

Figure 4: Performance comparis

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5. CONCLUSION

To achieve better image features, we pre-processed the input face images with our findings utilizing developed image processing methods like image denoising, bilateral filtering, and histogram equalization. We then implemented the same enhanced image processing methods on training set and image blending techniques to certify first-class training sets. The pre-processed image set is separated into k2 areas, and the LBP code will be determined for each intensity value in the area by contrasting the center with the adjacent intensity values. Binary 1 directs the adjacent pixel if it is equal or greater than to the center value; otherwise, binary 0 is used. This technique enhances the LBP code, and the outcomes of our tests demonstrate how effective and reliable it is for a face recognition mechanism that is used in a real-world setting. Also, crucial to note that our analysis doesn't tackle the problems of obstruction and mask faces. However, doing so would make a superb follow-up to this publication.

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