AMRITA SCHOOL OF ARTIFICIAL ENGINEERING

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April - 2025

B.TECH ARTIFICIAL INTELLIGENCE IN DATA SCIENCE AND MEDICAL ENGINEERING

23MAT112 Mathematics for Intelligent Systems 2

24AIM111 Introduction to Data Structures & Algorithms

Face Recognition Attendance System

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Abstract--- **In this study we introduce a real-time face recognition system for attendance management which integrates classical machine learning techniques with a very simple desktop interface for making the use of it easier. The system integrates global and local feature extraction methods, namely Principal Component Analysis (PCA) and Local Binary Patterns (LBP), to produce robust face representations. A Linear SVM classifier is used to make identification faster and accurate, while the proposed design is a dimensionality reduction approach that employs SelectKBest along with hyperparameter tuning through GridSearchCV to guarantee maximum performance. The system has a graphical user interface (GUI) built using Tkinter, so that real-time attendance checks may be made by interfacing the application with a camera. The experimental results show high training and testing accuracies while maintaining computationally efficient algorithms required for real-time applications.**

Keywords--- Facial Recognition, Biometric Identification, Principal Component Analysis (PCA), Local Binary Pattern (LBP), Support Vector Machine (SVM), Attendance System.

I. INTRODUCTION

During the emerging age of fast-paced technology and automation, modern biometrics have formed the modern foundation of modern means and processes of identification and verification. Among all forms of biometrics, face recognition stands out remarkably as it is nonintrusive and user-friendly. Once made convenient and practical for widespread application, it would allow everybody from unlocking their phones to surveillance in public places. Such technology is now carried into people's routines with many things. Such potential for face features would have set apart great interest and innovation in research consideration in this space. This project will extend the integration of intelligent graphical user interfaces (GUIs), which is developed for real-time face recognition. Now, the generated attendance would not be harmed by proxy attendance, manual errors, or inefficient time consumption, but will instead be highly robust, accurate, and easy.[1-6]. This has become crucial especially in institutional or organizational contexts where attendance data feeds into academic records, payroll systems, access

control, etc., thus reliability of such a system becomes necessary.

Face recognition as a pattern recognition task has multiple difficulties arising due to the diverse light effects occurring from poses to changes in the facial expressions, overlaps, and aging. For the work to tackle these challenges, a hybrid feature extraction methodology comprising both the global and local image descriptors is incorporated in this work. Basically, the great facial structure is captured by employing Principal Component Analysis (PCA), while Local Binary Patterns (LBP) are then used to extract the minutiae texture information. Such a dual scheme adds to the strength of the system and ensures that it performs recognition consistently under varying conditions.[11-13].

Once the features are extracted, they are subjected to further processing as per their relevance and discriminative power. The classifier selected here is Linear SVM, which is known for its simplicity and effectiveness and efficiency on high-dimensional spaces. A grid search systematised in hyperparameter tuning is employed to attain optimum classification results. The system is built on a personalized facial dataset and tested with unseen samples to prove its accuracy and generalization ability.

To realize practical effectiveness of this system, a GUI-based desktop application has been developed using Tkinter framework in Python. Real-time video feed from the interface is used for face detection and recognition, recording timely attendance automatically. This design was more user-facing to facilitate both the technical and non-technical use of the solution for use in schools, colleges, offices, and other institutions. It emphasizes not only the integration of the latest techniques in machine learning with a functional software application, but the applicability of such an integration in real life.

II. LITERATURE REVIEW

i. Eigenfaces for Recognition

Turk and Pentland opened a new world of face recognition with the introduction of eigenfaces by using PCA for dimensionality reduction. They represented each face in terms of a linear combination of orthogonal eigenvectors (or "eigenfaces") derived from the covariance matrix of the training data [1]. This reduced dimensionality while retaining the most significant variations. However, eigenfaces were still sensitive to variations in lighting, expression, and pose, encouraging subsequent researchers to enhance PCA with local feature descriptors.

ii. Multiresolution Gray-Scale and Rotation Invariant Texture

Ojala et al. introduced the Local Binary Patterns (LBP) operator, a powerful and widely used tool for texture analysis

[2]. It is often integrated with global methods like PCA to manage global image variance. LBP works by thresholding pixel intensities in a local neighborhood and encoding them into binary patterns. Its invariance to monotonic gray-scale changes and rotations makes it highly suitable for face recognition tasks, especially in varying lighting and expressions.

iii. Improved LBP and HOG Features for Smart Face Identification

Sun and Li presented an enhanced face recognition method that refined both LBP and HOG descriptors [3]. They modified LBP for better texture detail representation and used HOG for capturing shape features. To manage the high dimensionality of the feature space, they employed a combination of two-dimensional PCA and standard PCA. Their method, validated on standard datasets, highlighted the effectiveness of combining diverse features and dimensionality reduction strategies.

iv. Real-Time Face Recognition System Using KPCA, LBP and SVM

Al-Mukhtar and AL-Dabagh proposed a real-time face recognition system combining Kernel PCA (KPCA), LBP, and SVM [4]. KPCA addressed non-linear variations better than linear PCA. LBP captured local texture information, and SVM provided a robust classification framework. Their hybrid model achieved higher accuracy than using PCA or LBP alone, illustrating the advantage of integrating global and local feature extraction methods with a strong classifier.

v. CS-NWALBP and HOG Fusion for Robust Face Recognition

Chen et al. introduced a fusion technique using Center Symmetric Neighbourhood Weighted Average LBP (CS-NWALBP) and HOG features [5]. CS-NWALBP improved the traditional LBP by averaging over symmetric neighbors, enhancing sensitivity to subtle textures. Fused with HOG, which excels at edge and gradient representation, their model demonstrated robustness against challenging illumination, boosting practical face recognition performance.

vi. PCAPooL: Unsupervised Feature Learning with PCA, LBP, and Pyramid Pooling

Alahmadi et al. proposed PCAPooL, an unsupervised feature learning method combining PCA, LBP, and pyramid pooling [6]. Pyramid pooling aggregated information across multiple scales, enhancing spatial robustness. This approach was especially effective with limited labeled data, capturing both global structures and local textures. Their strategy presents a practical solution for real-world face recognition under data-scarce conditions.

vii. Optimizing Face Recognition using LBP, SVM, and Random Forest Classifiers

Kumar et al. optimized face recognition by using LBP for feature extraction and comparing SVM and Random Forest classifiers [7]. Their research addressed issues of illumination variance and small datasets. With optimized hyperparameters, they achieved 97.5% recognition accuracy on benchmark datasets, demonstrating the strength of LBP when paired with robust classifiers and the importance of model tuning.

III. METHODOLOGY

The proposed Facial recognition system is made to be accurate and fast on truly real-time applications, like attendance systems. The system encompasses an image acquisition phase, image preprocessing, feature extraction via PCA and LBP, classification with SVM, and attendance logging, all using a Tkinter GUI. The entire architecture is aimed at achieving a good balance between recognition performance and computational efficiency and making it usable in practice with an intuitive interface. Figure 1 displays the five main steps of this recognition.

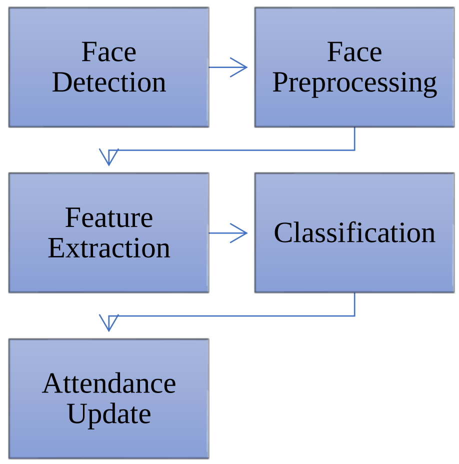

Figure 1.The Five Steps of Proposed Face Recognition

i) Image Acquisition and Face Detection

The system uses a connected webcam to continuously capture frames in real-time. Each frame undergoes face detection using the Viola-Jones algorithm based on Haar-like features and an AdaBoost cascade classifier. Let I(x,y) represent the input image where x and y are pixel coordinates.[12] The algorithm identifies bounding boxes Rf $\subset$ I(x,y) enclosing facial regions.

ii)Preprocessing

After detection, each facial region Rf is normalized and converted into Grayscale to reduce computational complexity. Histogram equalization is applied to reduce lighting variance. Then the image is resized to a fixed dimension (e.g., 100×100)

iii)Feature Extraction

Feature extraction stage is applied to obtain the most important feature from the face image. Without this stage, the recognition becomes very complex and it does not give good results. The PCA and LBP methods are used to implement this function.

HOG Feature Extraction

The Histogram of Oriented Gradients (HOG) is a feature descriptor that captures the overall shape and structure of an object by analysing the directions of edges within an image.[3] In face recognition, it helps the model understand facial outlines—such as jawlines, eyes, and brows—by encoding where and how the pixel intensities change.

To begin with, we compute the gradient of the image, which tells us how intensity changes across pixels. For each pixel, this involves finding the difference in intensity between neighbouring pixels in both horizontal and vertical directions:

$$Gx = I(x+1, y) - I(x-1, y)$$

$$Gy = I(x, y+1) - I(x, y-1)$$

The image is divided into cells (e.g.,8×8), and each cell generates a histogram of gradient directions.

All histograms are combined into a single feature vector representing the face's structure. These HOG features are then combined with LBP to improve the overall face representation.

Principal Component Analysis (PCA)

The aim of PCA is to extract feature from data through implementing an orthogonal transformation. PCA projects the high-dimensional image data onto a lower-dimensional subspace while preserving maximum variance. [1]
Let $xi \in Rd$ represent the vectorized form of the i^{th}image of dimension $d = m \times n$.
$LBP(x, y) = p = 0 \sum_{p=0}^{7} s(I_p - I_c) \cdot 2^p$ The mean of all samples is:

$$x^{-} = N1i = 1 \sum_{i=1}^{N} Nxi$$

The covariance matrix is computed as:

$$C = N \div 1i = 1 \sum_{i=1}^{N} N(xi - x^{-})(xi - x^{-})T$$

Eigenvectors $u_1, u_2, \ldots, u_k$corresponding to the top k eigenvalues $\lambda_1 \geq \lambda_2 \geq \cdots \cdots \geq \lambda_k$ are selected. The projection of a sample onto the reduced subspace is:

$$y_i = U^T(x_i - \overline{x})$$

Local Binary Patterns (LBP)

LBP is a well-known technique employed for image representation. LBP has been commonly used in many kinds of applications because of its great tolerance against lighting changes. It was initially created by Ojala et al. [2] as gray-scale and rotation invariant texture classification method LBP encodes local texture by comparing each pixel with its neighbourhood. For a pixel $I_c = I(x, y)$and its neighbours $I_0, I_1, \ldots, I_7$ the LBP code is:

$$LBP(x, y) = p = 0 \sum_{p=0}^{7} s(I_p - I_c) \cdot 2^p$$

Feature Fusion and Dimensionality Reduction

The global features and the local texture features from PCA and LBP are united into a single feature vector

$$z_i = [y_i, h_i]$$

where hi represents the histogram of LBP codes. SelectKBest method is applied to reduce dimensionality further by choosing the most relevant features based on statistical criteria.

Classification Using Linear SVM

A classification is the fourth stage of this system. The goal of this stage is to classify the entire face image based on the information that obtained through the training stage. There are many classification methods that can be applied. In this system, SVMs that are considered as one of the famous classification methods is used to do this job.

SVM is one of the important techniques that is used to classify features.[10] The objective of SVM is to find an optimal hyperplane that separates the feature vectors of different classes with the maximum margin.

Given a set of training data:

$$\{(x_i, y_i)\}N_{i=1,}x_i \in R^d,\ y_i \in \{-1, +1\}$$

where x_i is the feature vector and y_i is the class label, the decision function for a linear classifier is:

$$f(x) = w^T x + b.$$

- $w \in R^d$ is the weight vector,
- $b \in R$ is the bias.

The optimization problem is posed as: $y_i(w^T x_i + b) \geq 1, \forall i.$

Subject to, $y_i(w^T x_i + b) \geq 1 - \xi_i$. Hyperparameter tuning performed using GridSearchCV with k-fold cross-validation to ensure robust classification.

IV. EXPERIEMENTS AND RESULTS

Two datasets are used to estimate the efficiency of the proposal system. The first is the publicly available ORL face dataset and second is the custom face dataset created by us. Each dataset contains images of multiple individuals under varying conditions, allowing for a comparative analysis of system performance.

i) ORL Database

The ORL database consists of 400 images for 40 persons and each person has 10 images.[11] These images are taken under different lights, expressions, and perspectives. Figure 2 shows ten different images from ORL database. The types of these images are grayscale and their resolutions are 112 × 92 pixels. The proposed model, trained using LBP + HOG feature fusion, followed by PCA dimensionality reduction and classification via a grid-tuned SVM achieved 95% accuracy.

Figure 2.Samples of ORL Database

ii)AIM Students Database

This database consists of 270 images for 27 persons and each person has 10 images as same as the ORL database. This is a custom dataset which we collected from our classmates. These images are taken under different lights, expressions and perspectives. These images are converted into grayscale and resized into 100 X 100 pixels. The proposed model achieved 85% accuracy. Figure 3 shows sample images of our dataset.

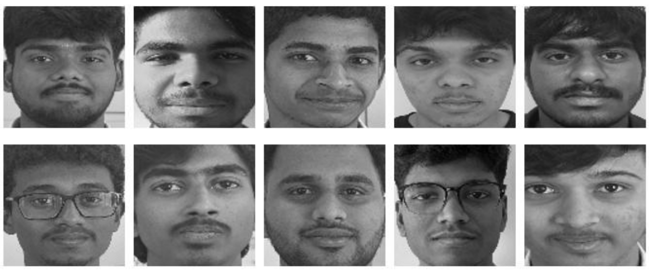

Figure 3.Samples of AIM Students Database

We tried the two datasets with different models like SVM, Neural Networks etc. Table 1 shows the results of models with these datasets and Table 2 shows the comparison of best models of the two datasets.

Model	Dataset	Accuracy
SVM	ORL	95%
Neural Network	ORL	71%
SVM	AIM	85%
Neural Network	AIM	40%
CNN	LFW	71%

Table 1.Comparison between the model results

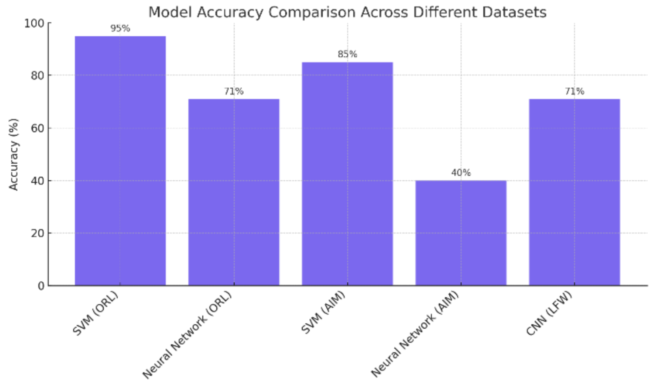

Figure 3. Model Accuracy Comparison Across Different Datasets

Model - Dataset	Precision	Recall	F1 Score
SVM (ORL)	0.97	0.96	0.95
SVM (AIM)	0.84	0.85	0.85

Table 2.Comparison between the best models.

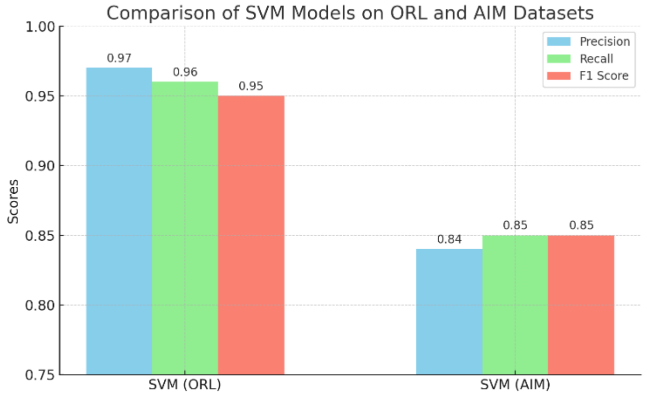

Figure 4. model accuracy comparison

From the table 1, we can say that the SVM performs very well in all datasets because of its capacity to find the patterns in the small datasets. As we know, the neural network models are less accurate than the SVM because they need more datapoints to find the patterns among the faces. In the comparison between the datasets, ORL dataset showed high performance due to its controlled capture conditions, consistent image quality, and sufficient samples per class.

In contrast, the images in our dataset may suffer from lower resolution, blur and may have significant variations in lighting, background, and facial orientation. These factors significantly affect the consistency of handcrafted features like LBP and HOG, leading to reduced classification accuracy.

V. CONCLUSION

The face recognition attendance system is an effective combination of several modern technologies like machine learning, computer vision, and web technologies for the real-time, contactless, and efficient verification of identity through attendance marking. The feature extraction and optimized Linear SVM classifier-based mechanism will handle the failures in face recognition with very high accuracy and reliability. The web-based user interfaces created using Flask,[8] live video feed and QR code-based secure access make the system user-friendly as well as platform independent.[13] Real-time attendance marking, automatic logging of entry and exit times, as well as access through secure channels, render the application not only functional but also deemed practical for real-world applications in a school setting, workplace, or secure zones. The system then shows how a classic well-structured machine learning architecture could create lightweight frontend technologies to create very strong authentication solutions for biometric identification. Future improvements might include deep learning methods or anti-spoofing mechanisms. Or perhaps cloud-based deployment for larger scale integration with future improvements.

VI. ACKNOWLEDGEMENT

For the completion of this project, we would like to thanks our Dean Dr. K P Soman for giving us the opportunity to do this project. We would like to extend our gratitude to our professors, Dr. S Manimaran and Dr. Prem Jagadeesan, for their constant support and guidance throughout the project duration. We would also like to thanks to all the people who have contributed to the successful completion of this project.

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