Face Recognition: Based Attendance System

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Abstract

Teachers often face a significant burden when it comes to manually managing attendance. To address this challenge, an intelligent automatic time attendance management system is employed. However, ensuring proper authentication poses a crucial concern for this system. Biometric data, particularly facial recognition, is commonly utilized to enhance these smart time attendance systems. Facial recognition serves as one of the biometric techniques aimed at improving the system. The key implementation steps in such a system involve face recognition and the recognition of identified faces. This article proposes a plan for introducing a system to track students' attendance automatically in schools. The model takes advantage of various methods for recognising human faces, such as Eigenface values, PCA, and CNNs. The model provides a useful tool for keeping track of students' attendance and records by matching images of their faces with those in a database.

IndexTerms: Eigenface values, Principle Component Analysis (PCA) and Convolutional Neural Network (CNN)

I. INTRODUCTION

In the era of widespread internet usage, computer technology has permeated various aspects of people's lives and work, leading to increased interaction with computers. Face recognition technology, which combines artificial intelligence and computer science, has emerged as an innovative and promising field with diverse applications. Face recognition is particularly valuable as an identity label for distinguishing individuals and has found its way into everyday life. One practical application is using face recognition for attendance purposes within organizations. Maintaining and evaluating attendance records is crucial for performance reviews in any organization. The development of an attendance monitoring system aims to automate the traditional manual method of taking attendance. The Automated Attendance Management System reduces the need for human involvement by automating daily tasks related to attendance marking and review. The traditional attendance marking process becomes time-consuming and complex when dealing with larger numbers. Automating the attendance system offers advantages such as time savings and monitoring capabilities. Two well-known methodologies used in face recognition are the feature-based methodology and the brightness-based methodology. The feature-based methodology relies on identifying key point features, such as eyes, nose, mouth, and edges, to extract relevant information from the face image. This approach only considers a subset of the image, reducing computational complexity. On the other hand, the brightness-based methodology, also known as holistic-based or image-based methodology, processes the entire image as a
whole. However, this method requires more processing time and is more intricate due to the consideration of the entire image. The face recognition framework involves several steps, with face detection and face

recognition being the primary ones. In the attendance marking process, images of students' faces are required, which can be captured using a camera installed in a classroom to capture the entire classroom view. These images serve as input to the system. To improve face identification accuracy, image processing techniques such as grayscale conversion and histogram equalization can be employed. After enhancing image quality, the image is subjected to face detection, followed by the face recognition process. Various face recognition methods, such as Eigenface, PCA, and LDA hybrid algorithms, are available. In the Eigenface method, faces are isolated and facial features are extracted using a feature extractor. The student's face is then matched with the face database to mark attendance. Developing a comprehensive face database is necessary to facilitate this process.

II. PROBLEM STATEMENT – OVERVIEW

Managing attendance for a large number of students in an organization can be a challenging and time-consuming task. The current manual entry system used in institutes suffers from inefficiencies, especially when dealing with a high student population. Maintaining attendance records becomes a tedious and complicated process, involving logbooks and manual record-keeping. Face recognition poses its own set of difficulties in computer vision. Challenges such as variations in lighting conditions, different poses, scale differences, low image quality, and partially obscured faces need to be addressed. Face recognition algorithms must be resilient to these variations and changes. Existing techniques often struggle when faced with alterations in lighting, background, or rotation, necessitating solutions to overcome these limitations. The objective of this project is to develop a system that is less affected by lighting conditions, invariant to rotations and scale variations, and robust enough to perform reliably in real-world scenarios.

III. SCOPE AND OBJECTIVE

The scope of this project is broad and extends to various domains and applications like Educational Institutions where schools, colleges, and universities can automate the attendance process for students and staff. this can eliminate the need for manual attendance marking, reduce administrative workloads, and provide accurate and efficient attendance management.Moreover, Companies can adopt face recognition-based attendance systems to streamline employee attendance tracking. This system can be integrated with HR and payroll systems, simplifying attendance management, and ensuring accurate records for payroll calculations. Which also include Event Management such as Face recognition technology that can be utilized in event management to facilitate participant check-ins, registration, and tracking attendance at conferences, seminars, exhibitions, and other large-scale events. It offers a convenient and efficient way to manage attendees and gather valuable data.

IV. LITERATURE SURVEY

Hajar Filaliet et al. [1] conducted a comparison of four machine learning techniques for complex tasks that conventional algorithmic methods struggle with. Haar-AdaBoost, LBP-AdaBoost, GF-SVM, and GF-NN were the tested methods. Both Haar-AdaBoost and LBP-AdaBoost use the Boosting method to pick the best classifier in a cascade. Features are extracted using Gabor filters in GF-SVM and GF-NN. The study found that the various approaches took different amounts of time to detect an event, with Haar-AdaBoost showing the highest performance in terms of output rate. Therefore, Haar-AdaBoost was adopted for use.

In another study [2], a scheme was proposed to address the limitations of manual attendance systems.

Attendance was taken using real-time facial recognition technology. The system used a classroom camera to take pictures, then performed face detection, created a database of student faces, extracted HOG features, performed face and eye detection, compared and recognised faces using a support vector machine, and recorded attendance. To do this, we used an SVM classifier in conjunction with the Viola-Jones and HOG methods. The study admitted that the device's sensitivity to light was a problem, but that it could be fixed by utilising high-resolution cameras and light-independent algorithms.
E. Varadharaja et al. [7] proposed a face recognition-based method for automatic attendance. The system consisted of four components: background subtraction, face detection and cropping, eigenvalue-based image recognition, and attendance registration. The eigen vector approach used in the paper achieved an accuracy of 60-70 percent. To improve the results, the suggested system recommended using Haar features for face detection instead of eigen vectors.
Shireesha Chintalapati, M.V. Raghunadh, and their colleagues [8] investigated numerous options for introducing a system to track attendance using facial recognition. facial detection and facial recognition were essential to the procedure. Viola-Jones's technique for recognising faces used the Adaboost algorithm, cascade functions, integral graphics, and Haar features to identify individuals. Recognising faces was accomplished with the help of Local Binary Patterns (LBP). For faster processing during facial detection and identification, the identified image was grayscaled. The machine took pictures of the kids, filed them away for future use, and tried to match the captured faces to those already in the database.
In summary, these studies highlighted the use of machine learning techniques, face detection algorithms (such as Viola-Jones), and face recognition methods (including Haar-AdaBoost and LBP) to develop face recognition-based attendance systems. The aim was to overcome limitations, improve accuracy, and automate attendance management processes in various settings.

V. PROPOSED WORK

We use one shot detection for face recognition a given face will be converted in to 128D vector which will be stored in the text file, we can train new face on the go using our dynamic training module which stores this face vector and other details like name, roll no into a SQLite database table. When the student appears in-front of the camera again, if his face feature vector is already present it will be recognized and attendance will be recorded into a csv sheet as form of observations. Our system uses pyQT5 as a front-end interface.

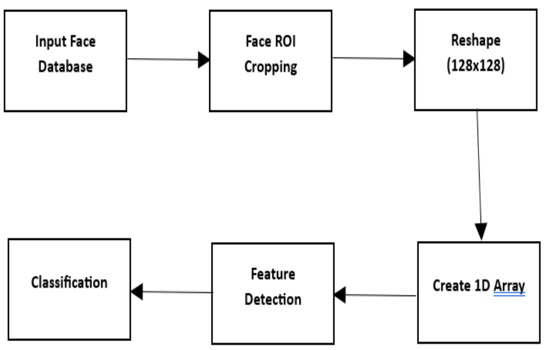


Fig .1: Block Diagram Face Recognition System

A. INPUT FACE DATABASE CREATION

To construct the database, videos were recorded capturing 11 individuals looking in various directions. From these videos, face detection was performed, and frames were extracted. The database was created using a 13MP mobile phone camera. Each class within the database comprises 234 images. The resolution of each image is 244x244 pixels.

Face ROI cropping

Since photos may contain both face and non-facial components, it is essential to extract the exact face region to improve face recognition accuracy. The process's primary goal is to identify faces. In this method, we use a face recognition strategy that relies on Deep Neural Networks (DNNs). The DNN-based method provides more precise results than competing state-of-the-art approaches. The caffe pre-trained module of face detection-optimized text files is used to implement the face detection capabilities. The OpenCV library provides easy access to this feature. ResNet serves as the foundational network for the DNN-based face detector built on top of it using the Single Shot Detector (SSD) framework.

Reshaping

The photos are downsized to a standard 128x128 pixels after being cropped to guarantee consistency in appearance. This standard size is reached by cropping and shrinking the facial photos after they have been discovered. The flattened pixel values of the reshaped images are then used to convert the images into a 1D array of size 1x(128)2.

Feature extraction is a crucial component in face recognition algorithms as it captures the distinctive characteristics that differentiate one face from another. In this approach, Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) techniques are employed for feature extraction. The database is partitioned into two subsets: the train images and the test images.

B. CLASSIFICATION

CNN (Convolutional Neural Network)

The Convolutional Neural Network (CNN) is a specialised form of feed-forward ANN that can learn and make precise predictions by extracting crucial elements from input images. Unlike traditional methods that require a separate feature extraction step, CNN automatically extracts important features directly from the input images during the training process. This capability allows CNN to capture and preserve essential spatial and temporal characteristics in the images while remaining invariant to common geometric transformations like rotation, translation, compression, and scaling. The There are three main components to CNN architecture: scalability, shiftability, and distortion invariance. The training process is quite similar to that used by backpropagation neural networks; the network is taught to classify inputs by performing a sequence of connection operations. As shown in the picture below, the standard CNN architecture for face recognition consists of five convolutional layers, a pooling layer, and fully connected layers.

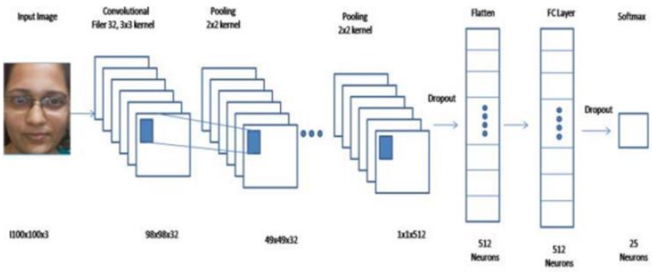


Fig.2: Architecture of CNN for proposed approach

In the convolutional layer, the input image undergoes a convolution operation with a kernel of size 3x3. Different types of filters can be used to create the convolutional mask. This operation involves convolving the input image I(x, y) with the kernel K(i-x, j-y).
The convolutional layer produces a smaller feature map as its output than the original input. Due to the linear nature of feature maps, non-linearity must be introduced. The nonlinear properties of the feature map are improved by using the Rectified Linear Unit (ReLU) activation function. This is required due to the instability introduced by linear functions into the system.
The pooling layer is utilized to preserve important image features while reducing the size of the feature maps. Various pooling techniques exist, such as mean pooling, max pooling, and sub-sampling. In max pooling, the maximum value within each cluster is selected, while in mean pooling, the average value is taken. An average is calculated using sub-sampling, which is a special case of mean pooling.
By using flattening, a two-dimensional picture can be reduced to a single-dimensional vector. This vector is then sent into the fully connected layer, where each cell represents a feature map.
The fully connected layer, or artificial neural network (ANN), links all of a given layer's neurons to all of those in the next higher layer. The SoftMax function is used to forecast class probabilities in classification jobs using mutually exclusive classes.
The output of the SoftMax function is a probability distribution, providing values between 0 and 1 that represent the likelihood of each class.

VI. IMPLEMENTATION

A. CASCADE CLASSIFIER

An efficient method for detecting objects is the Haar feature-based cascade classifier, which was proposed by Viola and Jones in 2001. It makes use of ML to learn a cascade function from both good and bad examples of imagery. In order to train a system for face detection, it needs access to a large number of both "good" (pictures with faces) and "bad" (images without faces) examples. Haar-like features, which are analogous to convolutional kernels, are used to extract features by the approach. Each feature is a discrete value determined by subtracting the total number of pixels lying within an area that has been coloured white from the total number of pixels lying within an area that has been coloured black. To compute the features, the algorithm considers all possible sizes and positions of each feature kernel, resulting in a large number of features to be evaluated (over 160,000 features for a 24x24 window, for example). The integral image technique is employed to efficiently calculate the sums of pixels under the rectangles, reducing computational complexity.
For each feature, the algorithm determines an optimal threshold that separates positive and negative classifications. Errors or misclassifications occur during this process. The features with the lowest error rates, indicating accurate classification of face and non-face images, are selected. It's important to note that this selection process is iterative and involves adjusting weights assigned to misclassified images.
This ensemble of rather unreliable classifiers is what forms the final classifier. The sum of their strengths creates a powerful classifier, even though the individual ones might not be enough on their own. The paper mentions achieving detection accuracy of 95% using as few as 200 features, while their final implementation employed around 6,000 features. This reduction in the number of features from over 160,000 to 6,000 demonstrates the substantial gains achieved by the cascade classifier approach.

B. MOBILE NET

Google's MobileNet is a computer vision model specifically developed for training classifiers and has been made available as an open-source resource. It distinguishes itself by utilizing depth-wise convolutions, which significantly reduce the number of parameters in comparison to other networks. This unique characteristic enables the creation of lightweight deep neural networks.

By employing depth-wise separable convolutions, MobileNet achieves parameter reduction while maintaining the same depth as networks with regular convolutions. This approach leads to the creation of highly efficient and compact deep neural networks.

MobileNet, being a convolutional neural network (CNN), has been introduced by Google as an open-source framework, providing an excellent foundation for training classifiers that offer exceptional speed and compactness.

The performance and power consumption of the network are directly related to the number of multiply-accumulate (MAC) operations, which serve as a metric for fused multiplication and addition operations.

C. MobileNet Depth wise Separable Convolution :

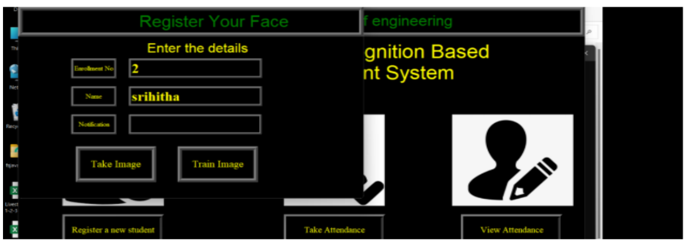
The concept of separable convolutions is based on the idea that the depth and spatial dimensions of a filter can be treated separately. Let's take the example of the Sobel filter used in image processing for edge detection.

In this approach, the height and width dimensions of the filter can be considered independently.The matrix product of [1 2 1] and [-1 0 1] in the inverted form gives rise to the Gx filter, for instance. This gives the impression that the filter has nine parameters when in fact it only uses six. Because height and width are treated as different variables, we may use fewer parameters to describe the system.

A depth-wise separable convolution is the outcome of separating the depth dimension from the horizontal (width * height) dimensions. A depth-wise convolution is then applied, followed by a depth-covering 1x1 filter.

The convolutional method has the advantage of using fewer parameters while still producing the same number of output channels. For instance, a depth-wise convolution using 3x3x3 parameters and additional depth-wise convolution requiring 1x3 parameters would be required to generate a single channel of output. However, if we required three output channels, we would only need a 3x1 depth filter, resulting in a total of 36 parameters (27 + 9). In contrast, for the same number of output channels using regular convolution, we would need 3x3x3 filters, totaling 81 parameters.

VII. INPUT AND OUTPUT



VIII. RESULT

The attendance system incorporates face recognition technology, utilizing computer algorithms to achieve accurate attendance results. This implementation demonstrates the practicality and effectiveness of the designed algorithm. Students who utilize this system experience the benefits of a streamlined attendance process, eliminating the complexities of traditional roll call methods. With efficient operation and functionality, the system enables quick and convenient attendance sign-in for students. Furthermore, innovations in system timing and attendance format have significantly improved the attendance rate and the reliability of face recognition technology. This remarkable progress calls for further exploration and realization by our scientific community.

XI. FUTURE SCOPE

At first, the proposed attendance system will just track pupils' physical presence in the classroom. But there is room for innovation and growth, which may see it used by global corporations to keep tabs on a far larger personnel database. This improved system could monitor and ensure security within the organization with greater efficiency while also keeping tabs on staff working hours to check for schedule adherence.

Moreover, this technology can also be implemented in banks, specifically by integrating facial recognition algorithms into ATM machines. Using this upgrade, users' bank accounts would only be accessible when their faces were recognised by the ATM and compared to those in the system. Incorporating this extra safety precaution into ATM transactions will dramatically improve safety by lowering the likelihood of theft and unauthorized access.

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