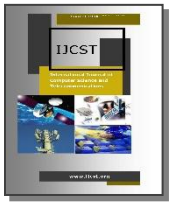

ISSN 2047-3338

Reinforcement Learning in Financial Markets: A Study on Dynamic Model Weight Assignment

Muhammad Jafar, Usman Ali, Muhammad Junaid Arshad

***Abstract*—In an era where educational institutions struggle with unreliable manual attendance systems and superficial participation tracking, our research addresses the critical need for technology that not only automates presence verification but also promotes meaningful classroom engagement by continuously monitoring student attendance throughout entire sessions. Unlike traditional methods, our system continuously monitors multiple faces simultaneously during live video capture, with attendance finalized when instructors close the camera. The technology employs a time-based presence threshold, marking students as present only when they attend more than 75% of the total class duration, effectively preventing superficial attendance and encouraging meaningful participation. Leveraging Dlib's robust recognition library alongside advanced deep learning models, our methodology achieves impressive accuracy metrics during train- test splitting on our dataset: 92% face detection accuracy using Histogram of Oriented Gradients (HOG) and 96% recognition precision with our optimized K-Nearest Neighbors (KNN) model implementation when testing on single face images. The multi- face processing algorithm enables simultaneous identification of all students in the same classroom context, achieving 88% overall attendance marking accuracy in real-world implementation. University attendance management now benefits from instant statistics functionality through an easy-to-use interface which advances institutions by converting administrative work into quality student engagement tools.**

***Index Terms*—Face Recognition, Attendance System, Real-Time Monitoring, Face Detection, OpenCV and Dlib**

I. Introduction

IMAGINE a classroom where attendance is taken silently, accurately, and continuously—without disrupting the flow of learning or consuming precious instructional time. In an era where artificial intelligence is revolutionizing industries, educational institutions remain surprisingly tethered to century-old attendance practices that are not only inefficient but vulnerable to manipulation. The intersection of computer vision technology and educational administration presents an untapped frontier with transformative potential.

Numerous institutions and universities find it tedious to mark student attendance using traditional methods. Furthermore, it may take up to five minutes for the instructors to call out each student's name over the full session to record attendance. This is a laborious process, and someone can act as a proxy. To incorporate extra techniques for monitoring attendance, some establishments have started utilizing RFID [1], iris recognition [2], fingerprint recognition, and other methods. However, these technologies can take longer and become more obtrusive because they operate in a queue.

Face recognition is a crucial biometric feature that is easy to learn and non-intrusive. Face-recognition systems are typically unaware of a wide range of facial emotions. A face recognition system comprises two categories: face identification and verification, which compares a query face image to a template face image using a 1:N matching procedure, whereas face verification compares a face image to a template face image using a 1:1 matching technique [3].

This study is based on developing a system that can mark student attendance. The system first captures the video and then detects the faces in the frame, compares the faces with known faces, recognizes the students, and performs it for the entire video. It then calculates the percentage of students present in the class during the lecture; if that percentage is greater than 75, the student is marked as present or absent. This attendance is maintained in the database and can be shared with the teacher on the app. An app with a simple interface for teachers to log in adds up the details of classes they might be taking and then receives the attendance in the app in an Excel file that can be saved on the phone.

A. Novel Contribution

- The proposed system integrates a hybrid face recognition framework that combines Histogram of Oriented Gradi- ents (HOG) for feature extraction with a Convolutional Neural Network (CNN)-based face encoding, enhancing recognition accuracy while maintaining computational efficiency.
- An advanced attendance verification mechanism is introduced, enforcing presence duration to ensure sustained student engagement rather than a one-time attendance check, thereby improving the reliability of attendance records.
- Optimized computational methodologies are implemented to reduce processing overhead while preserving high classification accuracy, ensuring the system's robustness and feasibility for real-time deployment.

B. Paper Organization

Rest of the paper is organized as follows: Section 2 presents a detailed review of related works, highlighting recent advancements and methodologies in face recognition and attendance systems. Section 3 introduces the proposed

Muhammad Jafar (corresponding author) is with the Department of Computer Science, University of Engineering and Technology, Lahore, Pakistan (email: clicktojafar457@gmail.com). Usman Ali is with the Department of Information Sciences, University of Education, Lahore, Pakistan (email: usman.ali@ue.edu.pk). Muhammad Junaid Arshad is with the Department of Computer Science, University of Engineering and Technology, Lahore, Pakistan (email: mjunaiduet@gmail.com).

system, outlining its architecture and dataset collection methods. Section 4 describes the methodology, including image acquisition, preprocessing, and the proposed deep learning-based techniques. Section 5 discusses the experimental setup and result analysis, comparing the performance of classifiers like KNN and SVM in terms of accuracy, precision, and recall. Section 6 concludes the paper by summarizing the key contributions, limitations, and potential areas for future work.

II. Related Works

[4] proposed a web application-based attendance system to enhance accuracy in face recognition for classroom attendance tracking. The system addresses variations in lighting and poses while prioritizing student privacy through secure storage of images and attendance records. It consists of a camera for capturing images, followed by image preprocessing to isolate the faces and remove background noise. Face detection is performed using algorithms like Haar Cascade or the Viola-Jones method, leading to recognition via Convolutional Neural Networks (CNNs). Once recognized, student attendance was recorded and a comprehensive database was maintained for data analysis and reporting.

[5] proposed an automatic attendance system leveraging a combination of CNN and LSTM. Their approach captures both spatial and temporal information to improve accuracy and efficiency. The system achieved a face recognition accuracy of 99.82% with a runtime of 6.93 seconds. A dataset of 2800 images was utilized to incorporate data augmentation techniques to enhance model generalizability.

[6] integrated Multi-task Cascaded Convolutional Neural Networks (MTCNN) for accurate face detection, VGGFace for feature extraction, and Support Vector Machine (SVM) for classification. Pre-trained on 2.6 million facial images, VGGFace demonstrated robust performance, achieving a 95% F1-score. They processed a diverse dataset of 18,036 images under varying conditions and excelled in real-time multi-face detection and recognition. Designed for attendance management, they enhanced efficiency, security, and scalability in educational and corporate settings.

[7] presented a facial recognition system that can recognize faces in live or recorded video streams using deep learning techniques, especially Convolutional Neural Networks (CNN). Based on the VGGFace architecture, the system used a proprietary dataset of 7,500 photos from 26 different people to apply transfer learning. The method achieved a mean recognition accuracy of 96%, with confidence levels ranging from 78.54% to 100% across real-time inputs, thereby demonstrating its high effectiveness for surveillance applications.

[8] proposed a real-time facial recognition attendance system that addresses the shortcomings of human processes and RFID/biometric systems by automating tracking in educational institutions. The system achieves 94.5% detection accuracy and 98.5% recognition accuracy using the LBPH algorithm for recognition and the Haarcascade classifier for face detection. Each person had 60 grayscale color photos in the database that depicted a range of postures and facial expressions. The images were aligned, and noise was reduced using normalization techniques. A static camera was used to identify unique faces and store information based on unique IDs.

[9] Proposed a classroom management system integrating facial recognition and speaker diarization to automate attendance and detect disruptions. Using 25 images per student, the system applied deep learning and the Eigenface algorithm, achieving a FAR of 0.055 and FRR of 0.01. Speaker diarization used GMM with MFCC features, yielding a DER between 0.0361 and 0.0973. The models accounted for variations in lighting, expressions, and angles.

[10] presented a facial recognition-based attendance system using a pipeline of machine learning techniques. The system employs HOG for face detection, aligns facial features using landmarks, and encodes faces into 128-dimensional embeddings using a deep CNN. The embeddings were then matched using a linear SVM for attendance recording, which showed promising results for automated attendance management.

[11] Proposed a facial recognition system for attendance tracking using student-submitted images. It employs OpenCV's deep-learning face detector (ResNet-SSD), FaceNet for 128-D embeddings with triplet loss, and scikit-learn for classification using SVM and other machine learning techniques.

[12] presented a face recognition attendance system that achieved 99.6% accuracy by utilizing FaceNet and Support Vector Machine (SVM). The system processes images from private datasets, including photos of over 80 individuals, resized to 160 × 160 pixels. It employs face detection for preprocessing and organizes the images into labeled folders. Although CNN models achieve approximately 95% accuracy, FaceNet and SVM are more efficient regarding training time. The system effectively handles multiface recognition in classrooms and accurately detects up to 20 individuals in a single frame.

[13] proposed a face recognition-based attendance system to replace proxy attendance and human error, which take a lot of time (10–15 minutes) during a 50-minute presentation. The system gathers 25 photos of each student from different perspectives in order to build a database using the Cognitive Face API and Principal Component Analysis (PCA). It instantly recognizes faces, compares them to attributes that have been saved, and automatically logs attendance in a spreadsheet that is then posted to a website. The system's recognition efficiency of 95.61% can be further enhanced by employing wide-angle cameras and raising image resolution.

[14] presented an auto-attendance marking system for students utilizing the Kth Nearest Neighbor (KNN) algorithm. The system captures images via a camera, which are then preprocessed using histogram equalization. The HAAR cascade algorithm was used for face detection and the Linear Discriminant Analysis (LDA) algorithm was used for feature extraction. Three methods are used for recognition: KNN, Support Vector Machine (SVM), and LDA. However, this system has limitations because it is sensitive to noise and missing data, and it has trouble processing large datasets. These restrictions were successfully addressed using the proposed approach.

[15] presented a facial recognition system designed explicitly for partial faces. The authors used a VGGF model

that was already trained for feature extraction. They used a Support Vector Machine (SVM) and cosine similarity for categorization. The results showed that cosine similarity remained accurate in the same scenarios, unlike SVM, which lost accuracy when processing images with unclear faces.

[16] presented a face recognition system for constant surveillance in educational settings. The system employs Active Student Detection (ASD) with two cameras installed on the classroom walls: one for sensing and the other for face detection. The methodology involved estimating the seating area using ASD and then capturing students' images with a capture camera. The system determines whether students are enrolled in class using interframe and background-frame subtraction algorithms. Additionally, the authors addressed the linear sum assignment problem by matching seats with students.

[17] presented a video based face recognition system for efficient attendance marking.FaceNet is used for feature extraction, MTCNN is used for face detection, and a Support Vector Machine (SVM) is used for person identification in this system. Testing on a custom dataset demonstrated that the system achieved an accuracy rate of 94.8%.

[18] proposed a machine-learning approach for classifying facial expressions through a multi-layer categorization process using Haar-like features and ROI configurations for initial face detection. The method then employs SVM and HOG for expression matching, achieving a higher accuracy than traditional techniques. This approach demonstrates potential applications in environments such as schools and traffic systems owing to its improved accuracy and effective facial expression recognition.

[19] presented a facial recognition system designed for unrestricted environments, combining deep learning techniques like FaceNet with traditional classifiers such as SVM, KNN, and RF. The system uses FaceNet for categorization and YOLO-Face for real-time facial detection. High accuracy is demonstrated by the experimental results: 99.7% for the FaceNet+SVM model, 99.5% for the FaceNet+KNN model, and 85.1% for the FaceNet+RF model. Using this system, FaceNet was 99.6% accurate.

[20] proposed system aims for high precision and low computational complexity while being cost-efficient and requiring minimal manual intervention. Three facial recognition techniques were used: K-nearest neighbor (KNN), convolutional neural networks (CNN), and support vector machines (SVM). Gabor filters were used to improve accuracy. KNN outperformed the others in terms of accuracy, reaching 99.27%; however, CNN showed the least amount of computing complexity. However, SVM was found to be less effective.

[21] proposed an automation framework for face recognition-based attendance. The system leverages OpenCV, face recognition, and Haar cascade classifier to achieve accurate face detection and recognition. The proposed system aims to replace conventional attendance methods and offers increased efficiency. The framework provides real-time monitoring and reporting features, allowing educators and administrators to track attendance seamlessly and effectively.

[22] presented a facial recognition attendance system that would automate and enhance the accuracy of attendance marking utilizing the HOG, CNN, and SVM algorithms. This technology overcomes the drawbacks of conventional techniques such as fingerprinting, card scanning, and manual records, all of which are susceptible to forgeries and manipulation. It assesses facial recognition in several scenarios, including changes in lighting and head movements. The results show that CNN achieves the highest accuracy of 99.2%, compared to 97% for KNN and 80.15% for SVM. The system maintains attendance records in Excel format, is dependable, efficient, and requires less manual labor.

III. Proposed System

The proposed system is designed to automate attendance management using real-time face recognition. It processes video streams to detect, recognize, and track students' presence throughout a lecture. By leveraging advanced algorithms and deep learning techniques, the system ensures efficient and accurate attendance tracking, reducing manual effort and minimizing errors.

A. Architecture

The proposed system, shown in Figure 1, was designed for seamless and efficient attendance management using face recognition technology. It maintains a database of students' facial images, along with their names. A camera was placed in the classroom to capture video continuously throughout the lecture, ensuring that all students were potentially within view.

As illustrated in figure 1, the system processes the video stream at a rate of 1 frame per second. Each frame was analyzed to detect and recognize faces. The system determines whether a student has been recognized for at least 75% of the class period if their face is identified. If this condition was met, the student's attendance was recorded in an Excel sheet.

B. Dataset

To develop our system for automating the attendance process, we collected data from 35 students in class. Each student was asked to provide 10-12 facial images via Google Forms, captured from different angles and postures under various lighting conditions to ensure diversity in the dataset. Students submitted their roll numbers and names along with images for proper tagging. The data are securely stored in Google Drive and accessible only to authorized personnel. To further enhance the dataset, data augmentation [23] techniques have been applied to increase the dataset while addressing potential ethical considerations for data privacy and security.

C. Integration with Web Application

The proposed system integrates a web application consisting of three key components: frontend (HTML, CSS, and JavaScript), backend (Python and php), and database (MySql). This integration ensures seamless communication between the user interface, data processing modules, and the underlying database, enabling an efficient and automated attendance management system.

Table I: Comparison of Different Face Recognition Based Attendance Systems

Year	Dataset	Algorithms Used	Accuracy	Strengths	Limitations
2024 [5]	2800 augmented images	CNN, LSTM	99.82%	High accuracy; captures spatial and temporal data; is efficient in real time.	Requires significant computational resources for training; sensitive to infrastructure quality.
2024 [6]	18,036 images (Pinterest + SPU dataset)	MTCNN (Detection), VGGFace (Feature Extraction), SVM (Classification)	F1-score 95%	High accuracy, real-time multi-face recognition	Limited dataset diversity, sensitivity to lighting/pose/occlusions, high computational requirements
2023 [7]	7,500 images from 26 individuals	VGGFace, CNN	96%	Real-time recognition; effective on moderately sized datasets; good for surveillance.	Limited generalization; potential overfitting.
2023 [8]	Classroom Dataset	Haarcascade, LBPH	Detection: 94.5%, Recognition: 98.5%	Addresses manual inefficiencies; Effective normalization; Good accuracy.	Varying performance in different environments; limited adaptability to lighting.
2021 [9]	Classroom dataset (25 images per student)	Eigenface, Deep Learning	False acceptance rate (5.5% for Eigen Faces , 3.9% for Deep Learning)	Real-time recognition, scalable, recognizes individuals and groups, and updates attendance	Sensitive to image quality, lighting conditions, and does not mark attendance based on presence duration
2019 [12]	Private dataset with photos of 80+ individuals	FaceNet, SVM	99.6%	Highly accurate for multi-face; efficient training; handles classroom settings well.	Limited dataset size may affect generalization; depends on proper image preprocessing.
2019 [13]	Dataset of 1500 images (25 images per student for 60 students)	Cascade Object Detector for face detection, PCA for feature extraction and matching	95% in face recognition	considers various expressions and lighting conditions; efficient processing	Does not handle cases of occlusion (e.g., veils or partially covered faces); requires high-quality images

Table II: Dataset

Dataset Details	Count
Original Images	350
Augmented Images	350
Total Images	700
Training Set (70%)	490
Testing Set (30%)	210

IV. Methodology

The system operates primarily through the following steps: Image Acquisition, Image Preprocessing, Image Enhancement, Face Detection, Face Alignment, Face Encoding, Classifier Training, Attendance Tracking, and Performance Evaluation.

A. Image Acquisition

A video consists of a series of images captured during rapid succession. Our method involves preprocessing each frame of the camera-captured video using OpenCV [24] to detect faces. We proceed by centralizing the face if one is detected; otherwise, we move on to the next frame.

B. Image Preprocessing

The acquired images were preprocessed by resizing the face images prior to face detection while preserving the shape ratios. Similarly, this resizing ensures uniformity in the size of the images in the input form of the facial recognition model. The images are rescaled such that they form images of 800 pixels on the largest dimension while maintaining their aspect ratio to ensure that the face sizes are correctly scaled for subsequent processing.

C. Image Enhancement

This study applies enhancement techniques to improve image quality and highlight key features for accurate face identification. Key methods include HOG-based face detection and face alignment.

1) Face Detection using HOG: HOG works by extracting distinctive features from images and capturing the gradient patterns of pixels to highlight important edges and shapes. These features are then used as the foundation for recognizing and differentiating faces.

HOG performs feature extraction using two key components: Gradient Direction and Gradient Magnitude. The Gradient Magnitude denotes the magnitude of the change, whereas the Gradient Direction indicates the direction of the greatest shift in intensity.

The formulas used to calculate these gradients are provided in Equations 1 and 2.

$$||\nabla f|| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2} \quad (1)$$

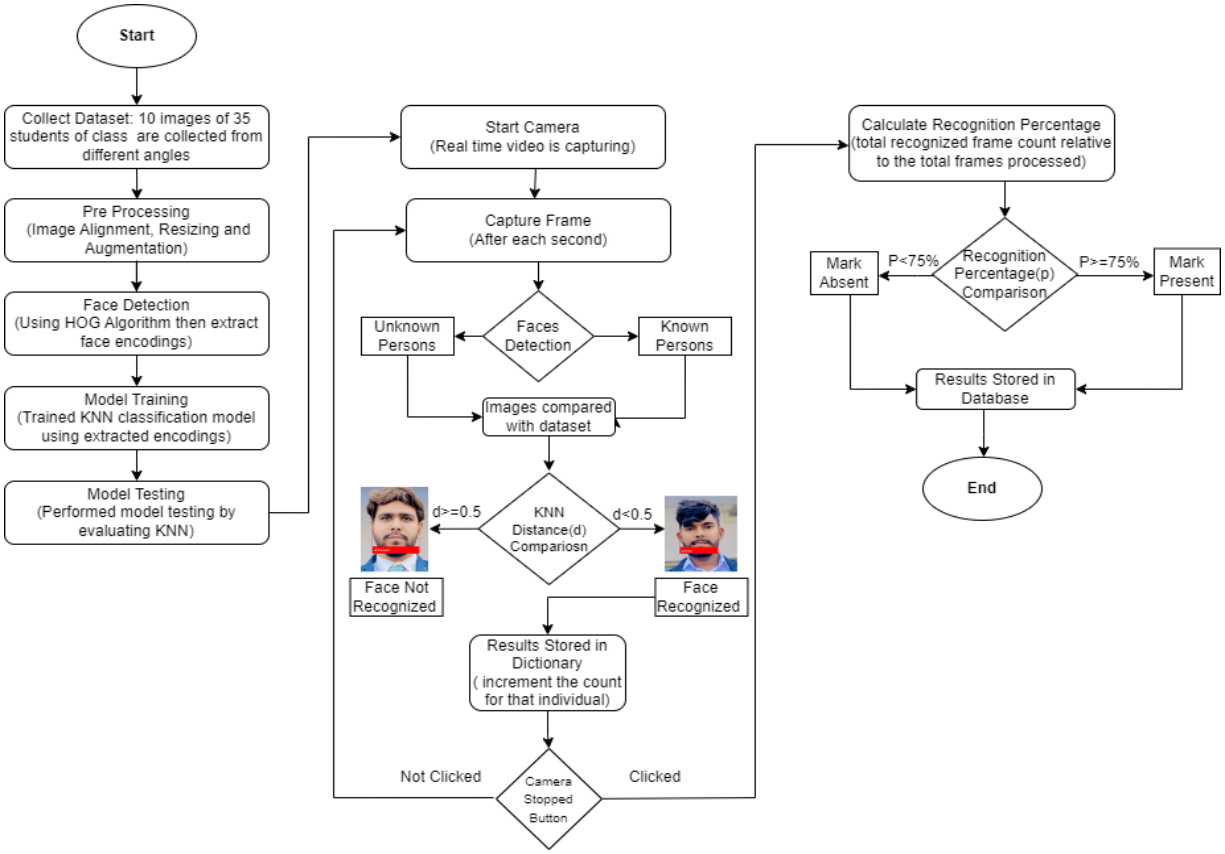

Fig. 1: System Flowchart

$$\vartheta = \tan^{-1} \frac{\partial f/\partial y}{\partial f/\partial x} \quad (2)$$

Fig. 2: HOG Image

This can then be used to find the face and mark it by creating a box around the face as follows:

Fig. 3: Detected Face

2) Face Alignment: After face detection, alignment is performed using landmark estimation to ensure consistent recognition across different poses. The system is trained to identify 68 key facial landmarks for accurate identification.

Once eye and mouth positions are known, affine transformations are applied to rotate, scale, and align the face properly while preserving geometric structure.

Fig. 4: Face Transformation

D. Proposed Method

Several crucial processes are involved in the proposed face recognition approach, including deep learning, face encoding, classifier training, attendance record keeping, and evaluation matrix provision. The face recognition process is performed to ensure that each student entering the classroom can be identified properly, thus minimizing the hassle in managing attendance using state-of-the-art machine learning models and techniques.

1) Face Encoding using CNN: The measurements that are detectable by the naked eye are not detectable by computers; therefore, the computer has to look for faces and find encodings using a deep learning architecture. To compute 128 encodings for a single face, a deep Convolutional Neural Network [25] should be constructed, and three face images should be viewed simultaneously during the training process:

- Load a face image of a familiar individual for training
- Load an additional image of the same well-known individual
- Load an image of someone entirely different

Subsequently, the algorithm examined the metrics produced for each of the three images. It gently changes the neural network to ensure that the measurements for images 1 and 2 become marginally closer, while simultaneously ensuring that the measurements for images 2 and 3 are marginally farther away.

Upon analyzing millions of photos, including thousands of distinct individuals, the neural network can consistently produce 128 measurements for every person. The measurements were approximately the same for each of the ten images with the same subject.

Because computing encodings involve a large amount of GPU power and time, we do not need to train the model beforehand because this is a one-time procedure already completed by Brandon Amos and his team in OpenFace[26]. Image encodings were calculated at an abstract level.

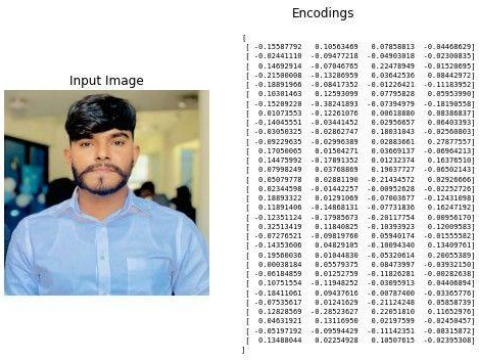

Fig. 5: Face Encodings Generated by CNN: 128-Point Representation

2) Training the Classifier: The final stage of facial recognition was straightforward. Finding an individual whose measures from our test image most closely match those in our database of known persons is what it comprises. Complex deep learning methods are not necessary to complete this assignment; a simple machine learning classification algorithm will do the job just fine. The K-Nearest Neighbors (KNN) [27] approach uses the similarity principle to predict the label or value of a new data point by considering the labels or values of its K nearest Neighbors in the training dataset. To determine the predicted class for a target data point based on the highest frequency, the KNN algorithm first selects the optimal value of K, which indicates the number of nearby neighbors considered for prediction. Next, it calculates the distance between each target point and every data point in the dataset, typically using Euclidean distance to assess similarity. Finally, it identifies the nearest neighbors, which are K data points with the shortest distances to the target point.

Support Vector Machines (SVMs) are powerful supervised classifiers used for classification, regression, and outlier detection, especially effective in high-dimensional spaces. They identify an optimal hyperplane that maximizes class separation, using kernel functions (e.g., linear, polynomial, RBF) to handle both linear and nonlinear data. This enables accurate and robust classification across diverse applications, including facial recognition and text analysis.

A straightforward linear KNN classifier, for example, is sufficient, while alternative classification techniques such as SVM might also work well; however, in our case, KNN was more suitable for large datasets with many students. The procedure comprises training the classifier to output the name of the known individual that represents the closest match based on measurements taken from a fresh test image. This classifier executes exceptionally quickly, usually taking milliseconds to process. Finally, the classifier's output yields the name of the identified person and effectively and precisely concludes the facial recognition procedure.

Fig. 6: Recognized Faces from Image

3) Save Attendance: The system maintains an attendance record array that updates as new faces are detected, which is then converted into a dictionary to count each face in the detected frames and calculate their presence percentage. These data were processed to determine each student's attendance percentage, with a specific check to ensure that students with attendance above 75% were flagged for good standing. Attendance below this threshold may trigger alerts or notifications for further follow-up. Attendance data were then saved in a database for easy access. A user-friendly web application interface allows teachers and administrators to view and manage attendance records, generate reports, and track trends in student attendance. Students can also access their attendance data, including attendance percentages for each course.

4) Evaluation matrix: The efficiency with which a facial recognition system can identify students and monitor their attendance is the basis for evaluating its success. The key metrics in the evaluation matrix are as follows:

- **Accuracy**: The ratio of correctly recognized faces to the total number of detected faces.

Algorithm 1 Face Recognition based Attendance System with Presence Duration

```
procedure PredictAndUpdateAttendance(frame, classifier, model_path, threshold, excel_file_path, presence_threshold)
    if classifier is None then
        Load classifier from model_path
    end if
    Detect faces and compute encodings using face_recognition
    if No faces found then
        return []
    end if
    Predict face identity using KNN or SVM classifier
    return predictions with locations
end procedure
procedure ShowLabels(frame, predictions)
    Draw boxes and labels around detected faces in the frame
    return updated frame
end procedure
procedure AttendanceStatus(predictions, presence_threshold)
    Count name occurrences and calculate attendance percentage for each student
    for each student in predictions do
        Calculate percentage as (count / total_frames) * 100
        if percentage is greater than presence_threshold then
            Mark as "P" (Present)
        else
            Mark as "A" (Absent)
        end if
    end for
    return status dictionary
end procedure
procedure UpdateExcel(file_path, new_data)
    Load or initialize Excel data
    Calculate attendance status using AttendanceStatus
    Merge and save updated data to Excel
end procedure
procedure Main
    Initialize webcam
    while True do
        Capture frame, process every 30th frame
        Get predictions using PredictAndUpdateAttendance
        Update attendance status in Excel using UpdateExcel
        if User presses "q" then
            Break the loop
        end if
    end while
end procedure
```

- **Precision**: The ratio of the number of true positive identifications to the total number of identifications given a particular ID.
- **Recall**: The ratio of true positives (TP) to all the true faces of that person.
- **F1 Score**: The harmonic mean of precision and recall, balancing both metrics.
- **Processing Time**: The time required for processing a face image and making predictions, which is crucial for real-time applications like marking attendance.

E. Confusion Matrix

Evaluation metrics are crucial criteria for assessing the performance of machine-learning or deep-learning-based study. The confusion matrix consisted of four parts, each serving to evaluate different aspects of the model's performance.

- **True Positive (TP)**: Refer to instances where the model correctly identified a student as themselves.
- **True Negative (TN)**: Represent cases where other students were correctly not recognized as the target student.
- **False Positive (FP)**: Occur when the model incorrectly identified another student as the target student.
- **False Negative (FN)**: Occur when the model failed to recognize the target student as themselves.

The formulae used to calculate the accuracy are provided in Equation 3.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{3}$$

The formulas used to calculate the precision are provided in Equation 5.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{4}$$

The formulas used to calculate the f1 score are provided in Equation 6.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5}$$

V. Experimental Setup

The model was trained using Google Colab, leveraging its powerful cloud computing resources to efficiently facilitate the training process. Once the training was completed, the models were deployed to run on a local machine equipped with an Intel Core i5 12th generation processor, operating at a speed of 1.6 GHz. This setup, combined with 16 GB of DDR4 RAM running at 3200 MT/s, provided the necessary computational power to effectively execute the models and ensure a smooth performance during real-time facial recognition tasks. We used the built-in camera of the laptop because of budget constraints to record video for testing purposes, allowing us to capture video data without incurring additional expenses.

A. Result Analysis

As shown in Table III , the KNN model for face recognition achieved the highest accuracy of 96.03% with a weighted average precision of 97.89%, making it the most effective option in our analysis. In contrast, the SVM model for face recognition had an accuracy of 91.27% and weighted average precision of 89.21%. These results indicate that the KNN model outperformed the other models in terms of both accuracy and precision, making it the optimal choice for our application.

Table III: Comparison of Model Matrices

Model	Accuracy	Precision	Recall	F1 Score
Face Recognition KNN	96.03%	97.89%	96.03%	96.48%
Face Recognition SVM	91.27%	89.21%	91.27%	89.52%

Figures 7 and 8 present the results in a grouped bar chart that provides a detailed overview of the performance of the KNN and SVM classifiers for 29 students. This chart displays the counts of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) for each student, allowing for an immediate visual assessment of the accuracy and error distribution of the models. Using distinct colors—blue for TP, green for TN, red for FP, and orange for FN—enhances clarity, making it easier to identify trends and pinpoint potential areas for improvement in the facial recognition system.

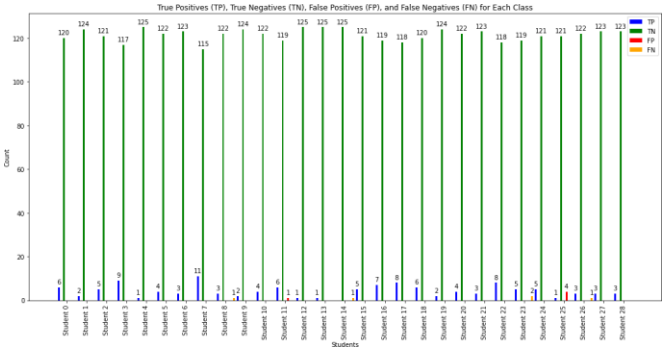

Fig. 7: performance metrics of the facial recognition KNN classifier

B. Accuracy Comparison

As shown in Figure 9, the Face Recognition KNN model exhibits the highest accuracy at 96.03%, significantly outperforming the Face Recognition SVM model, which achieves an accuracy of 91.27%. This clearly indicates that the KNN model is a more effective option between the two evaluated models.

C. Recall Comparison

As shown in Figure 10, the Face Recognition KNN model exhibits the highest weighted average recall of 96.03%, significantly outperforming the Face Recognition SVM model,

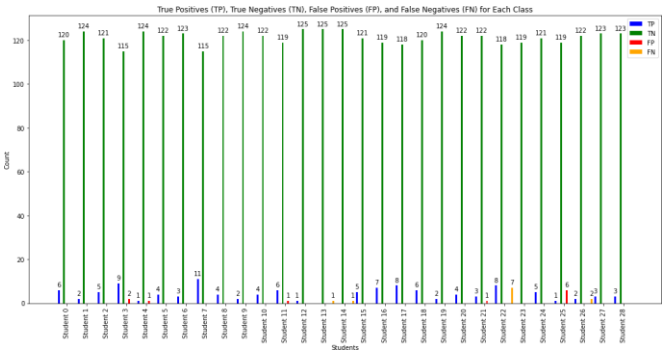

Fig. 8: performance metrics of the facial recognition SVM classifier

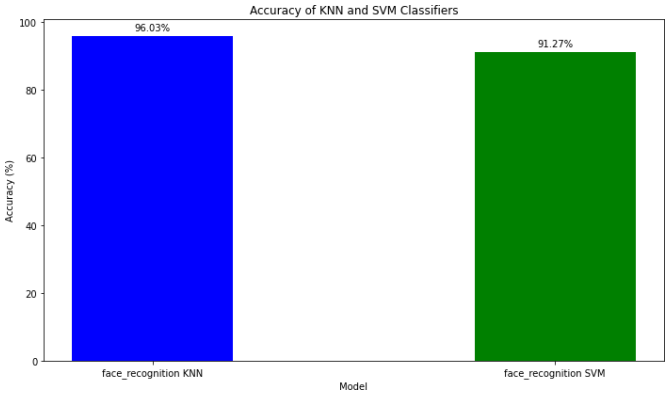

Fig. 9: Accuracy Comparison

which achieves a weighted average recall of 91.27%. This clearly indicates that the KNN model is the more effective option between the two evaluated models. The formulas used

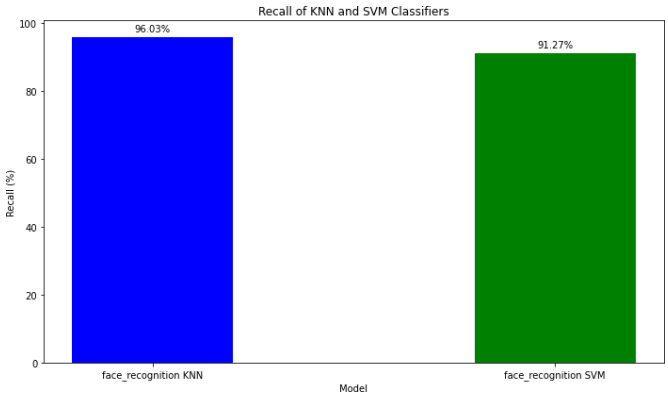

Fig. 10: Recall Comparison

to calculate the recall are provided in Equation 4.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{6}$$

D. Precision Comparison

As shown in Figure 11, the Face Recognition KNN model exhibits the highest weighted average precision of 97.89%, significantly outperforming the Face Recognition SVM model,

which achieves a weighted average precision of 91.27%. This clearly indicates that the KNN model is the more effective option between the two evaluated models.

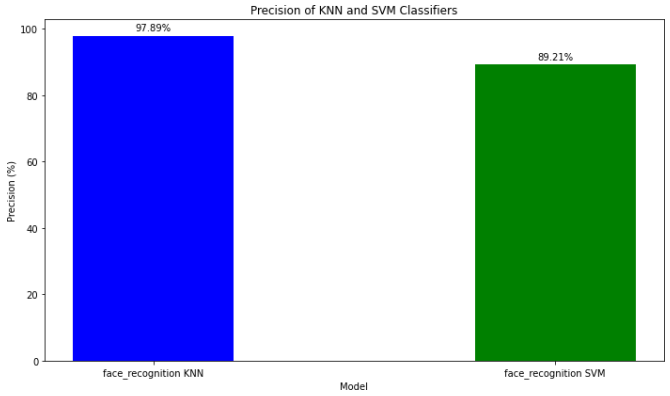

Fig. 11: Precision Comparison

E. F1 Score Comparison

As shown in Figure 12, the Face Recognition KNN model exhibits the highest weighted average f1-score of 96.48%, significantly outperforming the Face Recognition SVM model, which achieves a weighted average f1-score of 89.52%. This clearly indicates that the KNN model is the more effective option between the two evaluated models.

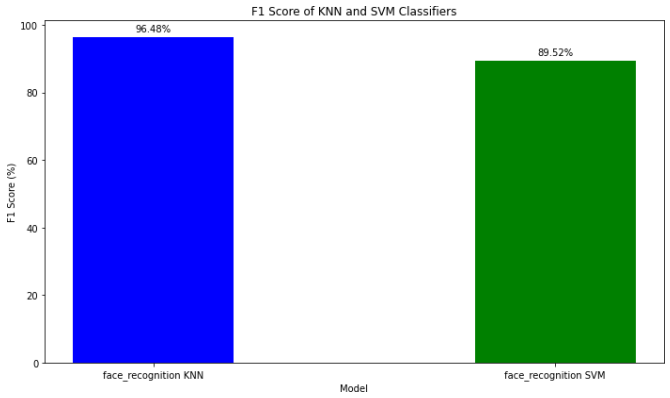

Fig. 12: F1 Score Comparison

F. Discussion

The system developed in this study is a step towards automating attendance management, but it still faces limitations, such as degrading performance under rapid frame rate change conditions, low lighting settings, distorted lenses, and twin recognition. Furthermore, its use is restricted in situations in which people conceal their faces or use veils. These techno- logical issues need to be addressed in future work to make the system more reliable and applicable in real-world scenarios. A larger dataset would further improve the accuracy, especially if advanced techniques of facial recognition are used. In addition, the ability to be used in more environments by expanding coverage to cover faces under coverings is key.

G. Comparison with state-of-the-study

Table IV: Comparison

Year	Real-Time Attendance	Presence Duration Tracking	Ease of Use (App Interface)	Low-Cost Implementation
This Paper	Yes	Yes	Yes	Yes
2024 [5]	Yes	No	Limited	Yes
2024 [6]	Yes	No	No	No
2023 [8]	Yes	No	Limited	Yes
2023 [7]	Yes	No	No	No
2021 [9]	Yes	No	Limited	Yes
2019 [12]	Yes	No	Limited	No
2019 [13]	Yes	No	Yes	Yes

VI. Conclusion

The developed facial recognition based attendance system provides an effective solution for managing attendances in various environments. The system exhibits impressive accuracy in face detection, recognition, and attendance marking using techniques such as Histogram of Oriented Gradients (HOG), face landmarks, and encoding algorithms. Implemented in Python3 with OpenCV for image processing and employing KNN and SVM classifiers, the architecture allows for real-time attendance monitoring. Even on low-end computers, the system achieved 92% accuracy for face detection using the HOG and 96% accuracy for face recognition using the KNN model.

Overall, the system marks attendance with an accuracy of 88%, demonstrating a significant potential improving attendance management processes. This represents a considerable advancement in integrating facial recognition technology with streamlined attendance tracking.

Despite its merits, the suggested system confronts obstacles such as dealing with frequent frame rate changes, bad illumination, lens distortion, and reliably discriminating between identical twins. Furthermore, it ignores situations such as people donning veils. Future research should concentrate on creating sophisticated algorithms to improve robustness in a variety of environmental circumstances, such as low light and fast motion, in order to overcome these constraints. Reliability will be increased by testing the algorithm on a wider range of demographics and enlarging the dataset to include a variety of facial traits.

Availability of Data and Materials

All data generated or analyzed during this study are included in this published article.

Funding and Acknowledgments

The authors are also thankful to University of Engineering and Technology, Lahore, Pakistan for their support.

REFERENCES

[1] Qureshi M. The proposed implementation of rfid based attendance system. *International Journal of Software Engineering & Applications (IJSEA)*, 11(3), 2020.

[2] Haq HBU and Saqlain M. Iris detection for attendance monitoring in educational institutes amidst a pandemic: A machine learning approach. *Journal of Industrial Intelligence*, 1(3):136–147, 2023.

[3] Smitha et al. *Face Recognition based Attendance Management System*. International Journal of Engineering and Technical Research, 2020.

[4] Khan E F et al. Face recognition based attendance system. *International Journal of Advanced Research in Science Communication and Technology*, April 2023.

[5] Shukla A K et al. Automatic attendance system based on cnn–lstm and face recognition. *International Journal of Information Technology*, 16(3):1293–1301, 2024.

[6] M. Ali et al. Attendance system optimization through deep learning face recognition. *International Journal of Computing and Digital Systems*, 15(1):1527–1540, 2024.

[7] Singh A et al. Automation of surveillance systems using deep learning and facial recognition. *International Journal of System Assurance Engineering and Management*, 14(Suppl 1):236–245, 2023.

[8] Rohini V et al. Attendance monitoring system design based on face segmentation and recognition. *Recent Patents on Engineering*, March 2023.

[9] Mohanty A et al. Classroom management system using facial recognition and speaker diarization. In *2021 International Conference on Communication information and Computing Technology (ICCICT)*, pages 1–6, 2021.

[10] Laddha B et al. Face recognition based attendance system. *International Journal for Research in Applied Science & Engineering Technology*, 11(1), January 2023.

[11] Chukwude O et al. Development of face recognition-based attendance system. *Sule Lamido University Journal of Science & Technology*, 6(1,2), April 2023.

[12] Nyein T and Oo A N. University classroom attendance system using facenet and support vector machine. In *2019 International Conference on Advanced Information Technologies (ICAIT)*. IEEE, 2019.

[13] V. Mekala et al. Face recognition based attendance system. *International Journal of Innovative Technology and Exploring Engineering*, 8(12):520–525, 2019.

[14] Patil V et al. Automatic students attendance marking system using image processing and machine learning. In *2020 International Conference on Smart Electronics and Communication (ICOSEC)*. IEEE, 2020.

[15] Elmahmudi A and Ugail H. Experiments on deep face recognition using partial faces. In *2018 International Conference on Cyberworlds (CW)*. IEEE, 2018.

[16] Kawaguchi Y et al. Face recognition-based lecture attendance system. In *The 3rd AEARU Workshop on Network Education*, 2005.

[17] Chaudhari V et al. Real time face recognition based attendance system using multi task cascaded convolutional neural network. In *2023 International Conference on Emerging Smart Computing and Informatics (ESCI)*. IEEE, 2023.

[18] Kim S et al. Facial expression recognition system using machine learning. In *2017 International SoC Design Conference (ISOCC)*. IEEE, 2017.

[19] Moreno S et al. Efficient face recognition system for operating in unconstrained environments. *Journal of Imaging*, 7(9):161, 2021.

[20] Dev S and Patnaik T. Student attendance system using face recognition. In *2020 International Conference on Smart Electronics and Communication (ICOSEC)*, pages 90–96. IEEE, 2020.

[21] Chanti Y et al. Face recognition-based automatic attendance system. In *IOT with Smart Systems*, pages 351–362, October 2022.

[22] Kapse A et al. Face recognition attendance system using hog and cnn algorithm. In *ITM Web of Conferences*, volume 44. EDP Sciences, 2022.

[23] Khalifa N E et al. A comprehensive survey of recent trends in deep learning for digital images augmentation. *Artificial Intelligence Review*, 55(3):2351–2377, 2022.

[24] Sharma A et al. Object detection using opencv and python. In *2021 3rd International Conference on Advances in Computing, Communication Control and Networking (ICAC3N)*, pages 501–505. IEEE, December 2021.

[25] Sanivarapu P V. Multi-face recognition using cnn for attendance system. In *Machine Learning for Predictive Analysis: Proceedings of ICTIS 2020*, pages 313–320. Springer Singapore, 2021.

[26] Amos B et al. Openface: A general-purpose face recognition library with mobile applications. Technical report, CMU-CS-16-118, CMU School of Computer Science, 2016.

[27] Guo X. A knn classifier for face recognition. In *2021 International Conference on Communications, Information System and Computer Engineering (CISCE)*, pages 292–297. IEEE, May 2021.