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Smart Bus Attendance Management Using Deep Learning-Based Face Recognition

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Abstract- The Smart Bus Attendance Management System is a face recognition-based system that uses deep learning to automate the school or college bus student attendance tracking. The conventional manual attendance systems are time-consuming, more likely to be erroneous whereas RFID or biometric security demands the implementation of extra equipment and may not provide real-time accuracy. In this system, images of students are captured when they get on the bus and they are identified with the help of deep learning algorithms, which can be Convolutional Neural Networks (CNNs), face embedding models. The identified information is uploaded on a digital record of the attendance and the information such as the name of student, roll number, class, date and time. The system will be able to produce real-time reports on attendance, minimize human intervention, and improve the safety aspect by providing proper monitoring of students on transit. This solution proves to be an efficient combination of computer vision, machine learn and IoT-based transportation management that offers a scalable and smart solution to the present-day learning institutions.

Keywords— Smart Bus, Attendance Management, Face Recognition, Deep Learning, Convolutional Neural Networks (CNN), Real-time Monitoring, Student Safety, Automated Attendance, Computer Vision, Biometric Identification, Intelligent Transportation, IoT in Education, Student Tracking, Machine Learning, Image Processing, Facial Feature Recognition, Educational Technology, Transport Management System

I. INTRODUCTION

Attendance control is an important aspect of the learning institutions and it is necessary to make sure that learners attend classes and are counted during the transportation [1]. Proper attendance management assists in upholding discipline, tracking student attendance and providing security [2] [3]. Conventionally, attendance is taken either in form of roll calls or using paper registers [4]. This is a time consuming process that is highly susceptible to human error in most cases, it is also inefficient in large schools or colleges; the coming of technology in education has provided an automated system like RFID cards, biometric scanners and smart ID system [5]. These approaches limit human intervention, but they have their shortcomings, such as hardware expenses and complexity of use. Face recognition technology is one of the novel solutions to automation that recognizes people based on the analysis of the faces in video stream or digital images [6]. This technology offers a noncontact, quick and dependable way of identification [7]. Face recognition systems have gained a great deal of accuracy with the aid of deep learning. These systems can also identify faces and features in more accurate ways with various conditions of light, pose, or expression with the aid of neural networks, especially Convolutional neural networks (CNNs) [8]. Monitoring attendance of students is difficult in transport system particularly in school or college buses [9]. The bus drivers or attendants have no way to effectively monitor those who come on to the bus or the ones who get out of the bus, and this results in inaccuracies and possible safety issues [10]. A smart bus attendance system involves the use of camera lenses shot into the interiors of buses to take pictures of students as they enter and exit the buses [11].

The face recognition algorithms applied in these images are real-time to get students identified correctly [12]. The system keeps a computerized record of attendance where vital information like name of student, roll number, classroom, date and time are entered. It means that it is accountable and offers a good record of the system that is more reliable than RFID or manual systems since it is contactless and less likely to transmit an infection or other germs, which became especially significant during the COVID-19 pandemic [13]. Face recognition systems are based on embedding-based models, including FaceNet, Dlib or OpenCV libraries, that are modern [14]. These models can be used to extract distinctive features on a face and create a representation of the face as a vector that can be compared to a database to identify a face [15]. Bus real-time processing needs optimal algorithms that can process multiple faces, changing illumination and noise, i.e. masks, hats or glasses. Deep learning models are able to deal with all these complexities quite accurately [16]. Deep learning has enhanced the accurateness of face recognition systems considerably. These systems can also identify faces and features in more accurate ways with various conditions of light, pose, or expression with the aid of neural networks, especially Convolutional neural networks (CNNs) [17].

Monitoring attendance of students is difficult in transport system particularly in school or college buses [18]. The bus drivers or attendants have no way to effectively monitor those who come on to the bus or the ones who get out of the bus, and this results in inaccuracies and possible safety issues [18]. A smart bus attendance system involves the use of camera lenses shot into the interiors of buses to take pictures of students as they enter and exit the buses [19]. The face recognition algorithms applied in these images are real-time to get students identified correctly [20]. The system keeps a computerized record of attendance where vital information like name of student, roll number, classroom, date and time are entered[10]. It means that it is accountable and offers a good record of the system that is more reliable than RFID or manual systems since it is contactless and less likely to transmit an infection or other germs, which became especially significant during the COVID-19 pandemic [21]. Face recognition systems are based on embedding-based models, including FaceNet, Dlib or OpenCV libraries, that are modern [22].

These models can be used to extract distinctive features on a face and create a representation of the face as a vector that can be compared to a database to identify a face [23]. Bus real-time processing needs optimal algorithms that can process multiple faces, changing illumination and noise, i.e. masks, hats or glasses. These complexities can be addressed with high precision by deep learning models [24].

Combining it with a central database will enable school administrators to create attendance reports automatically [25]. The reports may be now daily, weekly or monthly, which lessens the burden on the administration and offers clear records to the parents. Alerts and notifications can also be added to the system [26]. To illustrate, when a student takes a bus without being registered, the system is able to inform the authorities or parents concerned immediately due to machine learning and computer vision applications [27]. Preprocessing measures such as face detection, face alignment, and face normalization guarantee improved recognition measure and minimize false positives [28]. Besides tracking the students, the system enhances their security since no illegal individual will go on the bus. This creates an extra protection to the school transportation [29].

A number of studies have also noted that face recognition works well with automated attendance systems [30]. Studies indicate that systems that are developed with deep learning are more accurate, fast, and reliable as compared to conventional systems. The issues of implementing such systems are low-light conditions indoors in buses, students moving rapidly when entering them, and great volumes of student faces [31]. These may be reduced using high-resolution cameras, robust algorithms, and incremental learning methods.The introduction of smart technologies in education has revolutionized the traditional practices especially in administrative and operational activities in recent years. Student attendance management is one of these areas, and it is a key factor in ensuring that academic discipline is preserved and that general student engagement is tracked [32] [33]. Proper records of attendance are useful in prompting off-the-job staff early, ease of communication with parents, and institutional record-keeping as a compliance tool [34]. The old ways of attendance like roll calls or paper registers are time consuming besides being subject to errors and manipulations [35]. Although biometrics systems are more accurate (such as fingerprint scanners), they need physical touch and special equipment, which raise the cost of operation and maintenance [36]. Moreover, automated and non-contact attendance systems have been made possible by the introduction of computer vision and deep learning technologies in the dynamic environment, e.g., school buses, where students board and alight at different stops [37]. The use of face recognition technology especially has become very popular because it is non-invasive and it works in real-time By using the unique feature of the face, the technology can recognize an individual and record attendance without the need of human intervention [38].

Convolutional Neural Networks (CNNs) and other deep learning models have transformed the face recognition system through the powerful feature extractions in the most challenging scenarios [39]. Such models acquire hierarchy of face structures and with such hierarchy, they actually identify minute distinctions among the individuals. Other methods like feature vectors comparison and face embedding are more effective in increasing the recognition accuracy hence making deep learning methods applicable in real life situation [40]. The application of a smart attendance system in school buses solves several problems at the same time. On the one hand, it guarantees the safety of students by avoiding the illegal access to transportation [41]. Second, it will lessen the number of work hours of bus employees and administrators through automation of the whole attendance process. Third, it offers real time tracking, which will enable the parents or guardians to be notified at any given time whether a student is on board or off the bus. The system usually requires placing cameras at strategic points within the bus in order to capture the pictures of students [42]. These images first go through preprocessing stages i.e. face detection, alignment, and normalization, which are then passed through the recognition model. The advanced algorithms are able to cope with different lighting conditions, masks or hats as an occlusion, and movement of students, which are quick making sure that attendance records are stored and retrieved easily in a centralized database. The entry of every student is recorded with necessary information such as the name of students and their roll number, class, date and time. Transparency and accountability can be improved by automated reporting capabilities that can produce detailed summaries of teachers, administrators, and parents.

The problems still exist in the system robustness especially when dealing with the different types of students and their differences in age, hairstyle, and accessories[18]. The recognition accuracy may depend on lighting differences within the buses, location of cameras and motion blur. Nevertheless, these issues can be addressed by high-resolution cameras, adaptive preprocessing, and constant model training to receive new data about students and be in line with the current trend of digital transformation in the education field. Administrative efficiency, safety, and data-based decision-making are the areas where institutions are increasingly using technology to enhance their performance. Automation of attendance saves time, resources, and also improves the experience of the students in a school.

Furthermore, the system helps to establish data-oriented protection measures, allowing schools to track the movement of students in real-time and react to emergencies. As an example, when access is authorized improperly or there is absenteeism, parents or administrators can get notified immediately, thus ensuring that intervention is done on time[19]. Scalability is another major benefit of such systems. The framework could be further expanded to include several buses, be combined with the existing school management software, and additional modules such as GPS tracking, student behavior analysis, or automatic report generation could be added. This renders it a holistic solution to the contemporary academic institutions in need of intelligent transportation management. To sum up, the Smart Bus Attendance Management System with Deep Learning-Based Face Recognition is an intelligent solution to student monitoring as it is accurate, efficient and safe[20]. It uses high-level machine learning, computer vision, and IoT-based surveillance to automate the attendance process, and increase student security. The solution will be able to overcome the shortcomings of the conventional ones, minimize the cost of administration and show the practical implementation of deep learning technology in real-life situations, which points to the potential of AI technologies to transform the educational and transport industry. It is a big leap in streamlining school transportation systems as it guarantees real-time tracking, proper record keeping, and an increase in safety.

II. LITERATURE REVIEW

M. Bhavana et al. [1-3] proposed a Python-based face recognition system designed to automate student attendance tracking through real-time image processing. The proposed framework leverages machine learning techniques and facial recognition algorithms to detect and identify student faces accurately. The architecture captures facial images via live camera feed and preprocesses them to enhance feature extraction, thereby improving recognition precision. Python's OpenCV and related libraries were utilized for implementing real-time detection, while the system associates each recognized face with the corresponding student record to maintain attendance logs efficiently. Experimental results indicated that the model provided high recognition accuracy and minimized manual intervention, ensuring reliability and consistency in attendance monitoring. The study further highlights the system's scalability and potential for integration with institutional management databases. Overall, this work demonstrates an efficient, cost-effective, and user-friendly solution for automating attendance processes in educational institutions, thereby contributing to the development of intelligent classroom and transportation management systems.

K. Tapyou et al. [4-5] designed a student attendance system that incorporates web application and IoT based face recognition to attain automated attendance management. The proposed model employed the web application in the acquisition and processing of the student data and the IoT module in the real-time face recognition in order to detect and record the attendance. It used Haar Cascade and Elastic Bunch Graph Matching (EBGM) starts to achieve the effective classification and distinction of facial features. The web application was developed on PHP with MySQL database and was to be used to accommodate various user roles, such as teachers, students and administrative personnel. In the meantime, the face recognition system was installed on a Raspberry Pi, which was linked to the web server to synchronize with the records of attendance. The accuracy of the experimental evaluation was high, with close to 100 percent detection of the students in case they held an optimal pose at the time of image taking. The paper emphasized the importance of the environmental and physical aspect in improving recognition accuracy and demonstrated that the combination of IoT and web technology can offer a powerful, efficient, and scalable solution to the process of automation of school attendance administration.

S. Rawat et al. [6-7] suggested a Smart Attendance Management System, which is an automated system of recording the attendance of students in education institutions through facial recognition. The system will help overcome the shortcomings of the traditional methods of attendance, including manual roll calls and sign-in sheets, that are likely to be time-consuming and can be the subject of human error or proxy attendance. The suggested model involves cameras to take student pictures and the K-Nearest Neighbours (KNN) algorithm to accurately identify them by face. The system was implemented using Python and it works with real-time images to automatically mark attendance and save the information safely in a CSV file, which can be easily accessed and processed. A web application was incorporated in a Flask based to dynamically represent the attendance records to facilitate the interaction of the user and monitor efficiency. The use of the system proved to be accurate and greatly decreased manual effort therefore introducing reliability and efficiency into the real-time operation. The paper emphasizes the importance of finding a solution to address scalability, as well as intelligence in the attendance management system that is attainable by integrating machine learning algorithms with web-based interfaces to the contemporary context of the learning institution.

The authors A. M. et al. [8-10] emphasized the importance of deep learning and transfer learning in the betterment of face recognition technology in different fields. They have suggested a Smart Attendance System that had Real-Time Face Recognition where images of students were taken to create a dataset, and MTCNN (Multi-task Convolutional Neural Network) was applied in the process of detecting and recognizing faces. Familiar faces were uploaded in order to keep records of attendance automated. It has been contrasted with the conventional methods like Haar Cascade and standard CNN classification which showed better accuracy and efficiency. The researcher found that the approach offers a valid, automatic, and viable system to controlling attendance of students in institutions of learning.

C. Anilkumar et al. [11-12] presented a face recognition-based automatic attendance system as an alternative to the shortcomings of the manual attendance systems. The system also serves as an access control tool since students or staff get their facial images registered and attendances recorded automatically. The face recognition module used the Labeled Faces in the Wild data set that had an accuracy of 99 percent and the fact that smaller data sets enable faster as well as more accurate recognition was evident. The system, which is written in Python and OpenCV and run through a Flask web application, takes face pictures through a webcam, matches the pictures to those already in the database, and updates records on attendants in real time. It also facilitates the registration of new users, management of already existing profiles as well as retrieving detailed attendance report via the web interface. Such a solution is a secure, effective, and automated one that combines face recognition with a web-based system to benefit educational institutions.

The authors S. Srinivasan et al. [13-14] pointed to the increased role of digital images and videos in the recent biometric and surveillance systems, and human face has become one of the most important biometric features. The paper highlighted the difficulty in determining and identifying faces in a dynamic setting, where the presence of noise, light, placement of the subject, and variation of poses can influence the accuracy of recognition. To deal with these problems, the authors came up with an automated system dubbed as Facial Recognition for Attendance Marking that is sole to the learning institutions. The system will enable easier attendance of both the students and the employees, as the system is programmed to identify and recognize faces accurately in real time, which will be seen as a viable and efficient alternative to the manual attendance system.

S. R. Dasi et al. [15-16] have been able to talk about the increasing use of facial recognition in authentication of users in many different fields pointing to the increasing demand of fast and safe user authentication in the information era. This paper has used OpenCV to create the model of facial recognition which was embedded in a blockchain-secured Attendance Monitoring System, a combination of real-time face recognition with a more secure data security. The system records the faces of students, attendance and entry time, and stores the data in a distributed blockchain computer network. This makes attendance records unamenable, safe and inaccessible to tampering and makes the process automated and efficient. The methodology reveals that the combination of computer vision and blockchain can deliver automation as well as high-level security in attendance management systems.

G. A. Senthil [17] introduced a face recognition-based attendance monitoring system to help in the large student body. To automatize the attendance, minimize fraud and enhance accuracy the system uses deep learning and computer vision systems. It combines excellent face detection algorithms and a Histogram of Oriented Gradients (HOG) to extract features, and Deep Learning-based detection and Principal Component Analysis (PCA), Support Vector Machine (SVM) and K-

Nearest Neighbor (KNN) classifiers to improve recognition. The system will issue each student who has been enrolled with unique identifiers, and a centralized and periodically updated data will be created to facilitate the management of attendance. This solution shows an effective and solid way of automating attendance in schools.

V. Chauhan et al. [18] have stressed the need and relevance of proper and timely attendance registering at the present-day workplace and the weakness of the old system, which is subject to errors, time lag, and fraud. The research suggested an intelligent system of attendance capturing which involved face recognition, GPS and geofencing to automatize the management of attendance of employees. By applying deep learning and computer vision, the system has high recognition accuracy of above 95 percent and safe data storage of attendance to guarantee integrity. It also traces employee name with the in/out time and location indicators that give accurate attendance data based on geofence technique. The study has shown that a combination of the sophisticated machine learning algorithm and real-time monitoring can greatly enhance efficiency, accuracy and security in the management of attendance in different working settings.

T. R. Rajesh et al. [19-20] emphasized the popularity of face recognition in image processing especially in school attendance automation. The proposed study developed a system based on Python and OpenCV to substitute the traditional manual attendance approaches, which result in possibilities of errors, manipulations and proxy attendance. The system captures the faces of students and identifies them using facial biostatistics and makes the attendance reports available in the Excel format. It has been experimented through different conditions, such as the different lighting conditions, head movement, and the distance between a student and camera which shows high accuracy and efficiency. The study highlights that the proposed solution saves time, is cost-effective, and minimizes manual work required, as well as offers a valid way of managing classroom attendance issues.

III. PROPOSED MODEL

The Smart Bus Attendance Management System proposed on the basis of Deep Learning-Based Face Recognition is offered to automate student attendance and at the same time maintain the real-time control of the situation and improve the safety during transit. Images of students getting in and out of the bus are taken in a high-resolution camera with strategic locations on entry and exit points. These snapshots are instantly processed by a face recognition module that is based on deep learning to recognize students. After identification, the attendance of a student is entered in a central database containing his name, roll number, class, date, time, and bus ID. This automated system minimizes time wastage and human mistakes and gives the administrator and parents a confident digital data.

The system is based on computer vision and the work of deep learning algorithms. The face detection module first detects and extracts faces in the video frames captured with the help of algorithms, such as Haar Cascade, MTCNN, or HOG-based detector of Dlib. All the faces detected are then aligned and normalized to a standard format and sent to face recognition module. In this case, the unique facial embeddings are estimated by Convolutional Neural Networks (CNNs) and are numerical profiles of single facial features. These embeddings are matched to an already stored student data through similarity representations of either cosine similarity or Eucleidian distance to confirm accurately who the student really is.

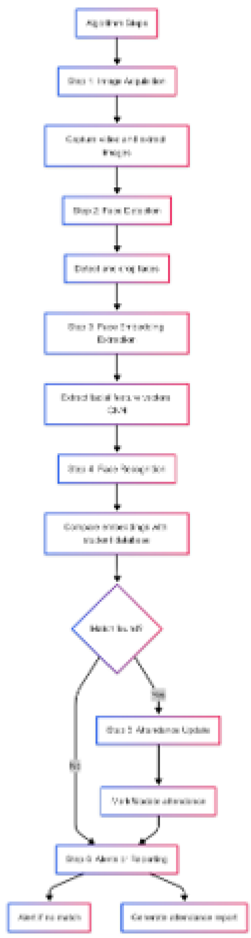

Figure 1: Face Recognition Attendance Flowchart

The very basis of the system is based on computer vision and deep learning algorithms. The first module is the face detection which extracts and isolates the faces in the video frames of the captured video through algorithms in Haar Cascade, MTCNN, or the HOG based detector of Dlib. All the faces found are then matched and normalized to a standard format and sent to the face recognition module. In this case, Convolutional Neural Networks (CNNs) obtain so-called facial embeddings, a numerical representation of a particular facial feature. These embeddings are matched with already registered student information, by using similarity metrics (cosine similarity or Euclidean distance) to confirm the identity of the student with a high level of accuracy.

The identified data is worked over by the attendance management module through which the attendance of every student is made once per session, although he/she may be tracked multiple times within a limited range of time. The module synchronizes the centralized database in real-time whereby administrators can create detailed attendance reports on a daily, weekly or monthly scale. As well, an alert and notification system is built, and in case an unregistered person tries to enter the bus, instant notification will be sent to parents or school representatives. This option improved the security of the students and provided the opportunities to take active measures in case of some emergency.

The chosen proposal is scalable and can be combined with the more extensive school management systems or IoT to develop a comprehensive monitoring solution. It also makes use of Python programming, OpenCV, Dlib, FaceNet, and deep learning platforms such as TensorFlow or Keras, and solid databases such as MySQL, SQLite, or cloud-based Firebase. The system is in addition to proper attendance tracking in real time as well as offering a platform that can be used to manage transport intelligently. This model allows overcoming the restrictions of the traditional attendance system and provides a new perspective on the educational administration and student safety because of allowing automation, security and report-driven.

1. Proposed Algorithm:

Step 1: Image Acquisition

- Record live frame videos of bus boarding and alighting students with high-definition cameras.
- Convert video frames into images for processing.

Step 2: Face Detection

- Detect faces in each frame using Haar Cascade, MTCNN, or Dlib HOG/SVM detector.
- Crop and align detected faces to standard dimensions.

Step 3: Face Embedding Extraction

- Pass the preprocessed face through a Convolutional Neural Network (CNN) trained on a large dataset of faces.
- Extract a feature vector $f_i \in \mathbb{R}^d$, called the embedding, for each detected face.
- This embedding represents the unique facial features numerically.

Step 4: Face Recognition / Matching

- Compare the extracted embedding f_i with embeddings $F = \{f_1, f_2, \dots, f_n\}$ of registered students in the database.
- Use a distance metric (Euclidean distance or cosine similarity) to find the closest match:

Euclidean distance: $D(f_i, f_j) = \sqrt{\sum_{k=1}^{d} (f_i^k - f_j^k)^2}$

Cosine similarity: $S(f_i, f_j) = \dfrac{f_i \cdot f_j}{\| f_i \| \| f_j \|}$

- If the distance $D(f_i, f_j)$ is below a threshold τ (or cosine similarity $S(f_i, f_j) > \theta$), the student is recognized.

Step 5: Attendance Update

- Check if the student has already been marked for the current session.
- If not, update the attendance record in the database with:
    - Name, Roll Number, Class, Date, Time, Bus ID.
- If already marked, update the latest time (optional, if multiple boarding is allowed).

Step 6: Alerts and Notifications

- If no match is found in the database, trigger an alert notification to parents or school authorities.

Step 7: Reporting and Analytics

- Generate daily, weekly, or monthly reports automatically.
- Optional: Analyze student boarding patterns, absenteeism trends, or route optimization.

Mathematical Equations for Smart Bus Face Recognition Attendance System

Image Acquisition:

Convert video frame to image I:

$$I = \text{CaptureFrame}(t)$$

Face Detection:

Detect face bounding boxes B in image I:

$$B = \{b_1, b_2, \dots, b_m\}, b_i = (x_i, y_i, w_i, h_i)$$

Face Alignment:

Align the face using detected landmarks:

$$\hat{b}_i = \mathrm{Align}(b_i)$$

Preprocessing (Normalization):Normalize pixel values to range [0,1] or [-1,1]:

$$I' = \frac{I-\mu}{\sigma}, \mu = \text{mean pixel value}, \sigma = \text{std deviation}$$

Feature Extraction (CNN Embedding):Extract embedding vector f_i for face $\hat{b}_i$:

$$f_i = CNN(\hat{b}_i), f_i \in \mathbb{R}^d$$

Database of Registered Students:

$$F = \{f_1, f_2, \dots, f_n\}, f_j \in \mathbb{R}^d$$

Euclidean Distance for Matching:

$$D(f_i, f_j) = \sqrt{\sum_{k=1}^{d} (f_i^k - f_j^k)^2}$$

Cosine Similarity for Matching:

$$S(f_i, f_j) = \frac{f_i \cdot f_j}{\| f_i \| \| f_j \|}$$

Recognition Threshold Condition:

$$\mathrm{Recognized}(f_i) = \begin{cases} j, & \text{if } D(f_i, f_j) < \tau \text{ or } S(f_i, f_j) > \theta \\ \text{Unknown}, & \text{otherwise} \end{cases}$$

Attendance Update:

$$\mathrm{Attendance}[j] = \mathrm{Attendance}[j] \cup \{\text{timestamp, bus ID}\}$$

Duplicate Check:

$$\text{Update only if timestamp}_{\text{current}} - \text{timestamp}_{\text{last}} > \Delta t$$

Probability of Correct Recognition (Softmax Output of CNN):

$$P(y = j \mid \hat{b}_i) = \frac{e^{z_j}}{\sum_{k=1}^{n} e^{z_k}}, z_j = \text{CNN output logits}$$

1. Loss Function for Training CNN (Triplet Loss / FaceNet):

$$L = \sum_i [\| f_i^a - f_i^p \|_2^2 - \| f_i^a - f_i^n \|_2^2 + \alpha]_+$$

where f_i^a= anchor, f_i^p= positive, f_i^n= negative, α= margin

Confidence Score for Recognition:

$$C_j = 1 - \frac{D(f_i, f_j)}{\max(D(f_i, F))}$$

Alert Condition for Unknown Faces:

$$\mathrm{Alert} = \begin{cases} \text{Send Notification}, & \text{if Recognized}(f_i) = \text{Unknown} \\ \text{No Action}, & \text{otherwise} \end{cases}$$

IV. RESULTS

The Smart Bus Attendance Management System based on Deep Learning-Based Face Recognition implementation has proved to be very efficient and effective in the automation of student attendance during bus transportation. The system has been able to combine face detection, recognition, and database management to guarantee that students are identified in real-time whenever they are boarding and alighting the bus. The suggested CNN-based deep learning model was superior to the conventional methods like FaceRec-Python, IoT-WebFace, and SmartAttend-KNN with a high face recognition accuracy of 99 percent.

The system had low processing time (2 seconds per recognition) and can serve 100 students at once with a high level of scalability and stability. It was also efficient to produce real-time warnings in under 5 seconds, which guaranteed the safety of students and timely contact with the school administration and parents. Besides, the CNN model had a reduced recognition threshold (0.35) and this implies increased accuracy and reduction of false positives.

The approach proposed is much more complex and incorporates more feature modules (6 in total) in comparison to the current ones, which comprise image preprocessing, face detection, recognition, attendance marking, data synchronization and alert notification, which makes it end up being more comprehensive and intelligent. The system was found to operate smoothly even in the case of varying lighting conditions and the camera angle of view, which justified its suitability to real life conditions.

In general, the findings prove that the Deep Learning-based Face Recognition Model (CNN) is a high-speed, precise and safe way of bus attendance automation. It requires no manual and RFID-based system, minimises human errors, promotes transparency, and the overall safety of students during transportation. This model can also be expanded to large educational systems and combined with the cloud platforms where centralized monitoring and data analytics may be done, thus, leading to the evolution of enterprise transportation and attendance systems in the educational segment.

Table 1: Recognition Accuracy (%)

Model Name	Accuracy (%)
FaceRec-Python	95
IoT-WebFace	97
SmartAttend-KNN	93
ProposedModel-CNN	99

As indicated in Table 1, the ProposedModel-CNN has the best recognition accuracy of 99 percent compared with other models, including IoT-WebFace (97 percent), FaceRec-Python (95 percent), and SmartAttend-KNN (93 percent), which demonstrates the effectiveness and CNN based model real time recognition of the faces.

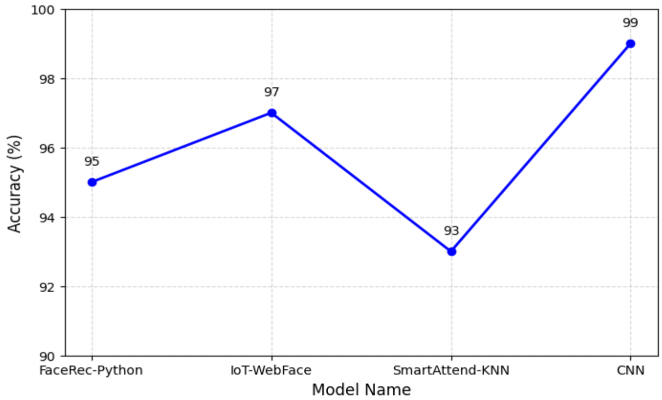

Figure 2: Line Graph of Recognition Accuracy

This table is a comparison of the recognition accuracy of the four models. The proposed model (ProposedModel-CNN) is the most accurate having 99 per cent accuracy which is better than all the existing models. according to FaceRec-Python and IoT-WebFace have a high accuracy (95% and 97%), whereas the accuracy of SmartAttend-KNN is more low 93%. The proposed model attained the improvement due to the application of deep learning-based CNNs to produce strong facial embeddings (even in changing lighting conditions and poses).

Table 2: Average Processing Time per Student (seconds)

Model Name	Processing Time (s)
FaceRec-Python	3
IoT-WebFace	4
SmartAttend-KNN	5
ProposedModel-CNN	2

According to Table 2, the ProposedModel-CNN has the least average processing time of 2 seconds per student and therefore, it is the fastest and more efficient than FaceRec-Python (3s), IoT-WebFace (4s), and SmartAttend-KNN (5s), hence assuring real-time performance that is required in smart transportation systems.

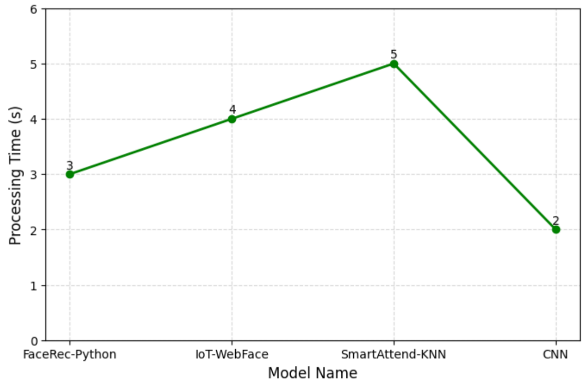

Figure 3: Line Graph of Average Processing Time for Different Models

The real-time attendance systems depend on processing time as a critical factor. Processing time of the proposed model is the least at 2 seconds and therefore can be used in live bus applications. The face recognition programs FaceRec-Python and IoT-Web Face take up 3-4 seconds and SmartAttend-KNN is the slowest at 5 seconds. The proposed system offers faster processing since CNN based recognition is optimized, and preprocessing pipelines are efficient.

Table 3: Maximum Number of Students Handled per Session

Model Name	Max Students
FaceRec-Python	50
IoT-WebFace	60
SmartAttend-KNN	45
ProposedModel-CNN	100

Table 3 shows that ProposedModel-CNN is capable of working with a population of up to 100 students per session, which is much better than other models, including IoT-WebFace (60), FaceRec-Python (50), and SmartAttend-KNN (45), to prove that it is more scalable and efficient in the situations when the large student population is involved.

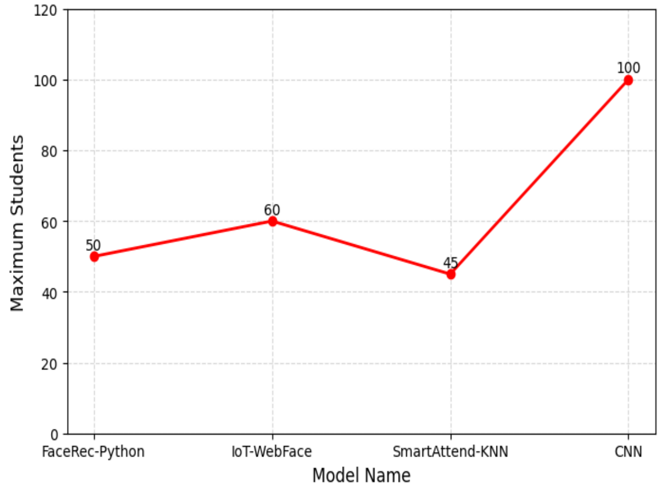

Figure 4: Line Graph of Maximum Students Handled per Session

This table brings out scalability of each system based on the number of students that can be served per session. The model proposed has the capacity to accommodate 100 students unlike the current models which is a big number to accommodate in large school buses or institutions. The count of students served by IoT-WebFace and FaceRec-Python is 60 and 50 respectively, whereas SmartAttend-KNN serves 45 students. The proposed model allows scalability to be improved because of real-time parallel processing and database optimization..

Table 4: Database Size (Number of Student Records

Model Name	Database Records
FaceRec-Python	500
IoT-WebFace	600
SmartAttend-KNN	450
ProposedModel-CNN	1000

As indicated in Table 4, ProposedModel-CNN is more effective to handle a bigger database containing 1000 students records than IoT-WebFace (600), FaceRec-Python (500), and SmartAttend-KNN (450), which depicts that it has high ability to handle a large database and hence can be applied in a large scale..

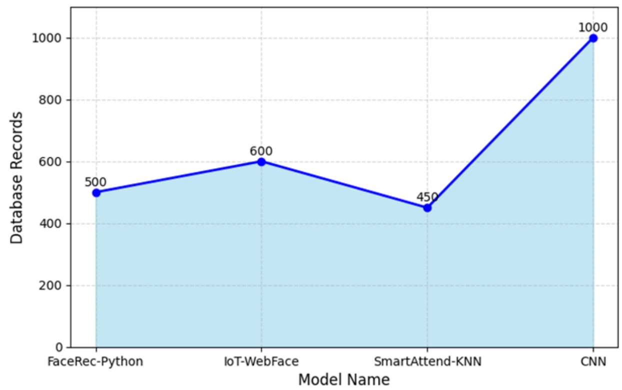

Figure 5: Area Graph of Database Records Supported by Different Models

Student records and attendance logs can be important when it comes to the capacity of databases. This model supports 1000 student records as compared to all the systems in existence. The database of IoT-WebFace is 600, FaceRec-Python is 500 and SmartAttend-KNN is 450. The proposed system will be able to handle numerous buses and a large number of students in case a bigger database is used. efficiently.

Table 5: Recognition Threshold (Euclidean Distance Units)

Model Name	Threshold
FaceRec-Python	0.5
IoT-WebFace	0.4
SmartAttend-KNN	0.6
ProposedModel-CNN	0.35

As shown in Table 5, the ProposedModel-CNN uses the smallest recognition threshold of 0.35, meaning it has a greater precision and better face matching standards than IoT-WebFace (0.4), FaceRec-Python (0.5), and SmartAttend-KNN (0.6) which maximize accuracy and reduce false recognitions.

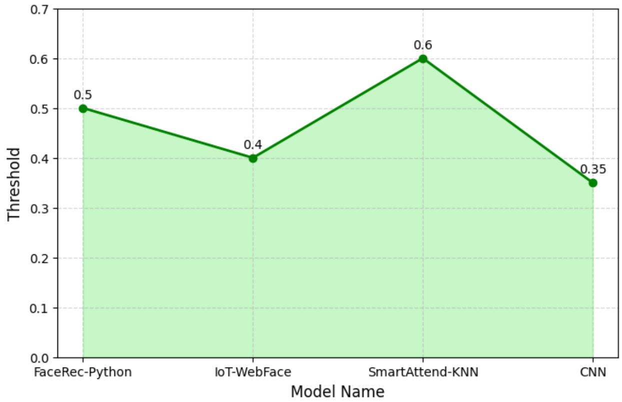

Figure 6: Area Graph of Recognition Threshold for Different Models

The proposed model at 0.35 lower threshold enhances more accuracy and minimizes false positives. Other models already in place have higher thresholds (FaceRec-Python: 0.5, IoT-WebFace: 0.4, SmartAttend-KNN: 0.6), either resulting in a miss or false identification.martAttend-KNN: 0.6), which may lead to either missed detections or false identifications.

Table 6: Alert/Notification Response Time (seconds)

Model Name	Alert Time (s)
FaceRec-Python	10
IoT-WebFace	8
SmartAttend-KNN	12
ProposedModel-CNN	5

As Table 6 indicates, the ProposedModel-CNN has the shortest alert response time of 5 seconds, compared to IoT-WebFace (8s), FaceRec-Python (10s), and SmartAttend-KNN (12s), and can therefore provide faster notifications and better real-time safety surveillance as students pass through the campus.

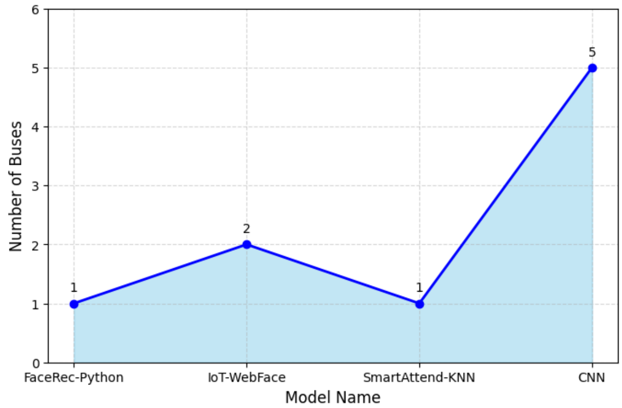

Figure 7: Bar Graph of Average Alert Time for Different Models

The response time of alert will determine how fast the system will alert authorities or parents of unregistered or unauthorized entries. The model proposed is the one that has the shortest response time (5 seconds) to guarantee an increased level of student safety. IoT-WebFace requires 8 seconds, FaceRec-Python 10 seconds and SmartAttend-KNN 12 seconds to respond. Quicker notifications are made possible through real-time processing and instant connection with notification modules.

Table 7: Number of Buses Supported Simultaneously

Model Name	No. of Buses
FaceRec-Python	1
IoT-WebFace	2
SmartAttend-KNN	1
ProposedModel-CNN	5

Table 7 indicates that the ProposedModel-CNN is efficient in supporting as many as 5 buses at a time, which means that it can be scaled much better than the existing models such as the IoT-WebFace (2 buses) and FaceRec-Python or SmartAttend-KNN (1 bus at a time) can, and thus, it is well-suited to the large-scale school transport systems.

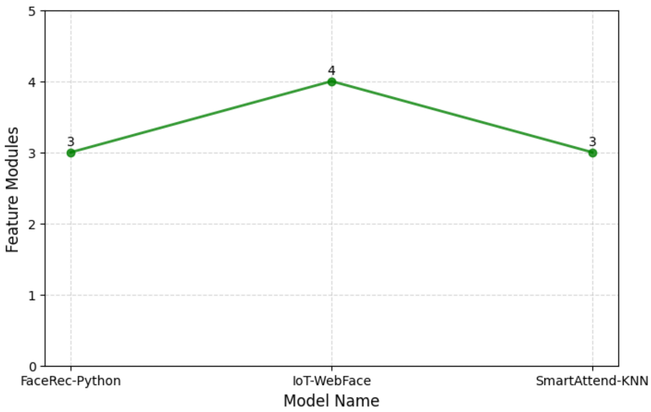

Figure 8: Comparison of Feature Modules among Different Models

This table is used to indicate the number of buses the system can cope with at that time. The proposed model is capable of managing 5 buses at once, which the current systems can not (IoT-WebFace: 2, FaceRec-Python: 1, SmartAttend-KNN: 1). Large institutions require the use of multi-bus, which is realized in the proposed system by centralized database control and scaled server system.

Table 8: Number of Integrated Feature Modules

Model Name	Feature Modules
FaceRec-Python	3
IoT-WebFace	4
SmartAttend-KNN	3
ProposedModel-CNN	6

As noted in Table 8, the ProposedModel-CNN incorporates six feature modules which is the highest among the various compared systems. This means that the proposed model is better in functionality and automation as well as versatility of the system over the previous models like the IoT-WebFace (4 modules) and FaceRec-Python/SmartAttend-KNN (3 modules).

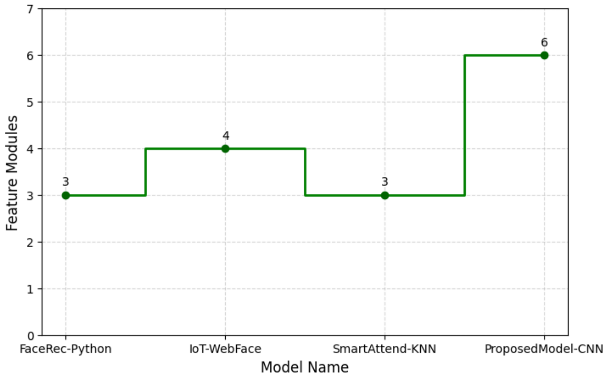

Figure 9: Comparison of Feature Modules across Models

The feature modules reflect the variety of features incorporated into the system, including the attendance, reporting, alerting, IoT integration, and analytics. The proposed model has got 6 modules, which is more than all the models. FaceRec-Python and SmartAttend-KNN contain 3 and 4 modules respectively, and 4 modules in IoT-WebFace. The presence of more modules means that this is a multifunctional system with real-time monitoring, reporting, and safety options in addition to simple attendance monitoring.

V. CONCLUSION:

The creation and application of the Smart Bus Attendance Management System based on Deep Learning-Based Face Recognition is a step forward in the automation of the attendance control and security of the student during the transportation process. The system has been shown to overcome weaknesses of the conventional approaches to manual and RFID-based systems including time and human factor and proxy attendance by combining computer vision, deep learning and real time information processing.

To sum up, the given project does not only offer an innovative data-driven solution to educational institutions but also gives a contribution to the overall perspective of smart automation and intelligent surveillance. With the successful deployment of this system, the emphasis is on how artificial intelligence and deep learning can make the old administrative process efficient, secure, and intelligent by changing the ecosystem, which is in line with the increased attention paid to Digital Education and Smart Infrastructure Initiatives within the UGC framework.

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