Class Pulse
AI-Powered Intelligent Academic System

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***Abstract*—Class Pulse is an intelligent academic system designed to streamline and enhance classroom operations by integrating a diverse set of features aimed at improving student engagement, attendance monitoring, and academic performance tracking. Unlike traditional systems that focus solely on attendance, Class Pulse offers a comprehensive solution, incorporating real-time student tracking, participation insights, and personalized learning analytics. The system employs advanced facial recognition and AI algorithms for accurate identification and tracking, allowing for seamless student monitoring. To overcome the limitations of conventional 2D-based systems, Class Pulse integrates 3D facial recognition through Neural Radiance Fields (NERF) technology, which enables precise identification under varying conditions such as diverse lighting, angles, and poses. This 3D technology, combined with deep learning models, significantly improves the accuracy and reliability of student recognition, addressing common challenges like occlusion and non-standard poses. Additionally, Class Pulse is designed to support data-driven decision-making, providing educators with real-time insights into classroom dynamics and individual student performance. By leveraging cutting-edge technologies, Class Pulse presents a transformative approach to modernizing education, offering a holistic, AI-powered system that enhances both classroom management and the learning experience.**

I. Introduction

Historically, educational institutions have used manual attendance tracking techniques, which are time-consuming, error-prone, and disrupt the flow of class activities. Traditional methods, such as calling out names or having students sign in, interrupt instruction time and provide room for errors, making it increasingly challenging to manage attendance accurately. As class sizes grow, manual attendance management becomes an even greater administrative burden for teachers and staff, affecting classroom efficiency and diverting time away from instructional goals.

Class Pulse is a computer vision-based student attendance and attentiveness monitoring system designed to overcome these limitations by using advanced facial recognition and real-time tracking technologies. Unlike traditional attendance systems, Class Pulse uses a robust combination of 3D face modeling, Neural Radiance Fields (NERF) for detailed facial representation, and deep learning algorithms for real-time facial detection and recognition. This approach significantly enhances accuracy, minimizes classroom disruptions, and integrates seamlessly into the educational environment. By automating attendance and attentiveness tracking, Class Pulse not only improves efficiency but also provides valuable data-driven insights into student engagement, helping institutions support student performance.

A. Background and Motivation

Manual attendance monitoring disrupts classroom flow and requires teachers to pause instruction frequently, reducing valuable teaching time. Additionally, verifying attendance records manually is prone to error, especially in large institutions, where tracking and maintaining accurate logs become complex. Minor discrepancies in attendance records can lead to inaccuracies that affect student records and institutional reporting.

Paper-based or manual systems offer limited insights into attendance trends and engagement patterns. This lack of data makes it difficult for institutions to identify students who may need additional support or to identify broader patterns indicative of engagement issues. The absence of automated analytics also hinders data-driven decision-making that could improve student outcomes and well-being.

Computer vision-based attendance systems, like Class Pulse, offer a modern solution to these issues. Leveraging facial recognition technology, Class Pulse can accurately monitor student presence without manual intervention, enabling teachers to focus on teaching while attendance is recorded in real-time. Additionally, by capturing images every minute, Class Pulse tracks students' attentiveness by analyzing gaze direction to identify when a student is facing the board, which serves as an indicator of attentiveness. Over time, the system aggregates attendance data, providing valuable insights that aid institutions in making data-driven decisions related to student engagement, resource allocation, and identifying students at risk. Scalable, adaptable to various classroom environments, and capable of integrating with school management platforms, Class Pulse is well-suited to modern educational settings.

B. Technical Approach and Implementation

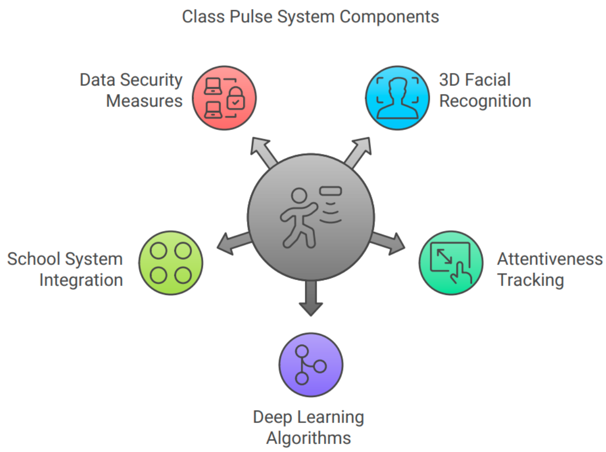

Fig. 1

Class Pulse employs a combination of 3D facial modeling, Neural Radiance Fields (NERF), and computer vision algorithms to provide reliable attendance and attentiveness data. The technical components of Class Pulse include:

1) **3D Facial Recognition and Neural Radiance Fields (NERF)**

   - Traditional 2D face recognition systems are highly sensitive to environmental factors, such as changes in lighting, occlusions, and variations in face orientation. Class Pulse overcomes these limitations by creating 3D models of students' faces, which allows for accurate identification across a wide range of conditions.
   - NERF is utilized to generate 3D representations of students' faces, capturing minute details from multiple angles and enabling consistent identification even when students are not facing the camera directly. The NERF-based approach improves the system's robustness by accounting for different angles, lighting variations, and partial occlusions, which are common in classroom settings.

2) **Facial Detection and Gaze Analysis for Attentiveness Tracking**

   - The system captures 50 discrete frames over the duration of a 50-minute class, analyzing the angle of each student's gaze to determine attentiveness. By identifying when a student is facing the board, Class Pulse can assess attentiveness and assign a percentage based on the number of frames a student appears attentive.
   - Students are then categorized into different attentiveness levels, such as active participation, passive participation, or no participation, based on their percentage of attentive frames. This approach enables educators to gauge student engagement in real-time and provides metrics on attentiveness trends over time.

3) **Deep Learning Algorithms for Real-Time Detection and Recognition**

   - **Class Pulse** incorporates deep learning models for facial detection and recognition. Convolutional Neural Networks (CNNs) are used to detect faces within each frame, and embeddings generated from the 3D face models are matched against known profiles for identification.
   - The system continuously refines recognition accuracy over time through model training on collected data, improving recognition performance by adapting to variations in student appearances (e.g., facial hair growth, hairstyles, and glasses).

4) **Integration with School Management Systems**

   - To streamline attendance management, Class Pulse is designed to integrate with widely used school platforms like Google Classroom and Moodle. This allows automatic updating of attendance records, easing administrative workflows and reducing manual data entry.
   - The system provides detailed reports and attendance logs that can be customized to align with institutional requirements, offering insights into overall classroom engagement and attendance patterns.

5) **Data Security and Privacy Considerations**

   - **Class Pulse** is designed with data security and privacy as primary concerns. All facial data is stored securely, with encryption and strict access controls, to protect students' personal information.
   - The system complies with privacy regulations such as GDPR, ensuring that all data processing and storage practices meet stringent security standards. Additionally, data anonymization techniques are applied when compiling attendance and engagement insights to protect student identities.

C. Project Objectives

The primary objectives of this computer vision-based student attendance system are:

1) **Automated Attendance Tracking**: To design a reliable system that can automatically record student attendance using advanced 3D facial recognition technology, reducing the need for manual intervention.
2) **Seamless Classroom Integration**: To develop the system to function unobtrusively within the classroom environment, minimizing disruptions to instructional time.
3) **Accurate and Adaptive Identification**: To ensure that the system can recognize students accurately under various conditions (e.g., changing lighting, partial occlusions, and minor appearance changes over time) by leveraging 3D modeling and deep learning.
4) **Attentiveness Tracking for Engagement Insights**: To provide educators with a metric of student attentiveness by analyzing gaze direction, enabling the classification of students into categories of engagement based on attentiveness percentages.
5) **Data Security and Privacy Compliance**: To implement comprehensive security protocols to protect student data, complying with privacy regulations such as GDPR.
6) **School System Integration**: To enable seamless integration with existing school management platforms, ensuring that attendance data is readily available for administrative reporting and analysis.

II. System Architecture

The system architecture of Class Pulse is designed to facilitate real-time attendance tracking and attentiveness monitoring in classroom environments by integrating advanced machine learning and computer vision techniques. The architecture comprises multiple interconnected modules that function in harmony to collect, process, and analyze visual data from the classroom, ensuring accuracy and responsiveness. These modules include:

1) **Data Acquisition**: Responsible for capturing frames (images) from classroom cameras at predefined intervals. This module ensures that sufficient visual data is gathered without causing interruptions or distractions, making the system suitable for real-time monitoring in academic settings.
2) **Preprocessing and Face Detection**: Once data is acquired, it enters the preprocessing stage where frames are optimized for face detection. This module isolates faces from each frame, enhancing detection accuracy by refining image quality and removing unnecessary background elements.
3) **3D Face Modeling**: To improve recognition reliability across various viewing angles, Class Pulse leverages 3D modeling techniques to create detailed representations of each individual's face. This model enables the system to match face data accurately, even if the captured images are not front-facing or are in less-than-ideal lighting conditions.
4) **Gaze Analysis**: This component assesses each individual's gaze direction and calculates their line of sight to determine if they are engaged with the instructor or classroom content. By analyzing gaze, the system can infer attentiveness levels and categorize individuals based on their observed behavior over time.
5) **Attendance Management**: The core module responsible for verifying and recording attendance. It works with the 3D models and gaze analysis results to identify and confirm the presence and attentiveness of each student, thus distinguishing passive and active participation levels within the session.
6) **Data Storage and Security**: Data integrity and privacy are prioritized by this module, which securely stores all processed data, including attendance logs and attentiveness records. Robust encryption methods and access control policies are implemented to ensure that only authorized personnel can access the stored data.
7) **User Interface**: The user interface allows instructors and administrators to interact with the system, view attendance and attentiveness summaries, and manage system settings. The interface provides an intuitive experience, enabling quick access to real-time insights without requiring technical expertise.

In this section, each module is discussed in detail, with a focus on the specific functions, inter-dependencies, and communication pathways that allow Class Pulse to operate as a cohesive, non-intrusive, and privacy-conscious system.

A. Data Acquistion

The Data Acquisition Module is the foundational entry point of the Class Pulse system, responsible for systematically capturing and handling still images from classroom cameras. This module plays a crucial role in gathering high-quality visual data needed for both attendance tracking and attentiveness monitoring. By optimizing data collection frequency and quality, it enables efficient processing in subsequent modules. Key elements of this module include:

1) **Camera Setup**: High-definition cameras are strategically positioned within the classroom to

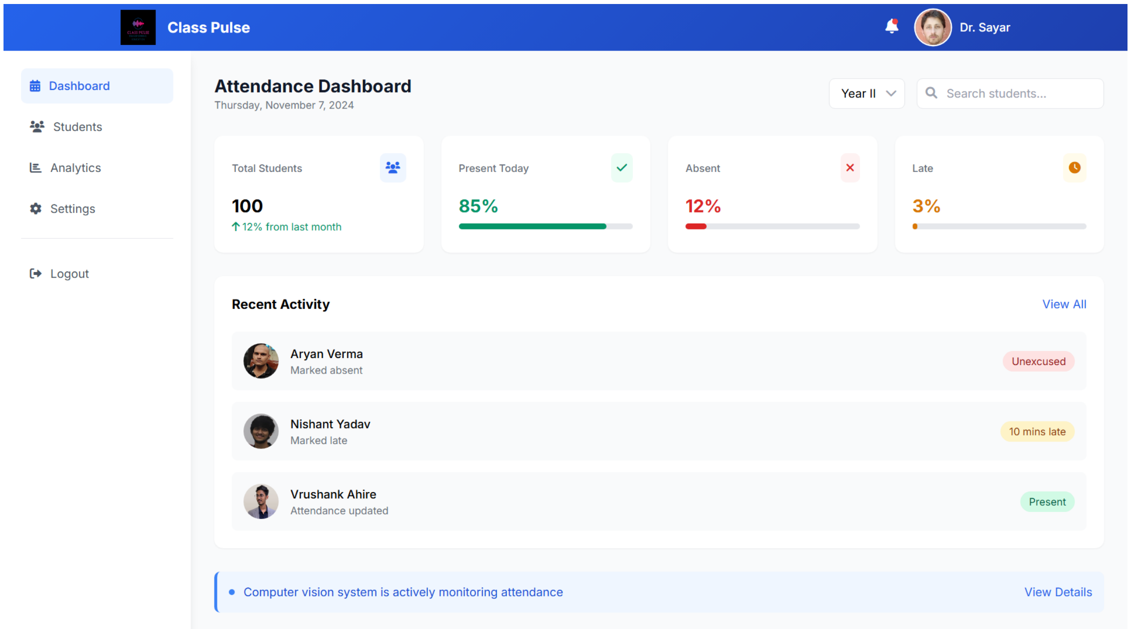

Fig. 2: Session Specific Learning Analytics

capture unobstructed, front-facing views of students seated in various positions. The cameras are carefully calibrated to ensure optimal lighting and focus, reducing visual noise and artifacts that could interfere with face detection and recognition accuracy. By adjusting settings such as exposure, white balance, and frame resolution, the cameras capture images with consistent quality across diverse classroom lighting conditions. This setup helps maintain a high resolution of facial features, essential for downstream 3D face modeling and gaze analysis.

2) **Frame Sampling**: Unlike traditional video-based systems, which continuously capture footage, Class Pulse relies on a periodic image-capture approach, where cameras capture single frames at fixed intervals. Typically, the interval is set to capture one frame per minute, striking a balance between efficient data processing and thorough monitoring. This sampling frequency is sufficient to capture a representative dataset of student behavior over the class duration without generating excessive data volume. The one-minute interval also ensures that subtle shifts in attentiveness can be detected without overwhelming the system with redundant frames.

3) **Data Handling**: Once an image is captured, it is immediately timestamped, adding an essential layer of temporal metadata that links the image to specific moments within the class. This timestamp aids in correlating attendance and attentiveness data over time, providing insights into participation patterns. Each image is promptly directed to the Preprocessing Module for real-time processing, minimizing latency in the system's response. The module's data pipeline is designed to efficiently handle large datasets from multiple cameras, ensuring that images are seamlessly transmitted to the next processing stage without bottlenecks. Furthermore, this design allows for scalability, accommodating larger classroom environments or additional cameras without compromising performance.

This detailed, image-based data acquisition strategy ensures that Class Pulse operates as a streamlined, privacy-conscious system, capturing and delivering relevant visual information without the complexity or privacy concerns associated with continuous video recording.

B. *Pre-Processing Module*

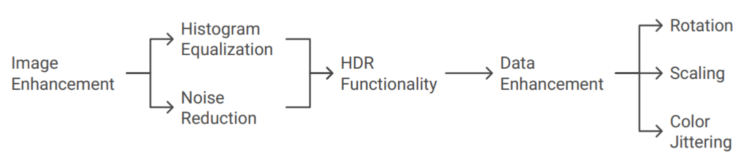

Fig. 3

The Pre-processing Module is a critical component in the Class Pulse architecture, preparing captured images for accurate face detection and recognition. By standardizing and refining the quality of each frame, this module ensures consistency and clarity in the data passed to subsequent stages. Its main functions include various image enhancement and alignment techniques, which are crucial for optimal performance in diverse classroom environments with varying lighting conditions and backgrounds. The key elements of this module are as follows:

1) **Image Enhancement**
To maintain high-quality visual data, this module applies several preprocessing techniques to improve the clarity and consistency of each frame:
    - *Brightness and Contrast Adjustment*: This step adjusts the brightness and contrast levels of each image to achieve a balanced exposure, compensating for differences in classroom lighting and ensuring that facial features are well-defined and distinguishable.
    - *Noise Reduction*: Visual noise can reduce the accuracy of face detection and recognition. Noise reduction algorithms, such as Gaussian or median filtering, are applied to smooth out pixel variations that do not contribute to meaningful details, helping the system maintain robust detection even in images with low-light artifacts or slight motion blur.
    - *Normalization*: Each image undergoes normalization, adjusting the pixel values to a common scale. This standardizes image data across different lighting conditions and cameras, enhancing the reliability of downstream analysis by reducing variability.
2) **Face Alignment**
Proper alignment of faces within each image is critical to maximize the accuracy of face recognition and attentiveness assessment. The face alignment process includes:
    - *Landmark Detection*: Key facial landmarks, such as the eyes, nose, and mouth, are detected within each image. These landmarks serve as anchor points for aligning each face to a standard orientation, correcting any tilts or rotations that could impact recognition.
    - *Rotation Correction*: Based on the positions of key landmarks, the system performs rotational adjustments to ensure that each face is vertically aligned. This process aligns faces to a frontal, upright position, significantly enhancing the model's ability to recognize faces accurately under varying head poses.
    - *Scale and Position Normalization*: Faces are scaled and positioned to occupy a consistent region within each frame, ensuring that facial features are centered and proportionate across images, which improves the reliability of subsequent recognition tasks.
3) **Background Filtering**
To improve both efficiency and accuracy, the Preprocessing Module filters out non-relevant areas of the image by isolating the region containing the face. This process involves:
    - *Region of Interest (ROI) Extraction*: The module identifies and extracts regions of interest within each image based on detected facial boundaries. By focusing processing efforts on these ROI areas, the system conserves resources, reducing computational load and enhancing processing speed.
    - *Background Masking*: Non-essential areas outside the facial boundaries are masked or blurred, which not only reduces processing time but also mitigates potential distractions or background noise that could interfere with face detection accuracy.
    - *Edge Detection and Smoothing*: Subtle edge-detection techniques are applied to define the boundaries of the face more accurately, enhancing the image for downstream analysis while ensuring that only the most relevant facial data is passed forward.

This Preprocessing Module's multi-step approach guarantees that each image undergoes rigorous standardization and refinement, resulting in high-quality, consistent data. These enhancements allow the system to maintain reliable performance in varied real-world conditions, setting the stage for precise face detection and recognition in the following stages of the Class Pulse pipeline.

C. Face Detection and Recognition Module

The Face Detection and Recognition Module is the heart of Class Pulse, responsible for accurately identifying students through a series of complex image processing, 3D modeling, and recognition steps. This module ensures reliable student identification, even in cases of varied head orientations or partial occlusions, by leveraging advanced neural networks and 3D modeling techniques. Its core components are Face Detection, 3D Face Modeling with Neural Radiance Fields (NERF), and Face Recognition, each optimized to handle the unique demands of real-time classroom environments.

1) **Face Detection**
The face detection sub-module initiates the identification process by locating and isolating faces within each frame.
    - **Convolutional Neural Network (CNN) Detection**: Class Pulse employs a highly trained

Convolutional Neural Network (CNN) for face detection, capable of identifying facial regions in each captured image with high precision. This CNN model is trained on an extensive and diverse dataset, ensuring robustness across a range of conditions, including:

  – *Varying Facial Expressions*: The CNN can detect faces regardless of different facial expressions, ensuring accurate detection whether students are smiling, looking serious, or displaying other expressions.
  – *Lighting Variations*: Training on diverse lighting conditions allows the CNN to perform reliably even when classroom lighting changes, such as when lights are dimmed for presentations.
  – *Partial Occlusions*: The model handles occlusions like hands or glasses, maintaining detection accuracy when parts of the face are momentarily obscured.

- **Face Localization and Cropping**: Once a face is detected, the system localizes its exact position within the frame. This localized region is then cropped, isolating the facial area from the background to prepare it for further analysis and 3D modeling.

2) **3D Face Modeling with Neural Radiance Fields (NERF)**
To enhance recognition reliability, Class Pulse constructs detailed 3D models for each detected face using Neural Radiance Fields (NERF), which are designed to capture complex facial structures and nuances.

- **3D Model Construction**: NERF technology allows the system to synthesize a 3D representation of each student's face by combining information from multiple 2D frames captured over time. NERF uses neural rendering techniques to interpret visual data from multiple angles, enabling a 3D reconstruction that accurately represents depth, texture, and subtle facial features.
- **High-Fidelity Model Creation**: NERF's sophisticated modeling allows the 3D face models to capture intricate details, including skin texture, facial contours, and minor asymmetries. These high-fidelity models are essential for distinguishing between individuals with similar features and for ensuring reliable identification even when students are not looking directly at the camera.
- **Orientation-Invariance**: The use of 3D models mitigates errors associated with head orientation changes. This orientation-invariance allows the system to identify students accurately, regardless of head position, enabling successful recognition even when students are facing away from the camera or looking down at their notes.

3) **Face Recognition**
With 3D models created for each detected face, the system proceeds to identify each student by comparing these models with stored profiles.

- Embedding Generation and Feature Extraction: The system uses a feature extraction process to generate embeddings—unique numerical representations—for each 3D face model. These embeddings capture the essential facial features of each student, encoding them in a format suitable for efficient comparison and retrieval.
- Similarity Scoring and Matching: The generated embeddings are compared with those in the system's database, where each stored profile also has a unique embedding based on previous 3D models. Using similarity scoring, the system calculates the likelihood of a match by measuring the distance between the embeddings of the captured model and each stored profile.
- Identity Verification and Attendance Marking: If a high-confidence match is identified, the system confirms the student's identity and records them as "present" in the attendance log. If a match falls below a confidence threshold, indicating possible ambiguity, the system triggers a secondary analysis or prompts manual verification to ensure accuracy. This problem is however mitigated by the use of 50 frames per 50 minute class, thus there is a very high probability that a student gets detected in most frames.
- Adaptive Model Updates: To accommodate natural changes in appearance over time, such as new hairstyles or glasses, Class Pulse periodically updates each student's profile with the latest 3D model data. This adaptive approach ensures that the system remains accurate even as students' appearances evolve.

The Face Detection and Recognition Module is designed to provide reliable and precise identification by leveraging advanced neural networks and 3D modeling techniques. Through these comprehensive steps, the module can handle variations in expressions, lighting, head orientation, and other factors, delivering accurate attendance and attentiveness tracking with minimal false positives or negatives.

D. Gaze Analysis Module

The Gaze Analysis Module in Class Pulse is dedicated to assessing student attentiveness by evaluating the direction and angle of each student's gaze. This module plays a crucial role in gauging engagement levels in real-time by analyzing where each student is looking, specifically whether their focus is directed toward the board. By leveraging gaze estimation algorithms, this module offers an objective measure of attentiveness based on gaze direction data captured across the class session.

Key Components of the Gaze Analysis Module

1) **Gaze Estimation Model**
The Gaze Estimation Model forms the foundation of the Gaze Analysis Module, calculating the gaze vector for each detected face to determine the direction in which the student is looking.
   - **Facial Landmark Detection**: The gaze estimation model begins by identifying key facial landmarks, such as the eyes, nose, and mouth, within each face detected by the previous module. These landmarks serve as reference points for determining both the head orientation and eye gaze.
   - **Gaze Vector Calculation**: Using these landmarks, the model calculates a gaze vector—a directional line extending from the eye position to indicate the student's line of sight. The vector's orientation is influenced by both head position and eye movement, which are detected by algorithms trained on datasets that capture variations in gaze direction, head tilt, and eye alignment.
   - **Robustness to Subtle Movements**: To accurately capture slight shifts in gaze, such as minor head tilts or small eye movements, the gaze estimation algorithm uses fine-grained analysis of eye region pixels and nose bridge orientation. This sensitivity ensures that even subtle changes are detected, allowing the system to precisely distinguish between attentiveness and minor distractions.

2) **Attentiveness Detection**
This sub-module evaluates each student's gaze direction in relation to the board and classifies them as "attentive" or "non-attentive" based on the calculated gaze vector.
   - **Gaze Direction Evaluation**: The system interprets each gaze vector in relation to predefined classroom coordinates, specifically the relative positions of the student, camera, and

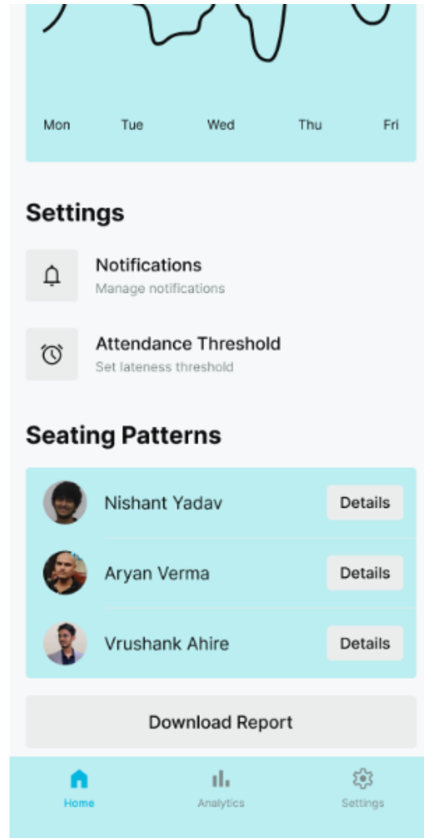

Fig. 4: Analytics Report

board. Given the alignment of the gaze vector, the student in the frame is classified as *attentive*, *passive-attentive* or *non-attentive*.
   - **Head Orientation Adjustment**: The model takes head orientation into account to avoid misclassifications when students look toward the board while slightly turning their heads. By combining eye position and head orientation data, the system can reliably infer gaze direction, minimizing the risk of falsely labeling students as "non-attentive" when they are, in fact, focused on the board.
   - **Real-Time Frame Analysis**: To ensure consistency, the module performs gaze detection over a series of frames—typically 50 frames in a standard class session—captured at intervals throughout the session. This frame-by-frame analysis allows the system to monitor gaze direction consistently, creating a robust measure of attentiveness.

3) **Attentiveness Scoring and Categorization**
The Gaze Analysis Module in Class Pulse uses a three-state classification to assess each student's attentiveness, assigning them to one of three cat-

egories—"attentive," "passive attentive," or "non-attentive." Each state is quantified by a point system (2, 1, or 0 points respectively), allowing for a nuanced measurement of engagement.The module tracks the gaze data over the session and calculates a cumulative attentiveness score for each student based on the three states:The Gaze Analysis Module in Class Pulse uses a three-state classification to assess each student's attentiveness, assigning them to one of three categories—"attentive," "passive attentive," or "non-attentive." Each state is quantified by a point system (2, 1, or 0 points respectively), allowing for a nuanced measurement of engagement.The module tracks the gaze data over the session and calculates a cumulative attentiveness score for each student based on the three states:

- **Attentiveness State Scoring**
  Attentive: If the gaze vector aligns closely with the board, indicating sustained attention, the student is marked as "attentive" and receives 2 points for that frame.
  Passive Attentive: If the gaze vector is generally directed toward the front but slightly off the board or shows brief interruptions in focus, the system marks the student as "passive attentive" and assigns 1 point.
  Non-Attentive: If the gaze is directed away from the board or focused on distractions, the student is classified as "non-attentive" and receives 0 points for that frame.
- **Total Attentiveness Score Calculation**
  For each session, the module sums the points across 50 frames, which are captured intermittently throughout the class. This cumulative score reflects overall attentiveness, with higher scores indicating more consistent focus.
- **Engagement Levels Based on Score**
  Active: A high total score indicates regular focus on the board, categorizing the student as "actively engaged."
  Passive: A moderate score suggests intermittent attention, placing the student in the "passive" engagement category.
  *Unengaged:*A low score reflects minimal attention and is classified as "no participation."

This scoring system enables Class Pulse to offer detailed insights into attentiveness by considering varying engagement levels across the session, providing a more comprehensive understanding of student focus and participation.

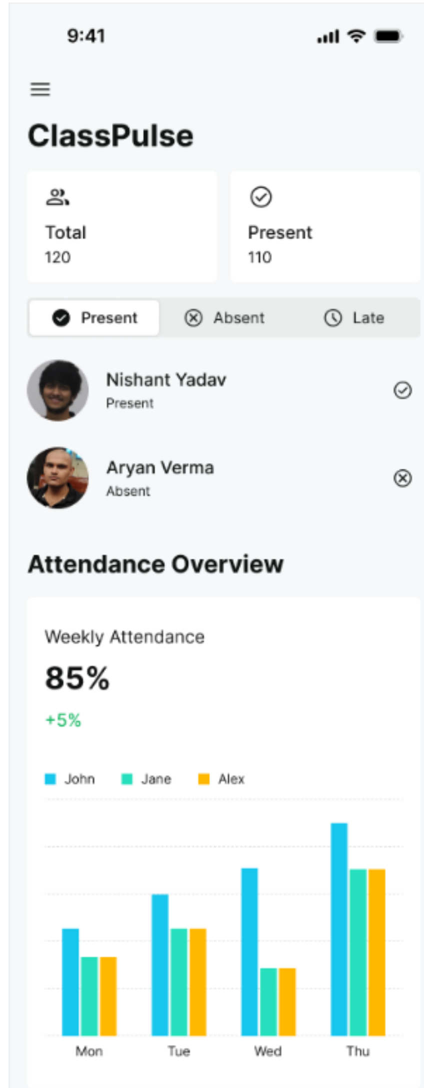

Fig. 5: Class Dashboard

E. Attendance Management Module

The Attendance Management Module records and manages attendance data based on the recognition results and gaze analysis outputs.

- *Attendance Logging:* For each session, attendance is logged with timestamps, student IDs, and attentiveness scores. The logs are stored in a database for future reference, analysis, and reporting.
- *Automated Reporting:* This module generates attendance reports that can be customized based on class, session, or individual students. Reports include participation summaries, attentiveness scores, and attendance trends over time.
- *Integration with School Systems:*The system can export attendance data to external school management platforms such as Google Classroom and Moodle,

streamlining reporting processes and ensuring compatibility with existing administrative tools.

F. Data Storage and Security Module

The Data Storage and Security Module is a critical component of Class Pulse, designed to manage the secure handling, storage, and access of all data generated by the system. This module is developed to ensure high-performance data storage while maintaining strict adherence to privacy standards and regulations, protecting both personal and sensitive information.

1) **Database Management**
The Data Storage and Security Module organizes and stores a wide range of data generated during each class session, including attendance records, 3D face models, session logs, and gaze data.

   - **Structured Database Design:**
   A robust database schema is implemented to accommodate the different types of data collected by Class Pulse. Attendance records and session logs are stored in relational tables for easy querying and reporting, while more complex data, such as 3D face models, may be stored in dedicated, optimized storage solutions that allow for efficient retrieval and manipulation.
   - **Optimized Storage Techniques:**
   The database employs indexing and caching strategies to optimize retrieval speeds. Indexes are created for frequently queried fields, such as student IDs and session timestamps, reducing query times and ensuring that large datasets can be handled smoothly. Caching techniques are implemented to store frequently accessed data temporarily, minimizing repeated database queries and improving overall system responsiveness.
   - **Data Redundancy and Backup:**
   To prevent data loss, the system performs regular backups and employs data redundancy methods. Copies of critical data, such as attendance records and student profiles, are stored in secondary storage locations, allowing for quick recovery in case of a system failure or data corruption.

2) **Data Encryption** To protect sensitive information, the Data Storage and Security Module uses advanced encryption methods for both data-at-rest and data-in-transit.

   - **Data-at-Rest Encryption:**
   All stored data, including 3D face models, attendance logs, and student identifiers, are encrypted while at rest. Strong encryption algorithms (such as AES-256) are applied, ensuring that unauthorized users cannot access or interpret the data, even if they gain access to storage.
   - **Data-in-Transit Encryption:**
   As data moves between system components or to external devices, it is secured using TLS (Transport Layer Security) protocols to prevent interception. This ensures that information remains confidential and intact as it travels between the data acquisition devices, database, and other modules.
   - **Secure Key Management:**
   Encryption keys are managed in a secure key vault, which restricts access to only the system components that require decryption capabilities. Key rotation and expiration policies are in place to minimize risk, with keys updated periodically to enhance data security.

3) **Privacy Compliance** The Data Storage and Security Module is built to comply with stringent privacy standards, such as GDPR, to safeguard user data and uphold student privacy rights.

   - **Access Control and User Authentication:**
   Access to stored data is tightly controlled through role-based access protocols. Only authorized personnel, such as system administrators or teachers, have access to specific datasets, ensuring that sensitive data is only available to those with permission. Multi-factor authentication and logging mechanisms are used to monitor and secure access points.
   - **Data Minimization and Anonymization:**
   To protect student identities, Class Pulse uses data minimization techniques, only storing data essential for system functionality. When data is aggregated for analysis or reporting, personal identifiers (such as facial images) are anonymized. For example, attendance or engagement metrics are displayed without revealing specific students' identities, preserving their privacy.
   - **User Consent and Transparency:**
   The system implements explicit user consent mechanisms, where students or their guardians are informed about data collection, storage, and usage practices. Consent forms are managed digitally, allowing students to view or withdraw consent if they choose, and providing transparency into how their data is used within Class Pulse.
   - **Data Retention Policies:**
   Class Pulse adheres to data retention guidelines, deleting or anonymizing records after a

defined period or upon request. This policy ensures that data is only stored for as long as necessary, preventing indefinite retention of sensitive information.

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    - **Access Control and User Authentication:** Access to stored data is tightly controlled through role-based access protocols. Only authorized personnel, such as system administrators or teachers, have access to specific datasets, ensuring that sensitive data is only available to those with permission. Multi-factor authentication and logging mechanisms are used to monitor and secure access points.
    - **Data Minimization and Anonymization:** To protect student identities, Class Pulse uses data minimization techniques, only storing data essential for system functionality. When data is aggregated for analysis or reporting, personal identifiers (such as facial images) are anonymized. For example, attendance or engagement metrics are displayed without revealing specific students' identities, preserving their privacy.
    - **User Consent and Transparency:** The system implements explicit user consent mechanisms, where students or their guardians are informed about data collection, storage, and usage practices. Consent forms are managed digitally, allowing students to view or withdraw consent if they choose, and providing transparency into how their data is used within Class Pulse.
    - **Data Retention Policies:** Class Pulse adheres to data retention guidelines, deleting or anonymizing records after a defined period or

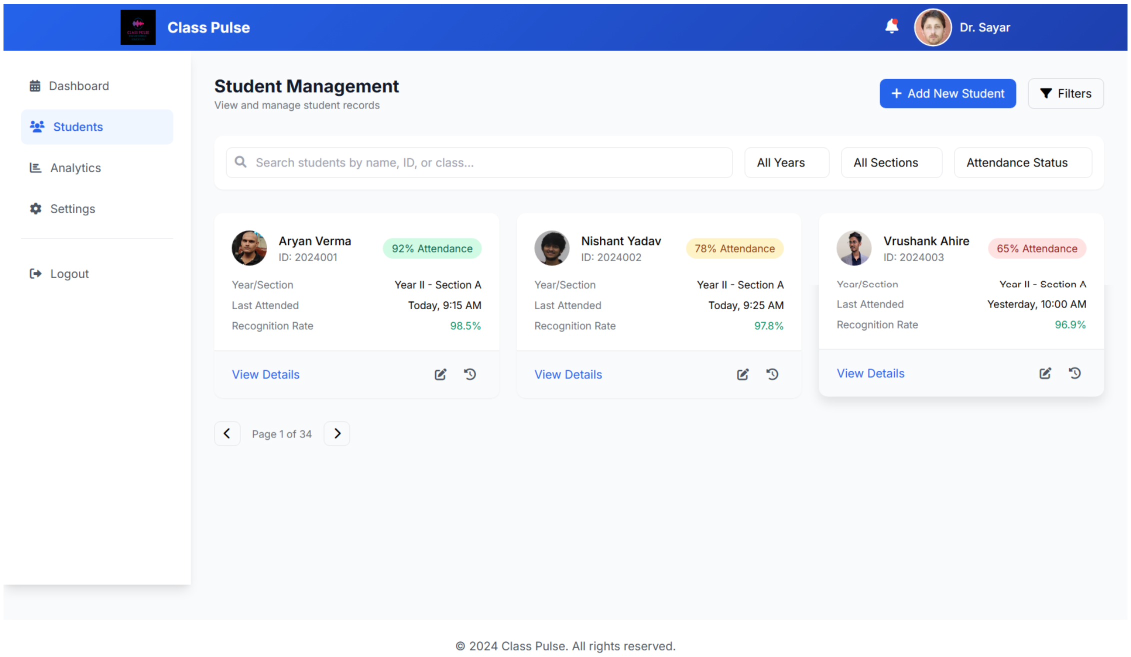

Fig. 6: Personalized Class Learning Analytics

upon request. This policy ensures that data is only stored for as long as necessary, preventing indefinite retention of sensitive information.

H. User Interface Module

The User Interface Module of Class Pulse serves as the central interaction platform, offering an intuitive and accessible way for teachers, administrators, and students to engage with the system's data and insights. It provides real-time information and analytics, enhancing classroom and administrative functions while offering tools for customized data visualization and reporting.

Key Components of the User Interface Module

1) **Dashboard** The dashboard is the main interface, accessible via a web-based platform, that provides real-time updates and a comprehensive overview of class and individual metrics.
   - **Real-Time Attendance and Attentiveness Tracking:** Teachers can monitor current attendance statuses and attentiveness scores for each student throughout the class session. The interface presents this data in an easy-to-interpret format, using color-coded indicators and icons to show whether students are marked as "present," "absent," or "late."
   - **Customizable Viewing Options:** Teachers and administrators can customize the dashboard view to focus on specific metrics, such as attentiveness scores or participation levels, based on their needs. Filters allow users to toggle between different class sections or focus on individual students' data.
   - **Administrator Insights:** In addition to real-time data, school administrators can access an aggregated view of attendance and engagement data across multiple classes or time periods. This view is particularly useful for tracking school-wide trends and evaluating overall student engagement.

2) **Reports and Analytics** The User Interface provides advanced tools for generating reports, visualizing data trends, and conducting data-driven analysis, helping users gain actionable insights
   - **Customizable Report Generation:** Teachers and administrators can create detailed attendance and attentiveness reports for specific dates, students, or classes. Reports are customizable, allowing users to select specific data points, such as total attendance, average attentiveness, or individual participation levels, to suit their needs
   - **Data Visualization:** Interactive graphs and charts visually represent attendance trends, attentiveness patterns, and engagement metrics, making it easy to spot trends and anomalies over time. For instance, line graphs can depict attentiveness levels across different class sessions, while bar charts might show attendance

distribution by grade or demographic.

- **Downloadable Reports:** Reports are exportable in various formats (e.g., PDF, Excel) for easy sharing or printing, allowing administrators to integrate Class Pulse data into broader institutional reports or records.
- **Filtering and Sorting Capabilities:** The UI provides robust filtering options, enabling users to sort and analyze data by class, date, student demographics, or specific engagement metrics. For example, administrators can filter to view attendance rates for a particular grade level or analyze attentiveness trends over specific periods.

III. Implementation Details

The Class Pulse system is built on a robust tech stack that integrates computer vision, data processing, and machine learning to capture and analyze classroom engagement metrics effectively. The system uses a combination of hardware and software components to ensure efficient data acquisition, processing, and reporting.

1) **Tech Stack**

- **Programming Languages and Frameworks** Class Pulse is primarily developed in Python, chosen for its extensive library support and ease of integration with machine learning and computer vision frameworks. Core libraries include OpenCV for face detection and landmark estimation, Dlib for advanced facial recognition, and NumPy for numerical data handling and manipulation.
- **Machine Learning and Data Analysis** The system relies on pre-trained convolutional neural networks (CNNs) for face detection, which have been fine-tuned for accuracy in various lighting and orientation conditions. Face recognition models further process these detected faces to create face encodings and track individual engagement over time.
- **Data Management** SQLite is used as the lightweight database solution for managing student profiles, attendance records, and session data. The database architecture is optimized to handle large sets of visual data efficiently, ensuring quick retrieval and data integrity.
- **3D Face Modeling (NERF-based approach)** Class Pulse stores a 3D model of each student, generated using Neural Radiance Fields (NERF). This enables the system to render accurate face models from various angles, enhancing face recognition even with limited viewpoints in 2D frames.

2) **Key Functional Processes**

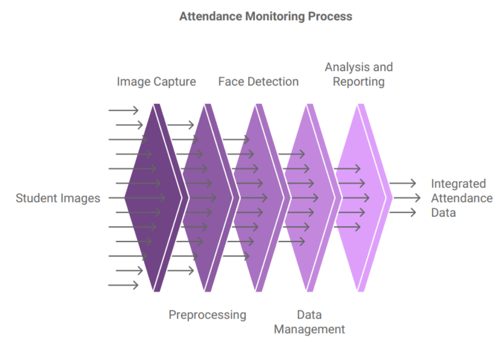

Fig. 7: Schematic: Process Flow in Class-Pulse

- **Face Detection and Recognition** Each frame captured in a class session undergoes face detection using OpenCV and Dlib models. Detected faces are cropped and preprocessed before generating facial encodings, which are compared with stored student profiles to identify individuals and track attentiveness.
- **Attentiveness Scoring and Data Aggregation** Based on facial landmarks and orientation, each student's attentiveness is scored on a per-frame basis. Scores are aggregated over the class session to classify each student's engagement level, which is subsequently stored for reporting and analysis.
- **Reporting and Visualization** The system generates summary reports on student participation and classroom attentiveness, using Matplotlib and Seaborn for data visualization. These reports provide insights into individual and group engagement trends, accessible to instructors for academic assessment and instructional adjustments.

IV. Data Analysis & Reporting

Class Pulse focuses on capturing and analyzing key metrics that provide a comprehensive view of classroom attentiveness and participation. By systematically assessing both individual and collective engagement levels, Class Pulse offers an objective, data-driven evaluation of the classroom environment. This information not only highlights trends in student attentiveness but also serves as valuable feedback for instructional strategies, supporting continuous enhancement of the learning experience.

1) Attentiveness Metrics Each student's attentiveness is quantified based on frame-by-frame data

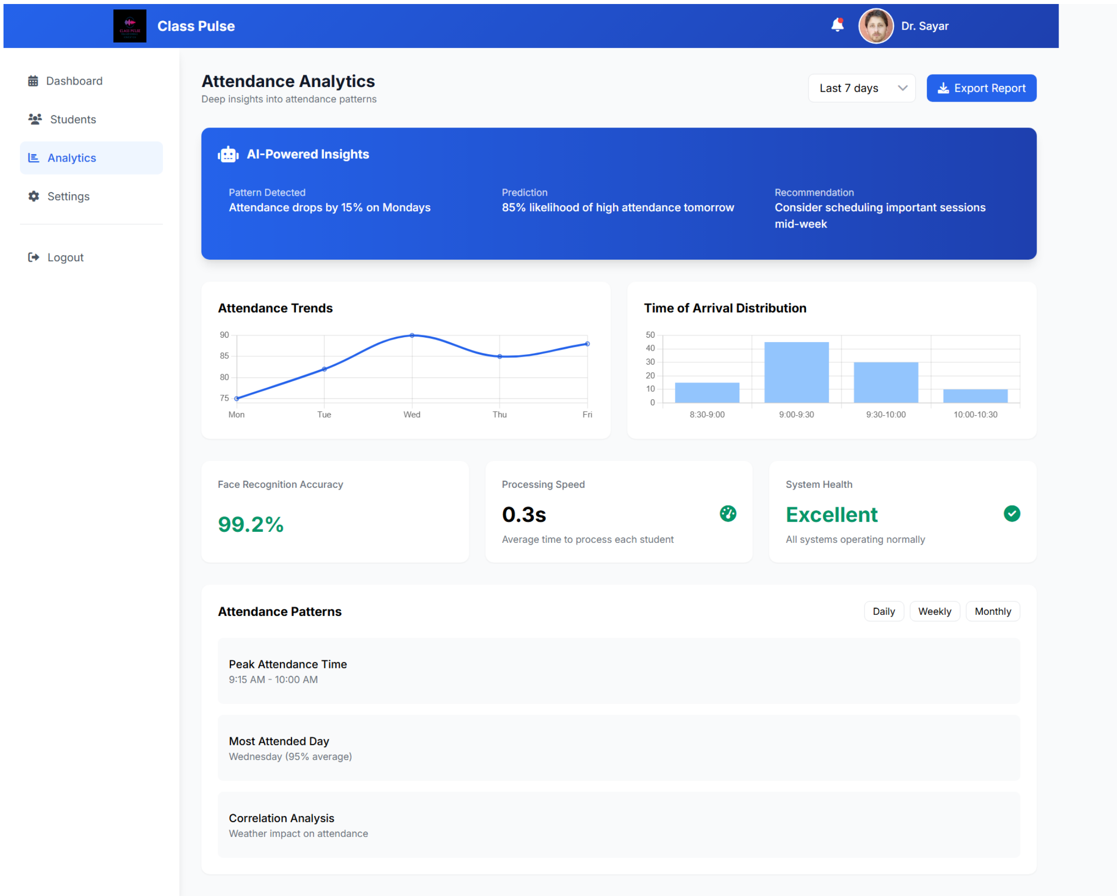

Fig. 8: Classroom Learning Analytics Dashboard

throughout a class session. This allows Class Pulse to evaluate the attention levels at an individual and classroom-wide level:

- **Frame-Based Attentiveness Score**: Class Pulse assigns attentiveness scores on a per-frame basis for each student, with three possible states:
  - Attentive: (2 points) - Student is looking at the board, indicating full engagement.
  - Passive Attentive: (1 point) - Student's gaze is partially directed at the board, suggesting partial engagement.
  - Non-Attentive: (0 points) - Student is not focused on the board, signaling disengagement.
- **Average Attentiveness Score**: By calculating an average attentiveness score across all frames captured in a session, Class Pulse creates a continuous metric that represents each student's engagement level throughout the class.

2) **Participation Classification**

Class Pulse classifies students into participation categories based on their average attentiveness scores over the session:

- **Active Participation**: Students who exhibit a high average attentiveness score, indicating consistent focus.
- **Passive Participation**: Students with moderate attentiveness, suggesting fluctuating engagement.
- **No Participation**: Students showing minimal or no attentiveness, indicating potential disengagement.

3) **Classroom Environment Metrics**

By aggregating individual metrics, Class Pulse assesses the broader classroom engagement environment:

- **Classroom Attentiveness Distribution**: The distribution of attentiveness states across students provides insights into the general classroom atmosphere. For instance, a high percentage of "Attentive" states may indicate an engaging class session, while a skew toward

"Non-Attentive" states may highlight potential areas for instructional improvement.
- **Session-Wide Engagement Trends**: Metrics reveal attentiveness trends throughout the session, such as variations in focus levels over time. These patterns can indicate moments of peak engagement or potential disengagement, assisting in the evaluation of instructional flow.

V. Challenges and Solutions

The development of Class Pulse came with several technical, practical, and design challenges. While the goal was to create an efficient, non-intrusive system for real-time student attendance and attentiveness tracking, achieving this objective was far from straightforward. In this section, we describe the major challenges faced during the design, implementation, and testing of the system, as well as the solutions we developed to overcome them.

A. Challenge 1: Transition from 2D to 3D Technology

One of the most significant challenges in the development of Class Pulse stemmed from the decision to rely on 2D face recognition as the foundation for attendance tracking. Initially, the system was designed to work by detecting and recognizing faces using traditional 2D image processing techniques. However, during testing in classroom settings, we quickly discovered that the performance of the 2D-based model was inadequate for several reasons:

- **Limited Accuracy in Various Angles**: The 2D model had difficulty accurately detecting faces when students were not facing the camera directly. Even slight deviations in head orientation (such as tilting the head up or down, or turning it to the side) led to poor recognition results. This was especially problematic during a live classroom setting, where students often move around or look at other areas of the room.
- **Impact of Occlusions and Lighting**: Variations in lighting and partial occlusions, such as students wearing glasses or having their heads partially blocked by objects (e.g., notebooks, hands), significantly degraded the recognition rate. This led to a high rate of false negatives where the system failed to detect or identify students.

Solution: Shift to 3D Technology
Recognizing the limitations of the 2D approach, we decided to transition to 3D face modeling to improve the robustness and accuracy of the system. This shift was motivated by the following key advantages that 3D technology offered:

- **Robustness to Head Movements**: 3D face modeling, particularly through the use of Neural Radiance Fields (NERF), allowed us to create highly accurate 3D models of students' faces, which could capture facial features from different angles. This eliminated the issues we encountered with the 2D model, such as difficulty detecting faces at various angles or under different lighting conditions.
- **Improved Recognition Accuracy**: By building 3D representations of faces, we were able to ensure that facial features, regardless of head tilt, lighting, or occlusions, were recognized more reliably. The system now uses depth information to create a comprehensive profile of each student, allowing for more accurate identification, even with partial occlusions or varying lighting conditions.

B. Challenge 2: Gaze Estimation Accuracy

Another challenge we faced was accurately estimating the students' gaze direction. Gaze estimation is a critical component for determining attentiveness in class, as it helps the system assess whether a student is actively engaging with the class by looking at the board.

However, gaze estimation is inherently difficult due to the following factors:

- Variation in Head Positions: Students often have their heads tilted, which can distort the gaze vector and make it harder to determine whether they are looking at the board.
- Eye Positioning and Occlusions: Students may wear glasses, hats, or even lean on their hands, causing part of their face or eyes to be obscured, complicating gaze estimation.
- Environmental Factors: Fluctuations in lighting, shadows, and reflections can create distortions in the image, further complicating the accuracy of gaze tracking.

Solution: Advanced Gaze Estimation Algorithms
To address the challenge of gaze estimation, we employed advanced gaze estimation models that combined eye-tracking technology with machine learning techniques. These algorithms were specifically designed to be robust to slight head tilts and occlusions. Key components of the solution included:

- Facial Landmark Detection: By using deep learning models trained to detect facial landmarks such as the eyes, nose, and mouth, we could accurately estimate the head orientation and compensate for minor tilts.
- Gaze Vector Calculation: The system computes the gaze vector based on the alignment of the detected landmarks and the relative position of the eyes. This enables more precise estimation of where a student

is looking, even if they are not directly facing the camera.
- Occlusion Handling: The gaze estimation algorithm was trained to handle partial occlusions, such as students wearing glasses or having their faces partially obscured, by using multiple facial features (e.g., eyebrow position, nose angle) to infer the direction of the gaze.

Through these improvements, the system achieved a higher level of accuracy in tracking gaze direction, allowing for reliable attentiveness classification.

C. Challenge 3: Privacy and Data Security

The handling of student data raised concerns regarding privacy and data security. Since the system uses facial recognition and gaze tracking, it collects sensitive data about students' identities and behavior, which must be carefully protected to prevent unauthorized access and misuse.

- Regulatory Compliance: The system needed to comply with regulations such as GDPR and other local privacy laws to ensure that student data was handled securely and ethically.
- Data Encryption: Storing facial data, attendance logs, and gaze information required strong encryption methods to ensure that sensitive data was protected from breaches or leaks.

Solution: Comprehensive Data Protection Measures To address privacy and security concerns, we implemented several measures:

- **Data Encryption**: All sensitive data, including 3D face models, attendance records, and gaze tracking data, were encrypted using advanced encryption algorithms (e.g., AES-256) to prevent unauthorized access.
- **Anonymization**: Personal identifying information was anonymized in the reports, ensuring that the system did not retain or expose identifiable student data.
- **Access Control**: We implemented strict access controls, limiting the ability to view or modify sensitive data to authorized personnel only. Additionally, all access to the system was logged and monitored to detect any suspicious activity.

These privacy and security measures ensured that Class Pulse operated within legal and ethical boundaries, protecting students' data while delivering its intended functionality.

VI. Conclusions & Future Directions

The Class Pulse system has demonstrated its potential as an intelligent academic tool, effectively analyzing attentiveness patterns to support enhanced engagement in the classroom. By capturing and analyzing frames at set intervals, Class Pulse provides insightful, quantitative data on student attentiveness. This data, processed through various attentiveness states, enables educators to monitor engagement patterns without intrusive measures, potentially supporting improvements in teaching strategies. While currently limited to attentiveness tracking, Class Pulse establishes a foundation for more comprehensive, intelligent classroom analytics. **Future Plan**

1) **Expanded Metrics for Classroom Analysis** To provide a more holistic understanding of classroom dynamics, additional behavioral metrics can be incorporated, such as:
   - **Posture Analysis:** Track body posture, such as leaning forward or sitting upright, to better understand engagement and active participation.
   - **Eye Movement Tracking:** Measure not only the direction of gaze but also focal attention shifts to estimate engagement with specific materials (e.g., slides, board).
   - **Emotion Recognition:** Using facial expressions to detect emotional states, like confusion or frustration, could allow educators to identify moments when students struggle to understand material.
2) **Technological Advancements in Face Analysis**
   - **Improved 3D Modeling and Analysis:** Using advanced 3D modeling technologies like Neural Radiance Fields (NeRFs) can enhance face recognition accuracy and enable better analysis of face angles from varied viewpoints.
   - **Real-time Data Processing with Edge AI:** Deploying edge AI devices in the classroom could facilitate real-time processing of frames locally, reducing dependency on cloud processing, improving data privacy, and decreasing latency.
   - **Generative AI for Frame Prediction:** Use generative AI to predict frames based on captured ones, minimizing the need for continuous frame capture and lowering processing load.
3) **Enhanced Attentiveness Metrics** In addition to the existing attentiveness classifications, new dimensions can be explored to refine student engagement insights:
   - **Interaction Frequency Analysis:** Capture data on hand-raising or gestures to measure interaction levels. This could provide additional insights into active participation.
   - **Focus Stability:** By analyzing the consistency of attentiveness over a session, Class Pulse could identify if engagement drops after cer-

tain points, helping educators adjust lesson pacing.

4) **Data Visualization and Reporting Tools**
   - **Teacher Dashboards:** Develop a dedicated dashboard to visualize attentiveness metrics, historical engagement trends, and comparative class-wide insights. Visual tools like heatmaps or temporal engagement graphs can assist educators in assessing overall classroom engagement patterns.
   - **Automated Report Generation:** Automate the generation of reports summarizing weekly or monthly trends, allowing educators and administrators to evaluate long-term engagement changes and track intervention impacts.
5) **Privacy and Ethics Enhancements** With the increasing focus on privacy, implementing anonymization techniques, such as blurring identifiable features in certain stored frames, would ensure student identity is protected. Additionally, enabling opt-in or opt-out options for students could enhance ethical transparency in system deployment.
6) **Longitudinal Tracking and Predictive Analysis** With longitudinal tracking, the system could build profiles over time, providing predictive insights on student attentiveness trends. Educators could use this information to identify patterns, adapt teaching methods for specific cohorts, or even detect early signs of disengagement.

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