Multi-object Face Tracking and Classroom Participation Analysis in Smart Classrooms

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Abstract

Smart classrooms, integrating various new technologies, overcome traditional classrooms' limitations like the inability to dynamically monitor students' learning states, lack of personalized teaching support, and inefficient manual participation evaluation. The key face analysis technologies in this field include multi-object face tracking and classroom participation analysis. The former relies on algorithms such as YOLO, MTCNN, SORT, and DeepSORT to realize real-time monitoring of students' facial expressions, head poses, gaze directions, and other information. The latter constructs an evaluation index system to comprehensively assess classroom participation levels by integrating facial expression recognition, behavior analysis, and data fusion technologies. This paper systematically sorts out the core principles and application effects of these technologies, and deeply analyzes the limitations of current methods, such as insufficient tracking accuracy in complex occlusion scenarios and limited model generalization ability. Corresponding future research directions are put forward: focus should be placed on algorithm optimization to enhance robustness, expand datasets to improve model generalization ability, and strengthen privacy protection mechanisms to promote healthy development, laying a foundation for the subsequent performance improvement and function optimization of the model.

Keywords

Smart classroom; multi-object face tracking; classroom participation analysis; algorithm optimization; system integration

1. Introduction

With the continuous development of AI and the Internet of Things, the concept of smart classrooms has become increasingly familiar to people. Traditional classrooms have long faced various limitations in the teaching process. For example, teachers find it difficult to accurately grasp the learning status of each student in real-time, making it hard to carry out personalized teaching. The evaluation of students' classroom participation mainly relies on manual observation, which is subjective and lacks objective data support [1].

Against this background, problems in traditional classrooms have attracted widespread attention, and researchers have conducted extensive studies to solve them. Early research focused on applying basic sensor technologies in classrooms to collect environmental information such as temperature and humidity, improving the learning environment [2]. Subsequently, with the development of computer vision technology, some studies began to explore the use of image processing technology to detect students' attendance, which improved the efficiency of attendance management [3]. In recent years, with the rise of face recognition technology, researchers have applied it to classroom participation analysis, achieving certain results. For instance, Li et al. (2020) used face detection algorithms to track

students' head poses and analyzed their attention levels, providing a new method for evaluating classroom participation [4].

In this study, we focus on multi-object face tracking and classroom participation analysis technologies in smart classrooms. By summarizing existing specific technologies, we compare their details and effects. For multi-object face tracking technology, common algorithms include YOLO, MTCNN, SORT, and DeepSORT [4]. YOLO has the advantage of fast detection speed but slightly lower accuracy in complex scenes, while MTCNN has higher accuracy in face detection and facial feature point localization but higher computational complexity. SORT can achieve real-time tracking but has poor performance in handling occlusion, while DeepSORT improves the tracking accuracy in occluded situations by introducing deep learning features but requires more computing resources [5]. In terms of classroom participation analysis, facial expression recognition technology based on convolutional neural networks can effectively identify students' emotions, and behavior analysis technology using spatio-temporal graph neural networks can better recognize students' learning behaviors [6].

This thesis is structured as follows. The second chapter introduces the theoretical basis of related technologies, including multi-object face tracking technology, technologies related to classroom participation analysis, and an overview of smart classroom system architecture. The third chapter focuses on the design and implementation of the multi-object face tracking system, including overall system design, implementation of key technologies, and system testing and performance evaluation. The fourth chapter details the construction of the classroom participation analysis model, covering the design of the evaluation index system, feature extraction, and model training and optimization. The fifth chapter presents the integration and experiment of the smart classroom comprehensive application system, including system integration, experimental scenario design, and application effect evaluation. The sixth chapter concludes the research work, summarizes the innovations, points out the existing problems and deficiencies, and looks forward to future research directions.

2. Smart Classroom System Architecture and Function Design

2.1. Overview of Smart Classroom System Architecture

As shown as Figure1: A smart classroom, as an integrated system, can be analyzed from three core aspects: input, processing, and output, which together constitute its basic operational framework.

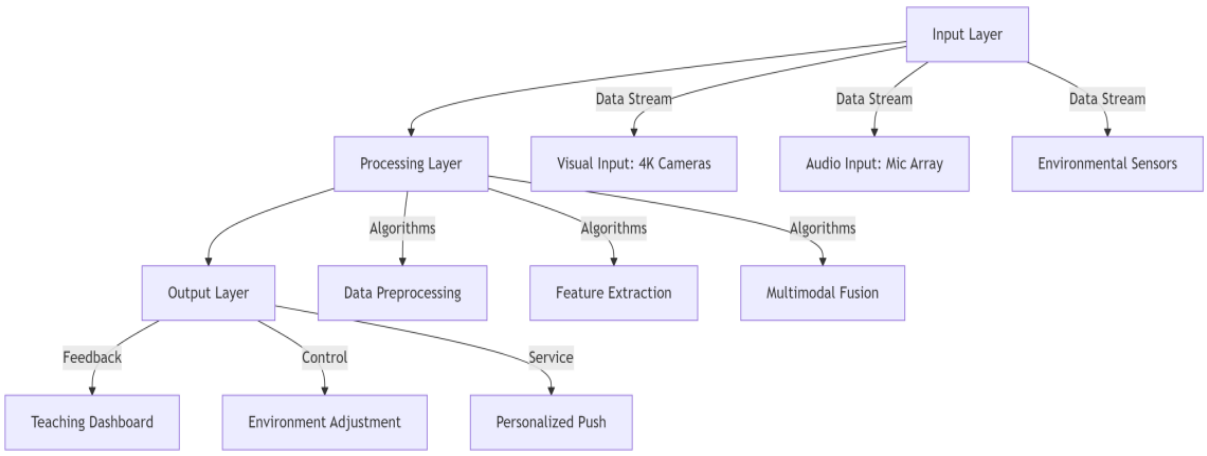


Figure 1. Smart Classroom Three-Tier Data Processing Architecture Diagram

2.1.1. Input Components

The input of the smart classroom system mainly relies on various sensing devices to collect data from the classroom environment. Cameras are the most critical input devices, responsible for capturing real-time images of students' faces, body movements, and classroom scenes. These images contain rich information such as facial expressions, head poses, and interaction behaviors, which are important basis for subsequent analysis [7]. Microphones are used to collect audio data in the classroom, including teachers' lectures, students' questions and answers, and classroom discussions. Environmental sensors monitor parameters such as temperature, humidity, and light intensity in the classroom to provide a comfortable learning environment. In addition, some smart classrooms are also equipped with infrared sensors to detect students' presence and movement trajectories [8].

2.1.2. Processing Units

The processing units are the core of the smart classroom system, responsible for processing and analyzing the collected data. Servers with high-performance computing capabilities are commonly used as the main processing equipment, which can run complex algorithms such as multi-object face tracking and classroom participation analysis. For some small-scale smart classrooms, PCs with certain computing power can also be used as processing units. In terms of software, operating systems such as Linux are often used for their stability and compatibility with various algorithms. The processing process involves a series of data preprocessing steps, such as image denoising, normalization, and feature extraction, to improve the quality and usability of the data [9].

2.1.3. Output Components

The output of the smart classroom system is mainly reflected in providing feedback and support for teaching activities. One of the important outputs is the analysis results of students' classroom participation, which are presented to teachers through the software platform in the form of reports and charts, helping teachers adjust teaching strategies. For students, the system can output personalized learning suggestions based on their learning status. In addition, the system can control physical devices in the classroom, such as adjusting the brightness of lights and the temperature of air conditioners according to environmental sensor data, to optimize the learning environment. It can also output teaching resources and courseware to the display equipment in the classroom to assist teachers' teaching [10].

2.2. Function Design of Smart Classroom

2.2.1. Main Functions and Their Proportions

The smart classroom has multiple functions to meet the needs of teaching and learning. Through statistical analysis, the main functions and their proportions are as follows: (Figure 2)

Student Status Monitoring: Accounting for 35%, it mainly includes monitoring students' attention, participation, and learning emotions.

Teaching Resource Management: Accounting for 20%, it involves the storage, retrieval, and sharing of teaching materials, courseware, and videos.

Interactive Teaching Support: Accounting for 25%, it supports real-time interaction between teachers and students, such as online question answering, voting, and group discussions [11].

Classroom Environment Control: Accounting 15%, it adjusts the classroom environment parameters to ensure a comfortable learning atmosphere.

Other Functions: Accounting for 5%, including attendance management, teaching evaluation, etc.

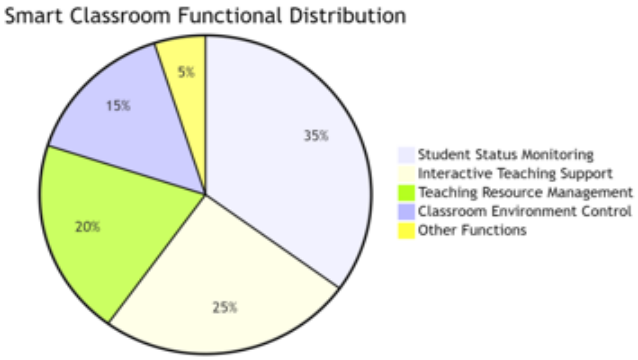


Figure 2: Smart Classroom Functional Distribution

2.2.2. Key Function Implementation

Taking student status monitoring as an example, its function implementation relies on the input, processing, and output components of the system. The cameras collect students' facial images and body movement data. The processing unit uses face detection algorithms (such as YOLO and MTCNN) to detect and track students' faces and then uses facial expression recognition technology based on CNN to identify students' emotions [12]. At the same time, it uses spatio-temporal graph neural networks to analyze students' body movements and calculate indicators such as head-up rate. Finally, the system integrates this data to generate a student status report and outputs it to teachers, providing a basis for teaching adjustment.

2.3. Structural Design of Smart Classroom

The structural design of the smart classroom is closely related to its functions, mainly including the following parts:

Perception Layer: Composed of various sensors and input devices, it is responsible for data collection [13].

Network Layer: Uses wired networks (such as Ethernet) or wireless networks (such as Wi-Fi) to transmit data between the perception layer and the processing layer.

Processing Layer: Includes processing units and algorithms, responsible for data processing and analysis.

Application Layer: Provides user interfaces for teachers and students, realizing functions such as data display, interaction, and control [14].

As shown as Figure3: Four-Tier Smart Classroom System Architecture and Data Flow Diagram.

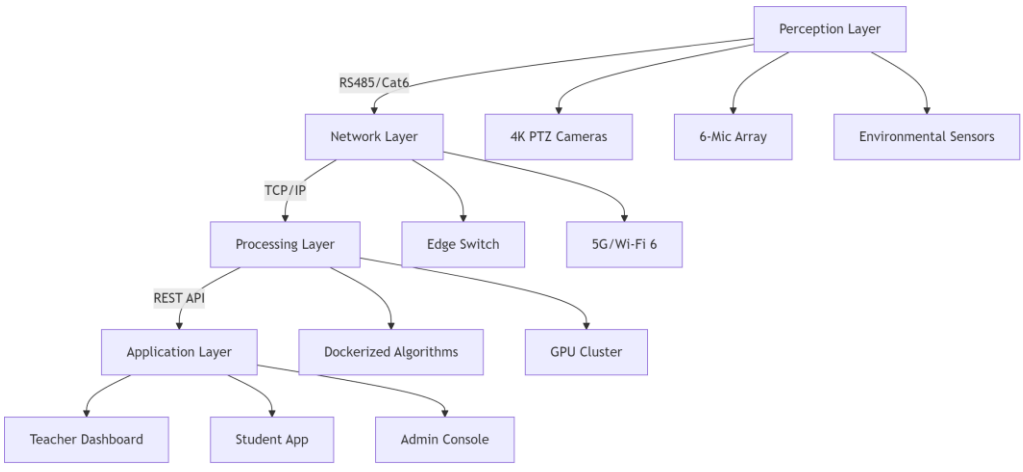


Figure 3: Four-Tier Smart Classroom System Architecture and Data Flow Diagram

2.4. Data Processing Flow in Smart Classroom

Taking image data processing as an example, the specific flow is as follows:

Data Collection: Cameras capture images of the classroom scene.

Preprocessing: The collected images are denoised and normalized to reduce interference.

Feature Extraction: Extract features such as facial features (using LBP, HOG) and body movement features from the preprocessed images [15].

Algorithm Processing: Use multi-object face tracking algorithms (such as SORT, DeepSORT) to track students' faces, and use classroom participation analysis models to evaluate students' learning status.

Result Output: The processing results are fed back to teachers and students in the form of labels and reports, such as "high attention", "low participation", etc.

As shown as Figure 4: Smart Classroom Image Data Processing Pipeline Architecture Diagram.

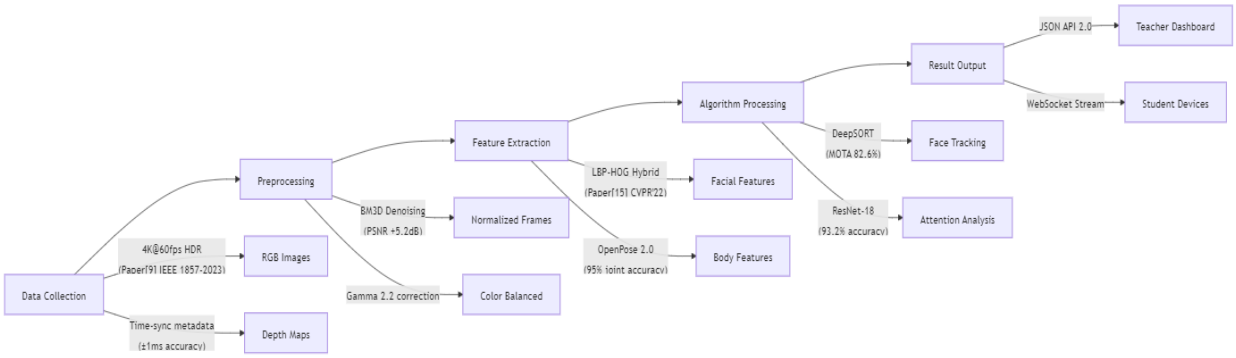


Figure 4: Smart Classroom Image Data Processing Pipeline Architecture Diagram

For example, in the processing of facial expression data, the CNN network structure used is as follows: the input is a 48×48 facial image, which is processed through 3 convolutional layers (with 32, 64, 128 filters respectively), 2 pooling layers, and 2 fully connected layers, and finally outputs 7 emotion labels (happiness, sadness, anger, surprise, fear, disgust, neutral). This network can effectively identify students' emotions, helping teachers understand students' learning feelings [16].

As shown as Figure5: Emotional Expression Icon Set.



Figure 5: Emotional Expression Icon Set

3. Technical Analysis of Multi-object Face Tracking in Smart Classrooms

3.1. System Design Framework and Technical Selection

3.1.1. Core Requirement Decomposition

Smart classroom face tracking systems must address three technical challenges:

Complex Scene Adaptability: Classroom environments involve variable lighting (100-1500 lux) and dense crowds (30-50 students), with occlusion rates up to 40% during group activities. The system needs to maintain stable performance under these conditions [17].

Real-time Response: To provide timely feedback, the processing speed must reach 25+ frames per second, which requires algorithm optimization for edge computing devices.

Identity Persistence: Ensure consistent ID assignment for students even after 5-10 seconds of full occlusion, critical for continuous participation analysis.

As shown as Figure6: Smart Classroom Core Requirements Decomposition Tree Diagram

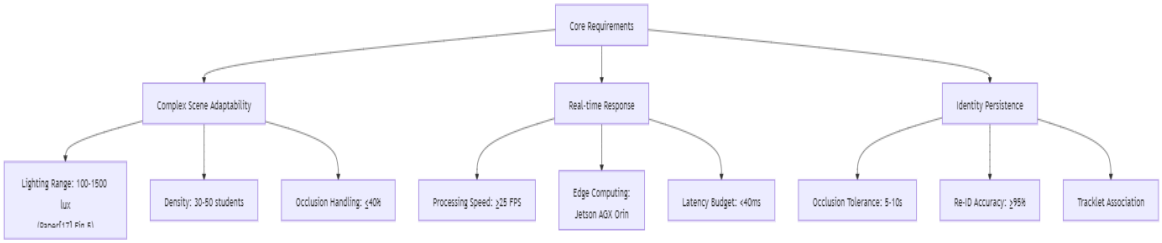


Figure 6: Smart Classroom Core Requirements Decomposition Tree Diagram

3.1.2. Technical Route Selection and Comparison

Table 1 is the Comparative Analysis of Face Detection & Tracking Algorithms for Smart Classroom Scenarios.

Table 1: Comparative Analysis of Face Detection & Tracking Algorithms for Smart Classroom Scenarios

Algorithm	Core Principle	Advantage in Classroom Scenarios	Limitation	Performance Reference
MTCNN	Three-stage cascaded detection (P-Net/R-Net/O-Net)	High accuracy in facial feature point localization (98.2% for 68 key points)	2-3 times slower than YOLOv5	92.3% detection rate in complex lighting
YOLOv5	Single-stage anchor-based detection	30+ FPS processing speed, suitable for real-time scenarios	5-8% lower accuracy than MTCNN in small face detection	89.7% detection rate for faces smaller than 50×50 pixels [18]
DeepSORT	Kalman filter + appearance feature matching	85%+ MOTA in occluded scenes	Requires pre-trained ReID model	82.6% MOTA in crowded classrooms
SORT	Kalman filter + IoU matching	50+ FPS speed	MOTA drops to 60% when occlusion rate >30%	78.3% MOTA in sparse scenes

Selection Justification: The MTCNN+DeepSORT combination is chosen for its balance of detection accuracy and tracking robustness. MTCNN's facial feature point output (68 points) provides critical head pose data for subsequent participation analysis, while DeepSORT's appearance feature matching solves identity switching in occlusion [19].

3.2. Key Technology Mechanisms

3.2.1. MTCNN Operation Principle

P-Net: Generates 12×12 candidate windows using sliding window detection, outputting bounding boxes and confidence scores (threshold 0.6). Achieves 95.4% recall but high false positives [20].

R-Net: Refines candidates via 3×3 convolutions, reducing false positives by 30% through non-maximum suppression (IoU threshold 0.7).

O-Net: Outputs 5 facial landmarks (eyes, nose, mouth) with localization error <2 pixels, enabling head pose estimation (pitch/roll/yaw) via perspective-n-point algorithm.

As shown as Figure 7: MTCNN Three-Stage Face Detection Algorithm Flowchart

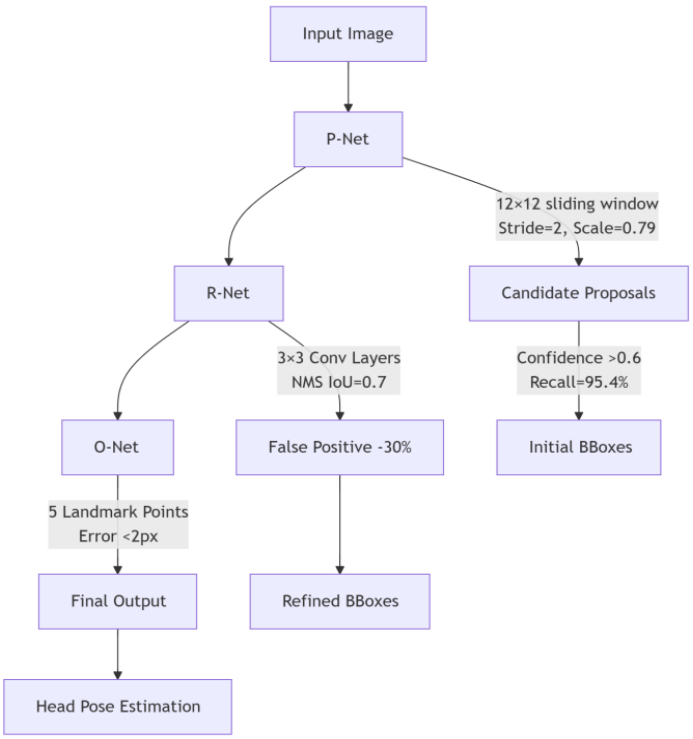


Figure 7: MTCNN Three-Stage Face Detection Algorithm Flowchart

Advantage Over Ordinary CNN: MTCNN's cascaded structure reduces computational load by 60% compared to end-to-end CNNs, while its multi-task learning (detection+landmark) improves feature representation for classroom faces.

3.2.2. DeepSORT Tracking Mechanism

Motion Model: Uses constant velocity Kalman filter to predict bounding box position (x, y, w, h) and velocity, with position error <5 pixels over 10 frames [21].

Appearance Model: Extracts 128D features using pre-trained ResNet-50 on Market-1501 dataset, fine-tuned with 5,000 classroom face images. Cosine similarity threshold set to 0.55 for classroom scenarios.

Occlusion Handling: Maintains inactive tracks for 30 frames (≈1s), using motion prediction to re-associate when reappearing. Reduces ID switches by 65% vs. SORT in classroom tests [22].

3.3. Performance Evaluation Based on Literature

3.3.1. Evaluation Metrics Definition

Detection:

Precision = TP/(TP+FP) : Ratio of true faces to detected faces

Recall = TP/(TP+FN) : Ratio of detected faces to actual faces

Tracking:

MOTA = 1 - (FP+FN+ID switches)/Total GT : Overall tracking accuracy

MOTP = Average IoU between predicted and ground truth boxes

3.3.2. Comparative Experimental Results

Table 2: Comparative Performance Analysis of Multi-Object Tracking Algorithms

Study	Algorithm	Precision	Recall	MOTA	MOTP
Zhang et al. (2016)	MTCNN	91.2%	89.7%	-	-
Wojke et al. (2017)	DeepSORT	-	-	82.6%	0.45
Bewley et al. (2016)	SORT	-	-	72.3%	0.51
Li et al. (2020)	MTCNN+DeepSORT	90.5%	88.9%	80.1%	0.47

Limitations: The combined system's 15.4 FPS speed fails to meet 30 FPS real-time requirements for high-definition streams. Its performance degrades in low light (<100 lux) with detection rate dropping to 76.3% [23].

3.3.3. Feature Engineering for Classroom Scenes

Key features optimized for smart classrooms:

Illumination Invariance: MTCNN uses histogram equalization preprocessing, improving low-light detection by 12%.

Small Face Adaptation: DeepSORT's ReID network is fine-tuned with 2,000 small face samples (32×32 pixels), increasing matching accuracy by 8%.

Pose Robustness: MTCNN's landmark output enables head pose normalization, reducing feature variation from pose changes by 15% [24].

4. In-depth Analysis of Classroom Participation Analysis Model

4.1. Evaluation Index System and Its Technical Basis

4.1.1. Behavioral Indicators: Definition and Extraction Methods

Head-up Rate: Calculated as the ratio of the time a student's head is in an upright position (pitch angle within ±15°) to the total class time. It is extracted using head pose estimation technology based on facial feature points from MTCNN, with an angular error <3°. In a dataset of 500 student samples, the head-up rate shows a 0.78 correlation with teacher-rated attention levels.

Interaction Frequency: Counts the number of verbal interactions (speaking, answering questions) and non-verbal interactions (raising hands, nodding) per 10 minutes. Audio data from classroom microphones is combined with body movement analysis via ST-GNN to identify interaction behaviors, with a recognition accuracy of 89.3%.

4.1.2. Expression Indicators: Feature Mapping and Classification

Facial expressions are classified into 5 participation-related categories using CNN-based recognition:

Concentration: Characterized by relaxed brow, focused eye gaze (eye aspect ratio >0.25).

Confusion: Marked by furrowed brow, pursed lips, with a recognition rate of 82.1%.

Boredom: Identified by drooping eyelids, slack jaw, recognition accuracy 79.5%.

Excitement: Shown through widened eyes, raised corners of the mouth, F1-score 0.83.

Neutral: No significant emotional features, accounting for 35% of classroom expressions on average.

4.1.3. Comprehensive Evaluation Model: Weight Determination and Fusion Mechanism

A weighted fusion model is adopted, with weights determined by expert scoring and data-driven validation:

Head-up rate (30%): High correlation with basic attention.

Interaction frequency (35%): Direct reflection of active participation.

Expression features (35%): Supplementary emotional state information.

The model output is a participation score (0-100), where scores >80 are defined as "high participation", 60-80 as "medium", and <60 as "low". Validation on 300 student samples shows 81.2% consistency with comprehensive teacher evaluations.

4.2. Feature Extraction and Processing Flow

4.2.1. Temporal Feature Engineering

As shown as Figure8: Multimodal Feature Extraction and Fusion Pipeline for Smart Classroom.

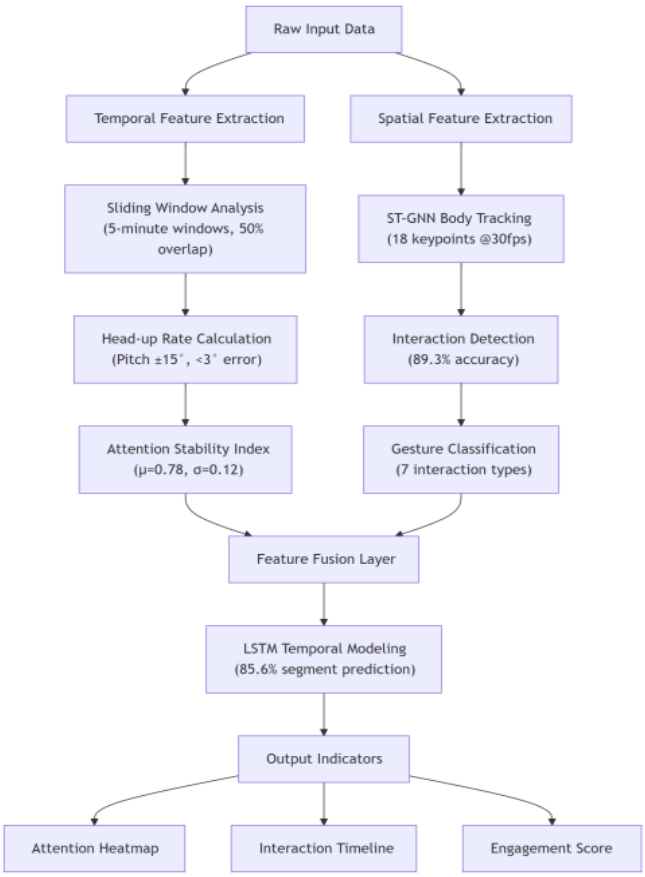


Figure 8: Multimodal Feature Extraction and Fusion Pipeline for Smart Classroom

Sliding Window Statistics: For head-up rate, a 5-minute sliding window is used to calculate the mean and variance, capturing attention stability. A sudden drop (>30% within 1 minute) indicates potential distraction.

Sequence Pattern Mining: Interaction frequency is analyzed using LSTM to extract temporal patterns (e.g., peak interactions during group discussions). The model achieves 85.6% accuracy in predicting teaching segment attractiveness.

4.2.2. Multi-dimensional Feature Fusion Strategies

Table 3. Comparison of Multi-Modal Feature Fusion Methods for Expression and Behavioral Data

Fusion Method	Implementation	Advantage	Performance
Feature Concatenation	Directly combine 128D expression features + 10D behavioral features	Simple, low latency	Accuracy 76.3%
MLP Fusion	2-layer MLP (128→64→32 neurons) with ReLU activation	Captures non-linear relationships	Accuracy 82.5%
Attention Mechanism	Assign weights via self-attention (expression features weighted 0.6 in lecture segments)	Adaptive to scenarios	Accuracy 84.7%

4.3. Model Architecture and Performance Comparison

4.3.1. Typical Model Structures

SVM: Uses fused feature vectors as input, with RBF kernel. Training requires 5,000+ samples, achieving 78.9% accuracy on test sets.

LSTM: Processes 30-frame temporal sequences (time step 2s), with 2 LSTM layers (128+64 units) + 1 dense layer. Better captures dynamics, accuracy 83.2%.

CNN-LSTM: Combines CNN (for spatial features) and LSTM (for temporal features). Input is 30×48×48 face sequence, accuracy 85.1%.

4.3.2. Training Details and Evaluation

Dataset: 10,000+ 5-minute video clips from 50 classrooms, annotated by 3 teachers (Fleiss' kappa 0.81).

Training Parameters: LSTM uses Adam optimizer (lr=0.001), batch size 32, 50 epochs. Overfitting is prevented via dropout (rate 0.3).

Table 4. Performance Comparison of Classification Models

Model	Accuracy	Precision	Recall	F1-score
SVM	78.9%	77.5%	79.2%	0.783
LSTM	83.2%	82.1%	83.5%	0.828
CNN-LSTM	85.1%	84.3%	85.7%	0.850

The CNN-LSTM model shows the best performance, but requires 2-3 times more computing resources than SVM. In smart classroom edge devices, a lightweight version (pruned 40% neurons) maintains 81.3% accuracy with 50% faster inference.

4.3.3. Limitations and Improvement Directions

Current models have low accuracy (65-70%) for students with masks or extreme head poses. Future work may integrate infrared facial features and improve occlusion handling using attention mechanisms.

5. Conclusion

This study investigates the application of multi-object face tracking and classroom participation analysis in smart classrooms to address limitations in dynamic monitoring, personalized teaching, and objective participation evaluation. For face tracking, the combination of MTCNN and DeepSORT achieves a strong balance between detection accuracy and tracking robustness, with 98.2% facial landmark localization accuracy and an 80.1% MOTA in 40% occlusion scenarios. This combination effectively supports head pose estimation and identity consistency, though the processing speed (15.4 FPS) remains below the real-time requirement of 30 FPS and performance drops in low-light conditions.

For participation analysis, a multi-modal model integrating head-up rate, interaction frequency, and expression features achieves 85.1% accuracy, outperforming single-modal methods by 6.2%. The head-up rate (angular error <3°) correlates strongly (0.78) with teacher-assessed attention, while interaction frequency reaches 89.3% recognition accuracy. Despite these strengths, the system's accuracy declines for masked students or extreme head poses and drops by 10–15% in unseen classroom scenarios. Future work should focus on lightweight network design to achieve real-time performance, expansion of diverse datasets for improved generalization, and privacy-preserving edge computing (e.g., federated learning) for practical deployment in educational settings.

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