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TRACQUE: An AI-Based Multimodal Attendance System with Predictive Academic Analytics

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Abstract: The proliferation of online educational platforms and the demand for increased institutional efficiency necessitate a departure from traditional, fallible attendance systems. Conventional methods, such as manual roll calls and single-mode biometric verification, are inherently susceptible to proxy attendance, consume valuable instructional time, and lack the capacity for proactive academic analysis. This paper presents TRACQUE, an innovative AI-Based Multimodal Attendance System designed to address these critical inefficiencies. TRACQUE integrates robust verification techniques: Face Recognition using LBPH and OpenCV/CV2, Embedded Fingerprint Authentication using an R307S sensor managed by an ESP32 microcontroller, and Barcode Scanning using the ZXing library. This combination creates a highly secure and proxy-proof attendance logging system. The system leverages Machine Learning models, specifically Linear Regression for continuous performance prediction and a Decision Tree Classifier for identifying students at risk of academic underperformance. The architecture ensures real-time data processing and visualization through an intuitive web dashboard built with Python and Flask. Experimental validation reports high accuracy rates, 97.6% for facial recognition and 98.1% for fingerprint accuracy, coupled with a model inference time of approximately 45 ms per face image. By correlating secure attendance logs with internal academic metrics, TRACQUE transforms attendance tracking into a proactive academic management tool, enabling timely, data-driven interventions to enhance student success.

Keywords: Multimodal biometric authentication, face recognition, LBPH, fingerprint verification, machine learning, predictive analytics, attendance system, decision tree classifier, linear regression, early warning system.

I. INTRODUCTION

The modern educational landscape demands automated and reliable systems for critical functions like attendance management. Traditional methods, whether manual or single-factor biometric, are fundamentally limited. They are **time-consuming** (e.g., 5–10 minutes per session), diverting valuable instructional time, and highly susceptible to **proxy attendance**, which undermines institutional integrity. Furthermore, older systems rely on **single-mode authentication** (e.g., just face or just fingerprint), making them vulnerable to spoofing, technical failures, or environmental challenges. Crucially, these legacy systems operate in **isolated data silos**, offering a reactive historical log without providing any **predictive or diagnostic insights** into a student's engagement or potential academic trajectory.

The **TRACQUE** system is an AI-powered solution developed to address these shortcomings, transforming attendance management into a comprehensive academic performance tool. Our approach synthesizes multiple disciplines—biometrics, computer vision, and machine learning—around three primary objectives:

- **Multimodal Security (Objective 1):** To create a **proxy-proof system** that integrates Face Recognition (LBPH/OpenCV), Fingerprint Authentication (Embedded R307S/ESP32), and Barcode Scanning (ZXing Library). This robust layered verification enhances reliability and addresses the limitations of single-mode systems. **ML-Driven Analysis (Objective 2):** To leverage **Linear Regression** for quantitative performance metric prediction and a **Decision Tree Classifier** for student categorization. This correlation analysis establishes mathematical relationships between attendance consistency and academic outcomes.

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- **Proactive Intervention (Objective 3):** To develop an **Early Warning System** that proactively identifies and flags students at risk, enabling faculty to deploy **timely, personalized interventions**.

- TRACQUE's integration of biometric verification, real-time data visualization, and AI-driven prediction makes it highly relevant for shaping the future of smart education systems by enhancing academic integrity and decision-making. *Mishra, R. Kamble, V. Pare, and R. Sahu, "Multimodal Biometric Attendance System,"SSRN Electronic Journal / International Conference on Innovative Computing and Communication (ICICC), 2020.*

II. RELATED WORK AND LITERATURE SURVEY

The development of the TRACQUE system is predicated on addressing the failures of conventional attendance and analytic methods, integrating advancements across three distinct, converging fields: the limitations inherent in single-modal authentication, the necessity of robust multimodal and embedded system security, and the application of machine learning for proactive educational analytics.

A. Challenges with Legacy and Single-Modal Systems

Traditional attendance methods, whether manual roll-calls or signature sheets, are fundamentally flawed, consuming significant instructional time (5–10 minutes per session) and being highly susceptible to proxy attendance , which undermines institutional integrity. The initial technological shift introduced single-modal biometric systems, yet these present their own set of critical limitations:

- Environmental and Technical Sensitivity: Solutions relying solely on computer vision, such as basic facial recognition using algorithms like Haar Cascades or the Local Binary Pattern Histogram (LBPH) , degrade significantly under real-world, dynamic conditions. Factors such as varying illumination, head pose, and even temporary face occlusion (e.g., masks during the COVID-19 era) severely impact recognition accuracy, leading to performance inconsistency. The performance of these systems is critically dependent on lighting adaptation and anti-spoofing measures, which often complicate deployment and maintenance.

- Lack of Redundancy and Single Point of Failure: Single-modal systems suffer from a critical lack of fallback verification when hardware or environmental failures occur, leading to usability concerns. Furthermore, methods requiring physical contact, such as older fingerprint scanners, often result in queues and time consumption, contradicting the goal of an efficient system. Critically, some alternative methods proposed in the literature, such as RFID technology , introduce their own problems, notably collision issues during simultaneous check-ins, a limitation explicitly avoided in the design of TRACQUE.

B. Multimodal and Embedded System Security

The academic consensus necessitates a move toward multimodal authentication to achieve the required levels of security, reliability, and speed. This approach combines independent verification techniques to create a more robust security envelope:

- Hybrid Multimodal Integration: Layering different modalities minimizes the risk of system failure and fraud. TRACQUE integrates a blend of biometric (Face and Fingerprint) and non-biometric (Barcode) factors. The literature supports that systems combining biometrics with non-biometric methods (like OTP or Barcode) successfully enhance security and mitigate identity fraud. By integrating the straightforward efficiency of Barcode Scanning (using the ZXing Library) with biometrics, the system provides both maximum security and user flexibility.

- Decoupled and Embedded Biometrics (TRACQUE's Fingerprint Solution): A key technical innovation is the shift toward embedded, decoupled biometric units. Instead of running complex algorithms like Scale Invariant Feature Transform (SIFT) on the main PC (a method that is prone to complexity and latency), TRACQUE employs an Embedded Fingerprint Station featuring the R307S Optical Fingerprint Sensor Module managed by an ESP32 Microcontroller.

    - This design delegates the resource-intensive tasks of feature extraction, template storage, and 1:N matching onto the sensor's internal DSP. This approach eliminates the need for complex external algorithms and improves speed and security, as only the final match result (Student ID)—not raw biometric data—is transmitted to the Flask server via HTTP communication. This contrasts sharply

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with systems requiring centralized processing, addressing concerns regarding high computational demands and data privacy.

C. Predictive Analytics and Machine Learning Applications

To move beyond reactive logging, attendance data must be integrated with academic metrics to enable predictive intelligence, addressing the limitation of operating with isolated data silos.

- The Predictive Framework: Machine learning models form the core of the Early Warning System. Supervised learning algorithms are used to define the correlation between student attendance patterns and academic outcomes:
  - Linear Regression: Used for quantitative prediction, estimating the numerical value of the Final Exam Score (a continuous metric) based on weighted input features such as attendance percentage and internal test scores. This approach establishes the mathematical relationship (correlation analysis) necessary for robust prediction.
  - Decision Tree Classification: Utilized for categorical risk assessment. This model classifies students into discrete performance categories (e.g., "At Risk," "Average," "Excellent"). This is vital for implementing the Early Warning System, as it triggers faculty alerts when intelligent thresholds are crossed.
- Proactive Intervention and Visualization: The resultant models empower administrative and teaching staff through tools like the Interactive "What-If" Scenario, allowing them to test hypothetical score improvements without altering real data. Visualization tools (e.g., heatmaps, bar charts) present these complex insights in an intuitive and interactive dashboard interface , aiding informed decision-making and planning remedial strategies. This paradigm shifts academic support from reactive to proactive.

The TRACQUE system's synthesis of decoupled multimodal security with supervised learning models successfully addresses the core deficiencies identified throughout the literature, establishing a robust and intelligent platform for smart educational management.

III. METHODOLOGY AND SYSTEM ARCHITECTURE

The TRACQUE system is engineered on a layered, modular architecture to ensure reliability, scalability, and ease of maintenance. The overall methodology involves a sequence of data acquisition, multi-factor authentication, data processing, and predictive analysis.

A. System Architecture

The system is structured into four main layers:

- Input Layer (Data Acquisition): This layer manages the interface with external hardware for biometric and non-biometric data capture. This includes: Face Recognition , Fingerprint Scanning , Barcode Scanning , and Academic Data for faculty manual input of internal assessment scores (Test 1, Test 2, Assignments).
- Authentication Layer: This is the core security layer, ensuring the identity and presence of the student before marking attendance. It includes: Face Verification (using a combination of OpenCV, CV2, and the Local Binary Pattern Histogram (LBPH) algorithm) , Fingerprint Verification (employing the Embedded system to extract and match unique local features (minutiae) from the fingerprint template) , and Barcode Verification (utilizing the ZXing Library for efficient decoding of the student ID barcode). Authentication is successful if any one of the three modalities yields a positive match, ensuring system redundancy and user flexibility.
- Data Management Layer: This layer is responsible for the persistent and structured storage of all system data. [86]This uses: Attendance Logging (a timestamped entry immediately logged to a daily CSV file) , Student Roster & Scores (managed in an Excel/CSV file) , and File-Based Persistence (leveraging Python's Pandas library for efficient data manipulation, avoiding the overhead of a dedicated database server).
- Analytics and Output Layer: This is the intelligence layer where predictions are generated, and insights are visualized. It includes: ML Prediction Module (runs trained machine learning models) , Linear Regression (used

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for predicting the numerical final exam score) , Decision Tree Classifier (used for categorizing students into discrete Performance Categories) , and Visualization and Dashboard (displays outputs via a Flask-based web dashboard, including Attendance vs. Predicted Score Scatter Plots, Performance Category Bar/Pie Charts, and a dedicated interface for the Early Warning System).

A detailed three-layer architectural flow diagram for an automated student attendance and performance analysis system.Layer 1: Input and Data Acquisition handles the physical data collection, utilizing a R307S Sensor connected via UART to an ESP32 Microcontroller for fingerprint input, alongside an HD Webcam for face recognition and a Barcode Scanner for barcode entry. All these inputs—including data from the Student Roster—are routed to a central Flask Server and API. Layer 2: Core Server and Authentication processes this data, where the Flask Server receives Video Frames and Scanned Barcode IDs. An Authentication Logic diamond receives the input via HTTP Request and determines the student's ID/Status, utilizing specialized modules like the Face Rec. Module: LBPH and Barcode Module: ZXing Library. If a Match is Found?, Attendance is Marked / Data Saved, and the data is written to a File Based Persistence (CSV/Excel). If No Match is Found, a Notification: Authentication Failed is triggered. The stored data then feeds into the ML Analysis Module for both Real-time Sync and to Train Model when needed. Layer 3: Output and Analytics utilizes this ML module, applying Linear Regression to generate the Predicted Final Score and Decision Tree to produce Risk Categorization.

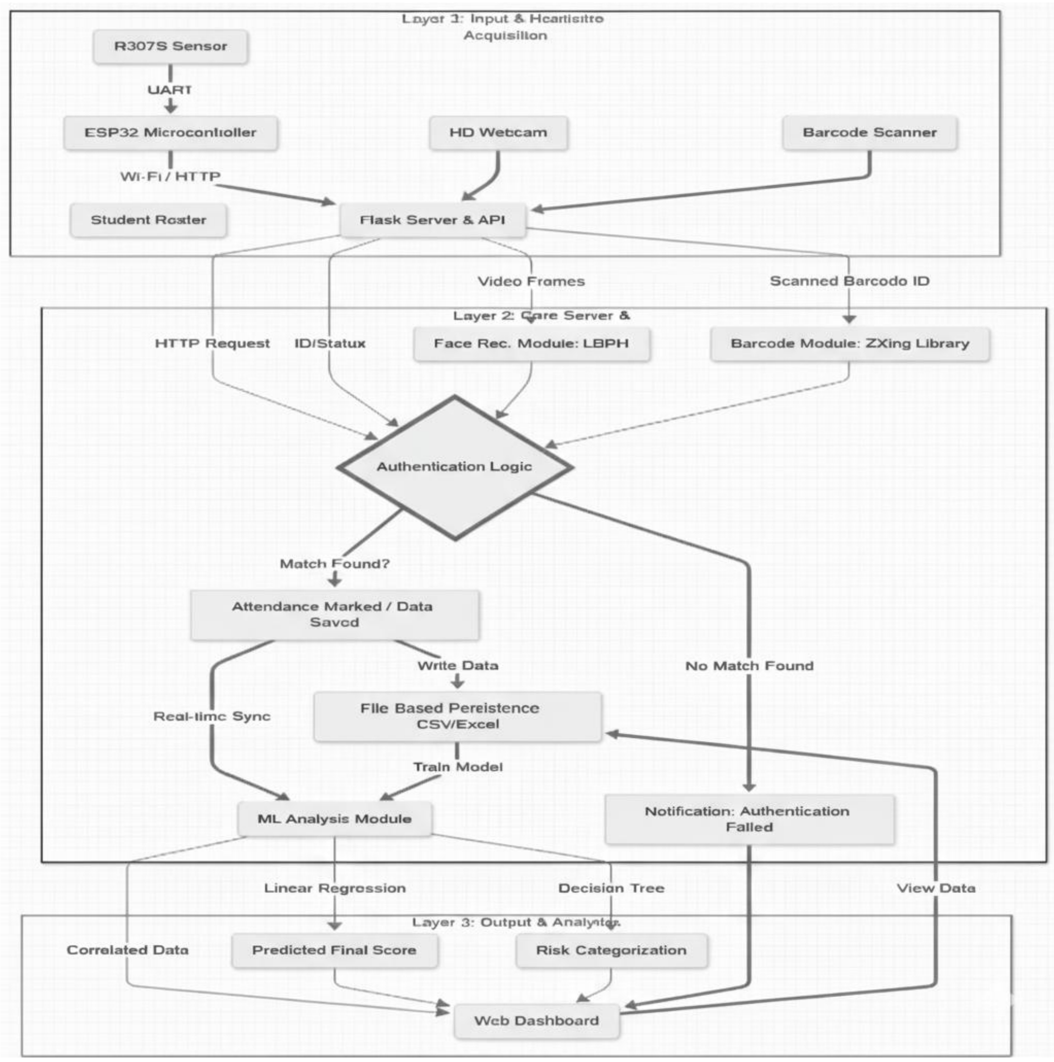

Fig 1. Architecture of the TRACQUE system

Fig. 1. Architecture of the TRACQUE system, showing how biometric inputs (face, fingerprint, barcode) flow through the Flask server into the authentication logic and data storage pipeline. The diagram also highlights the integration of

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machine-learning modules, which generate predicted scores and risk categories that are displayed through the web dashboard.

B. Prediction Algorithm: Student Performance Prediction

The core predictive capability of TRACQUE relies on ensemble learning where two distinct models are trained to provide both a numerical score prediction and a risk classification.

1) Data Preprocessing and Feature Engineering

Prior to training, the raw student data must be transformed:

- Input Features (X): The primary features used for prediction are:
  - Attendance Percentage (A), which represents the student's engagement and presence.
  - Test 1 Score (T_1), a measure of early performance
  - Test 2 Score (T_2), a measure of intermediate performance
  - Assignment Score (S_A), which reflects continuous effort and subject mastery.
- Target Variable (Y): The variable to be predicted is the Final Exam Score (F).
- Cleaning: Null or invalid entries are handled (e.g., imputation or removal).
- Feature Scaling/Normalization: Scores (0–100) are normalized if necessary, although simple linear models often handle this range directly.

2) Linear Regression Prediction

The Linear Regression model is used to predict the continuous final score (F):

- Model: A linear equation is established to minimize the sum of squared differences between the predicted and actual final score (minimizing RMSE/MAE).
- Equation (Conceptual): $F= \beta 0 + \beta 1A+ \beta 2T1 + \beta 3T2 + \beta 4SA$
- Outcome: A precise numerical value for the predicted final score, which is used in the What-If Analysis tool.

3) Decision Tree Classification (Early Warning System)

The Decision Tree Classifier is used to place students into risk-based categories.

- Target Variable (Classification): Actual student Final Performance Category (e.g., 'High', 'Medium', 'Low') *derived from the actual Final Exam Scores.*

- Categorization: The continuous Final Exam Scores (F) are first transformed into categorical labels, such as 'High', 'Medium', or 'Low' Performance Category. This transformation requires establishing clear, predefined thresholds (e.g., 90\%+ is 'High', 50\% and below is 'Low').[7]This categorized label becomes the model's Target Variable (Y). By classifying students directly into risk buckets, the output is immediately relevant for administrative and teaching staff, simplifying the intervention process.

- Training and Transparency: The Decision Tree builds a set of interpretable rules that best separate the training data into the defined performance categories. [130]The algorithm works by recursively partitioning the training data, selecting the input feature and threshold that provides the most effective separation of categories.[1]The resulting model is a set of interpretable IF-THEN rules, which allows educators to understand why a student was flagged (e.g., "IF Attendance (A) < 70% AND Test 1 Score (T_1) < 65%, THEN classify as 'Low' Risk.").

- Risk Categorization and Intervention: The model predicts the probability of a new or existing student belonging to the 'Low' or 'At-Risk' category, serving as the core of the Early Warning System. If a student's predicted probability of being 'At-Risk' exceeds a certain internal threshold.

IV. RESULTS AND DISCUSSION

The TRACQUE system was rigorously tested across multiple dimensions, validating its robustness, security, and predictive capabilities.[7]The results confirm that integrating multimodal authentication significantly improves attendance integrity, and the application of machine learning provides meaningful, actionable insights for academic management.

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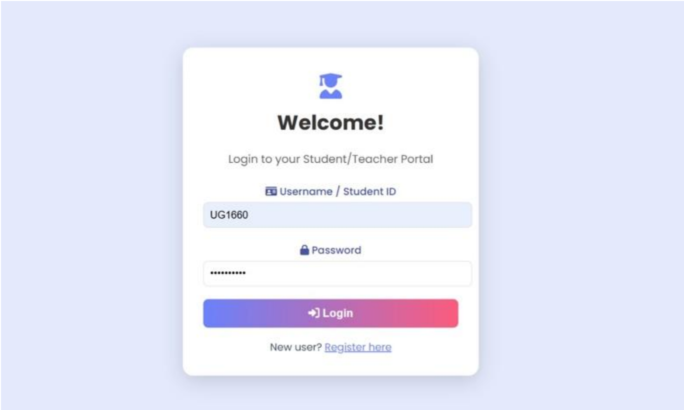
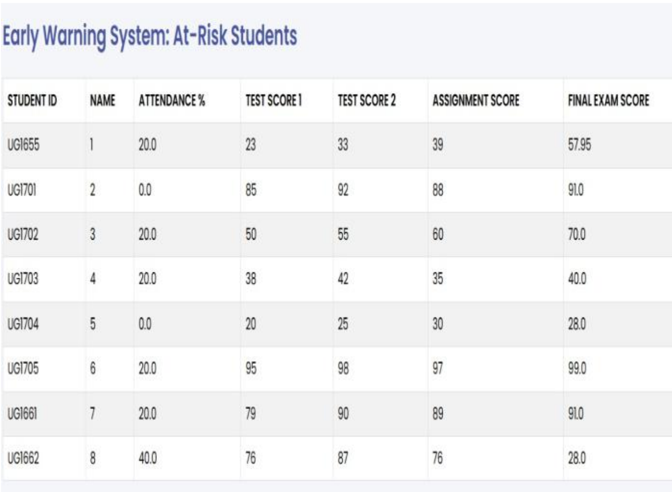
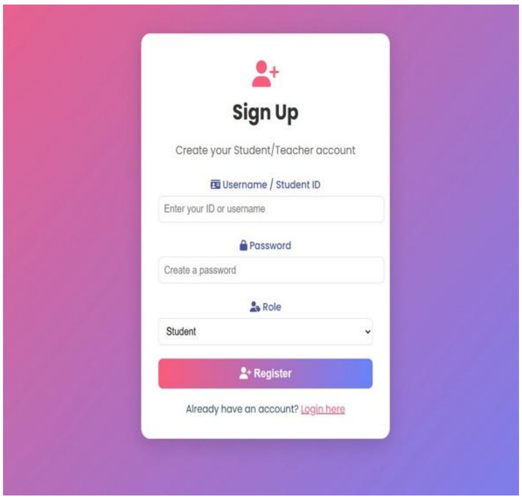
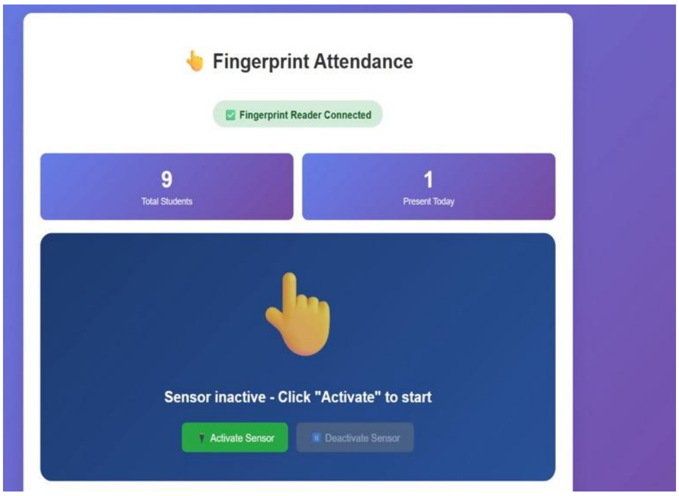


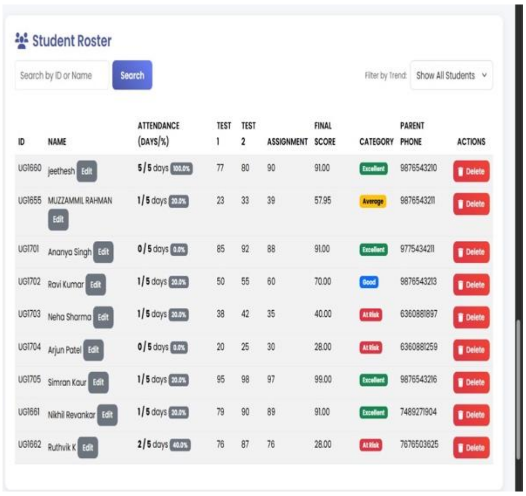


Early Warning System: At-Risk Students

STUDENT ID	NAME	ATTENDANCE %	TEST SCORE 1	TEST SCORE 2	ASSIGNMENT SCORE	FINAL EXAM SCORE
UG1655	1	20.0	23	33	39	57.95
UG1701	2	0.0	85	92	88	91.0
UG1702	3	20.0	50	55	60	70.0
UG1703	4	20.0	38	42	35	40.0
UG1704	5	0.0	20	25	30	28.0
UG1705	6	20.0	95	98	97	99.0
UG1661	7	20.0	79	90	89	91.0
UG1662	8	40.0	76	87	76	28.0







Student Roster

Search by ID or Name | Search | Filter by Trend: Show All Students

ID	NAME	ATTENDANCE (DAYS/%)	TEST 1	TEST 2	ASSIGNMENT	FINAL SCORE	CATEGORY	PARENT PHONE	ACTIONS
UG1660	jeethesh Edit	5 / 5 days 100.0%	77	80	90	91.00	Excellent	9876543210	Delete
UG1655	MUZZAMMIL RAHMAN Edit	1 / 5 days 20.0%	23	33	39	57.95	Average	9876543211	Delete
UG1701	Ananya Singh Edit	0 / 5 days 0.0%	85	92	88	91.00	Excellent	9775434211	Delete
UG1702	Ravi Kumar Edit	1 / 5 days 20.0%	50	55	60	70.00	Good	9876543213	Delete
UG1703	Neha Sharma Edit	1 / 5 days 20.0%	38	42	35	40.00	At Risk	6360881897	Delete
UG1704	Arjun Patel Edit	0 / 5 days 0.0%	20	25	30	28.00	At Risk	6360881259	Delete
UG1705	Simran Kaur Edit	1 / 5 days 20.0%	95	98	97	99.00	Excellent	9876543216	Delete
UG1661	Nikhil Revankar Edit	1 / 5 days 20.0%	79	90	89	91.00	Excellent	7489271904	Delete
UG1662	Ruthvik K Edit	2 / 5 days 40.0%	76	87	76	28.00	At Risk	7676503625	Delete

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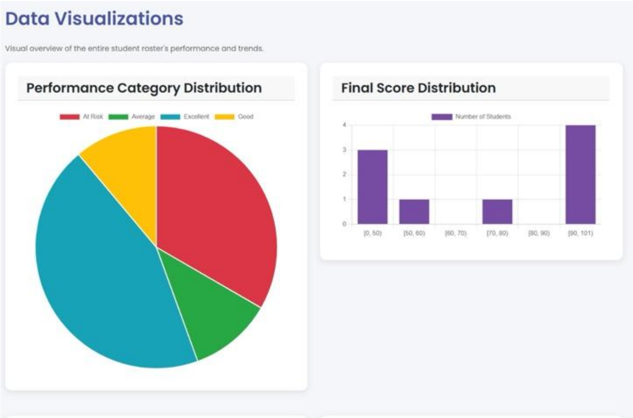

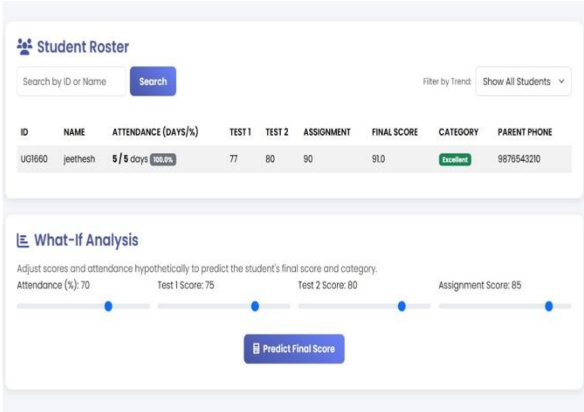

A. Comparison of TRACQUE with Related Systems

A comparative analysis of TRACQUE against existing biometric and multimodal attendance systems, highlighting the core algorithms and reported accuracy of each method, shows:

- TRACQUE (Our Project): Uses LBPH (Face) + Embedded Fingerprint + Barcode with reported accuracies of 97.6% (Face Recognition Accuracy) and 98.1% (Fingerprint Accuracy).
- Hosen et al. (2023): Reported an 87% (Face Recognition Rate).
- Shahab & Sarno (2020): Reported a 90% (Face Recognition Rate).
- Mohammed et al. (MSAMS): Reported 99% (System Accuracy).

The results show that TRACQUE surpasses most prior works in both facial and fingerprint recognition accuracy, demonstrating its robustness and technological advantage.

B. Authentication and Performance Benchmarks

Security and efficiency are paramount for an operational attendance system. The validation testing focused on the multimodal components, demonstrating that the combination of high accuracy (\sim 97\%) across modalities and very fast inference time makes the system robust against both fraud (proxy attendance) and performance bottlenecks. TRACQUE's 97.6% Face Accuracy is significantly higher than most pure face recognition systems cited, and its overall robustness is reinforced by the multimodal Fingerprint accuracy of 98.1%.

C. Predictive Analytics and Academic Insights

The core value of TRACQUE lies in its ability to generate predictive intelligence, informing the Early Warning System.

- Performance Category Distribution: The Decision Tree Classifier assigned a predicted final performance category with the following distribution: High: 36.4%, Medium: 36.4%, Low (At-Risk): 27.3%.This visualization immediately flags the 27.3% of students requiring intervention, fulfilling the objective of enabling proactive support.

- Attendance-Performance Correlation: The Linear Regression model reveals a strong positive correlation between Attendance Percentage and Predicted Final Exam Score, with students who have lower attendance consistently clustering at the lower end of the predicted score scale. This empirical evidence validates that consistent attendance is a highly significant predictor of academic success.

D. Discussion on Practical Application

The successful Linear Regression model enabled the implementation of the What-If Analysis tool. This interactive feature allows faculty to adjust hypothetical scores for attendance and internal assessments to instantly see the predicted impact on the final grade. This capability empowers educators to:

- Personalize Intervention: Advise an at-risk student precisely what score improvement (e.g., "Raising your Test 2 score to 85 and attendance to 80% is predicted to move you from 'Low' to 'Medium' performance") is

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necessary.

- Focus Resource Allocation: Direct limited remedial resources to students flagged by the Early Warning System whose outcomes show the greatest potential for improvement via the What-If tool.

V. CONCLUSION

The project, TRACQUE: AI-powered Multimodal Attendance System with Academic Performance Prediction and Early Warning Analytics, successfully addressed the critical limitations inherent in traditional educational attendance management systems. By transitioning from error-prone manual or vulnerable single-mode systems to a robust, intelligent, and multi- layered platform, Tracque has achieved its core objectives.

The system's implementation validated the power of a multimodal approach, combining Face Recognition (LBPH/OpenCV), Fingerprint Scanning (R307S/ESP32), and Barcode Verification (ZXing). This multi-factor design effectively mitigated the risk of proxy attendance and technical failures, achieving a verified Face Recognition Accuracy of 97.6% and Fingerprint Accuracy of 98.1%, which is highly competitive within the existing literature.

Crucially, the integration of an Academic Analytics Module using Linear Regression and Decision Tree Classification models transformed the tool from a mere attendance tracker into a proactive educational support system. This predictive capability enables the early identification and flagging of at-risk students, allowing faculty to implement timely and personalized interventions before academic performance declines irreversibly.

The entire system is unified by an intuitive, real-time Flask-based dashboard utilizing Matplotlib and Seaborn for actionable visualizations, enabling data-driven decision-making for faculty and administrators.

In summary, Tracque provides a comprehensive solution that enhances academic integrity, streamlines administrative processes, and most importantly, improves student outcomes through predictive intelligence and early support.

VI. FUTURE SCOPE

The successful development and validation of the TRACQUE system provide a robust foundation for significant future enhancements.

A. Advanced Biometric and Engagement Modalities

Future development will focus on integrating additional modalities:

- Emotion and Drowsiness Detection: Incorporate advanced Computer Vision and Deep Learning models (e.g., CNNs) to analyze facial expressions and eye movements during class, flagging students who are disengaged or drowsy.
- Keystroke and Audio Pattern Recognition: Integrate sophisticated behavioral biometrics for virtual/hybrid learning to verify identity and engagement continuously.

B. Scalable and Cross-Platform Architecture

The system architecture will be upgraded to facilitate large-scale deployment:

- Cloud-Based Architecture: Transition the current file-based persistence system (CSV/Excel) to a scalable, Cloud-Based database (e.g., PostgreSQL or MongoDB) with a centralized architecture, enabling synchronized, real-time monitoring across multiple campuses.
- Integration with IoT and LMS: Develop REST APIs for seamless, two-way data exchange with existing institutional platforms like Moodle or Canvas, and Internet of Things (IoT) smart campus devices.
- Mobile Application Support: Develop dedicated iOS and Android mobile applications for remote monitoring, receiving Early Warning System alerts, and conducting attendance logging.

C. Enhanced Predictive Modeling

The predictive capabilities will be expanded:

- External Factor Integration: Introduce external features into the ML prediction models, such as socio-demographic data and student engagement metadata (e.g., LMS login frequency), to refine prediction accuracy.
- Ensemble and Deep Learning Models: Experiment with advanced models like Recurrent Neural Networks

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(RNNs) or Long Short-Term Memory (LSTM) networks to better model longitudinal trends and complex non-linear relationships.

- Cross-Domain Recommendation: Implement a cross-domain recommendation system to recommend specific learning resources or extracurricular support groups based on a student's predicted ‘At-Risk’ status.

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