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ExaMind: A Multimodal AI-Based Online Examination System with Behavioral Analysis and Performance Evaluation

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Abstract: ***The rapid adoption of online examination systems has introduced significant challenges in ensuring academic integrity and effective performance evaluation. Conventional systems primarily rely on basic monitoring techniques such as webcam surveillance and browser control, which are insufficient for capturing deeper behav- ioral patterns including student engagement, attention, and cognitive effort. To address these limitations, this paper presents ExaMind, a multimodal AI-based online examination system that integrates real-time monitoring with be- havioral performance analysis. The proposed system combines facial authentication, emotion recognition, head pose estimation, object detection, and mouse interaction tracking to analyze student behavior during examina- tions within a client–server architecture, where a PyQt-based examination interface captures interaction data and a Django-based backend processes and analyzes the collected information. The system classifies student behav- ior based on response time and correctness, enabling the identification of problem-solving patterns, and employs a weighted performance evaluation model that integrates accuracy, emotional state, and behavioral analysis to generate comprehensive performance metrics. Furthermore, the system provides detailed analytical dashboards for both students and instructors, enhancing feedback and evaluation quality. Experimental results demonstrate that the proposed approach improves examination integrity while offering meaningful insights into student engage- ment and learning behavior, thereby contributing to the development of intelligent and adaptive online assessment systems.***

Keywords: Online Examination, Behavioral Analysis, AI Proctoring, Multimodal Systems, Performance Evaluation

I. INTRODUCTION

The increasing adoption of digital learning platforms has significantly transformed the way examinations are conducted in modern education systems. Online examination platforms offer advantages such as flexibility, scalability, and accessibility, enabling students to participate in assessments from remote locations. However, ensuring academic integrity and accurately evaluating student performance remain major challenges in such environments. Traditional online examination systems primarily rely on basic monitoring techniques, including webcam surveillance, screen recording, and browser restrictions. While these approaches are effective in detecting visible irregularities, they are limited in capturing deeper behavioral aspects such as student engagement, attention, hesitation, and cognitive effort, resulting in evaluations that depend largely on final scores with limited insight into the learning process. Recent advancements in artificial intelligence and computer vision have introduced new possibilities for improving online examination systems. Techniques such as facial recognition, emotion detection, head pose estimation, and object detection have been widely explored to enhance exam security and monitoring. In addition, behavioral analytics methods, including mouse tracking and interaction analysis, have shown potential in understanding user engagement and performance patterns. However, many existing systems rely on a single modality and lack the integration of multiple data sources, leading to incomplete analysis and limited capability in providing comprehensive performance evaluation. To address these limitations, this paper presents ExaMind, a multimodal AI(Artificial Intelligence)-based online exam- ination system that integrates real-time monitoring with behavioral performance analysis. The proposed system combines facial authentication, emotion recognition, head pose tracking, object detection, and mouse interaction analysis within a unified framework to provide a holistic evaluation of student behavior. It introduces a structured behavioral classification approach based on response time and answer correctness, enabling the identification of patterns such as confident, analytical, guessing, and difficulty-based responses. Furthermore, a weighted performance evaluation model is designed by combining accuracy, emotional state, and behavioral insights to generate detailed performance metrics. The novelty of the proposed sys- tem lies in the integration of interaction-based and vision-based data, providing a comprehensive and intelligent assessment approach beyond traditional online examination systems.

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II. RELATED WORK

Online examination systems[1] have evolved significantly with the advancement of artificial intelligence and machine learning technologies. Early approaches to online exam monitoring primarily relied on webcam-based proctoring, where visual data was analyzed to detect suspicious activities such as the presence of unauthorized persons, unusual head move- ments, or prohibited objects. These systems commonly utilized computer vision techniques, including face detection, object detection, and gaze tracking, to automate the invigilation process. While effective in identifying visible irregularities, such approaches are limited in understanding deeper behavioral aspects of students during examinations.

Several studies have explored continuous authentication[2] mechanisms to ensure the identity of candidates throughout the examination process. These methods incorporate biometric techniques such as facial recognition and keystroke dynamics to verify user identity continuously. Although these systems enhance security, they mainly focus on authentication and do not provide comprehensive insights into student performance or engagement.

Despite these advancements, most existing systems suffer from key limitations. Many rely on a single data modality, resulting in incomplete analysis of student behavior. Furthermore, the majority of systems focus primarily on cheating de- tection rather than providing meaningful post-examination analytics. The lack of multimodal data fusion and comprehensive performance evaluation limits the effectiveness of current solutions in educational contexts.

In addition to vision-based monitoring, recent research has investigated behavioral analytics using interaction data. Mouse tracking and heatmap analysis have been used to study user behavior, providing insights into attention patterns, hesitation, and problem-solving strategies. These approaches demonstrate that interaction-based data can be a valuable indicator of cognitive processes during assessments. However, such systems often operate independently and do not integrate with other monitoring techniques.

To overcome these limitations, the proposed ExaMind system adopts a multimodal approach by integrating visual moni- toring, behavioral interaction analysis, and performance evaluation into a unified framework. This integration enables a more holistic understanding of student behavior, improving both exam integrity and the quality of assessment.

III. PROPOSED SYSTEM

The ExaMind system is developed as a multimodal online examination platform that incorporates artificial intelligence[3],[4]- based monitoring along with behavioral performance analysis. In this implementation, multiple data sources and analytical techniques are combined within a unified framework to improve both examination integrity and the effectiveness of student evaluation. Figure 1 shows the architecture of the proposed ExaMind system.

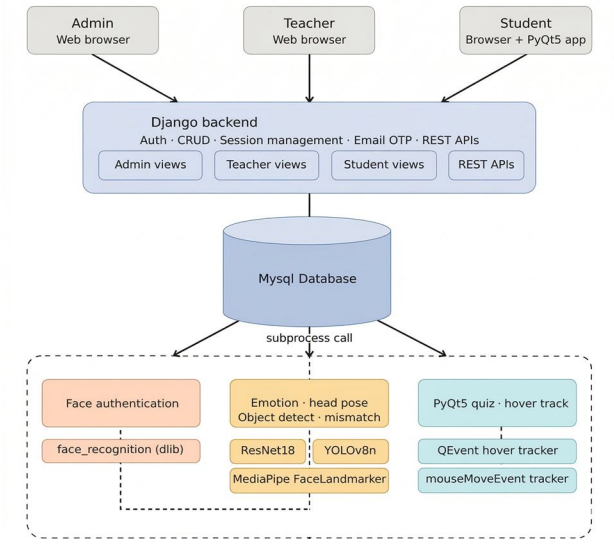


Fig. 1: Architecture of the Proposed Multimodal ExaMind System

The overall architecture of the ExaMind system is based on a client–server model. On the client side, a desktop-based examination application developed using PyQt is used to conduct the exam in a controlled environment. This interface presents the questions to the student, records their responses, and captures interaction data such as mouse movements[5], clicks, and hover durations during the session.

Along with interaction data, the client system also uses a webcam to collect visual inputs required for modules such as facial authentication, emotion detection, and head pose observation.

On the server side, the system is implemented using the Django framework, which manages key functionalities including user authentication, exam handling, and result processing. The backend receives the data collected from the client application and processes it using different analytical components. The processed information is then stored in a MySQL database, which supports further analysis and generation of performance reports.

It integrates multiple modules to achieve comprehensive monitoring and evaluation:

1) Face Authentication Module: Ensures candidate identity using facial recognition.
2) Emotion Detection Module: Identifies emotional states such as focus and confusion.
3) Head Pose Estimation Module: Used to observe student activity
4) Object Detection Module: Detects unauthorized objects or persons.
5) Mouse Tracking Module: Captures cursor movement, clicks, and hover time.
6) Behavioral Analysis Module: Classifies student behavior based on interaction patterns.

By integrating these modules, the system performs multimodal data fusion, combining visual and behavioral signals to provide a comprehensive understanding of student performance. Unlike traditional systems that focus only on cheating detection, the proposed system emphasizes both monitoring and post-examination analytics.

ExaMind generates detailed analytical reports for both students and instructors. These reports include performance metrics, behavioral insights, and engagement analysis, enabling a more informed evaluation process. Figure 2 shows the workflow of the proposed ExaMind system.

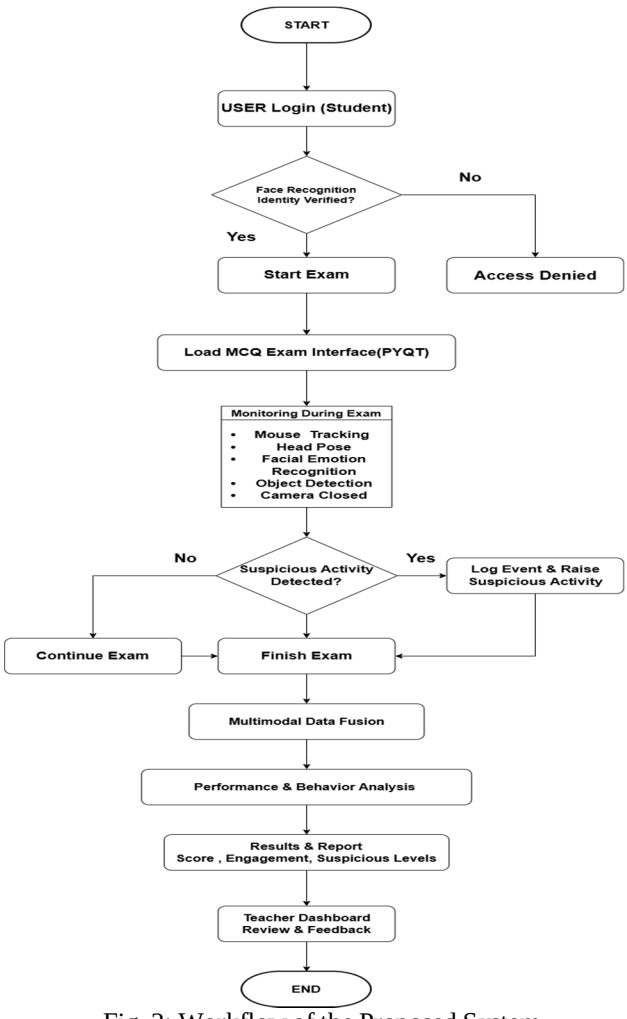


Fig. 2: Workflow of the Proposed System

IV. METHODOLOGY

The methodology of the ExaMind system is centered on collecting multimodal data and analyzing student interaction patterns to generate meaningful performance metrics. In this implementation, the workflow is organized as a sequence of stages, including data collection, behavior classification, evaluation, and performance analysis. Unlike traditional systems that depend only on final responses, the system combines both interaction-based and vision-based inputs to obtain a more detailed view of student activity during the examination. This includes tracking cursor movement, response timing, facial expressions, head pose, and surrounding conditions through a combination of client-side and vision-based modules.

Before analysis, the collected data is preprocessed and aligned to maintain consistency across different data sources. In- teraction data such as mouse movement and response time are synchronized with visual inputs, including facial expressions and head pose, to support accurate interpretation of behavior. The system makes use of pretrained deep learning models for tasks such as emotion detection and object detection, allowing inference during the examination without requiring addi- tional training at runtime. By combining multiple data sources, the system is able to relate interaction patterns with visual observations, improving the overall quality of analysis.

During the examination session, data is continuously collected and processed in the background without affecting the user interface. The processed information is then used to identify behavioral patterns, classify response types, and compute performance-related measures. This approach enables the system to provide a structured evaluation that considers not only correctness but also interaction behavior and observed student activity, offering a more informative alternative to conventional score-based assessment.

A. Data Collection

During the examination, the system gathers different types of data to support detailed analysis, including both interaction- based and vision-based inputs. Interaction data is captured through the PyQt-based client application, where user actions such as mouse movements, click events, hover duration, and response time for each question are recorded. These interaction patterns help in understanding student engagement, hesitation, and answering behavior.

Along with interaction data, visual information is collected using the webcam, which includes facial images and the surrounding environment. This visual data is processed using computer vision techniques such as object detection, imple- mented with pretrained models like YOLOv8[6], and head pose estimation using MediaPipe-based models[7]. To maintain consistency, the visual inputs are synchronized with the corresponding interaction data collected during the same time inter- val.

In addition, computer vision[8] and deep learning techniques[9], [10] are applied to extract relevant features from the captured data. Emotion detection is used to observe states such as focus, confusion, or distraction, while object detection helps identify the presence of unauthorized items or additional persons in the examination setting.

The processed multimodal data[11] is then sent to the Django-based backend, where it is stored and prepared for further analysis and performance evaluation.

B. Behavior Classification

In this system, student behavior is classified using two main factors: response time and answer correctness. A simple threshold-based method is applied to distinguish between fast and slow responses. If a student submits an answer within a predefined time limit, it is treated as a fast response; otherwise, it is considered slow.

This classification approach is designed to reflect common patterns observed during problem-solving. When a response is both fast and correct, it generally indicates that the student is confident and familiar with the concept. On the other hand, a slow but correct response often suggests a more analytical approach, where the student takes additional time to evaluate the question before answering. In contrast, fast but incorrect responses may point to guessing or impulsive decisions, while slow and incorrect responses can indicate confusion or difficulty in understanding the question.

Based on the combination of response time and correctness, student behavior is classified into the following categories:

Confident: Fast and correct responses Analytical: Slow but correct responses Guessing: Fast but incorrect responses Difficulty: Slow and incorrect responses Skipped: Questions viewed but not answered Unaware: No interaction with the question

This classification provides valuable insights into student problem-solving patterns and engagement levels during the examination.

C. Performance Evaluation

The performance of the proposed system is evaluated using three main metrics: accuracy score, emotion score, and behavior score. These metrics capture different aspects of student performance, including correctness, emotional state, and interaction patterns.

Accuracy Score: Accuracy measures the number of correct answers provided by the student and is calculated as:

$$Accuracy = \frac{CorrectAnswers}{TotalQuestions} \times 100$$

This metric directly reflects academic performance and contributes 50% to the overall score.

Emotion Score: Emotion score represents the student's emotional state during the examination. It is calculated based on the proportion of positive emotional frames (such as happy and neutral) detected from the total captured frames:

$$EmotionScore = \frac{PositiveEmotionFrames}{TotalFrames} \times 100$$

Emotion detection is performed using a pretrained ResNet18[12] model, and this metric contributes 30% to the overall score.

Behavior Score: Behavior score is derived from the behavioral classification [13]. The system analyzes the distribution of behavioral categories such as confident, analytical, guessing, difficulty, skipped, and unaware responses to determine overall student interaction patterns. This metric contributes 20% to the overall score.

D. Behavior Scoring Mechanism

After classification, the system computes the distribution of each behavior type across all questions. Let B_i denote the number of occurrences of a behavior category and N represent the total number of questions attempted by the student. The percentage of each behavior is calculated as:

$$P_i = \frac{Bi}{N} \times 100$$

Based on these percentages, the dominant behavior is identified as the category with the highest value of P_i. Positive behaviors such as confident and analytical indicate better understanding, while guessing, difficulty, skipped, and unaware indicate lower engagement or uncertainty.

The behavior score is derived from this distribution, providing a summarized representation of student interaction pat- terns during the examination.

E. Performance Evaluation Model

The final performance of the student is evaluated using a weighted scoring model that combines accuracy, emotion score, and behavior score. These components are assigned predefined weights based on their importance:

Accuracy Contribution: 50%

Emotion Contribution: 30%

Behavior Contribution: 20%

$$OverallScore = 0.5 \times Accuracy + 0.3 \times Emotion + 0.2 \times Behavior$$

The overall performance score combines correctness, emotional state, and behavioral patterns into a single metric. Ac- curacy reflects academic performance, emotion score indicates focus or distraction, and behavior score captures interaction patterns such as confidence and hesitation. This integrated approach provides a more comprehensive evaluation compared to traditional score-based systems.

V. RESULTS AND DISCUSSION

The ExaMind system was evaluated through examination sessions conducted with multiple students. During these sessions, different types of data were recorded, including interaction data, emotion detection outputs, and behavior classifi- cations obtained throughout the examination. The experiments were carried out in a controlled environment using standard computing systems equipped with webcams.

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The evaluation process follows the metrics described in the methodology, such as accuracy, emotion-based observations, behavioral distribution, and overall performance score. In the implemented setup, emotion detection is performed using a pretrained ResNet18 model, while object detection is handled using YOLOv8[14]. The classification of student behavior is carried out using a rule-based approach[15], where response time and answer correctness are used as the primary factors.

Table 1: Performance Evaluation Metrics Example

Student	Accuracy (%)	Emotion (%)	Behavior (%)	Overall (%)
S1	80	70	75	75.5
S2	65	60	55	61.5
S3	90	85	88	88.9
S4	72	68	70	70.4
S5	60	55	50	57.5

A. Performance Analysis

The results demonstrate that students with higher accuracy and consistent positive behavioral patterns tend to achieve higher overall performance scores. For instance, Student S3, who exhibits high accuracy along with strong emotion and behavior scores, achieves the highest overall score. In contrast, students with lower interaction quality and inconsistent behavioral patterns tend to obtain lower performance scores.

B. Behavioral and Emotional Analysis

The system offers detailed insights into student behavior by grouping responses into categories such as confident, ana- lytical, guessing, difficulty, skipped, and unaware. This classification helps in understanding how students approach different questions and how engaged they are during the examination. In practice, students showing confident and analytical patterns tend to perform better, while frequent guessing or difficulty often indicates lower confidence or weaker understanding.

In addition, emotion analysis is used to observe the student's state during the examination. Consistent emotional patterns, such as neutral or focused expressions, are generally linked to better performance. On the other hand, noticeable fluctuations or signs of distraction may suggest reduced attention levels and lower engagement.

C. Instructor and System Insights

The teacher dashboard provides a consolidated view of student performance, allowing instructors to analyze both indi- vidual results and overall class trends. It displays measures such as average accuracy, behavioral distribution, and overall performance, which help in identifying common areas where students face difficulty. Based on these observations, instructors can make informed adjustments to their teaching approach.

The use of multimodal data improves the reliability of the evaluation process. By combining interaction-based data[16] with visual inputs, the system offers a broader understanding of student behavior during the examination. For instance, irregular answering patterns along with inconsistent interaction behavior may suggest reduced engagement, whereas steady interaction patterns with confident responses often indicate better understanding. Visual modules such as head pose tracking are used mainly for observing student activity. However, in the current implementation, the interpretation of behavior is primarily derived from interaction data, particularly response time and answer correctness.

D. Discussion

The results indicate that the proposed system effectively captures meaningful behavioral and emotional patterns in addition to academic performance. Unlike traditional online examination systems that rely solely on final scores, ExaMind provides a deeper level of analysis by incorporating multimodal data. Figure 3 shows the student-side performance analysis interface, which presents metrics such as accuracy, behavioral distribution, and emotional observations. Figure 4 illustrates the teacher dashboard used for monitoring student performance and analyzing overall examination metrics.

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Fig. 3: Student Side Performance Analysis Interface

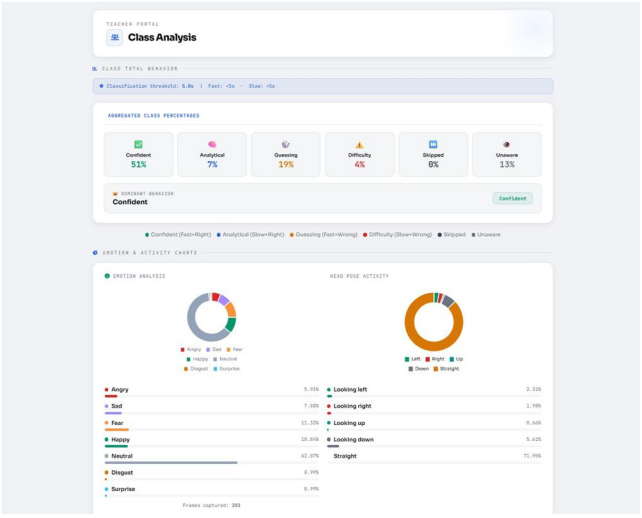


Fig. 4: Teacher Dashboard Showing Performance Metrics

VI. ADVANTAGES OF THE SYSTEM

The ExaMind system provides several advantages over conventional online examination platforms by combining multi- modal monitoring with behavioral analysis. One of its main strengths is the ability to use both interaction-based data, such as mouse movement and response time, along with visual data captured through the webcam. This combination allows a more complete understanding of student activity during the examination, making the analysis more reliable compared to systems that depend on a single type of data. In addition, the system classifies student responses into categories such as confident, analytical, guessing, difficulty, skipped, and unaware, which helps in identifying problem-solving patterns and engagement levels beyond simple score-based evaluation.

Another advantage lies in the integration of continuous monitoring during the examination with post-examination ana- lytics[17]. During the exam session, the system observes student activity and detects the presence of unauthorized objects or additional persons using object detection techniques. It also utilizes Convolutional Neural Network (CNN)[18]-based models for facial emotion recognition, which helps in observing student engagement levels. After the examination, the sys- tem generates detailed performance reports that include accuracy, emotion-based observations, and behavioral distribution, allowing both students and instructors to review performance in a structured manner. The use of a combined evaluation approach, incorporating accuracy, emotional state, and behavioral patterns, supports a more balanced assessment process. Additionally, dedicated dashboards are provided for students and teachers to support feedback, performance tracking, and data-driven decision-making[19]. Overall, the system enhances the traditional online examination process by providing a more informative and analysis-oriented evaluation platform[20].

VII. LIMITATIONS

Despite the advantages of the ExaMind system, there are several limitations that need to be considered for further improvement and large-scale deployment. One key limitation is the absence of large-scale experimental validation, as the current evaluation has been carried out in a controlled environment with a limited number of users. When deployed in real- world scenarios, the system performance may vary due to differences in hardware configurations, network conditions, and user behavior. In addition, the lack of standardized benchmark datasets[21] makes it difficult to perform direct quantitative comparisons with existing online examination systems. The system also relies on pretrained models for tasks such as emotion detection, object detection, and face recognition, which may introduce bias depending on the training data and may not always perform consistently under varying lighting conditions or environmental settings.

Another limitation arises from the use of a rule-based approach for behavior classification. In this method, predefined thresholds for response time and answer correctness are used to categorize student behavior into patterns such as confident, analytical, guessing, and difficulty. While this approach is suitable for basic interpretation, it may not capture more com- plex cognitive patterns or adapt well to individual differences among students. The system is also dependent on hardware components such as webcams and system performance, where variations in camera quality, lighting conditions, and device capabilities can influence the accuracy of modules implemented using YOLOv8 and MediaPipe. In addition, continuous data collection from these modules may introduce computational overhead, especially on lower-end systems.

Privacy and ethical concerns are also important considerations, as the system involves video monitoring, facial anal- ysis, and behavioral tracking. This requires proper data security mechanisms[22], user consent, and adherence to privacy standards. Finally, the system depends on stable network connectivity for data transmission between the PyQt[23]-based client and the Django[24] backend. In situations with poor connectivity, issues such as incomplete data capture or delayed processing may affect overall system reliability.

VIII. FUTURE WORK

The ExaMind system can be further improved by incorporating more advanced machine learning and deep learning techniques to enhance the accuracy and adaptability of behavioral analysis. In the current implementation, behavior classi- fication is based on rule-based methods; however, this can be extended by introducing predictive models[25] that analyze complex interaction patterns and provide a more adaptive evaluation of student behavior. Techniques such as recurrent neu- ral networks (RNNs)[26], long short-term memory (LSTM)[27] networks, or transformer-based models can be explored to capture temporal relationships in student responses, mouse movements, and behavioral sequences. Additionally, adaptive learning mechanisms[28] can be integrated to adjust evaluation criteria dynamically based on individual student patterns, enabling more personalized assessment.

Further enhancements can focus on expanding the multimodal capabilities of the system. For example, incorporating audio-based analysis could help detect background conversations or unusual sounds during examinations, improving moni- toring effectiveness. The system can also be extended into web-based or mobile-based platforms to improve accessibility and support deployment across a wider range of devices. To address privacy concerns, techniques such as on-device processing, data anonymization, and secure encryption can be incorporated. Moreover, predictive analytics can be used to generate per- sonalized feedback and learning recommendations based on historical performance data. Finally, large-scale validation using real-world datasets and deployment in institutional environments would help evaluate the system's scalability, robustness, and practical applicability under diverse conditions.

IX. CONCLUSION

This paper presented ExaMind, a multimodal AI-based online examination system designed to enhance both examina- tion integrity and performance evaluation. The system integrates multiple monitoring techniques, including facial authentica- tion, emotion detection, head pose estimation, object detection, and mouse interaction tracking, within a unified client–server architecture. By combining a PyQt-based examination interface with a Django-based backend, the system enables efficient real-time data collection, processing, and analysis, ensuring a structured and reliable examination environment.

Unlike traditional online examination systems that rely solely on final scores, the proposed approach incorporates be- havioral analysis and a weighted performance evaluation model that considers accuracy, emotional state, and interaction pat- terns. This integration enables a more comprehensive understanding of student performance, capturing not only correctness but also engagement, attention, and cognitive effort. The system further enhances usability by providing detailed analytical dashboards for both students and instructors, supporting improved feedback mechanisms and data-driven decision-making in educational environments.

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Experimental observations indicate that the proposed system effectively captures meaningful behavioral patterns and generates insightful performance metrics. The integration of multimodal data improves the robustness and reliability of evaluation compared to conventional systems that rely on single-modality analysis.

X. DECLARATIONS

A. *Availability of Supporting Data*

The datasets generated and analyzed during the current study are available from the corresponding author upon reason- able request.

B. *Competing Interests*

The authors declare that they have no competing interests.

C. *Funding*

No external funding was received for this research work.

D. *Authors' Contributions*

Alan C B contributed to system development, implementation, experimentation, and manuscript preparation. The co- authors contributed to analysis, documentation, review, and validation of the proposed system.

E. *Acknowledgements*

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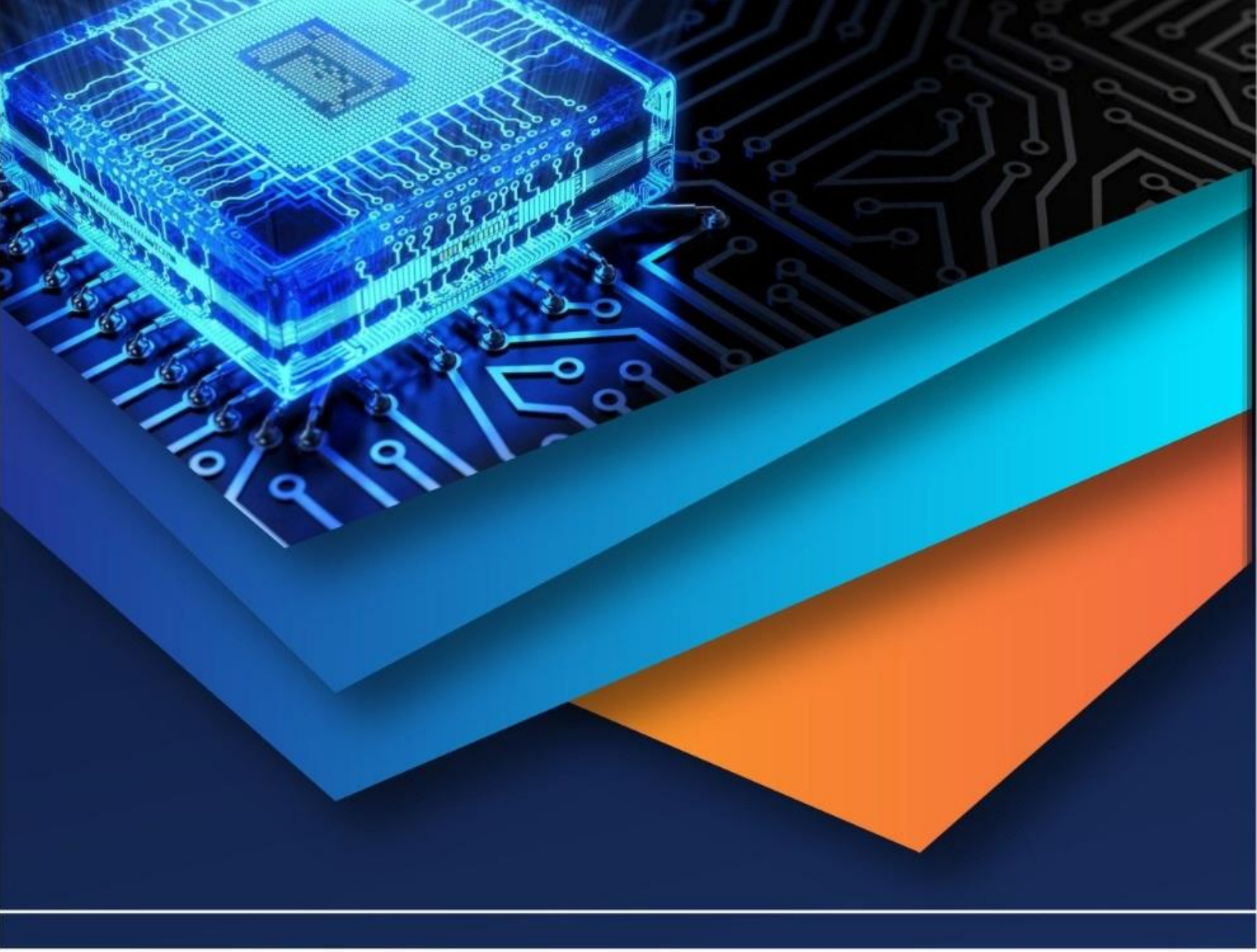
F. *Authors' Information*

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