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Smart Online Participation Monitor

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ABSTRACT This project offers the creation of a Smart Online Participation Monitor, a smart system capable of monitoring and assessing user participation in online platforms. In contrast to traditional monitoring systems targeted at students only, this system targets a wider user base, including IT personnel, by giving direct views into attendance during virtual sessions, webinars, online courses, and remote meetings. Taking advantage of sophisticated technology like facial recognition, activity tracking, and interaction logging, the system guarantees proper monitoring of user engagement. It also incorporates an administrator and host-friendly dashboard for viewing engagement patterns. By enhancing accountability and productivity, the Smart Online Participation Monitor facilitates more informed decision-making for teachers, corporate trainers, and project managers alike, guaranteeing active and meaningful engagement on various digital learning and working platforms.

KEYWORDS: Intelligent participation, virtual monitoring, online engagement, IT experts, student monitoring, facial recognition, activity tracking, online sessions, online learning, digital workplace.

I. INTRODUCTION

To overcome the shortcomings of current systems for tracking participation, this paper proposes a Smart Online Participation Monitor for both academic and working environments. The system allows for real-time monitoring and assessment of user participation during online sessions through the incorporation of technologies such as facial recognition, activity tracking, and interaction analysis. It is flexible for use across different platforms employed in remote learning and teleworking. The system can effectively detect user attentiveness levels and presence, enabling scalable deployment in classrooms, corporate sessions, and webinars. By allowing hosts and event planners to monitor and evaluate participation from a single dashboard, the system increases accountability and encourages more participatory and productive virtual events. This method enables enhanced decision-making through substantiated participation trends, leading to enhanced learning outcomes and professional effectiveness.

This paper provides three significant contributions to enhancing participation monitoring in online settings. We introduce, first, a scalable system for participation monitoring that can be implemented without difficulty into a range of online platforms utilized in education and work environments. It delivers real-time user engagement tracking via facial recognition, activity detection, and interaction logging. Second, we integrate a smart analysis module that assesses levels of attentiveness and participation during real-time virtual meetings so that organizers can detect inactive or disengaged attendees. Third, we test the efficacy of the system through a sequence of user-controlled studies, proving that it is effective in increasing accountability, enhancing interaction quality, and improving overall productivity in virtual learning and remote work environments.

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II. RELATED WORKS

Methodology

1. Ingestion and Integration of Data

- Real-time Video Stream Gathering: The system collects live webcam streams during online sessions to determine the presence of users and visual attention. Facial detection and behavior analysis rely on this video data as the main input.
- User Interaction Tracking: Besides video, the system tracks keyboard use, mouse movements, and focus on windows/tabs in order to estimate the level of user engagement. Multimodal input in this way enhances accuracy in distinguishing between active and passive participants.
- Data Synchronization and Preprocessing: Cleaned data, timestamped data, and synchronized data are used for effective real-time processing. Face alignment and frame selection are methods used for stable and precise detection.

2. Engagement Detection and Monitoring

- Eye Tracking and Facial Recognition: Deep learning technologies like CNN-based face detectors are employed to recognize participants and detect gaze direction to ascertain attentiveness.
- Activity Recognition: The system uses machine learning algorithms (e.g., Random Forest, SVM) to recognize behaviour such as head pose, blink rate, and mouse/keyboard activity. These are used to predict levels of participation and attention.
- Real-Time Monitoring and Alerts: The system dynamically monitors each participant's activity and alerts hosts to disengagement risk, enabling timely intervention if required.

3. User Interface and Interaction

- Web-Based Dashboard: An elegant and intuitive dashboard enables session hosts, be they teachers or managers, to easily see participation status from users. Participants are represented through attention indicators (e.g., focus score or color-coded status).
- Privacy and Consent Compliance: The system provides user consent prior to enabling video monitoring, and personal information is processed in conformity with privacy policies. Data is encrypted and access is limited to the authorized personnel only.

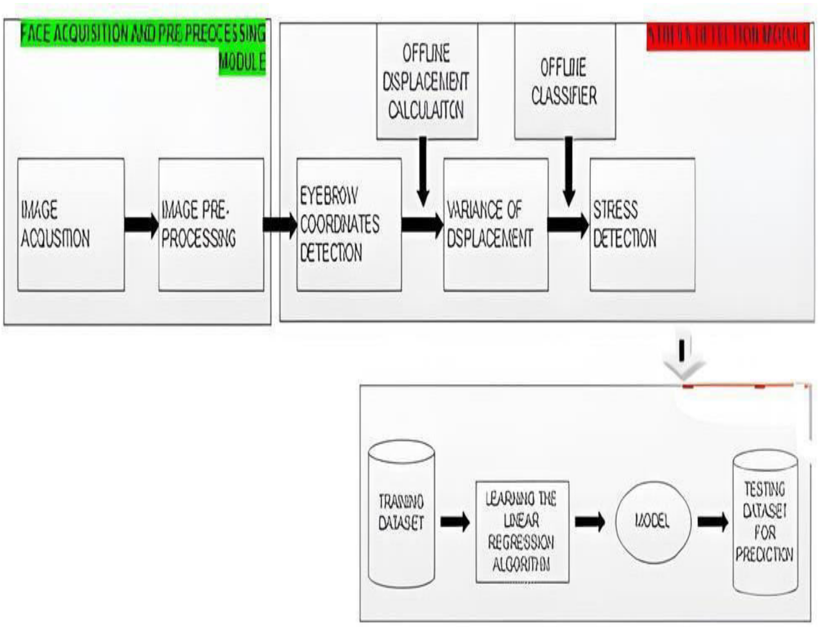

Fig 1: System Architecture

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Datasets Used

Datasets Used

1. Facial Detection and Recognition Datasets

[WIDER FACE Dataset]: It's a large-scale face detection dataset employed for training and testing face detection models in a broad spectrum of conditions, from varying poses, illumination, to occlusions. It enhances the accuracy of the system in detecting faces within real-time video streams.

[LFW (Labeled Faces in the Wild)]: Trained facial recognition models using this dataset, which helps establish systems that can recognize and distinguish individual users throughout online sessions.

[FER-2013 or AffectNet] (Optional, in case emotion detection is utilized): These datasets contain facial expressions marked with emotional states that are used to infer levels of attentiveness or emotional engagement.

2. User Behavior and Interaction Datasets

Custom Captured Dataset: A company-owned dataset harvested from artificial online sessions (e.g., virtual classes or meetings) to train and test the system's function for detecting attention using mouse movement, keyboard activity, screen focus, and webcam data.

Tab/Focus Tracking Logs: Datasets that record browser activity, including tab switching and window focus, to assist the system in detecting when users are multitasking or are distracted during a session.

3. Benchmark and Evaluation Datasets

Real-World Online Session Data (with permission): Anonymized session recordings from educational or corporate settings (where available) are utilized to prove the validity of engagement detection algorithms in real-world scenarios.

Performance Evaluation Metrics

1. Face Detection and Recognition Accuracy

The face detection and recognition accuracy in live sessions is tested using measures like Precision, Recall, and F1-Score. These assess the capability of the system to detect and recognize participants under varying light levels, orientations, and expressions.

2. Real-Time Responsiveness

The performance of the system in handling video input and displaying engagement status is gauged in terms of latency (in milliseconds) and frames per second (FPS). These measurements ensure smooth, real-time execution during webinars or meetings, free from delays.

3. User Experience and Usability

Feedback questionnaires and System Usability Scale (SUS) ratings are captured from participants and instructors to assess the system's overall ease of use, interface clarity, and utility of the monitoring dashboard. These assist in fine-tuning the system for increased adoption and satisfaction.

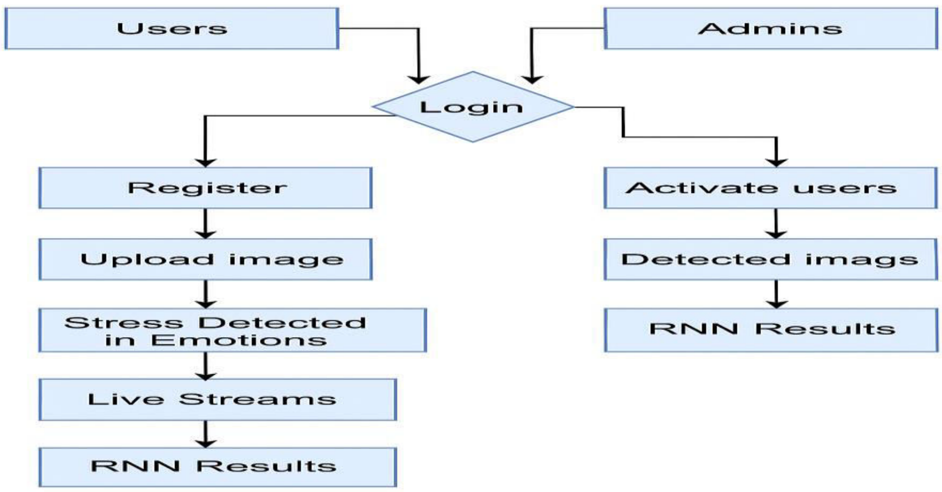

Fig 2: Proposed Model

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III. CASE STUDY APPLICATION

1. Tracking Participation in Virtual Classrooms and Web-Based Trainings

Session Configuration and Data Collection: The system was used during live online sessions with students and IT professionals. Live video streams were recorded using webcams, in addition to user interaction data like keyboard and mouse movements.

Participation Tracking: The system tracked the facial presence, direction of gaze, and level of interaction of participants to determine attentiveness and level of participation during the session.

2. Participation Level Analysis and Visualization

Dashboard Visualization: Real-time participation levels of each participant were shown on a user-friendly dashboard available to instructors and session moderators. This facilitated rapid detection of inactive or distracted participants. Historical Data Analysis: The system aggregated participation patterns across sessions to give insights about individual and group engagement patterns.

3. Enhancement of Online Engagement and Accountability

Intervention and Feedback: Session hosts based on tracked data could actively counteract disengagement by prompting participation or offering breaks, hence enhancing overall session effectiveness.

Impact Assessment: Follow-up surveys and system logs validated participants' enhanced attentiveness and participation, affirming the usefulness of the system in educational and work environments alike.

IV. RESULTS

Fig 3: Home page

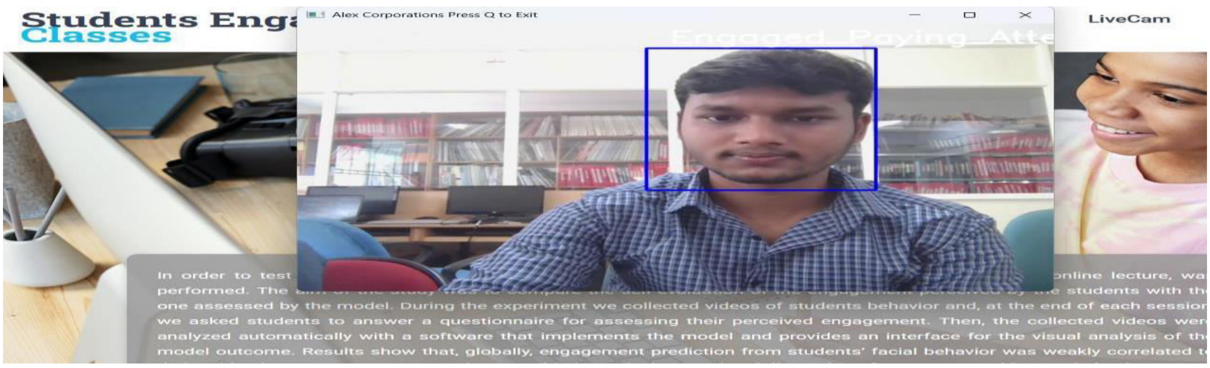

Fig 4: Live-Cam page.

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V. CONCLUSION

The Smart Online Participation Monitor is an important evolution of remote participation tracking for academic and professional online settings. Through the incorporation of live video analysis, behavioral observation, and user interaction metrics, the system offers precise and timely observations into participant attentiveness and engagement. This maximizes the capability of educators and administrators to establish active participation, enhance session effectiveness, and sustain accountability.

Our strategy focuses on the need for continuous, privacy-aware monitoring respectful of user permission without compromising engagement data actionable in an easily understandable dashboard. The system's flexibility across various groups of users—students and IT personnel—is evidence of its applicability and utility.
Future research will involve broadening the capabilities of the system through the addition of more sophisticated emotion recognition, optimizing attention estimation models, and creating automatic alerts to further support session facilitators.

Also, optimizing integration with widely used online meeting platforms and expanding the system to accommodate hybrid and in-person settings will be critical to enhancing its reach.

Finally, the Smart Online Participation Monitor will evolve to become an indispensable instrument in facilitating participation, cooperation, and productivity in online learning and workplaces.

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