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Random Interval Attendance Management System (RIAMS): A Novel Multimodal Approach for Post-COVID Virtual Learning

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ABSTRACT The exceptional circumstance caused by the COVID-19 pandemic demands substantial modifications in the teaching-learning processes across the globe. Teachers and students are making use of online learning in virtual classrooms as an alternative for face-to-face learning in physical classrooms. However, students' attendance management during virtual learning is a challenging problem. It is quite difficult to identify students' disengagement and even to know whether they are in front of their smart devices or not. In this paper, we introduce the 'Random Interval Attendance Management System' (RIAMS), which is an innovative solution for attendance monitoring issues, students' disengagement, and attendance faking during virtual learning. In RIAMS, we employed a face recognition module built using the Dlib open-source software library. In order to improve the efficiency of the system, we introduced two ancillary modalities – verifying students' responses to CAPTCHAs and UIN (Unique Identification Number) queries. Both the face recognition and ancillary modalities operate at random intervals of time. This distinctive feature of randomness in our design ensures that students' attention and engagement in virtual learning are enhanced. Furthermore, the RIAMS' multimodal architecture and its sub-modalities' adaptive weight system enable teachers to customize their attendance strategy for every course. The output analysis of each of the RIAMS modalities and the combined results emphasize the effectiveness and reliability of our system in the attendance management for virtual learning. The novel RIAMS model has the potential to be extensively deployed for virtual learning in post-COVID settings.

INDEX TERMS Attendance management, COVID-19, face recognition, RIAMS, virtual learning.

I. INTRODUCTION

The COVID-19 pandemic outbreak has resulted in an unprecedented crisis across the globe [1], [2]. The pandemic created an enormous demand for innovative technologies to solve crisis-specific problems in different sectors of society [3]. In the case of the education sector and allied learning technologies, significant issues have emerged while substituting face-to-face learning with online virtual learning [4]. The existing structures and processes of face-to-face learning have been disrupted because of the unforeseen situation that emerged out of COVID-19 [5], [6].

Owing to the mandatory social distancing compelled by the pandemic, the standard operating mode of educational institutions around the world has changed into virtual mode significantly [7]–[9]. Several countries have closed educational

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institutions temporarily to alleviate the COVID-19 spread. The closure of educational institutions compelled the teachers across the globe to use online meeting platforms extensively [10], [11]. The virtual classrooms created by online meeting platforms are adopted as the only alternative for face-to-face interaction in physical classrooms [12]. Subsequently, online meeting platforms like Zoom, Google Meet, Microsoft Teams, and Cisco Webex Meetings are used to create virtual classrooms [13]. Educational institutions, teachers, and students are finding more advantages in using virtual learning that were not previously popular [14], [15].

On the other hand, researchers have identified several challenges associated with the widespread use of virtual learning, which is characterized by quite a lot of interrelated features pertaining to students, teachers, and the technologies involved [16]–[18]. In this regard, students' attendance management in virtual classes is a major challenge encountered by the teachers [19], [20]. Student attendance is a measure of their engagement in a course, which has a direct relationship with their active learning [21], [22]. Attendance in a course is a prerequisite as mandated by various universities for the students to take their final examinations in every course [23]. Further, the inclusion of attendance data on students' grade cards is a strategic decision of many universities across the globe to enhance students' attendance and engagement [22]. However, during virtual learning, it is exceptionally challenging to keep track of the attendance of students. Calling students' names in virtual classrooms to take attendance is both trivial and time-consuming [24].

Due to the inherent characteristics of virtual learning, students may resort to unethical activities like not attending the class but still keeping their status as 'online'. Moreover, any student can go offline at any time without letting the teacher know. Further, it is not easy to find out whether the student is really attending the class or just being online without paying attention [25], [26]. In this case, teachers may not be able to check whether the student is actually present and paying attention to the class, as the student might have turned off the video camera. Thus, in the backdrop of the COVID-19 pandemic and the extensive usage of virtual meeting platforms, there is a crisis-specific immediate necessity to develop a proper tracking system to monitor students' attendance and engagement during virtual learning [27]–[29]. In this paper, we are addressing the pandemic-induced crucial necessity by introducing a novel approach.

In order to realize a highly efficient and robust attendance management system for virtual learning, we introduce the Random Interval Attendance Management System (hereafter, RIAMS). To the best of our knowledge no such automated system has been proposed so far for tracking students' attendance and ensuring their engagement during virtual learning. The key objective of RIAMS is to develop a robust system that monitor students' attendance and engagement in a virtual classroom, at random intervals of time. It encompasses a novel design using the AI Deep CNN (Convolution Neural Network) model to capture face biometric randomly from students' video stream and record their attendance automatically. Thus, the main component of the proposed model is a face recognition module built using the AI-DL tools. RIAMS also incorporates ancillary submodules for assessing students' responses to CAPTCHAs and UIN queries, to ensure active engagement in virtual classrooms.

The proposed method is the simplest and the best approach to automatically capture the attendance during virtual learning. The significance of the RIAMS model is that it precisely monitor attendance in virtual classrooms without hindering the learning process. Further, it can generate dedicated attendance reports, pinpointing students' attention during virtual learning at random time intervals. Moreover, the novel random attendance tracking approach can also prevent the dropping out of participants from the virtual classroom. Randomness ensures that students cannot predict at which instant of time the attendance is registered. Another added advantage of the RIAMS approach is that it requires only nominal internet bandwidth in comparison with the existing face recognition based attendance tracking systems. Existing face recognition systems require students' video cameras to be kept 'ON' throughout the virtual classroom session. The proposed model can be easily scaled and integrated into a wide variety of virtual meetings, including business meetings.

Our design of the RIAMS is in such a way that it does not affect the learning process in any way. Neither the students nor the teachers will have to face any difficulties in virtual classrooms with the RIAMS design. As the random intervals required for executing RIAMS attendance tracking modalities are too short (30 seconds, or less), the teaching-learning process is not affected. For instance, the students need to switch on their cameras for less than a minute only (assuming the attendance is taken twice based on face recognition). Similarly, the CAPTCHA and UIN queries are also fast processes which take less than 30 seconds, on each turn. Thus, the teaching-learning process will remain focused on obtaining the learning outcomes, even as the attendance is automatically monitored in the background. Educational institutes applying the RIAMS system can effectively monitor the attendance without affecting the learning objectives of the class.

A. CONTRIBUTIONS TO THE BODY OF KNOWLEDGE

The significant contributions of the present research study to the existing literature are enumerated below.

1) Introduces the novel feature of randomness in an AI-based face recognition system to effectively track and manage students' attendance and engagement in virtual classrooms.
2) Enhances the efficacy of the attendance management in virtual classrooms by integrating two ancillary modalities – students' real-time response to CAPTCHAs and UIN (Unique Identification Number) queries.

3) Monitors students' attendance and engagement during virtual learning without affecting their focus on learning.
4) Unlike the existing attendance monitoring systems using face recognition techniques, the RIAMS does not require students' video cameras to be ON all the time. Its unique design allows the students' cameras to be turned ON only for a short period. Consequently, it introduces an innovative way to preserve internet bandwidth while efficaciously monitoring attendance in virtual classrooms.
5) Develops a user-friendly attendance recording system for teachers that can automatically record students' attendance and generate attendance reports for virtual classrooms.

II. BACKGROUND AND RELATED WORK

This section presents a critical review of various strategies and technologies currently used for attendance management. Since the related literature pertaining to virtual classrooms' attendance monitoring is limited, an extensive review of the same could not be carried out. However, the rationale for adopting the face recognition method in the proposed prototype model is elaborated by discussing the related literature.

A. EXISTING TECHNOLOGIES FOR ATTENDANCE MONITORING AND THE SIGNIFICANCE OF FACE RECOGNITION

In the case of physical classrooms, the automation process of students' attendance tracking is a widely explored research area [30]–[32]. In this regard, the biometric-based attendance methods are preferred over other methods like radio-frequency identification [33], [34]. This is mainly due to the simplicity, reliability, and efficiency of the biometric systems [30]. Such biometric-based attendance monitoring systems are essentially based on face, fingerprint, and iris recognition technologies. Out of these three, the face recognition systems are widely used due to its major advantages of enhanced security, improved accuracy, and capability to easily integrate with other systems [35]–[37]. In addition, the fingerprint [38] and iris [32], [39] recognition systems have their own critical limitations in attendance monitoring. A major shortcoming with the fingerprint-based attendance system is that it cannot recognize a dirty or wet fingerprint [40]–[42]. The disadvantages with iris recognition based attendance tracking are its complexity and inaccuracy as the allied technology is still in its evolving stage [32], [39]. Both the fingerprint and iris recognition systems are not so user friendly in comparison with face recognition. Further, the evolution of advanced image sensing technologies and increased image quality of cameras in smartphones and laptops have paved the way for relatively cheap production of face recognition systems. In the case of academic institutions, face recognition systems can be used as a part of automated registration, and campus security systems [30], [43], [44].

Face recognition is a technology that identifies a person and validates it by the comparison of the face features previously stored in a database [24]. The underlying technologies in the face recognition method are based on artificial intelligence and machine learning [45]–[47]. There are two major approaches presented in the literature for face recognition. The first approach relies on the facial expressions of eyes and nose to recognize the face. The second approach uses the entire face of a person for identification. 'Face detection' is the first task performed, while processing images that may contain human faces [24]. The face detection results are used for subsequent steps of automated human face recognition [48]. Thus, face detection is differentiating the face from any other object, while face recognition is differentiating one's face from the other [49].

Convolutional Neural Networks (CNNs) technology have significantly improved the performance of face recognition systems in recent years. The high capacity of CNN in learning discriminative face features has reformed face recognition techniques. In RIAMS we adopted CNN based model for the design of its face recognition module. Further, we decided to employ the Dlib ResNet-34 model, which uses HOG features for face recognition. The main motivation for selecting Dlib ResNet-34 was its higher accuracy as compared to other existing face recognition models. Accuracy is one of the widely used metrics for evaluating the performance of pattern classification models and hence face recognition. It refers to the fraction of correct face predictions made by the model to the total number of predictions. The accuracies of the state-of-the-art CNN based face recognition range from 90 to 100%. For the performance evaluation with respect to accuracy, the Labeled Faces in the Wild (LFW) dataset is widely used. LFW is a standard benchmark for automatic face verification, which contains 13233 facial images from 5749 individuals, with variations in pose, expression, and illuminations.

A comparison of accuracies of various face recognition models found in literature is presented in Table 1. The accuracies are based on the LFW benchmark dataset. The authors in [50] implemented a VGG based face-embedding learning approach that yielded a recognition accuracy of 98.95% with respect to the LFW dataset. On the other hand, the authors in [51] viewed face recognition as a metric learning problem (learning large-margin face features using a distance function). They employed a modified ResNet-20 model with an additive margin softmax activation function and reported a recognition accuracy of 99.12%. It was found that deep CNNs' standard softmax loss lacks discrimination capacity. To address this issue, several other loss functions have been proposed, including angular softmax, large margin softmax and center loss. These enhanced losses are based on the maximisation of inter-class variance while minimising intra-class variance. Consequently, in [52], the authors noted that feature normalization is critical for boosting face recognition performance. They trained the Resnet-28 model using a modification of softmax loss and reported a classification accuracy

TABLE 1. Performance comparison of the CNN-based face recognition models.

Sl. No.	Authors	Model used for Face Recognition	Accuracy (%)
1	Omkar M. Parkhi et al.	VGG + Face Embedding	98.95
2	Feng Wang et al.	ResNet-20 + Additive Margin Softmax Loss	99.12
3	Feng Wang et al.	ResNet-28 + Contrastive Loss	99.19
4	Yandong Wen et al.	Lenet-7 + Center Loss	99.28
5	Hao Wang et al.	ResNet-64 + Margin Cosine Loss	99.33
6	Weiyang Liu et al.	ResNet-64 + Angular Softmax Loss	99.42
7	Davis E. King et al.	HOG + ResNet-34 (Dlib)	99.38
8	Jiankang Deng et al	ResNet-100 + Additive Angular Margin Loss	99.83

of 99.19%. Yandong Wen *et al.* proposed a new loss function titled 'center loss' to enhance the discriminative power of the deeply learned features efficiently [53]. They proved that by the joint supervision of the center and softmax loss, highly discriminatory features could be obtained for robust face recognition. They obtained a recognition accuracy of 99.28% for their modified Lenet-7 model.

In [54], the large margin cosine loss was proposed for deep face recognition. With the LFW database, Hao Wang *et al.* achieved a recognition performance of 99.33% using the Resnet-64 model. In another method, Liu *et al.* [55] proposed the angular softmax (A-Softmax) loss that allows CNNs to learn angularly discriminative features. They reported a recognition accuracy of 99.42% using their deep hypersphere embedding method for face recognition. In 2017, King [56] modified the standard ResNet structure and re-build it with 29 convolution layers. The model takes $150 \times 150 \times 3$ sized facial images as input, and each of them are represented by 128-dimensional vectors. They reported 99.38% accuracy with respect to the LFW benchmark. Deng *et al.* [57] introduced an additive angular margin loss function for face recognition that can effectively improve the discriminatory ability of feature embedding's learned from deep CNN. They registered a recognition accuracy of 99.83% for their ResNet-100 model with the LFW database.

In the RIAMS face recognition module, we adopted the modified ResNet structure proposed by King [56]. Their face recognition model is built from the Dlib open-source software library. The Dlib library contains state-of-the-art machine learning (ML) tools for creating complex face recognition software applicable in real world problems. The adopted model trains the Resnet-38 model using the Histogram of Oriented Gradients (HOG) features derived from the face images. The literature reveals that HOG combined with the Resnet provides better results than those achieved with other techniques. Further we considered the high accuracy (99.38%) and the architectural simplicity of the model. Moreover, Dlib's open-source licensing allows us to use it in our application, free of charge. These are the motivations for choosing the proposed deep learning model.

B. CHALLENGES WITH ATTENDANCE MANAGEMENT IN VIRTUAL CLASSROOMS

Universities across the globe have mandated their teachers to track students' attendance in the virtual classrooms as if in a physical classroom [58]. Quite often, a student will be deemed as 'present' if he or she has logged into the online meeting platform. Nevertheless, the logged-in status of a student cannot ensure whether the student is actively engaged in the virtual class or not. In practice, student accountability and responsibility are directly proportional to the learning effort made by the student despite his/her online presence [59], [60]. Thus, teachers use other strategies for attendance monitoring instead of merely tracking whether the students are online.

In this backdrop, some strategies that are employed by the teachers to monitor students' attendance in virtual classrooms are manual attendance calling, self-reporting attendance systems (using tools like Google forms), video calling students, short quizzes or polls, questions and discussions by selecting random students, and timed assignments [61]–[64]. The manual attendance calling strategy in virtual classrooms is both difficult and monotonous. This process will consume valuable lecturing time and will affect the teaching efficiency [65]. Attendance calling in virtual mode can also lead to errors, as a few students may engage in calling proxy attendance for students who are absent. In self-reporting attendance systems like the one using Google forms, the teacher makes an online attendance sheet, which is shared amongst all the students attending the virtual class [66]. The students will self-report their own attendance with an automatic timestamp. To some extent, this method may prevent attendance faking as the login through email is mandatory. Furthermore, certain institutions adopt a strategy in which every student has to login to the virtual classes only through their institutional email credentials. However, a major limitation of self-reporting attendance systems is the time consumption associated with the process. It is also a repetitive and exasperating task for the students to self-report their attendance by logging into their email and filling the attendance form for every virtual class [66]. Other strategies that are employed to track students' attendance in virtual classrooms have also got similar limitations. In addition, several issues are found in the attendance recording and management as well, especially in virtual classroom settings. In existing systems, the teacher has to manually enter the attendance of each student for every virtual class into their respective campus software. Creating multiple copies of the attendance record for further academic purposes is also a difficult task.

In the case of virtual classrooms, a primary issue with fingerprint and iris recognition is the unavailability of fingerprint and iris scanners in students' devices. Not all smartphones are equipped with these scanners. Moreover, in the existing online meeting applications, there are no interfaces to recognize the fingerprint and iris patterns of the students. However, the face recognition method can be used because facial images of students can be captured in real-time from the video stream of the virtual class. According to [67], the accuracy rate of the face recognition systems using video frame extraction can be up to 82%, in comparison with the traditional methods. Therefore, in the present scenario, face recognition is the best method to monitor students' attendance in virtual classrooms. It is the rationale for adopting the face recognition module as the dominant component of the proposed RIAMS model.

However, the face detection and recognition processes in a virtual classroom environment are complex tasks because the processing of faces with the poor image quality from captured video frames is highly challenging. Further, real-time image processing with varied camera positions, image blur issues, students' poster changes, background structures, and other occlusions adds to the existing challenges of Video-based Face Recognition (VFR). A few of these issues had addressed by Ding C by proposing a CNN-based framework for VFR [67]. To develop a more effective solution, we designed a novel, customized face recognition module specifically suited for virtual learning requirements.

Nevertheless, if we go for an attendance monitoring system having a face recognition module only, the reliability and efficiency of the system cannot be enhanced beyond a certain level. Thus, a multimodal system consisting of three modalities (Face, CAPTCHA, and UIN) is introduced in this paper. It is quite noteworthy that none of the past research studies had explored the combination of these three modalities and their potential to be efficiently deployed in virtual classrooms.

III. RESEARCH DESIGN AND METHODOLOGY

Random Interval Attendance Management System (RIAMS) is an innovation based on Artificial Intelligence - Deep Learning, specially designed to help the teachers/instructors across the globe for effective management of attendance during virtual learning. RIAMS facilitates precise and automatic tracking of students' attendance in virtual classrooms. It incorporates a customized face recognition module along with specially designed ancillary submodules. Both the face recognition and the sub modalities are for students' attendance monitoring in virtual classrooms. The submodules check students' responses to CAPTCHAs and UIN queries. The system captures face biometric from the video stream of participants and gathers the timely responses of students to CAPTCHAs and UIN queries, at random intervals of time. An intelligible and adaptive weighting strategy is employed for finalizing the decisions from the three modalities. RIAMS could be integrated with any existing virtual meeting platform through an application interface like a web page or a specific App.

A. DESIGN ARCHITECTURE

Fig. 1 illustrates the design architecture of the proposed prototype model. Various design steps of RIAMS with regard to Fig. 1 are enumerated and explained below.

1) Teachers and students should log in to the virtual classroom using their smart devices. We considered 'N' as the total number of students registered for a course.
2) In the first virtual class, capture M_1 video frames with all students' faces at random intervals and store it in the host server. For each student' images are extracted from the M_1 video frames, $M < M_1$.
3) Extract all students' faces from the M_1 video frames to generate facial keys for each faces $(N \times M)$, and store it in the host server.
4) $N \times M$ images are labeled for each student, and the same number of facial keys generated using AI techniques, are stored in the database as templates for testing.
5) In each session, students should turn ON the camera k_1 times for a period 'T' and M_2 frames of the video are captured at random intervals t_1, where $(t_1 < T)$.
6) After fake face identification, extract facial keys from the remaining M_3 frames, $(M_3 < M_2)$.
7) Keys generated from each 'genuine faces' are compared with all the $M \times N$ keys stored in the database.
8) If match scores value of a student in 'N' is greater than a predefined threshold λ_1 set for face recognition, the face of the student is authenticated - Method 1 (P_1).
9) Students should respond to the CAPTCHAs, k_2-times, prompted by pop-ups at random intervals - Method 2 (P_2).
10) Students should enter their UIN (Unique Identification Number) k_3-times, prompted by pop-ups at random intervals - Method 3 (P_3).
11) Attendance is registered based on the weighted sum (R) of the face matching, CAPTCHAs, and UIN responses.
12) If the normalized R, $R_N > \lambda_2$ (pre-set threshold), attendance of the student is registered successfully. R_N is given by the following equation.

$$R_N = \left(\frac{\sum_{i=1}^{3} w_i P_i}{w_1 k_1 + w_2 k_2 + w_3 k_3} \right) \times 100 \tag{1}$$

Here w_1, w_2, and w_3 denote the weights assigned for the decisions from the face, CAPTCHA, and UIN sub-modules respectively.

The particulars of each student, for instance, name, Unique Identification Number (UIN), and passport size photographs are added to the institutional portal (host server) either by the administrator, faculty, or student of the institution, using their respective login credentials. The corresponding faculty/advisors shall verify the student credentials added to the database. The creation of the portal and database is implemented using the Mysql database, Apache server, and PHP

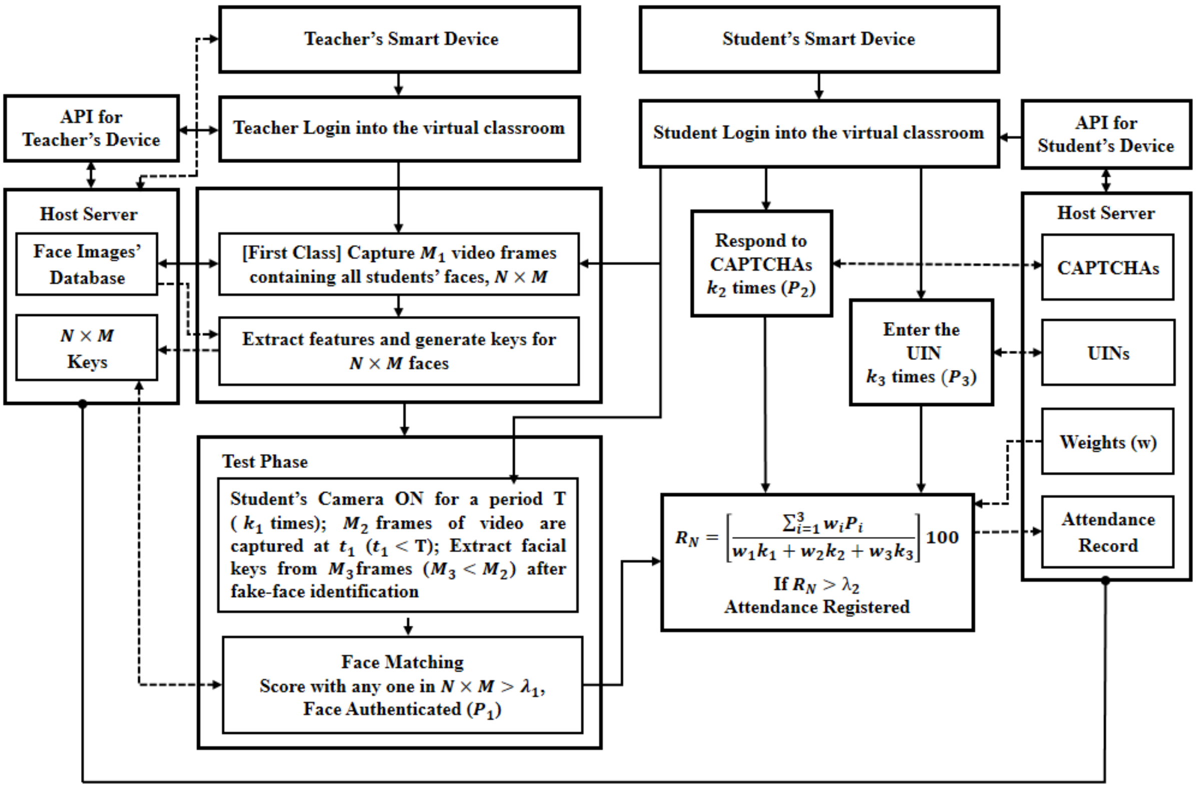


FIGURE 1. Design architecture of random interval attendance management system (RIAMS).

engine. All the relevant students' information that is available on the server will be stored in the SQL database, with a separate folder for keeping the face images of students.

The interface between RIAMS and online meeting platforms are facilitated through a web interface that runs on the teachers and students smart devices in master and slave modes, respectively. The faculty, as well as students, should log in to the online learning platform with their smart devices. The web interface page should remain active during the entire course of the class. Here, the web interface at the teachers' smart device facilitates two things.

1) It provides the teacher with a timely reminder to click the web-screen for capturing all students' faces of the virtual class for initiating the attendance entry.
2) It performs the extraction of face images from the web screen.

Specific instructions to teachers and students for RIAMS operation on their smart devices are provided in Appendix A and B, respectively. The RIAMS application/web interface will send a pop-up message to the teachers' device like: "Ask students to turn on the video camera for taking attendance". After some time, another message will pop-up that says, "Click/swipe now to take the attendance". Both these reminders are designed to operate at random intervals to ensure the efficiency of the system. These procedures can be repeated a minimum of two times in a learning session and can be pre-setted by the teacher. This approach ensures flexibility for the faculty as well.

At the virtual class, the teacher should click/swipe the web screen k_1 times as he/she wishes. If more than one screen is available, the teacher has to manually switch between the various pages. When the teacher clicks/swipe the web screen, face images from the screen are detected automatically, and a fake-face identification test is performed. Later on, the system extracts features from each genuine face, and the matching module performs face verification. The matching module compares each test face features with the templates stored in the database, and if the matching score is higher than a pre-set threshold, the face of the student is successfully recognized. The specifications of the RIAMS face recognition module and the fake-face identification process are detailed below.

B. RIAMS FACE RECOGNITION MODULE

The face recognition module in the proposed model is the heart of the system. The face recognition technology enables us to authenticate a person from his/her facial features extracted from the still photograph or a video frame. In the RIAMS system, we used the face recognition model built using the Dlib open-source software library. The Dlib library contains state-of-the-art machine learning (ML) tools for creating complex face recognition software applicable in real world problems. We adopted Dlib as its open-source licensing allows us to use it in our application, free of charge.

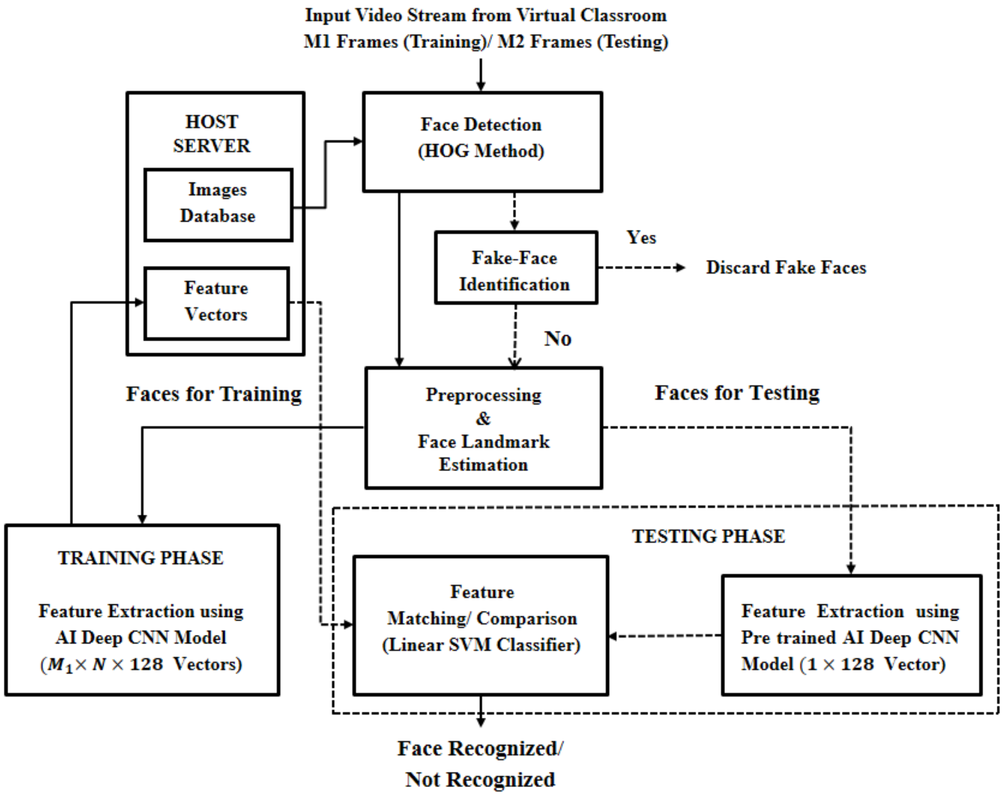


FIGURE 2. Block diagram of RIAMS's face recognition module.

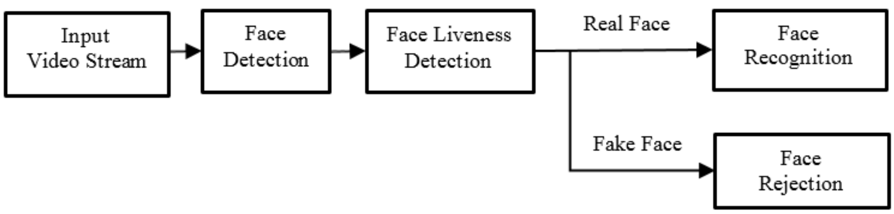


FIGURE 3. Fake-Face identification.

The block diagram of the proposed face recognition module is shown in Fig. 2. In general, face recognition involves two stages of operation viz., training, and testing. In our system, 'training' refers to a supervisory method of AI machine learning in which the Deep Neural Network (DNN) learns unique features from each student's face input. The unique features extracted from each face image are stored in a database server. During 'testing' the features extracted from each input face image are checked against the facial features stored in the reference database. In Fig. 2, the training steps are indicated by bold lines, whereas the dotted lines indicate the testing steps.

A significant security issue with face recognition systems is their inability to discriminate original 'live' faces from duplicate 'non-live' faces. They are susceptible to face faking by printed facial images, recorded videos containing faces, and 3D face models. Deceiving the face recognition system by such means defeats the whole purpose. In order to safeguard against face faking, we used the 'face liveness detection' method in our RIAMS face recognition module [68]. The block diagram of the fake-face identification submodule is shown in Fig. 3. In this method, after the facial images are captured, and pre-processing techniques are applied, correlation coefficients and image extension techniques are used for the feature extraction. Subsequently, facial images are discriminated, and skin elasticity is calculated using the Linear Discriminant Analysis (LDA) process [69]. Then, the outputs obtained are compared with the stored database values. If a particular output is less than the stored value, then the image captured is identified as a fake face image. Conversely, if an output is greater than the stored value, then it can be regarded as a real live facial image. We used only the real images identified by the face liveness detection for further processing in the RIAMS face recognition module.

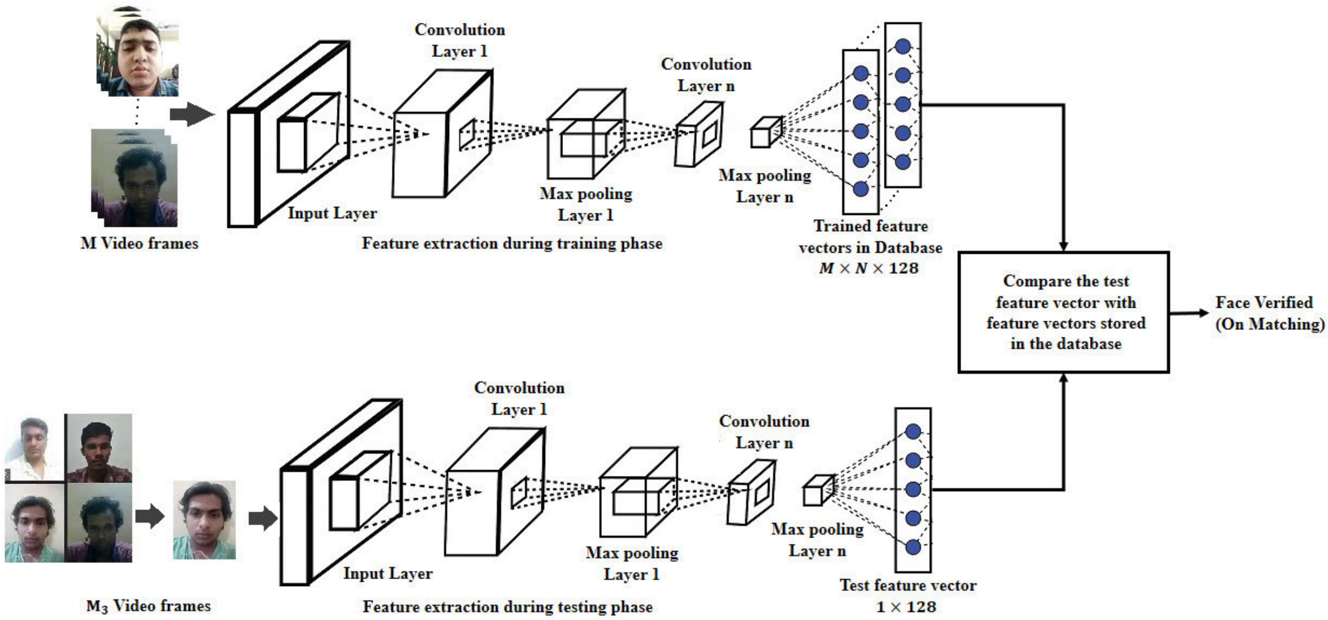


FIGURE 4. Training and testing of RIAMS face recognition module.

1) TRAINING STAGE IN FACE RECOGNITION

The first step in DNN training is students' face images' database creation. The database of N students is created from the still photographs of students or video frames (M_1) captured during the first virtual class. Prior to training, the still photographs of students stored in the database should be authenticated by the respective teacher. Similarly, the teacher should check and verify the credentials of students who attended the first virtual class. From these input images in the database, students' faces are located using the Histogram of Oriented Gradients (HOG) method [70]. Then preprocessing is applied to the detected faces for lighting normalization. Also, the face images extracted after the face detection might be oriented in different directions. Such images are difficult to process further. Hence, we performed a face landmarking operation to align faces to a standard pose. In the next step of training, face feature extraction is performed using a deep CNN [56], [71]. Fig. 4 illustrates the structure of the CNN model, which consists of convolutional, pooling, and fully connected neural network layers. CNN in our system is implemented using ResNet-34 architecture with fewer layers and filters [71]. This CNN model converts each face image into a 128 dimension vector, and the corresponding feature vectors are stored in the database for testing. Hence, during the training phase, $M_1 \times N \times 128$ sized feature-vectors are generated and stored.

2) TESTING STAGE IN FACE RECOGNITION

The first step in testing is to extract each student's facial image from the input video frames (M2) in every virtual class. Again, the face detection is performed using the HOG method. Then, to tackle face faking by students, a fake-face identification test is performed. The genuine faces extracted are then aligned to a standard pose, and features are extracted using the pre-trained CNN model. This leads to the generation of a 1×128 dimension feature vector. This feature vector generated by CNN is compared with the feature vectors stored in the database. The feature vector comparison/matching is performed using a Linear Support Vector Machine (LSVM) classifier [72]. If the match score value is greater than a pre-defined threshold λ_1, then the test face is recognized and the attendance status of the student concerning face recognition P_1 is registered in the database.

C. RIAMS ANCILLARY MODULES

The efficiency of the proposed system is improved by introducing students' responses to CAPTCHA (P_2) that pop-up k_2-times in the students' device at random intervals. Also, the students have to enter their UIN k_3-times (P_3), when they are directed to do it randomly. The random intervals of time are designed in such a way that it follows the attention span distribution of the students. Most psychologists claim the typical student's attention span is about 10 to 15 minutes long. The timely response of students to the random queries like CAPTCHAs and UINs, set by the teacher can be considered for attendance along with the decision of the face recognition system. The details of these two processes will be stored in the server for later retrieval. The faculty could automatically receive the report regarding the response of the students to the random CAPTCHAs and the entry of their UIN, from the server through his/her application/web interface.

The attendance of the students is based on an adaptive weighted sum (R) of the decisions from the face recognition module and the ancillary modules. This follows the following mathematical model,

$$R = \sum_{i=1}^{n} w_i P_i \tag{2}$$

Here, if $R > \lambda_2$ (a pre-defined threshold set by the teacher), attendance of the student is registered successfully. As per any particular requirement demanded by the situations, the teacher can change the weights associated with each modality. This increases the reliability and tractability of the proposed design.

IV. RESULTS AND DISCUSSION

This section provides the results of the experimental procedures carried out while realising the RIAMS prototype model. Specific results obtained by implementing the RIAMS face recognition module and the ancillary modalities are critically discussed. The results from the face recognition module are discussed in accordance with its training and testing phases. The training and testing phases are implemented at the Google Colab platform using Python 3.8 programming language. Our software code has been tested in Windows and Ubuntu machines, and optimal performance is observed in both cases. As mentioned earlier, we developed the RIAMS face recognition module based on the Dlib open-source software library [56]. The face recognition package in the Dlib has an accuracy of 99.38% with the Labeled Faces in the Wild (LFW) benchmark dataset.

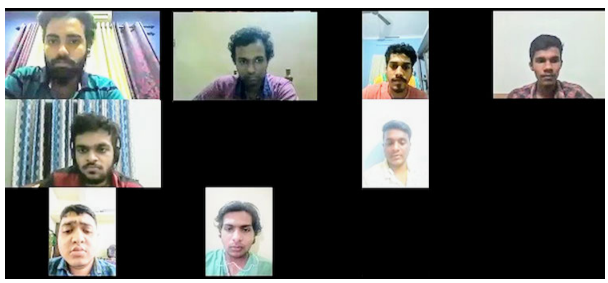
A database containing students' facial images and their UINs was developed initially for training the RIAMS modules. The face image database was created using students' passport-size photos and the image frames obtained from the video stream captured during the first virtual class. For the pilot study, a face image database comprising of ten students was developed as depicted in part (a) of Fig. 5. The performance evaluation of the RIAMS model is validated with the prototype database. Even though five images of every student were used for training the face recognition module of RIAMS, we have shown only one training set in part (a) of Fig. 5. In part (b), (c) and (d) of Fig. 5, three such video frames (frame-1, frame-2, frame-3), which were captured in real-time are displayed for illustration. We used the most common Zoom platform to create a virtual classroom and captured video frames from the same during random intervals of time. As evident from the part (b), (c), and (d) of Fig. 5, face images of some students were not seen in every frame. This can be attributed to the physical absence of students or the poor internet connection so that some students may not be able to switch on their video cameras.

For testing and verification, each test sample was compared with all the five images stored in the database. Face recognition can be regarded as successful if at least one of the five training samples matches with the test sample. Thus, if the test images extracted from the video frames of the virtual class are matching with the training samples, attendance from the face recognition module is recorded. A detailed analysis of the RIAMS face recognition module output is presented next.

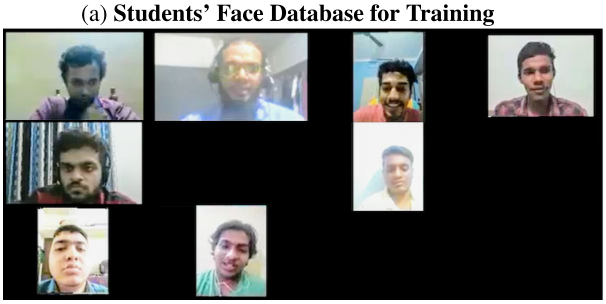
A. ANALYSIS OF RIAMS FACE RECOGNITION MODULE OUTPUT

In the RIAMS prototype model, the captured frames-1, 2, and 3 (part (b), (c) and (d) of Fig. 5) are used for comparison

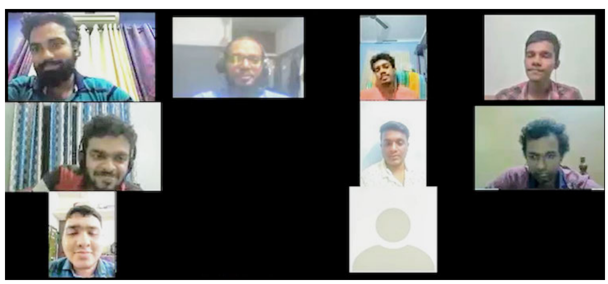
(a) **Students' Face Database for Training**



(b) **Captured Frame-1 (First Interval)**



(c) **Captured Frame-2 (Second Interval)**



(d) **Captured Frame-3 (Third Interval)**

FIGURE 5. Students' face database for training and captured video frames for testing.

TABLE 2. Face recognition output of captured frame-1 in comparison with database images.

Students' UINs	Comparison with DB images I_1	I_2	I_3	I_4	I_5	Face Recognition Status $A_i = I_1 \vee I_2 \vee I_3 \vee I_4 \vee I_5$
TKMCE01	1	1	0	0	0	1
TKMCE02	1	0	1	0	1	1
TKMCE03	1	0	0	0	1	1
TKMCE04	1	1	1	0	0	1
TKMCE05	0	0	0	0	0	0
TKMCE06	1	1	1	0	1	1
TKMCE07	1	1	1	0	1	1
TKMCE08	0	0	0	0	0	0
TKMCE09	0	1	0	0	1	1
TKMCE10	1	0	1	0	1	1

TABLE 3. Output of RIAMS face recognition module (method 1).

Students' UINs	Recognition Attempts A_1	A_2	A_3	Recognition Output $P_1 = \sum_{i=1}^{k_1} A_i$	Normalized Output P_1n
TKMCE01	1	1	1	3	1
TKMCE02	1	1	0	2	0.66
TKMCE03	1	0	1	2	0.66
TKMCE04	1	1	1	3	1.0
TKMCE05	0	0	0	0	0
TKMCE06	1	1	1	3	1.0
TKMCE07	1	1	1	3	1.0
TKMCE08	0	1	1	2	0.66
TKMCE09	1	1	1	3	1.0
TKMCE10	1	1	1	3	1.0

with the images previously stored in the database. In this regard, Table 2 shows the face recognition output of captured frame-1 by comparing it with the database images. Here, 1's represent successful matching status with the database images, whereas 0's represent the failure matching. Each test image in captured frame-1 has been compared with all the five training images corresponding to that student's image stored in the database. For instance, in the case of the student with UIN TKMCE03, the test image from the captured video frame has been matched with the first and the fifth training images, which is represented by 1's in the corresponding row of Table 2. The output of the face recognition attempt is obtained by the 'logical OR' ($\vee$) operation, $A_i = I_1 \vee I_2 \vee I_3 \vee I_4 \vee I_5$. Hence, for extracted frame-1, the face recognition status of student with UIN TKMCE03 is recorded successfully and is indicated as 1. The same process is repeated for each student as shown in Table 2. Likewise, such tables can be constructed for the other extracted frames-2, and 3, in comparison with the trained images in the database. For illustration purposes, the face recognition status of only one extracted frame is shown as in Table 2.

The final output of the face recognition module is obtained by a linear combination of each face recognition attempts $(A_1, A_2, \ldots A_p)$ happening at k_1 times in a virtual class. We have performed three such attempts which are illustrated in Table 3. Here, the face recognition process in the RIAMS is referred to as Method-1 (P_1). The first column of Table 3 indicates students' UINs. Subsequent columns point out the face recognition attempts (A_1, A_2, A_3) performed at random intervals, and the last two columns give the face recognition outputs P_1 and their normalized values P_1n. Thus, the face recognition output can be represented as,

$$P_1 = \sum_{i=1}^{k_1} A_i \tag{3}$$

For instance, In the case of UIN - TKMCE008, the student's face is not recognized in the first attempt, whereas it is recognized in subsequent attempts. Consequently, the linear sum of the three attempts (0, 1, 1) results in face recognition output '2'.

B. ANALYSIS OF ANCILLARY MODULE OUTPUTS

The output of the first ancillary modality, the CAPTCHA verification unit, is shown in Table 4. Here, the CAPTCHA verification process is referred to as Method-2 (P_2). In the proposed design, we implemented two such CAPTCHA verification at random intervals of time, in every virtual class. In Table 4, the last two columns give the CAPTCHA verification outputs P_2 and their normalized values P_2n respectively. Students' response to CAPTCHAs (C) in a virtual class is recorded at k_2 times, and a linear sum of the same is represented by the following equation.

$$P_2 = \sum_{i=1}^{k_2} C_i \tag{4}$$

The implementation of the second ancillary modality, the response to UIN queries (Method-3, P_3) by students taken

TABLE 4. Output of captcha verification process (method 2).

Students' UINs	CAPTCHA Response		Total CAPTCHA Response	Normalized Response
	C_1	C_2	$P_2 = \sum_{i=1}^{k_2} C_i$	P_2n
TKMCE01	1	1	2	1.0
TKMCE02	1	1	2	1.0
TKMCE03	1	0	1	0.5
TKMCE04	0	1	1	0.5
TKMCE05	0	0	0	0
TKMCE06	1	1	2	1.0
TKMCE07	0	1	1	0.5
TKMCE08	0	1	1	0.5
TKMCE09	1	1	2	1
TKMCE10	1	0	1	0.5

TABLE 5. Output of UIN verification process (method 3).

Students' UINs	UIN Response		Total UIN Response	Normalized Response
	U_1	U_2	$P_3 = \sum_{i=1}^{k_3} U_i$	P_3n
TKMCE01	1	1	2	1.0
TKMCE02	0	1	1	0.5
TKMCE03	1	1	2	1
TKMCE04	1	0	1	0.5
TKMCE05	0	0	0	0
TKMCE06	1	1	2	1.0
TKMCE07	1	1	2	1.0
TKMCE08	0	1	1	0.5
TKMCE09	1	0	1	0.5
TKMCE10	1	1	2	1

at random intervals is demonstrated in Table 5. In the reported method, we implemented two such UIN query verification in a virtual class. The last two columns of Table 5 give the students' UIN verification outputs P_3 and their normalized values P_3n. Response to UIN queries (U) is taken at k_3 times. The following equation represents a linear sum of such responses.

$$P_3 = \sum_{i=1}^{k_3} U_i \tag{5}$$

C. COMBINING MODALITIES AND THE FINAL ATTENDANCE DECISION MAKING

The decision fusion from the face, CAPTCHA, and UIN sub-modules (P_1, P_2, P_3) leads to the final result of the RIAMS attendance registration, which is demonstrated in Table 6. The weighted sum of decisions from each sub-modality is considered for a concluding result (R), which can be represented as,

$$R = \sum_{i=1}^{3} w_i P_i \tag{6}$$

In the proposed design, we considered dissimilar weights $w_1 = 0.5$, $w_2 = 0.3$ and $w_3 = 0.2$ for illustration purpose. The rationale for giving greater weightage (w_1) to face recognition can be attributed to its higher significance as compared to the other modalities. The final attendance status will be registered as 'Present', if the weighted sum (R) is greater than a predefined threshold (λ_2). During the training phase, we observed that $\lambda_2 = 65\%$ gives optimal results, and hence the same value has been used in the testing phase to compare with the 'R' values. The normalized value of 'R' in percentage can be obtained by the following equation.

$$R_N = \left(\frac{\sum_{i=1}^{3} w_i P_i}{w_1 k_1 + w_2 k_2 + w_3 k_3} \right) \times 100 \tag{7}$$

In the proposed system, we considered $k_1 = 3$, $k_2 = 2$, and $k_3 = 2$ and the results obtained therein are depicted in the last column of Table 6.

The high performance of the system is evident from the analysis of Table 6. For instance, the status of two students (TKMCE05 and 08) are registered 'Absent', as their 'R' values are less than the decision threshold. Here, the first student is 'Absent' because, the corresponding outputs of Face, CAPTCHA, and UIN submodules were zero. This can be observed from the captured video frames (Fig. 5) and from the respective Tables (Table 3- 5). In the second case, (TKMCE08), even though face recognition output is 66%, the response to CAPTCHA and UIN queries made by the student are only 50% each. Thus, the student is absent as per the final decision, even though he is having a 66% score from the face recognition module. This indicates the efficacy of the ancillary modalities in continuously monitoring students'

TABLE 6. Final result of RIAMS attendance registration (decision fusion from face, captcha and UIN sub-modules).

Students' UINs	Results			Final Result (in %)	Attendance Status
	Method 1 (P_1)	Method 2 (P_2)	Method 3 (P_3)	$R_N = \left(\frac{\sum_{i=1}^{3} w_i P_i}{w_1k_1+w_2k_2+w_3k_3}\right) \times 100$	(Present if $R_N \geq \lambda_2$
TKMCE01	3	2	2	100	Present
TKMCE02	2	2	1	72	Present
TKMCE03	2	1	2	68	Present
TKMCE04	3	1	1	80	Present
TKMCE05	0	0	0	0	Absent
TKMCE06	3	2	2	100	Present
TKMCE07	3	1	2	88	Present
TKMCE08	2	1	1	60	Absent
TKMCE09	2	2	1	72	Present
TKMCE10	3	1	2	88	Present

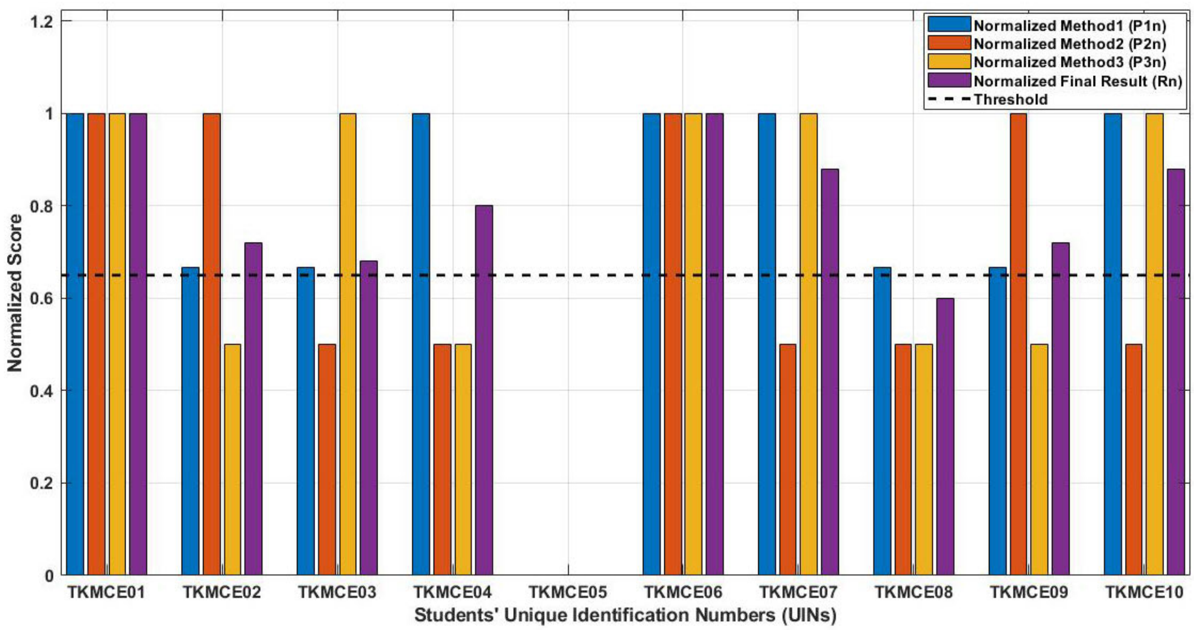


FIGURE 6. Analysis chart of RIAMS face recognition module (method-1) and ancillary modalities (methods 2 & 3).

attendance in virtual classrooms even without their facial image input.

The performance analysis chart of the RIAMS face recognition module (method-1) and ancillary modalities (methods 2 & 3) is demonstrated in Fig. 6. The normalized values of the outputs of methods-1, 2, and 3 (P_1n, P_2n, and P_3n) are depicted in the bar chart. It also illustrates the normalized final results in comparison with a predefined threshold ($\lambda_2 n = 0.65$), shown by a horizontal line. It is evident from the Fig. 6 that the attendance is registered if the normalized output is greater than the threshold value. Thus, the RIAMS submodules are of high performance which ensures proper response of students to random queries as well as physical presence in terms of face recognition.

RIAMS face recognition process took approximately one millisecond for verifying a single face, as it uses the Dlib face recognition module. This implies that the module can process 10 frames of video stream per second in real-time. However, the present RIAMS model is a prototype that does not require real-time processing. Detecting individual faces is not a time-critical issue in the case of attendance management. Students' faces can be detected from the screenshots fetched at any later point in time. Detecting faces and sending the information in real-time is not necessary. The screenshot, once captured, can be used to detect the face at any time during the entire period of the class or even after class.

The accuracy of the face recognition module is high, as we designed it using the Dlib library, which has an accuracy of 99.38%. However, we have obtained 100% accuracy for the pilot study which incorporates facial images of a sample of 10 students. Similarly, for the UIN and Captcha verification performed by the ancillary modalities, we obtained 100% accuracy for the pilot study. We did not analyze the performance and accuracy of RIAMS because It is irrelevant to compare a prototype model with other systems, which are in no way related to the proposed model. Since the proposed model is unique in terms of the introduction of randomness and ancillary modalities in its design, it cannot be compared with other models available in the literature.

V. CONCLUSION

The Random Interval Attendance Management System (RIAMS) is based on a novel and innovative design, the first of its kind, which resolves the unavailability of a proper attendance management system for virtual learning. The experimental results show that the RIAMS device model is highly efficient and scalable. Its modest design allows teachers to precisely monitor and manage students' attendance and generate reports as per the administrative requirements. The automated system reduces wastage of time and manual labour involved in tracking and managing attendance in virtual classrooms. RIAMS is very user-friendly and robust and can be easily integrated with any existing virtual meeting platform. It offers the following innovative and efficient features.

1) The proposed design has a robust and efficient AI-DL based face recognition module, customized for virtual learning applications with an added fake-face identification subsystem that monitors only genuine faces in the virtual classroom.
2) Integration of ancillary modalities such as CAPTCHA and UIN subsystems to RIAMS further improves its efficiency. Students' responses to the queries provided by these subsystems, along with the timestamps, help teachers in assessing students' attention and engagement in virtual classrooms. Ancillary modalities also help teachers in maintaining the attention span (10-15 minutes) of students, by setting a minimum time interval between each CAPTCHA and/or UIN query.
3) Both the face recognition module and ancillary modalities (CAPTCHA and UIN) are designed to operate at random intervals of time. The randomness ensures that students cannot predict at which instant of time the attendance is going to be monitored. This can effectively reduce dropping out of participants during virtual learning.
4) RIAMS's final decision to register the attendance is obtained by a multi-mode fusion of decisions from the face recognition, CAPTCHA, and UIN subsystems. This multi-mode approach enhances the adeptness of the system and reduces discrepancies in attendance.
5) RIAMS requires only a nominal bandwidth for internet usage, as the students' video cameras are supposed to be ON only for short periods at random intervals.
6) RIAMS has a novel, non-obvious, intelligible, and modest design that can be suitably scaled as per the academic or industrial attendance management requirements. This industrially relevant design can be implemented worldwide for any virtual meeting in post-COVID settings.

A. LIMITATIONS OF THE STUDY

The design and development of RIAMS are not free from limitations. Even though many research articles are available on using the face recognition method for attendance monitoring of students, there is a scarcity of relevant studies in attendance management for virtual learning. Thus the literature background for the present study was limited, so that we develop our novel prototype design from scratch. This paper attempted to bring an efficient attendance management system within the limitations of a prototype design. We developed the RIAMS as a prototype model and implemented it in a pilot study with ten students only. Extensive testing in large virtual classrooms with more students is yet to be carried out. Moreover, the overall performance of the RIAMS could not be compared with other attendance monitoring systems as its design is unique and novel. There are no similar systems for attendance monitoring in virtual classrooms using the random interval technique and ancillary modalities. We used the Dlib open source software library for developing the RIAMS face recognition module as it is highly accurate and efficient. Therefore the accuracy of the RIAMS face recognition module is limited to Dlib's accuracy. In our design, we considered only static weights for face recognition and ancillary modalities. The scalability issues and potential problems that may arise while adding further modalities into the RIAMS design are not considered in this paper, as they fall outside the scope of the present work.

B. FUTURE SCOPE

There is a critical necessity to carry forward this research on attendance management in virtual classrooms, especially in the post-COVID scenario. By incorporating other ancillary modalities like speech recognition and adding suitable adaptive weights for each modality, the efficiency and reliability of the system can be further enhanced. It may be worthwhile to convert the RIAMS module to a commercially viable product for broader availability. The future scope of the proposed design rests on its suitability to scale as per the academic or office needs to achieve the desired performance. Effective attendance management by the RIAMS in post-COVID virtual learning could enhance the quality of the teaching-learning process, which will be benefited by millions of teachers, students, and other stakeholders across the globe.

APPENDIX A
INSTRUCTIONS TO TEACHERS FOR RIAMS IMPLEMENTATION

1) Log in to the virtual classroom using your smart devices.
2) Open the RIAMS web interface page and keep it active during the entire virtual class session.
3) In the web interface, configure how many times you are going to monitor students' attendance using each modality (Face, CAPTCHA and UIN).

4) A pop-up message like "Ask students to turn on the video camera for taking attendance" will appear in teachers' smart device. Then teachers can prompt students to turn on their camera for a limited period of time (say 30 seconds).
5) On receiving another pop-up message "Click/swipe now to take the attendance", the teacher can click/swipe their smart device to take the attendance (based on the face recognition).
6) Repeat these procedures at least two times or any number of times as configured earlier.

P. S.: The teacher cannot alter randomness of the system in any way. That is the teacher can only decide and configure how many times the attendance will be monitored using each modality (Face, CAPTCHA and UIN). The teacher cannot control the time at which each modality is operating. That is attendance monitoring using face, CAPTCHA and UIN will happen at random intervals.

APPENDIX B
INSTRUCTIONS TO STUDENTS ON RIAMS OPERATION

1) Log in to the virtual classroom using your smart devices.
2) Open the RIAMS web interface page and keep it active during the entire virtual class session.
3) On receiving teacher's instruction, turn on your camera and keep it ON for at least 30 seconds. Repeat this whenever prompted by the teacher.
4) A CAPTCHA code will pop-up on your screen at random intervals. The pop-up will disappear when you enter the code correctly within 30 seconds.
5) Another pop-up to enter your UIN may also appear at random intervals. Again, it will disappear when you rightly type the UIN within 30 seconds.

HUMAN RESEARCH DISCLOSURE

Our research study involves human subjects, and this article contains their facial images (Figures 4 and 5). We have obtained informed consent statements from all the students who participated in the virtual classes designed for research purpose. The research study protocol has been approved and certified by the Institutional Ethics Committee of TKM College of Engineering, Kollam, Kerala, India (Certificate Reference Number – P1/1/108/21, dated 18-03-2021).

DETAILS OF PATENT FILED

Based on the basic concept of the novel RIAMS design a patent application is filed (No. 202041034477, dated 11^{th} August 2020) under the Intellectual Property India, Government of India.

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