WEB-BASED ATTENDANCE MONITORING SYSTEM WITH SAPTIO-TEMPORAL HUMAN ACTION RECOGNITION

A PROJECT REPORT

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BONAFIDE CERTIFICATE

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ABSTRACT

The attendance system project aims to revolutionize traditional attendance tracking methods by introducing an innovative intelligent monitoring system. Leveraging spatio-temporal human action recognition technology, the system integrates various advanced features to address challenges such as face masking and identity fraud. One key aspect of the system is the integration of human skeleton gait recognition, multi-action body silhouette recognition, and face recognition technologies. By combining these technologies, the system can accurately identify individuals even in scenarios where face masking or other forms of disguise are present. The use of 3D masks adds an additional layer of security against identity fraud attempts. The project addresses the shortcomings of manual attendance tracking methods by enhancing administrative efficiency and improving student engagement. By providing user accessibility through a secure web interface, both administrators and students can benefit from real-time attendance tracking and analysis. Administrators can monitor in-person availability trends and view present percentage metrics for individual users. The system utilizes advanced algorithms such as temporal weighted K-nearest neighbors for skeleton gait recognition and multiple K-nearest neighbors for multi-action body silhouette recognition. The expected impact of the attendance system includes improvements in data accuracy and processing speed, as well as the streamlining of attendance management processes. By automating the attendance tracking process and leveraging cutting-edge technologies, the system aims to provide a more efficient and reliable solution compared to traditional methods. Overall, the project represents a significant advancement in attendance tracking technology.

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LIST OF ABBREVIATIONS

LBPH	Local Binary Patterns Histograms
CNN	Convolutional Neural Networks
RFID	Radio Frequency Identification
STIGPN	Spatio-Temporal Interaction Graph Parsing Networks
STV-GCN	Spatial Temporal Variation Graph Convolutional Networks
RPN	Region Proposal Network
R-CNN	Regions with CNN Features
KNN	K-Nearest Neighbors
API	Application Programming Interface
MySQL	My Structured Query Language
SVM	Support Vector Machine
UHD	Ultra High Definition
TF	TensorFlow
HTTP	HyperText Transfer Protocol
CI/CD	Continuous integration and continuous deployment
ELB	Elastic Load Balancing
UAT	User Acceptance Testing

CHAPTER 1
INTRODUCTION

1.1 GENERAL

The attendance system previously managed using traditional methods are time-consuming and less efficient. Web-Based Attendance Monitoring System with Spatio-Temporal Human Action Recognition methods can overcome the ineffectiveness of attendance. Therefore, the introduction of image processing techniques to perform face recognition in an attendance system where the appearance of a student's face can be labeled and compared with images in the classroom with an accumulated database Using face recognition smart attendance system automatically marks students attendance in a class by recognizing their faces. The system is divided into several steps, but face detection and face recognition are the main steps. First, database is to be created for each face to mark attendance. The camera device takes all facial images in the classroom, then face detection is carried out, and then face recognition is carried out on the faces detected earlier by comparing the faces in the database containing images and the attendance is updated in the database. By smart attendance system, attendance errors, can be reduced using this. It makes it easy for the parties concerned to use smart attendance automatically and can save time in registering attendance. Over the last ten years in the use of deep learning, interesting results were obtained from various fields, one of which is face recognition. The use of deep learning to perform face detection and face recognition in recent years and has been widely applied in everyday life based on algorithms that perform learning on a lot of data by studying many factors such as faces, expressions, angles, and light. There are several methods of face detection that have been proposed. In this projects RetinaFace method is used to perform face detection which achieves stable face detection with evaluation results of average precision of 96.713%, 96.082%. The proposed method which functions as face detection and feature extraction on images to obtain input with an accuracy rate of 95.23% in the synthesis dataset. This system integrates CNN-based facial detection with providing real-time attendance tracking and alerts. The purpose of this system is to build a attendance system which is based on face recognition techniques. Here face of an individual will be considered for marking attendance.This new system will consume less time than compared to traditional methods.

Eigenfaces and Local Binary Patterns Histograms (LBPH) are traditional computer vision methods used for facial recognition tasks. These methods have been effective but may not perform as well in certain scenarios, especially when dealing with variations in lighting, facial expressions, and poses.

Convolutional Neural Networks (CNNs), on the other hand, have shown remarkable success in various computer vision tasks, including facial recognition. CNNs can automatically learn hierarchical features from raw data, making them highly effective in handling complex patterns and variations in input data.

When compared to traditional methods like Eigenfaces and LBPH, CNNs generally offer higher accuracy and robustness in facial recognition tasks, especially when dealing with real-world data with variations. CNNs can learn intricate features from facial images, capturing both global and local patterns, which can significantly improve recognition accuracy.

In summary, while Eigenfaces and LBPH are existing methods for facial recognition, CNNs have emerged as a more powerful alternative, offering higher accuracy and robustness, particularly in challenging real-world scenarios.

1.2 OBJECTIVE

The primary objective of this project is to develop an advanced smart attendance system that integrates cutting-edge face detection and recognition methods utilizing deep learning techniques. This system aims to revolutionize the traditional attendance monitoring process by automating the identification and recording of individuals' attendance accurately and efficiently within classroom or organizational environments.

To achieve this objective, the project entails several key steps. Initially, a comprehensive data collection process is undertaken, gathering datasets comprising student photos captured under diverse conditions to ensure robust model training and performance. Subsequently, a neural network architecture is designed and implemented using the Keras API, which operates atop the TensorFlow framework. This neural network is meticulously trained with the collected dataset, with careful consideration given to selecting appropriate hyperparameters to optimize model learning and accuracy.

The essence of the system lies in its ability to extract intricate features from input images, facilitating the precise identification and detection of students within a given context. Through extensive training, the neural network learns to discern unique facial characteristics and patterns, enabling it to accurately recognize individuals and mark their attendance accordingly.

Upon successful completion of the training phase, rigorous testing is conducted to evaluate the neural network's performance and accuracy in real-world scenarios. This testing phase ensures that the system meets the requisite standards of reliability and effectiveness, thereby validating its suitability for deployment in practical settings.

Once validated, the system is seamlessly integrated into the classroom or organizational environment, where it automatically updates attendance records in the centralized database in real-time.

By adhering to this comprehensive approach, the smart attendance system aims to streamline attendance monitoring processes, mitigate errors, and enhance overall efficiency. Through the fusion of advanced technology and innovative methodologies, this project endeavors to deliver a transformative solution that revolutionizes attendance management in educational and organizational contexts.

1.3 EXISTING SYSTEM

The landscape of existing attendance systems within organizations and institutions is characterized by a diversity of approaches, each with its own set of advantages and limitations. These systems encompass a spectrum of methodologies, ranging from traditional paper-based methods to sophisticated biometric verification systems.

Traditional paper-based attendance systems involve individuals manually signing or marking attendance sheets, which are subsequently processed by administrative staff. While this approach is straightforward and familiar, it is inherently susceptible to errors such as incorrect entries and proxy attendance. Additionally, the manual handling of attendance sheets can be time-consuming and labor-intensive for administrative personnel, leading to inefficiencies in attendance tracking and record-keeping.

Alternatively, manual entry systems entail staff inputting attendance data into computerized systems using spreadsheets, databases, or specialized software. While these systems offer improved organization and data management compared to paper-based methods, they still pose challenges related to human error and data entry inconsistencies. Moreover, the reliance on manual data input can result in delays and inaccuracies in attendance recording, particularly in larger organizations with high volumes of data to process.

Proximity card systems leverage RFID (Radio Frequency Identification) technology to provide a convenient and secure means of tracking attendance. Each individual is assigned a proximity card encoded with unique identification information, which is then scanned upon entry to record attendance. While proximity card systems offer advantages such as ease of use and enhanced security, they may be susceptible to issues such as card loss or theft, leading to potential disruptions in attendance tracking and data integrity.

Some organizations opt for hybrid attendance systems that combine multiple techniques to enhance accuracy and security. These hybrid systems often integrate biometric verification methods, such as fingerprint or facial recognition, with RFID scanning technology. By combining these approaches, organizations aim to mitigate the limitations of individual systems and achieve greater reliability in attendance tracking. However, the implementation of hybrid systems may require significant investment in infrastructure and technology integration, making them more suitable for organizations with larger budgets and technological capabilities.

Overall, the selection of an attendance system is influenced by various factors, including the size and complexity of the organization, security requirements, and available technological infrastructure. While each system has its strengths and weaknesses, organizations must carefully evaluate their specific needs and considerations to choose the most appropriate solution for their unique context. The evolution of attendance systems continues to be driven by advancements in technology and the ongoing pursuit of greater efficiency, accuracy, and convenience in attendance monitoring processes.

1.4 PROPOSED SYSTEM

The proposed system represents a significant advancement in attendance monitoring through the integration of cutting-edge face recognition technology. At its core, the system leverages Convolutional Neural Networks (CNNs), a powerful deep learning technique, implemented using the open-source Deep Face image processing API. By harnessing the capabilities of CNNs, the system achieves accurate recognition and authentication of pupils in the classroom through real-time facial detection and recognition techniques.

The key functionality of the system lies in its ability to instantly update attendance records in a centralized database upon detecting individuals. This real-time updating mechanism ensures that attendance data is always up-to-date and readily accessible for analysis and reporting purposes. Moreover, the system incorporates functionality to provide guardians with timely notifications of their ward's attendance status in real time. This feature enhances communication and transparency between educational institutions and guardians, fostering a collaborative approach to student monitoring and support.

One of the primary objectives of the Smart Attendance Monitoring System is to improve accuracy and efficiency in the classroom environment. By automating the attendance monitoring process and reducing reliance on manual data entry, the system minimizes errors and administrative overhead associated with traditional attendance methods. This, in turn, allows educators to focus more time and resources on delivering quality instruction and engaging with students.

Furthermore, the integration of state-of-the-art technologies such as face recognition and notifications enhances the overall effectiveness of attendance monitoring. The system's reliance on facial detection and recognition techniques ensures high levels of accuracy and reliability in identifying individuals, even in dynamic classroom environments with varying lighting conditions and angles. Additionally, the inclusion of functionality provides guardians with immediate updates on their ward's attendance, enabling proactive involvement in their educational journey.

In summary, the proposed Smart Attendance Monitoring System offers a comprehensive solution to the challenges associated with traditional attendance monitoring methods. By leveraging advanced technologies and real-time communication channels, the system enhances accuracy, efficiency, and communication in the classroom environment. As educational institutions continue to embrace digital transformation, innovative solutions like the Smart

Attendance Monitoring System play a crucial role in shaping the future of student monitoring and support.

1.5 SUMMARY

In this chapter, we provided an overview of the objectives, existing systems, and proposed system for attendance monitoring. The primary objective of the project is to develop a smart attendance system that combines face detection and recognition methods using deep learning techniques. This system aims to accurately identify and mark attendance for individuals in various settings, such as classrooms or organizational environments.

We discussed the shortcomings of existing attendance systems, including paper-based methods, manual entry systems, proximity card systems, and hybrid systems. These systems are prone to errors, time-consuming, and may lack the accuracy and efficiency required for effective attendance monitoring.

In contrast, the proposed system utilizes face recognition technology and Convolutional Neural Networks (CNNs) to automate attendance monitoring. By leveraging real-time facial detection and recognition techniques, the system can instantly update attendance records in a centralized database.

Overall, the Smart Attendance Monitoring System aims to improve accuracy, efficiency, and communication in educational and organizational settings. The subsequent chapters of this report will delve deeper into the technical aspects of system development, implementation, and evaluation, providing a comprehensive understanding of its capabilities and potential impact.

CHAPTER 2
LITERATURE REVIEW

1. Ramani GEt.al . ,Exploring Spatio–Temporal Graph Convolution for Video-Based Human–Object Interaction Recognition, IEEE Transaction on and system for video technology.

STIGPN, introduced in 2023, stands as a pioneering model in the realm of video-based human-object interaction recognition. Unlike conventional approaches, STIGPN doesn't isolate spatial, temporal, and spatio-temporal aspects; instead, it integrates them seamlessly. This fusion enables a holistic understanding of video sequences, capturing intricate human-object interactions with remarkable accuracy. By concurrently considering spatial relationships between objects, temporal dynamics within frames, and spatio-temporal correlations across sequences, STIGPN achieves unprecedented performance.

The significance of STIGPN lies in its ability to discern nuanced interactions that traditional models might overlook. Whether it's a person grasping an object, manipulating it, or engaging in complex activities, STIGPN excels at recognizing these actions accurately. Its proficiency extends to scenarios with varying backgrounds, lighting conditions, and object scales, ensuring robust performance across diverse settings.

The competitive edge of STIGPN stems from its comprehensive feature extraction and integration mechanisms. By leveraging spatio-temporal graph convolution techniques, the model captures rich contextual information, enabling nuanced interpretation of visual scenes. This multi-level analysis facilitates the identification of subtle cues indicative of human-object interactions, leading to superior recognition performance.

Furthermore, STIGPN's architecture facilitates efficient learning of complex interaction patterns through deep neural networks. By incorporating convolutional layers for spatial feature extraction and recurrent layers for temporal modeling, the model achieves a delicate balance between local and global context comprehension. This balanced approach enhances the model's interpretability while minimizing computational overhead, making it suitable for real-time applications.

The practical implications of STIGPN span various domains, including surveillance, robotics, and human-computer interaction. In surveillance scenarios, the model can accurately detect suspicious behaviors or interactions, aiding in threat identification and security monitoring. In robotics, STIGPN enables robots to understand and respond to human gestures and commands effectively, enhancing human-robot collaboration. Additionally, in human-computer interaction, the model facilitates intuitive interfaces that respond intelligently to user actions, paving the way for more natural and immersive user experiences.

In summary, STIGPN's groundbreaking approach to video-based human-object interaction recognition signifies a significant advancement in computer vision research. Its holistic perspective, coupled with its robust performance and broad applicability, positions it as a valuable tool for understanding and interpreting complex visual data, with far-reaching implications across various domains.

2. Nuzhat Yasmeen, Intelligent Systems Powered Hourly Attendance Capturing System, Journal Name; IEEE 7th International Conference on Trends in Electronics and Informatics (ICOEI 2023), 7th International Conference on Trends in Electronics and Informatics (ICOEI 2023)

The research presented by Nuzhat Yasmeen introduces an innovative solution titled the "Intelligent Systems Powered Hourly Attendance Capturing System." Published in the proceedings of the IEEE 7th International Conference on Trends in Electronics and Informatics (ICOEI 2023), this system addresses the challenge of efficiently and accurately capturing hourly attendance in various contexts, such as educational institutions, workplaces, and events.

The system leverages intelligent technologies to automate the attendance tracking process, eliminating the need for manual entry or cumbersome paperwork. By integrating advanced features like facial recognition, biometric authentication, and real-time data processing, it offers a seamless and reliable solution for monitoring attendance.

Key components of the Intelligent Systems Powered Hourly Attendance Capturing System include sophisticated algorithms for facial recognition, which enable the identification and verification of individuals based on unique facial features. This ensures that attendance records are associated with the correct individuals, minimizing errors and preventing fraudulent entries.

Furthermore, the system incorporates biometric authentication methods, such as fingerprint or iris scanning, to enhance security and accuracy. By requiring individuals to provide biometric data for verification, it adds an extra layer of authentication, reducing the likelihood of unauthorized attendance.

Real-time data processing capabilities enable the system to capture attendance information promptly and accurately. Whether it's tracking attendance in classrooms, office spaces, or large-scale events, the system can handle high volumes of data efficiently, providing instant insights and reports to stakeholders.

The implementation of the Intelligent Systems Powered Hourly Attendance Capturing System offers numerous benefits, including improved efficiency, accuracy, and accountability in attendance tracking. Educational institutions can streamline their record-keeping processes, monitor student attendance patterns, and identify potential issues or trends. Similarly, workplaces can enhance workforce management, track employee attendance, and ensure compliance with labor regulations.

Overall, Nuzhat Yasmeen's research presents a valuable contribution to the field of attendance tracking systems, showcasing the potential of intelligent technologies to revolutionize traditional processes. The Intelligent Systems Powered Hourly Attendance Capturing System offers a glimpse into the future of attendance management, where automation, intelligence, and efficiency converge to simplify administrative tasks and enhance organizational productivity.

[3] Kanageswari Alagasan, A Review Paper on Advanced Attendance and Monitoring Systems, Journal Name; IEEE A Review Paper on Advanced Attendance and Monitoring Systems

Kanageswari Alagasan's review paper on Advanced Attendance and Monitoring Systems, published in an IEEE journal, delves into the evolution of attendance tracking methods, focusing on the rise of innovative technologies and their impact on workforce management. The paper, released in 2021, underscores the growing trend of leveraging smartphones for attendance monitoring, marking a departure from traditional paper-based systems.

The review highlights the effectiveness of various authentication methods, including fingerprint recognition, iris scanning, RFID (Radio-Frequency Identification), and GPS (Global Positioning System), in enhancing the accuracy and efficiency of attendance tracking. These methods offer viable alternatives to manual processes, enabling organizations to streamline their operations and ensure compliance with attendance policies.

Fingerprint recognition systems utilize biometric data to verify individuals' identities, offering a reliable and secure means of authentication. Similarly, iris scanning technology leverages unique iris patterns for identification, providing a non-intrusive and highly accurate method of attendance tracking.

RFID technology enables automatic identification and tracking of individuals through radio-frequency signals, allowing for seamless and contactless attendance monitoring. This approach is particularly suitable for environments where high throughput and convenience are paramount.

GPS-based systems utilize location data to track individuals' movements and attendance, offering flexibility and scalability in monitoring remote or mobile workforce. By leveraging smartphone capabilities, organizations can monitor attendance in real-time, regardless of employees' physical locations.

Overall, Kanageswari Alagasan's review paper sheds light on the transformative potential of advanced attendance and monitoring systems, illustrating how emerging technologies are reshaping traditional workforce management practices. By embracing smartphone-based solutions and innovative authentication methods, organizations can enhance operational efficiency, reduce administrative burdens, and ensure accurate attendance tracking in diverse settings.

4. Pavel ZlatarovEt.al, Design and Development of a Smartphone-Enabled Smart Card-Based Attendance Tracking Module for Personalized Education, Journal Name; IEEE 7th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)

Pavel Zlatarov and colleagues present a cutting-edge solution in their paper titled "Design and Development of a Smartphone-Enabled Smart Card-Based Attendance Tracking Module for Personalized Education," published in the IEEE 7th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT). Released in 2023, their research addresses the evolving landscape of e-learning and the heightened significance of personalized education, especially in response to the challenges posed by the pandemic.

The proposed system offers a novel approach to attendance tracking by integrating smart cards and mobile devices, leveraging their combined capabilities to streamline the process and enhance tailored learning experiences. This integration represents a significant advancement in educational technology, enabling educators to collect attendance data efficiently and utilize it to personalize students' learning journeys.

With the increasing adoption of e-learning platforms and the shift towards remote or hybrid learning models, the need for effective attendance tracking mechanisms has become more pronounced. Traditional methods, such as manual attendance registers or online check-ins, often lack accuracy and efficiency, leading to challenges in monitoring student engagement and participation.

By combining smart card technology with smartphone-enabled tracking modules, the proposed system overcomes these limitations and offers a comprehensive solution for attendance management in educational settings. Smart cards, equipped with unique identifiers, allow for seamless authentication and attendance recording, while mobile devices serve as convenient tools for data collection and analysis.

One of the key advantages of the system is its ability to provide real-time attendance tracking, enabling educators to monitor student attendance remotely and intervene promptly if necessary. This real-time visibility into student engagement facilitates personalized interventions and support, ensuring that each student receives the attention and resources they need to succeed.

Furthermore, the integration of smart card technology and mobile devices opens up possibilities for additional functionalities, such as access control, resource allocation, and personalized feedback mechanisms. By harnessing the power of data analytics and machine learning algorithms, educators can gain valuable insights into student behavior and learning preferences, enabling them to tailor educational content and activities accordingly.

Overall, Pavel Zlatarov and his team's research represents a significant contribution to the field of educational technology, offering a practical and innovative solution for attendance tracking in personalized education settings. By leveraging smart card-based systems and smartphone-enabled modules, their proposed system promises to enhance the effectiveness of personalized learning initiatives and improve student outcomes in the digital age.

5. Purvaja Pradip Godbole, Intelligent Systems Powered Hourly Attendance Capturing System, Journal Name; IEEE 7th International Conference on Engineering Technologies and Applied Sciences (ICETAS)

Purvaja Pradip Godbole's paper, "Intelligent Systems Powered Hourly Attendance Capturing System," presented at the IEEE 7th International Conference on Engineering Technologies and Applied Sciences (ICETAS), introduces an innovative solution for attendance tracking. The system proposes leveraging intelligent systems to capture hourly attendance efficiently, replacing traditional methods with a Wi-Fi-based approach.

The paper highlights the limitations of traditional attendance tracking methods, such as manual entry or biometric systems, which can be time-consuming and prone to errors. In response, the proposed system harnesses Wi-Fi technology to automate the attendance capture process, offering several advantages over conventional methods.

One key feature of the system is its ability to track attendance using Wi-Fi signals, eliminating the need for physical check-ins or biometric authentication. By leveraging Wi-Fi access points installed in the workplace or educational institution, the system can detect when employees or students enter or leave the premises, automatically recording their attendance.

Additionally, the system incorporates location tracking capabilities, allowing administrators to monitor employees or students' movements within the premises. This feature enhances security and enables real-time visibility into attendance patterns, facilitating better resource allocation and workforce management.

Moreover, the system ensures data security through secure cloud storage, where attendance records are stored in encrypted format. This mitigates the risk of data loss or unauthorized access, ensuring compliance with privacy regulations and safeguarding sensitive information.

By replacing traditional attendance tracking methods with a Wi-Fi-based system, organizations can streamline HR tasks, reduce administrative overhead, and improve accuracy and efficiency in attendance management. The proposed solution offers a scalable and cost-effective alternative to manual processes, empowering organizations to adapt to changing work environments and enhance productivity.

CHAPTER 3

BACKGROUND AND RELATED WORK

3.1 INTRODUCTION

In this section, we describe the relevant technologies required for the proposed system. We discuss the Posenet architecture (Papandreou et al. 2018) and the Faster R-CNN (Ren et al. 2017) and Mask R-CNN (He et al. 2017) deep learning object detection models and review prior technologies that are similar to the proposed system. We also review the STV-GCN (Tsai and Chen 2021), GCN-NAS (Peng et al. 2020) and 2S-AGCN (Shi et al. 2019) deep learning motion detection systems, which are used in our performance analysis and experimental comparison.

3.2 POSENET SKELETON KEY POINT DETECTION

Our system applies Posenet (Papandreou et al. 2018) detection technology for the key points of the human skeleton, as proposed in a previous study. A total of 17 key points on the skeleton are used to carry out the human action detection and action pose drawing functions. The key point detection method uses a GCN model for training and identification, and a CNN is used to capture the heat- map information for each skeleton key point in the image. The possible positions and a short-range offset feature are used to calculate the heatmap error, and Hough voting is then applied via an integrated voting function to obtain the lowest distortion of the skeleton key points stored in Hough arrays, based on the Hough score. The heatmap process divides the image into a 28 9 28 grid, calculates the probability of key points in each area and accurately cor- rects the coordinates through the use of a short-range off- set. This approach is supplemented by the use of a mid- range offset feature to detect the links between the key points on the skeleton in order to reduce the distortion in the key points and improve the recognition accuracy, as shown in Fig. 1.

3.3 FASTER R-CNN DEEP LEARNING OBJECT DETECTION MODEL

The Faster R-CNN (Ren et al. 2017) deep learning object detection model includes Region Proposal Network (RPN) as the recognition box capture architecture, which gener- ates detection box ranges of different proportions and sizes for different anchors and classifies the content of multiple detection boxes to obtain a detection box with high relia- bility, which is output as the recognition result. As shown in Fig. 2, RPN will be performed to generate region pro- posals after the image has been convolved. Based on the output region, the bounding box will be generated, and then, multiple identification boxes of different sizes will be generated in the middle of the box to obtain the correct identification target. Region of interest pooling is applied to the frame selection target to obtain the identification

result. Faster R-CNN uses parallel processing via the Convolutional Neural Network (CNN) and RPN and combines them to form the object recognition model. For example, the access control system produces the recogni- tion results based on face recognition and face box selection.

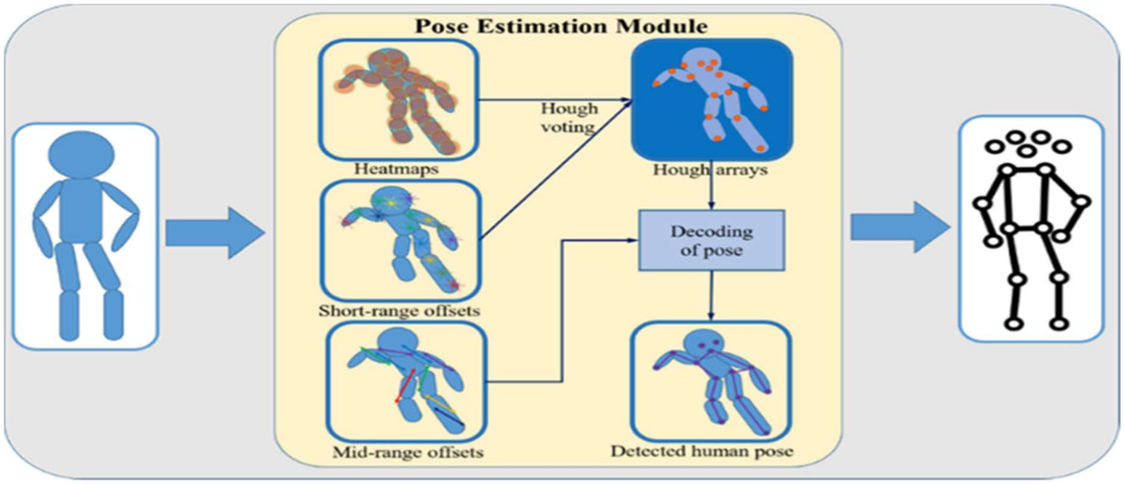

Fig. 1 Pose estimation based on detection of human skeleton key points

3.4 MASK R-CNN DEEP LEARNING OBJECT DETECTION MODEL

Our scheme uses the Mask R-CNN (He et al. 2017) deep learning object detection model proposed in related work to identify the silhouette features of the human body. We use the semantic segmentation technology of the Mask R-CNN deep learning target detection model to obtain information on the silhouette. Our Mask R-CNN deep learning object detection model is based on a traditional Faster R-CNN model and combines the semantic segmentation algorithm with the FCN architecture. The first stage of the model uses a standard CNN to learn the image features; in the second stage, deconvolution feedback is applied to dynamically adjust the learning parameters, and the feature maps that have been classified are interpolated to achieve deconvo- lution learning. The final output of the system is a semantic segmentation map that is classified for each pixel. The use of semantic segmentation to give silhouette information allows us to obtain a silhouette map of the human body, as shown in Fig. 3. For the region of interest, a branch is generated for the segmentation mask. Each branch uses a small fully convolutional network to predict the segmen- tation mask in a pixel-to-pixel manner.

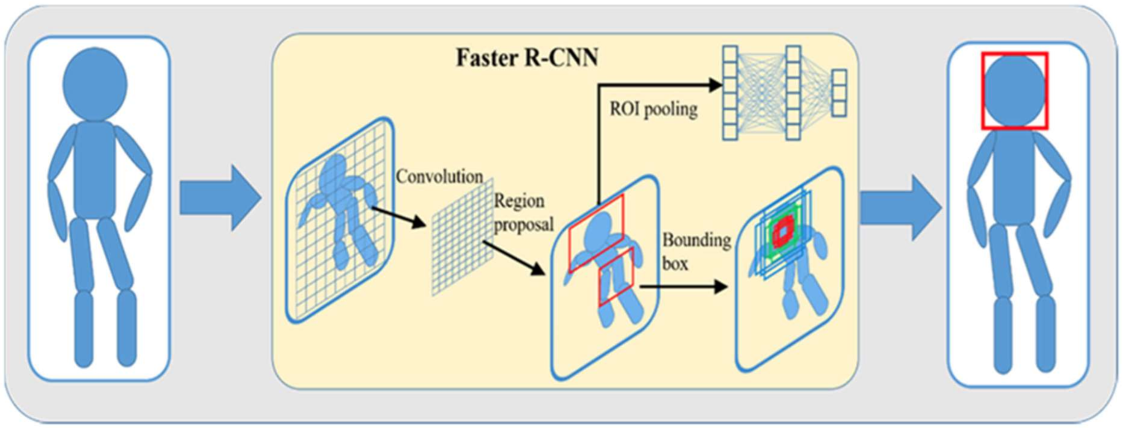

Fig. 2 Facial recognition architecture based on Faster R-CNN

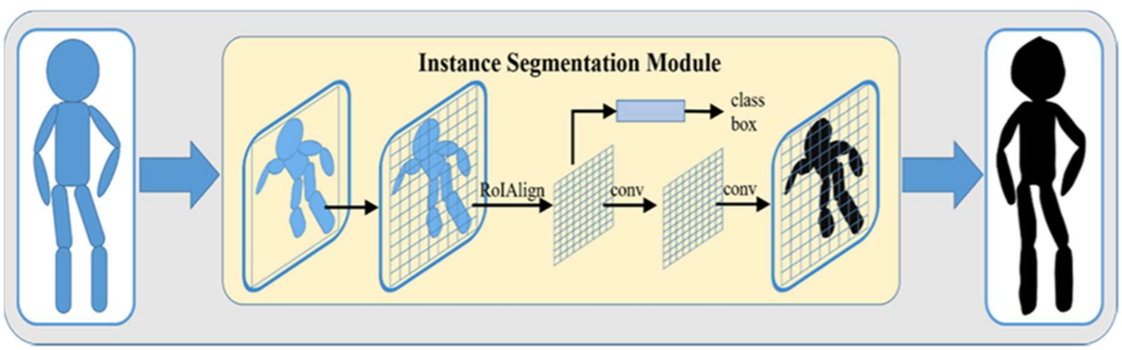

Fig. 3 Silhouette recognition architecture using Mask R-CNN

3.5 STV-GCN DEEP LEARNING ACTION DETECTION SYSTEM

The STV-GCN (Tsai and Chen 2021) deep learning action detection system was developed in a prior study to train and identify human motion recognition models in the form of non-traditional image files. The information used for training and identification by the deep learning motion detection system is the key point features of the human body skeleton. STV-GCN is a human motion recognition system that combines the KNN algorithm with an ST-GCN deep learning motion detection system. The GCN used in the ST-GCN model performs pattern recognition that is not limited to traditional two-dimensional graphs: it can be trained to recognise topological graphs or three-dimen- sional graphs composed of points and lines. The recogni- tion model applies graph convolutional neural network learning to the spatial and temporal changes in the key points of the human skeleton. Its architecture relies on spatial GCN and TCN. The graph convolutional neural network uses nine alternately overlapping spatial and temporal feature extraction layers for computational learning, and a fully connected layer is finally applied to classify the action features of the key points of the human

skeleton. In a prior study, human actions were classified based on different emotions and different speeds of motion, and good recognition accuracy was obtained. Our access control system involves the application of deep learning motion detection technology to the recognition of human gait. That is, the training of the recognition model and identification are carried out based on the spatial and temporal changes in the key points of the skeleton gener- ated by walking and other types of movement. However, the recognition accuracy of the recognition model that the current deep learning motion detection system performs the same motion on different human bodies still needs to be strengthened.

3.6 GCN-NAS DEEP LEARNING ACTION DETECTION SYSTEM

In order to strengthen the recognition performance of the ST-GCN deep learning action detection model, a prior study added a NAS function in the model training stage, with the main aim of optimising the learning network structure. In the search space stage, reinforcement learning was used to find the model with the highest recognition accuracy. Traditional GCN convolution operations all use a stable embedding matrix (a first-order Chebyshev polyno- mial) to control the correlation between the nodes of the topology graph. The developers of GCN-

NAS used multi- order Chebyshev polynomials to generate multiple embedding matrices for convolution operations. The use of a neural architecture search function to find the best solu- tion in the search space stage can avoid long learning and calculation times. It was shown in one study that GCN- NAS (Peng et al. 2020) still exceeded the ST-GCN deep learning motion detection system in terms of the training time of the model. This motion detection model can be applied to identify different types of motion and has achieved good recognition accuracy. However, the recog- nition accuracy of the recognition model that the current deep learning motion detection system performs the same

3.7 2S-AGCN DEEP LEARNING ACTION DETECTION SYSTEM

The 2S-AGCN (Shi et al. 2019) deep learning detection system was developed with the aim of strength- ening the GCN convolution operation weight of ST-GCN. In order to improve the traditional GCN convolution operation, which uses a stable embedding matrix to control the correlation between the nodes of the topology graph, a two-stream convolutional network architecture was devel- oped. One of the streams used three embedding matrices as the weight change of the convolution operation: the first had the original form, the second was used to strengthen the learning of the correlations between nodes, and the last used a Gaussian embedding function to capture the rela- tionships between nodes. These three different embedding matrices were used to perform an integrated calculation, and obtained the convolution operation weights more efficiently. The other stream focused on learning the con- nection relationships between nodes and use motion detection model training input the connections between the topological graph nodes to perform convolution operations, with the final output being the correlation features. The training time for 2S-AGCN in a motion detection model has been shown in prior work to be longer than for GCN- NAS.

This motion detection model can be applied to identify different types of motion and obtains good recognition accuracy. However, the recognition accuracy of the recognition model of the current deep learning action detection system performing the same action on different human bodies still needs to be strengthened. The system proposed in this paper can effectively address the problems identified in the above-mentioned related work.

3.8 HUMAN EMOTION RECOGNITION USING ST-GCN

One study (Tsai and Chen 2022) in the literature proposed an emotional action recognition system in which ST-GCN was applied to the human skeleton to achieve recognition of different emotional actions. However, due to the loss of subtle features caused by the use of convolutional neural network technology in the training process, it is proposed to extract facial action features to further improve the recognition effect. The swing and degree of change in the characteristics of the human face are analysed. As shown in Fig. 4, we record the change in the up-down and left–right swings of the face, capture the continuous changes along the two axes of the face and use the K-nearest neighbours classifier for classification and identification, combining the two identification results to achieve better identifica- tion. However, for the recognition of human walking movements, the scheme in the literature cannot distinguish the subtle differences between different people with the same emotion, resulting in a low recognition ability for gait, and it cannot analyse facial changes when a person is wearing a mask.

3.9 HUMAN ACTION RECOGNITION SYSTEM USING SKELETON POINT CORRECTION

When using a skeleton for human action recognition, a system is often limited by the image shooting angle and visual occlusion, which leads to misjudgement of the key points of human skeleton and affects the accuracy of action recognition. The study in Tsai and Huang (2022) proposed an action recognition system that included key point cor- rection of the human skeleton, and the recognition accu- racy was improved by corrections to the skeleton. A basic correction algorithm is used to correct points based on the symmetry of the human body, as shown on the left of Fig. 5, while an advanced correction algorithm is used to correct keypoints based on the range of the human shield map, as shown on the right of Fig. 5. In view of the problems with skeleton masking, in this paper, we use skeletons from different perspectives for synthesis and obtain the correct continuous changes in the skeleton positions by synthesising the skeleton. Compared with motion on different human bodies still needs strengthened.

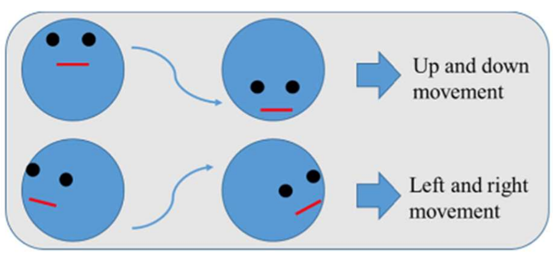

Fig. 4 Schematic diagram of face swing

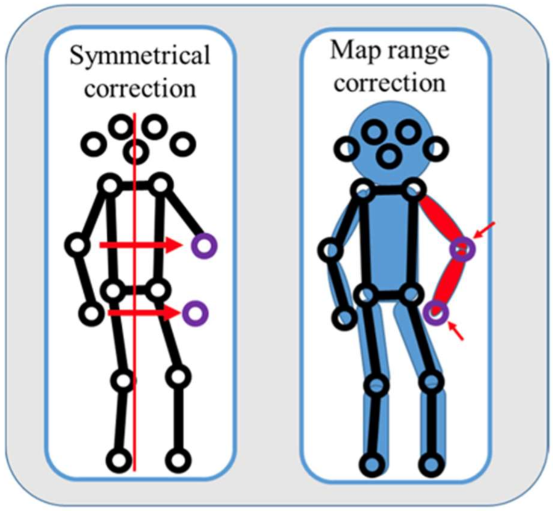

Fig. 5 Schematic diagram of skeleton point correction

prior schemes, we use skeleton features from different perspectives with higher correlation and achieve a better identification effect.

3.10 INTEGRATING MEDIAPIPE FOR LANDMARKS

In this section, we discuss the integration of MediaPipe, an open-source library, for landmark detection in our proposed system. Landmark detection plays a crucial role in various applications, including human action recognition and pose estimation. We utilize the holistic model provided by MediaPipe, which includes face, hand, and pose detection capabilities.

3.10.1 KEY COMPONENTS

Holistic Model: The holistic model combines face, hand, and pose detection into a single pipeline, allowing for simultaneous detection of multiple landmarks in real-time.

Face Connections: Media Pipe provides predefined connections for facial landmarks, allowing for easy visualization and tracking of key points on the face.

Hand Connections: Similarly, predefined connections are available for hand landmarks, enabling accurate tracking of hand gestures and movements.

Pose Connections: Connections for pose landmarks facilitate the detection and tracking of body movements and postures.

Out[18]:

	class	x1	y1	z1	v1	x2	y2	z2	v2	x3	...	z499	v499	x500	y500	z500	v500
0	aakash	0.561317	0.455289	-1.237239	0.999902	0.595445	0.389986	-1.168707	0.999734	0.616828	...	-0.007561	0.0	0.634240	0.409288	0.020139	0.0
1	aakash	0.559927	0.457307	-1.518386	0.999875	0.594320	0.390263	-1.444111	0.999679	0.614261	...	-0.008796	0.0	0.632821	0.405045	0.019261	0.0
2	aakash	0.558857	0.457407	-1.546302	0.999870	0.593095	0.390138	-1.468121	0.999669	0.612246	...	-0.009895	0.0	0.632139	0.403225	0.017700	0.0
3	aakash	0.555815	0.457412	-1.475124	0.999866	0.590974	0.389575	-1.399982	0.999660	0.609453	...	-0.009857	0.0	0.632037	0.404404	0.017994	0.0
4	aakash	0.553668	0.457411	-1.458497	0.999860	0.589467	0.389016	-1.384010	0.999648	0.607657	...	-0.009616	0.0	0.631843	0.404531	0.018260	0.0

5 rows × 2005 columns

In [20]:

```
df[df['class']=='vijay']
```

Out[20]:

	class	x1	y1	z1	v1	x2	y2	z2	v2	x3	...	z499	v499	x500	y500	z500	v500
64	vijay	0.580253	0.450183	-1.232768	0.999879	0.606391	0.381364	-1.156899	0.999703	0.624655	...	-0.003314	0.0	0.641535	0.392122	0.035598	0.0
65	vijay	0.582188	0.451068	-1.449746	0.999855	0.606400	0.381280	-1.370742	0.999650	0.624642	...	-0.001746	0.0	0.649100	0.392292	0.041402	0.0
66	vijay	0.587777	0.448338	-1.391887	0.999840	0.607689	0.377271	-1.310856	0.999620	0.625187	...	0.003041	0.0	0.660845	0.388686	0.052536	0.0
67	vijay	0.591586	0.446461	-1.371051	0.999831	0.608570	0.374734	-1.290210	0.999599	0.625571	...	0.001232	0.0	0.659547	0.388162	0.049237	0.0
68	vijay	0.594716	0.446334	-1.413439	0.999817	0.610290	0.374502	-1.331548	0.999554	0.626734	...	0.002553	0.0	0.663695	0.385518	0.052308	0.0
69	vijay	0.601622	0.446246	-1.438620	0.999799	0.613601	0.374305	-1.357344	0.999502	0.628974	...	0.002928	0.0	0.664063	0.386405	0.052923	0.0
70	vijay	0.604095	0.445750	-1.442902	0.999784	0.614946	0.373684	-1.361735	0.999456	0.629883	...	0.003185	0.0	0.664131	0.385960	0.053727	0.0
71	vijay	0.603601	0.444225	-1.418541	0.999782	0.614904	0.372495	-1.338439	0.999446	0.629786	...	0.004012	0.0	0.667276	0.382891	0.054397	0.0
72	vijay	0.618015	0.438802	-1.407272	0.999761	0.622857	0.366599	-1.327021	0.999386	0.636228	...	0.000428	0.0	0.669831	0.381820	0.050742	0.0
73	vijay	0.620531	0.436873	-1.406369	0.999740	0.624731	0.364161	-1.325835	0.999330	0.637936	...	0.002421	0.0	0.668862	0.380971	0.053545	0.0
74	vijay	0.621294	0.435129	-1.408801	0.999720	0.625651	0.362090	-1.328105	0.999274	0.638865	...	0.002614	0.0	0.669103	0.381050	0.054334	0.0
75	vijay	0.622147	0.432788	-1.400619	0.999704	0.625949	0.359127	-1.319894	0.999226	0.639183	...	0.002499	0.0	0.669803	0.381766	0.054075	0.0
76	vijay	0.621622	0.431734	-1.367081	0.999708	0.625851	0.357992	-1.286659	0.999236	0.639161	...	0.002209	0.0	0.668838	0.380054	0.053220	0.0
77	vijay	0.621594	0.430633	-1.392944	0.999704	0.625941	0.356789	-1.309705	0.999218	0.639257	...	0.001438	0.0	0.669789	0.380782	0.051951	0.0
78	vijay	0.622405	0.429857	-1.399493	0.999699	0.626397	0.355861	-1.316167	0.999199	0.639640	...	0.001573	0.0	0.669413	0.381783	0.051829	0.0

```
In [21]: X = df.drop('class', axis=1) # features
         y = df['class'] # target value

In [22]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1234)

In [23]: y_test

Out[23]: 93      vijay
         72      vijay
         82      vijay
         64      vijay
         63     aakash
         55     aakash
         39     aakash
         32     aakash
         103     vijay
         68      vijay
         40     aakash
         42     aakash
```

3.10.2 IMPLEMENTAION

To integrate MediaPipe into our system, we initialize the holistic model and configure it with appropriate parameters for detection confidence and tracking reliability. We then capture video frames from the webcam using OpenCV and feed them into the holistic model for processing. After obtaining the detection results, we visualize the detected landmarks on the video feed using OpenCV's drawing functions.

CHAPTER 4

SPATIO-TEMPORAL HUMAN ACTION RECOGNITION IN AN INTELLIGENT ATTENDANCE MONITORING SYSTEM

4.1 INTRODUCTION

We propose an intelligent attendance monitoring system that combines continuous human gait features with sil- houette feature recognition technology to perform plural recognition model voting. We also use multiple cameras for multi-directional continuous image capture to avoid problems associated with the angle of view and body occlusion, to improve the overall recognition accuracy. In this section, we describe the system architecture, the data collection process, the training of the recognition model and the overall process of the proposed system.

4.2 SYSTEM ARCHITECTURE

In view of the fact that training of our human movement recognition model and identification of a specific person is based on gait and silhouette features, the image frame of the human body movement process must reduce the problems related to viewing angle and body occlusion. Our system uses multiple cameras to capture image frames representing the motion of the human body. We use real-time images captured by multiple cameras to position the human body, to ensure that a specific person is located in the correct recognition area. The images captured by multiple cameras are also used to draw the key points of the human skeleton and to synthesise the gait or action based on these key points. We can use a dual camera as an example. This system captures dynamic images of the user while walking: the left camera captures dynamic images of the left side of the face and body, while the right camera captures images of the right side. The skeleton key points in the left body image are combined with those in the images of the right side, and the system identifies the key points of the synthesised skeleton to carry out motion recognition for a specific person. The motion recognition process can be divided into the following three main actions:

The system performs specific identification of human body gait features, uses the Posenet human body skeleton key point detection model to obtain the skeleton key point information from each image and calculates the continuous angle and distance changes based on the key point information from the continuous image. This information is used as an identification feature for the time-sequenced gait of a specific person and to carry out classification training of the KNN recognition model and identification with weighted parameters.

The system recognises a specific person based on the silhouette features of the human body and uses the continuous changes in the angles of the skeleton key points to determine the periodicity of the gait of the person. Multiple time points of the same angle are used as the basis of sampling for a time-sequenced gait. The Mask R-CNN deep learning object detection model is used to generate time-sequenced multiple silhouette feature information and then to perform classification training of the KNN recognition models and identifica- tion of the silhouette features. Finally, the identification results from the multiple KNN recognition models are submitted to a voting process to determine the predic- tion results for a specific person.

The system recognises a specific person based on the symmetry features of the human face and carries out face recognition from the face images captured by the multiple cameras. It then confirms that the angle and position state of the face recognition result conform to the principle of the left–right symmetry characteristic of the human face. The Haar facial feature cascade classifier is applied to determine whether a human face exists, and this stage uses a Faster R-CNN deep learning object detection model as the network archi- tecture. In future work, this module will be replaced by a new network architecture or deep learning object detection model with higher recognition accuracy and will be supplemented by the use of continuous human gait and silhouette feature recognition technology for specific actions to obtain the final recognition result.

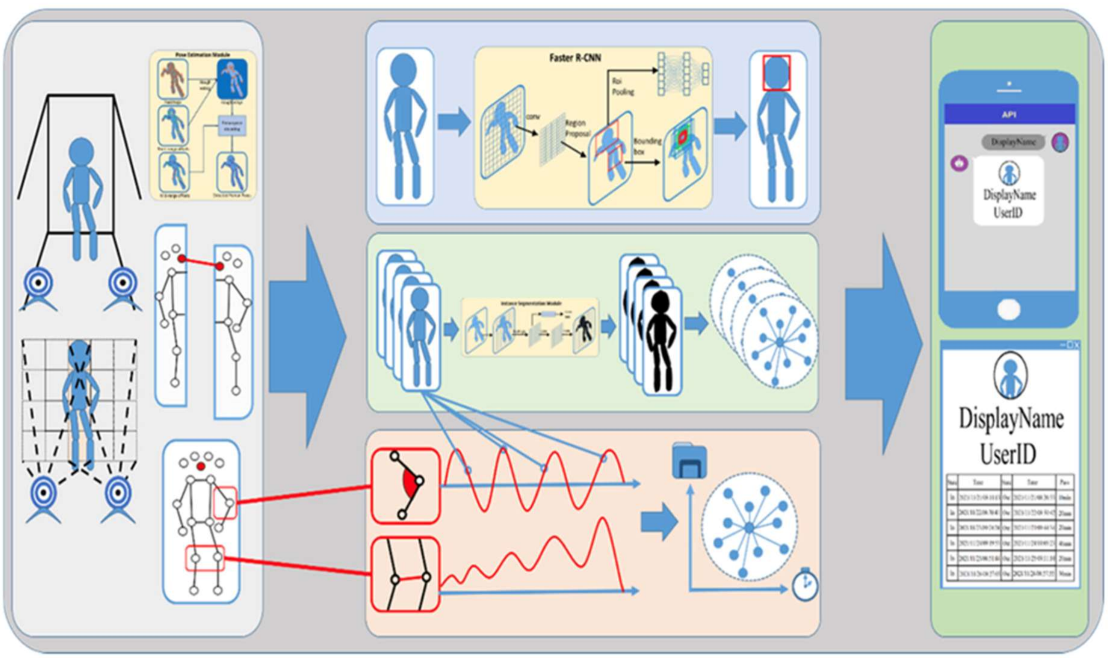

Fig. 6 Overview of the architecture of the proposed system

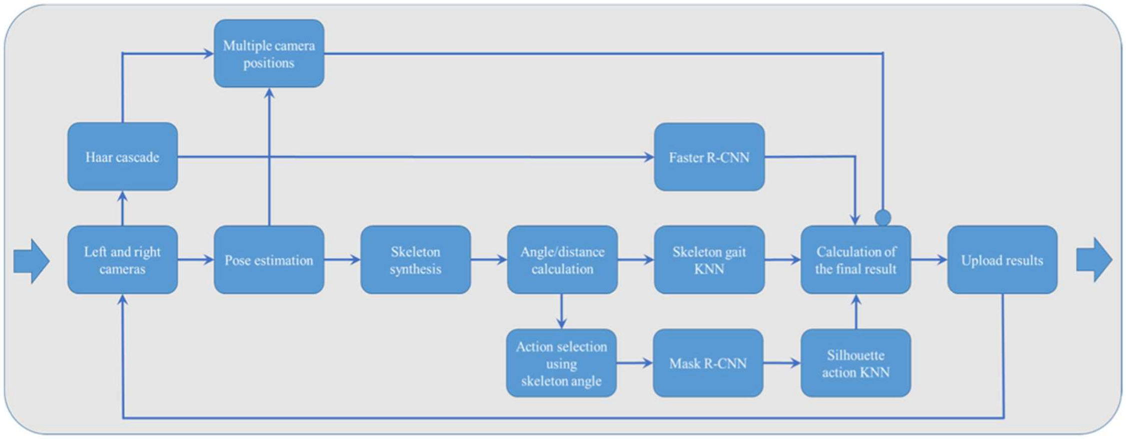

Fig. 7 Flowchart for the proposed system

The proposed intelligent attendance monitoring system uses the above-mentioned three types of recognition pro- cess to identify a specific person based on their actions, and will then allow them to enter the monitored area. The system can perform access control system management actions when a specific person has been successfully identified. A LINE messaging API is used to notify specific personnel that they have clocked in or out of work, and a responsive web platform can display historical information related to attendance or absence, as shown in Fig. 6.

A flowchart for the proposed intelligent attendance monitoring system is shown in Fig. 7. A flowchart is given

and supplemented with pseudocode (number of lines). First, left and right cameras (1) capture left and right videos of people walking. Pose estimation (4) and a Haar cascade (5) are then used to identify and generate skeleton and face data representing human actions. We calculate the multiple camera positions (6) from the two pieces of data, measure the distance and map the pixels of the video in equal proportions, and judge the position based on the coordinate pixels of the data. We then use skeleton synthesis (16) to create the coordinates of the left and right skeletons. At the angle/distance calculation stage (22), we calculate the angle and distance of the skeleton by using three-point

coordinates to calculate the angle (23) and two-point coordinates to calculate the distance (32). We perform action selection using the skeleton angle (40) according to the skeleton angle data, mainly bend the left and right elbows by 150–170° and then input the selected action into a Mask R-CNN (55) to obtain the silhouette. We use the skeleton gait KNN (57) to identify the angle distance data and the silhouette action KNN (62) to identify silhouette data. Faster R-CNN (72) is applied to identify the face data, and we then calculate the final results (73) and upload them (74).

When the position of the person is outside the maximum range for image capture, no motion processing will be performed. When the position is between the maximum and minimum ranges for image capture, the system will recognise the skeleton key points and convert them into angle and distance data. The silhouette information is also recognised and processed based on the angle information. When the person's position is below the minimum range for image capture, calculation of the skeleton key points and silhouette recognition are stopped in order to perform face recognition processing. Based on the above-mentioned gait and silhouette features and face recognition technol- ogy, information fusion is performed to give the recogni- tion result, as shown in Fig. 8.

4.3 SENSING AND POSITIONING USING MULTIPLE CAMERAS

Image capture with a single camera is likely to cause problems associated with the viewing angle and body occlusion, and we can illustrate this by taking as an example the Posenet skeleton key point detection model, which is used to obtain the key point information on the skeleton in each image. Continuous walking behaviour will cause the body to swing, with the front half of the body covering the back half, meaning that the key points of the skeleton cannot be identified and leading to a misjudgement.

The design of the system relies on two cameras to capture images from multiple angles. The left and right facial dynamic images captured by the two cameras are used for face recognition, to confirm that the angle and position of the face recognition results match the principle of left–right symmetry for a human face. The system applies the Posenet skeleton key point detection model to the continuous images captured by the two cameras to obtain the key point information of the human body skeleton. The information on the position of the face is used to synthesise the skeleton key points from the con- tinuous images on both sides, to avoid problems arising from the viewing angle and body occlusion and the feature point information that strengthens the recognition of

human action state, as shown in Fig. 9. The image captured by the left camera locates the position of the face in the image, such as the upper right quarter, while the image captured by the right camera locates the position of the face in the image, such as the upper left quarter. The position of the face on the actual level is determined by combining the positions of the left and right faces to locate the test subject.

4.4 GAIT AND CONTOUR CHARACTERISTICS

The Posenet skeleton key point detection model is used to obtain the key point information from each image, and the key points of the ears, eyes and nose are used as positioning reference points for the synthesis location of the key points of the continuous human skeleton. The key points of the left and right shoulders, left and right elbows, left and right wrists, left and right arms, left and right knees and left and right ankles are synthesised with the key points of the left and right skeleton to recognise an action by a specific person, as shown in Fig. 10.

The system calculates the changes in the continuous angles and distances based on the synthesised skeleton key point information. The angle information refers to the angles formed between the key points of the skeleton and the joints. The change in the angle of the skeleton key points is used as the basis for calculating the continuous change in an action by a specific person. For example, the key points of the left and right shoulders, elbows and wrists of the human body can be used to generate eight sets of angle information. The distance information relates to the relative change in distance between the left and right joints of the skeleton. The changes in distance between the key points of the continuous skeleton are used to calculate the change in walking frequency of a specific person. For example, the key points of the left and right elbows and wrists of the human body can be used to generate four sets of distance information. The system is supplemented by the recognition of body silhouette features, in order to improve the accuracy of action recognition for a specific person. The system uses the continuous changes in angle as a basis for judging the periodic actions of the gait and takes the plural same angle time points for completing a time sequential gait action as the sampling basis. At the same time, the time-sequenced changes in the gait are used to classify training and identify using a multiple recognition model, and the movement far and near zooming of human action must be considered to normalise the images captured by the cameras. The system therefore uses the changes in the distances between the key points of the skeleton as the basis for normalisation of the image. A Mask R-CNN deep learning object detection model is used to generate time- sequenced multiple human silhouette feature information

Fig. 8 Pseudocode for the proposed algorithm

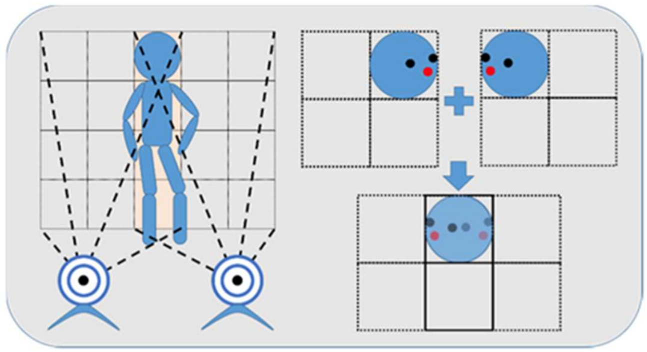

Fig. 9 Sensing and positioning using multiple cameras

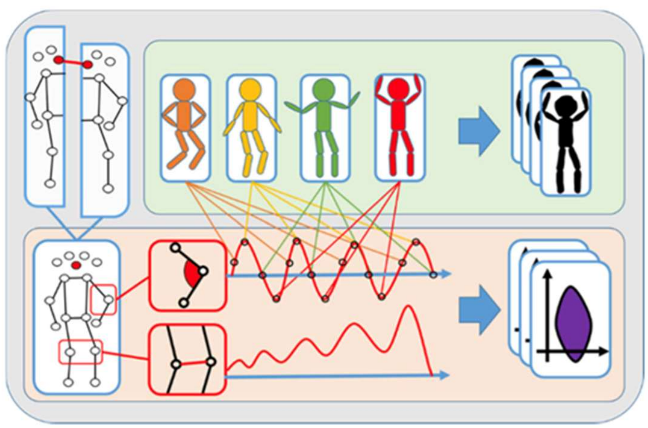

Fig. 10 Synthesis of the key points of the skeleton

and then to perform time-sequenced multiple KNN recognition model classification training and identify for multiple human silhouette. Finally, multiple KNN algo- rithms are used to identify the results of the recognition model and to vote on the final prediction result. The lower part of Fig. 10 shows how the timing changes of the joint angles are calculated, and how the action pictures are captured at different time points. The top part of Fig. 10 shows how a Mask R-CNN is used to generate the action silhouette data from the action pictures. The action sil- houette data at similar time points are collected together and used for KNN image recognition. A KNN identifica- tion model is generated at each time point. The final con- tinuous action silhouette identification result can be

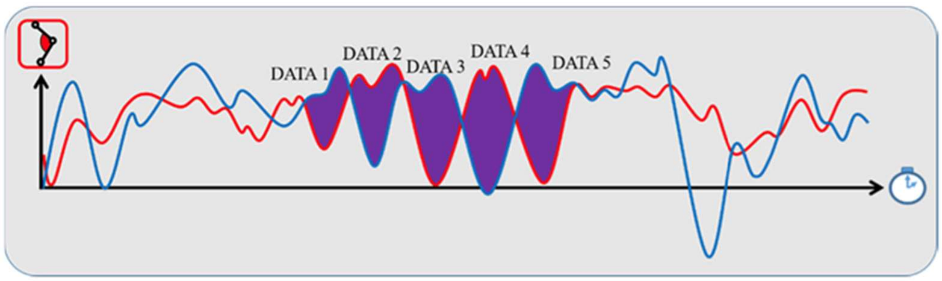

Fig. 11 Fixed cyclic sine wave

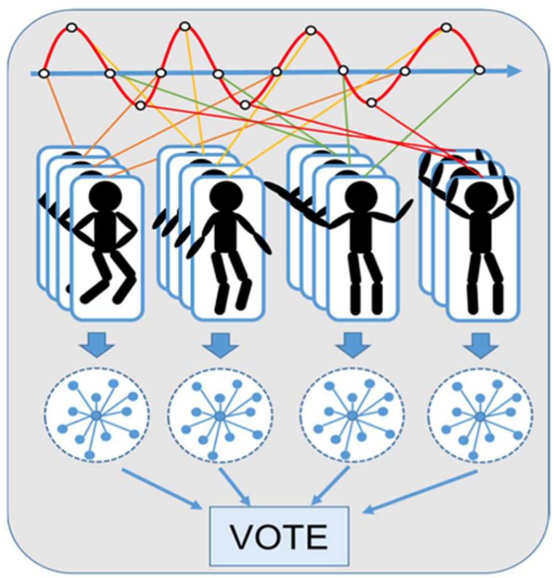

Fig. 12 Action silhouette training process

obtained by voting on the identification results from all the KNN identification models.

CHAPTER 5
DATA PREPROCESSING

5.1 INTRODUCTION

Data preprocessing, annotation, and embedding are essential steps in the pipeline of machine learning and computer vision tasks, particularly in domains like image recognition and natural language processing. These processes play a crucial role in preparing raw data, enhancing its quality and extracting meaningful representations to facilitate effective model training and analysis.

5.1.1 REQUIREMENTS FOR BINARY CLASSIFICATION

Logistic regression is a binary classifier, meaning it separates data into two categories or classes. To perform meaningful classification, there must be at least two distinct classes present in the dataset. If there's only one class, logistic regression cannot differentiate between different outcomes, rendering it ineffective for classification tasks.

5.1.2 EARLY DETECTION OF ISSUES

Checking the number of unique classes in the training data helps identify potential problems early in the modeling process. If there's only one class present, it indicates issues such as data imbalance, labeling errors, or incomplete data collection. Addressing these issues at the outset ensures that subsequent modeling efforts are based on reliable and representative data.

5.1.3 ENSURING MODEL APPLICABILITY

Logistic regression assumes a binary outcome variable, making it suitable for problems where the response variable has two possible states. By verifying the presence of multiple classes, practitioners can confirm the suitability of logistic regression for the task at hand. If only one class is present, alternative modeling approaches may need to be considered.

5.1.4 DIVERSITY OF CLASSES

The presence of multiple classes ensures that the logistic regression model can learn meaningful relationships between input features and target labels. A diverse dataset with multiple classes provides the necessary variability for the model to generalize well to unseen data. Without this diversity, the model may overfit to the available data or fail to capture the complexity of the underlying classification problem.

5.1.5 ADDRESSING IMBALANCE AND ERROR

Single-class data may indicate imbalanced class distributions or labeling errors, which can adversely affect model performance. Imbalanced data can bias the model towards the majority class, leading to poor predictive performance on minority classes. By detecting and addressing class imbalances or labeling errors early on, practitioners can take corrective measures such as data augmentation, resampling techniques, or model adjustments to mitigate these issues.

```
Number of unique classes: 2
Unique classes: ['aakash' 'vijay']
Consider whether logistic regression is the appropriate model for your task.
Debugging:
  - Double-check data loading and preprocessing steps.
  - Verify label assignment and data splitting.
  - Ensure that the data is correctly formatted and labeled.
Class counts: {'aakash': 45, 'vijay': 31}
Imbalance ratio: 1.4516129032258065

In [27]: fit_models = {}
         for algo, pipeline in pipelines.items():
             model = pipeline.fit(X_train, y_train)
             fit_models[algo] = model

In [28]: fit_models

Out[28]: {'lr': Pipeline(steps=[('standardscaler', StandardScaler()),
                         ('logisticregression', LogisticRegression())]),
          'rc': Pipeline(steps=[('standardscaler', StandardScaler()),
                         ('ridgeclassifier', RidgeClassifier())]),
          'rf': Pipeline(steps=[('standardscaler', StandardScaler()),
                         ('randomforestclassifier', RandomForestClassifier())]),
          'gb': Pipeline(steps=[('standardscaler', StandardScaler()),
                         ('gradientboostingclassifier', GradientBoostingClassifier())])}

In [29]: fit_models['rc'].predict(X_test)

Out[29]: array(['vijay', 'vijay', 'vijay', 'vijay', 'aakash', 'aakash', 'aakash',
                'aakash', 'vijay', 'vijay', 'aakash', 'aakash', 'vijay', 'aakash',
                'vijay', 'vijay', 'vijay', 'vijay', 'aakash', 'vijay', 'aakash',
                'aakash', 'aakash', 'aakash', 'aakash', 'aakash', 'aakash',
                'aakash', 'vijay', 'aakash', 'vijay', 'aakash', 'aakash'],
               dtype='<U6')
```

5.2 DATA PREPROCESSING:

The system uses eight sets of angle information, based on the key points of the left and right shoulders, elbows and wrists of the human body, and four sets of distance infor- mation based on the key points of the left and right elbows and wrists, as data for preprocessing. Angle–time and distance–time relationship diagrams of the above infor- mation show that the human walking gait takes the form of a sine wave with a fixed cycle and maintains a certain degree of symmetry between the left and right sides. The system therefore uses a single period of this sine wave as the gait feature. When the key points of the right and left hands of the human body are at a particular angle, these become the starting point of a single cycle, and when they return to the same angle, this indicates the end of the cycle. As a piece of human gait feature data. In order to avoid misjudging the key points of the skeleton due to noise, Gaussian filtering is applied to remove the noise from the preprocessed data. For each human body, gait feature data to classification and judgment are performed to filter the incomplete, off-peak and irregular feature data for a second time. The system finally obtains human gait feature data in the form of eight sets of continuous angle changes and four sets of continuous distance change information.

The above-mentioned gait feature data include contin- uous time changes that are equivalent to the walking speed, as shown in Fig. 11. The X axis shows the joint angle, the Y axis represents time, and the blue line indicates the continuous changes in the joint angle of the left skeleton, while the red line shows the continuous changes in the joint angle of the right skeleton. The joint angle gait data from the starting points of the left and right skeleton joint angles being the same to the next time the left and right skeleton joint angles are the same as the end point. The purple block shows the gait data after filtering. A complete walk con- tains four to six sets of gait data, and the figure shows the process for five sets of data.

5.3 ACTION SILHOUETTE AND FACE RECOGNITION

Our system uses the KNN algorithm to train the network to identify the body motion of a specific person. The recog- nition model distributes the feature data on the feature plane, calculates the closest K data feature classification results of the feature data to be measured and uses a majority decision method to obtain the final classification. The recognition model described above is used to classify the gait and body silhouette features. The system includes angle and distance features in the training of the gait recognition model and adds time-sequenced weight changes

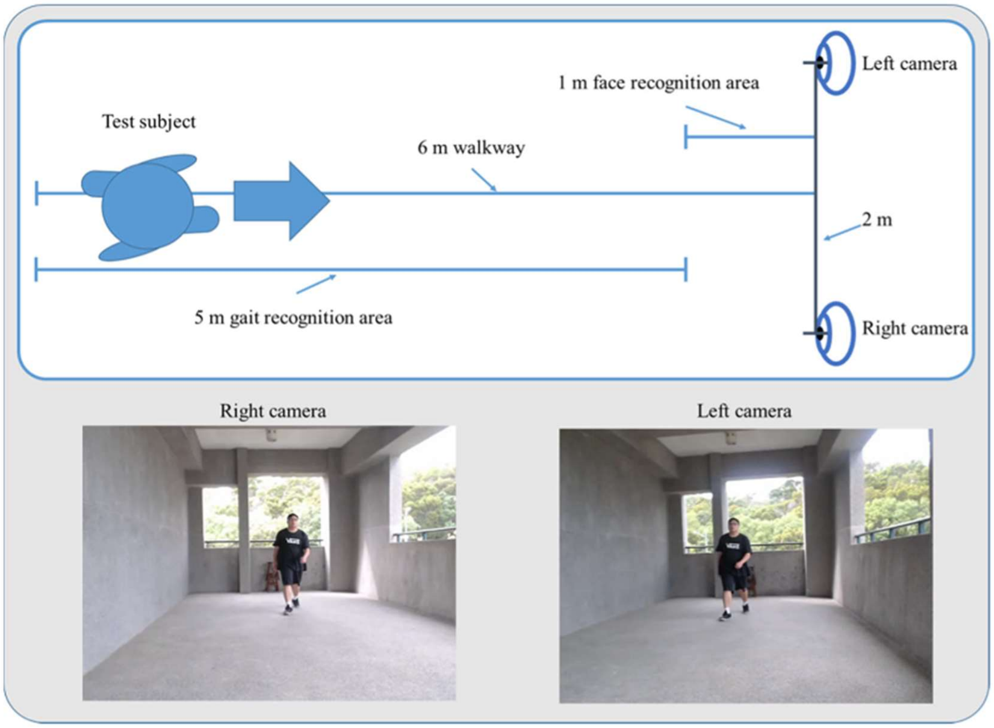

Fig. 13 Diagram showing the experimental setup and example images from the two cameras

That is to say, weights are set in sequence for the time of human silhouette gait actions to strengthen feature learning and improve recognition accuracy. The system is designed to recognise the body silhouette features and uses multiple sequential KNN recognition models for classifi- cation training and identification. It uses a single cycle of a continuous silhouette gait action to sample multiple points at the same angle over time, and the KNN recognition model is applied for classification training and identifica- tion based on the silhouette features of each human body at the same angle. The system therefore generates a classifier based on multiple-KNN recognition model, and then adds the gait sequence to generate the weight settings, in order to strengthen the feature learning and improve the recog- nition accuracy. Finally, the recognition results of the multiple-KNN recognition model are subjected to a vote, to give the final prediction result in terms of identifying a specific person.

As illustrated in Fig. 12, the silhouette features of the test subject are extracted at different time points, and the silhouette features at the same feature time points are put together for KNN training and identification. At each time point, a set of KNN silhouette identification models is generated, and the identification results from all KNN identification models are voted on to give the continuous silhouette identification results for the complete walking gait. The system design combines the face recognition method of a traditional intelligent attendance monitoring system with Haar features, which are used in image pro- cessing and recognition technology, to extract non-specific

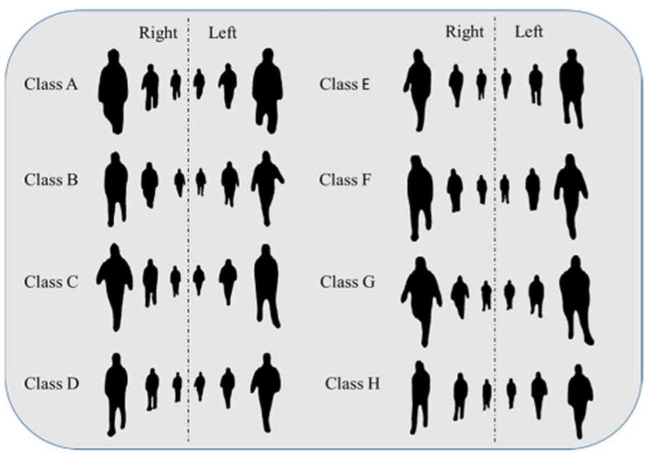

Fig. 14 Images from the dataset

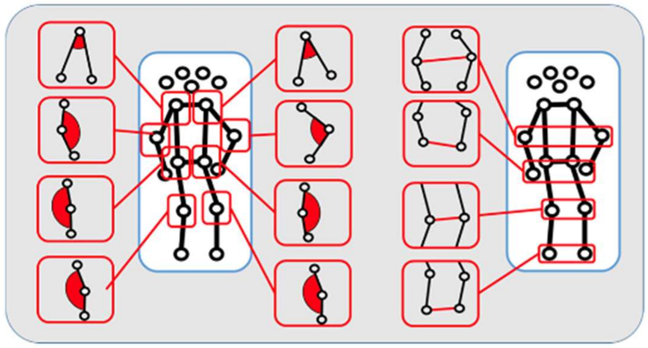

Fig. 15 Data collection for the gait recognition system

features of human faces, where the range is obtained using a cascade classifier. The system also uses the Faster R-CNN deep learning object detection model, as used in deep learning recognition, to perform specific face recog- nition for the above non-specific human face range. In future work, this part of the model will be replaced by a new network architecture or a deep learning object detec- tion model with higher recognition accuracy. The system

Table 1 Accuracy of the proposed gait and action silhouette recognition system

Accuracy of all data			
Distance data	Angle data	Combined data	Final accuracy
Skeleton recognition			
73.42%	79.83%	83.33%	83.33%

Left hand 150° data	Left hand 160° data	Left hand 170° data	Right hand 150° data	Right hand 160° data	Right hand 170° data	Final accuracy
Silhouette recognition						
61.79%	63.98%	65.98%	63.50%	63.79%	67.65%	72.38%

can therefore prevent problems such as the use of a 3D face mask to fake an identity and the reduction in accuracy due to a mask covering a face. The recognition system is supplemented by the use of continuous silhouette gait features for specific actions and the body silhouette fea- tures, meaning that the final results will have higher accuracy in terms of the recognition of a specific person.

5.4 INTELLIGENT ATTENDANCE MONITORING SYSTEM

This paper proposes an intelligent attendance monitoring system, based on temporal and spatial face (static) and motion (dynamic) recognition. It uses the LINE messaging API as the communication medium between system administrators and employees. When the system success- fully recognises a specific person entering or exiting the monitored area, it will use the human–computer interaction API to notify the person of the check-in, via a confirmation message for commuting. At the same time, the user can also communicate with the management system via the human–computer interaction API and can carry out actions such as adding and deleting users, uploading images for face recognition training and viewing attendance manage- ment information. The intelligent attendance monitoring system is built using an Apache Web Server and a MySQL database and provides a background management web interface that allows administrators to control related information such as the user LINE display name, API transmission ID, user avatar, images for face recognition training and work records.

CHAPTER 6

EXPERIMENTAL RESULTS

6.1 INTRODUCTION

In this chapter, we describe the experimental environment and parameter settings, and analyse the experimental per- formance in comparison with three alternative deep learning motion detection systems: ST-GCN, GCN-NAS and 2S-AGCN.

6.2 EXPERIMENTAL ENVIRONMENT AND PARAMETER SETTINGS

We use a dual camera system based on Logitech C925e webcams as the image sensing devices, and the system is implemented in Python development software in the Ana- conda environment. We use TensorFlow, an open-source software library developed by Google, as a deep learning runtime package. The Posenet skeleton key point detection architecture, the Faster R-CNN deep learning object detection model and the Mask R-CNN deep learning object detection model all use the TensorFlow package. The KNN algorithm recognition model is based on the Scikit-learn

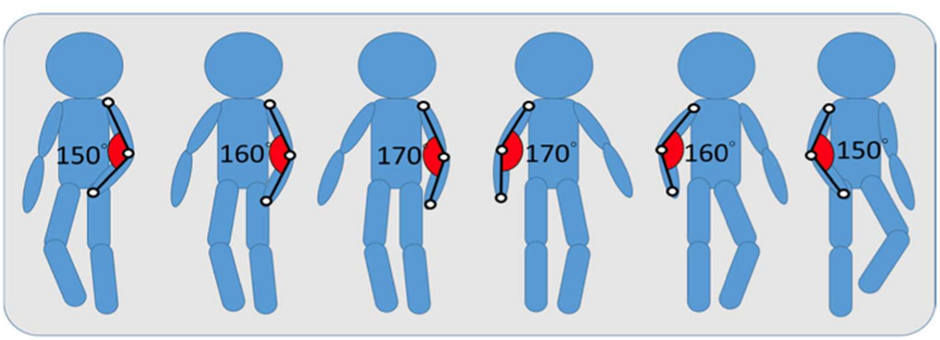

Fig. 16 Data collection for the action silhouette recognition system

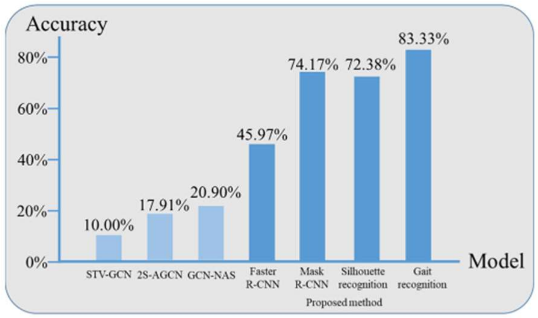

Fig. 17 Identification accuracy for specific people under various conditions

open-source machine learning software library, which is used as a training package, and the access control human– computer interaction API relies on the messaging API officially provided by the LINE developers to communi- cate with users. The intelligent attendance monitoring system platform uses an Apache Web Server and a MySQL database system.

As shown in Fig. 13, the spatiotemporal human action recognition training system used two cameras that were set up on a six-metre-long walkway. The test subjects con- sisted of seven people, who walked from a distance of six metres from the dual camera setup to one metre away. This gave a total walking distance of five metres for each test subject, which was used as a training sample. Each subject walked this distance 350 times, giving 1292 gait features and 14,536 body silhouette data points. Figure 14 shows walking data for a total of eight people from the left and right cameras. The left and right silhouettes of testers who are6 m,3.5 mand1 mawayfromthecameraareusedasa demonstration.

6.3 PERFORMANCE RESULTS

In this section, we analyse the recognition accuracy of our gait feature recognition system. This experiment used a total of 1292 gait features generated from seven people. The gait features included the angle and distance

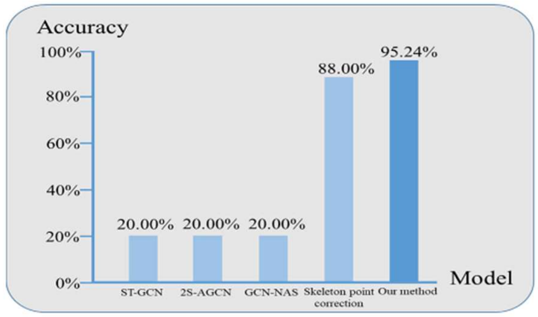

Fig. 18 Action recognition accuracy of our model and alternative schemes based on skeleton key point information

information, as shown in Fig. 15. The angle data for the skeleton were based on eight sets of key points: the left and right shoulders, the left and right elbows, the left and right hips, and the left and right knees. The distance data for the skeleton were based on four sets of key points: the left and right elbows, the left and right wrists, the left and right knees, and the left and right ankles. The angles and distances between the pairs of key points of the skeleton were used as the feature recognition data, and the KNN algo- rithm was used for training of the recognition model and identification based on the spatio-temporal weight characteristics.

As shown in Table 1, the experimental results show that the recognition accuracy is 73.42% when the distances between the key points of the skeleton are used as features, and the recognition accuracy is 79.83% when the angles between the key points of the skeleton are used as features. The overall recognition accuracy of the system when both the angles and the distances are used as recognition features is 83.33%. Finally, for recognition situations where the subject is wearing a mask and a jacket, our skeleton synthesis gait recognition system has a recognition accu- racy of 83.33%.

We now analyse the recognition accuracy of the action feature recognition system. The experiment used a total of 14,536 human silhouette feature data points drawn from seven people, and the recognition results from the multiple-

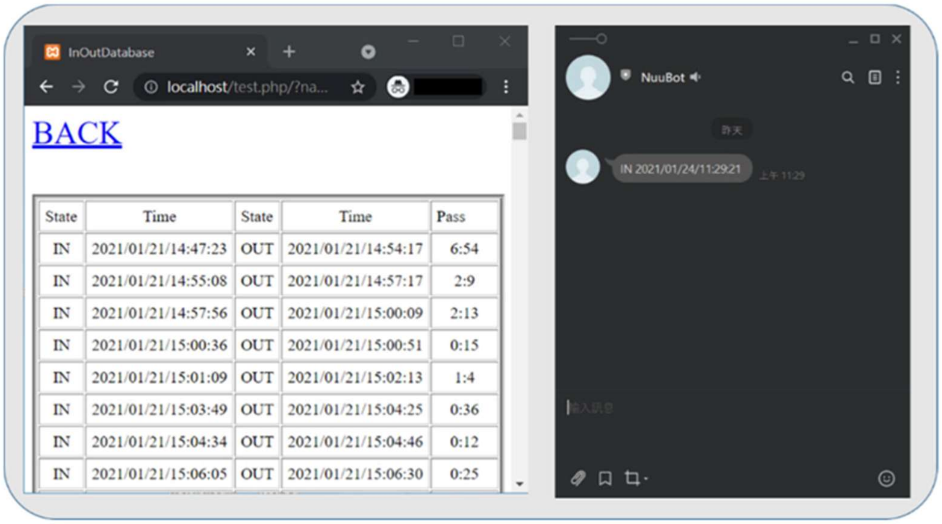

Fig. 19 Access control notification in our intelligent attendance monitoring system

KNN recognition model were subjected to a voting process to generate the final prediction results in terms of identi- fying specific people. The action feature information was based on the angles between the key points of the skeleton as the basis for classification, as shown in Fig. 16. Six actions were identified: the left hand bending forward by 150, 160 and 170°, and the right hand bending forward by 150, 160 and 170°. The systems are, respectively, multiple KNN recognition model is trained based on the above six actions. As shown in Table 1, the experimental results show that the values of the recognition accuracy for the multiple-KNN recognition model were 61.79, 63.98, 65.98, 63.50, 63.79 and 67.65%, respectively, for these six actions. An additional 20 untrained human gait sample data points were used to vote to generate the final results of the multiple-KNN recognition model in terms of predicting specific persons. A total of 1469 silhouette feature data points were generated through information processing, and based on these, the system was able to predict and recog- nise specific individuals with a recognition accuracy of 72.38% when each one was wearing a mask and jacket.

We now analyse the performance of our model in comparison to similar action recognition schemes based on the key point information of the human skeleton. The state- of-the-art STV-GCN, GCN-NAS and 2S-AGCN systems use continuous key point information of the human skele- ton as training data for the action recognition model. In this experiment, we used gait data samples from 20 people wearing masks and jackets to train our action recognition model based on the Posenet skeleton key point detection framework and trained the action recognition model for 5000 epochs. We obtained values for the recognition accuracy of 10% for STV-GCN, 17.91% for 2S-AGCN and 20.9% for GCN-NAS as shown in Fig. 17. Our approach uses a Faster R-CNN deep learning object detection model as the basic face recognition function, for which the

recognition accuracy will be reduced when a mask is worn over the face. The face recognition part of our intelligent attendance monitoring system has a recognition accuracy of 45.97% and an average confidence level of only 0.0441 when a mask is worn. When the Mask R-CNN deep learning object detection model is used in the face recog- nition function, its recognition accuracy when a specific person is wearing a mask is 74.17%. Based on these experimental results, it can be seen that the Faster R-CNN and Mask R-CNN deep learning target detection models cannot deal with a situation in which a person is wearing a mask, as this leads to a decrease in the recognition accu- racy. In our system, the silhouette feature recognition system has a recognition accuracy of only 72.38% when the subject is wearing a jacket. Therefore, the continuous gait features of specific actions and a body silhouette fea- ture recognition model are integrated to create a multiple recognition model, which uses voting to generate the final recognition result. Our intelligent attendance monitoring system is able to carry out gait feature recognition when a specific person is wearing a mask and jacket, and its recognition accuracy is 83.33%. The main reason for this is that the STV-GCN, GCN-NAS and 2S-AGCN deep learning recognition model systems have a high level of recognition accuracy for different human actions, but do not give good recognition accuracy for the same actions carried out by different people. Through the use of multi- view features, our scheme not only avoids the problem of occlusion caused by actions, but also has the effect of feature amplification, and thus a higher recognition accuracy.

We now compare the performance of our model to similar action recognition schemes based on the key point information of the human skeleton. As shown in Fig. 18, the related work provides a database of action recognition, which includes the action data on the human body during a golf swing. Using the feature extraction technology pre- sented in this article, a total of 135 pieces of motion data were captured. The proposed KNN human skeleton gait recognition system with temporal weights was used for training, and an accuracy rate of 93% was obtained. The limitations on the features used in the alternative scheme results in an accuracy of only 88%, which is about 5% lower than the skeleton merge feature zoom proposed in this paper. Traditional skeleton recognition technologies such as ST-GCN, GCN-NAS and 2S-AGCN have a recognition accuracy of only 20% and cannot handle the problem of skeleton occlusion at all, resulting in very low recognition performance. Our system offers access control based on the identification results of the specific person in the monitored area, and uses the LINE messaging API to send attendance-related information messages to specific personnel, as shown in Fig. 19. At the same time, the system saves attendance-related information to a cloud database and the responsive web platform to allow man- agers to track the footprints of specific personnel and monitor changes in personnel flow.

CHAPTER 7
CLASSIFICATION AND MODEL SELECTION

7.1 INTRODUCTION

After embedding using FaceNet, classifiers are used to classify or recognize faces based on the embeddings. FaceNet extracts facial features and represents them as high-dimensional vectors in a continuous space. However, these embeddings alone may not provide sufficient information for classification tasks. Classifiers are employed to learn patterns in the embeddings and make predictions about the identity or attributes of the faces. Essentially, classifiers help to map the embeddings to specific identities or classes, enabling tasks such as face recognition, verification or classification.

7.2 MODEL SELECTION

Model selection refers to the process of choosing the best machine learning model or algorithm for a particular problem or dataset. It involves evaluating multiple models with different configurations or hyperparameters and selecting the one that performs best according to certain criteria, such as accuracy, precision, recalled or other relevant metrics.

7.3 SELECT POTENTIAL MODELS

Choose a set of machine learning models that are suitable for the problem at hand. This might include algorithms such as KNN, random forests, support vector machines, etc.

7.3.1 Support Vector Machine (SVM)

- SVM is a popular choice for classification tasks, including facial recognition, due to its effectiveness in handling high-dimensional data and non-linear relationships.
- SVM aims to find the hyperplane that best separates the data points into different classes while maximizing the margin between them. In the context of facial recognition, SVM can be trained using FaceNet embeddings as input features and corresponding labels (e.g., student IDs, staff IDs).

Table7 .1 Support Vector Machine parameters

S.no	Parameter	Range
1	C	200
2	Degree	5
3	Kernel	Poly
4	Probability	True
5	Gamma	0.1

7.3.2 k-Nearest Neighbors (kNN)

- kNN is a simple yet powerful classification algorithm that works based on the similarity of data points in a feature space.
- kNN assigns the class label of an unseen data point based on the class labels of its nearest neighbors in the feature space.
- For facial recognition using FaceNet embeddings, kNN can be trained using labeled FaceNet embeddings, where each embedding represents a face and is associated with a class label.

Table 7.2 K-Nearest parameter

S.no	Parameter	Range
1	n_neighbors	5
2	Weights	Distance
3	Algorithm	ball_tree

7.3.3 Random Forest

- Random Forest is an ensemble learning method that consists of multiple decision trees trained on different subsets of the data.
- Random Forest combines the predictions of individual decision trees to make a final classification decision.
- It is known for its robustness to overfitting and ability to handle high-dimensional data efficiently.
- In the context of facial recognition, Random Forest can be trained using FaceNet embeddings as input features and corresponding class labels.

Table 7.3 Random Forest parameters

S.no	Parameter	Range
1	n_estimaters	10
2	max_depth	None
3	min_sample_split	2

- Construct each branch using the appropriate layers and parameters for the classifier.
- Train each branch separately using the corresponding training data.

During inference, pass the FaceNet embeddings through each branch to obtain predictions from all classifiers.

7.4 TRAIN AND VALIDATE MODELS

Train each model on the training data and evaluate its performance on the validation set using appropriate metrics. This step may involve hyperparameter tuning such as adjusting learning rates, regularization parameters, or model architectures.

Table 7.4 precision_score

MODEL / AVERAGE	SVM (Support Vector Machine)	RF (Random Forest)	KNN (k-Nearest Neighbors)
MACRO	99.58	88.95	95.64
MICRO	99.53	88.3	95.32
WEIGHTED	99.54	88.88	95.51

Precision_score.

Formula:

precision_score=tp\ (tp+fp)

(6.4.1)

Table 7.5 Recall_Score

MODEL / AVERAGE	SVM (Support Vector Machine)	RF (Random Forest)	KNN (k-Nearest Neighbors)
MACRO	99.55	88.67	95.40
MICRO	99.53	88.30	95.32
WEIGHTED	99.54	88.30	95.32

Formula:

Recall_Score = tp \ (tp+fp)

(6.2)

Table 7.6 F1_Score.

MODEL / AVERAGE	SVM (Support Vector Machine)	RF (Random Forest)	KNN (k-Nearest Neighbors)
MACRO	99.56	88.48	95.42
MICRO	99.53	88.30	95.32
WEIGHTED	99.53	88.22	95.31

Formula:

F1 = 2*(precision*recall) / (precision + recall) (6.3)

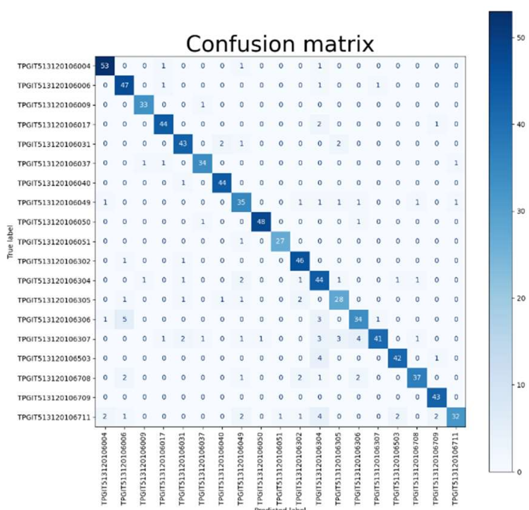

Figure 20
Random Forest Confusion Matrix

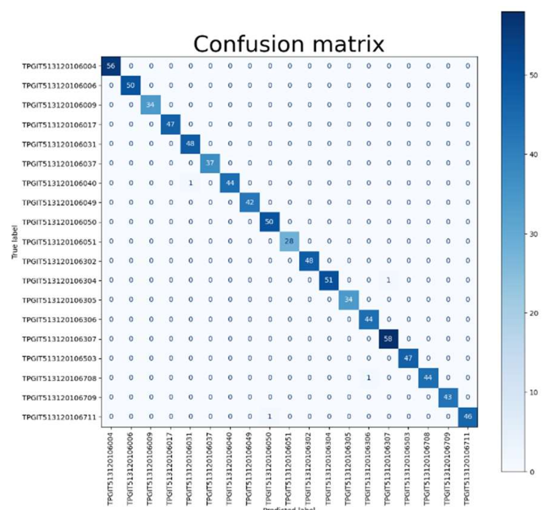

Figure 21
SVM Confusion Matrix

7.5 CONCLUSION

Choose the model that performs best on the validation set according to the predefined evaluation metric(s).

CHAPTER 8
TOOLS AND REQUIREMENTS

8.1 INTRODUCTION

This chapter discusses about software requirements and libraries required for deploying models on windows OS.

8.2 HARDWARE SPECIFICATION

To perform machine learning and deep learning on any dataset, the software/program requires a computer system powerful enough to handle the necessary computing power. Here is the hardware specification of the system which that is used for this project.

1. CPU: Intel® Core™ i5-1035G1 CPU @ 1.00GHz, 1201 Mhz, 4 Core(s), 8 Logigal Processor(s)
2. GPU: Intel® UHD Graphics 600
3. Operating System: Windows 11 Home
4. System memory: 8 GB, DDR4 SDRAM and 512 GB SSD

8.3 SOFTWARE SPECIFICATION

8.3.1 Anaconda

Anaconda Jupyter Notebook is a locally installed interactive computing environment that facilitates the training of machine learning and deep learning models. It provides a user-friendly interface for writing and executing Python code, making it particularly suitable for data analysis, visualization, and model development. In this project, we have utilized the Keras API within the Anaconda Jupyter Notebook environment. Keras, a high-level neural networks library, seamlessly integrates with TensorFlow, which serves as the backend for executing the computations required for training and evaluating deep learning models. With Anaconda Jupyter Notebook, we have the flexibility to harness the computational power of our local machine's CPUs and GPUs to train our models efficiently.

8.3.2 Keras API

Keras is an open-source neural network library that provides support for Python. It provides support for the implementation of Convolutional Neural Networks. Recurrent Neural Networks as well as both. It is capable of running seamlessly on the CPU and GPU. From Keras we also used keras.models, keras.layers and some other libraries for building CNN.

8.3.3 TensorFlow

TensorFlow (TF) is an open source API developed by Google mainly for Machine Learning and Deep Learning, but it is also applicable for other numerical computations. The framework can be used both as backend, with C++, and frontend with Python. One of the advantages of using TF are the many built in functions. For this project, we have used built in library files like tf.keras, tf.layers, tf.losses, tf.metrics, etc..,

8.3.4 OTHER LIBRARIES

- Matplotlib: for plotting and for data visualization.
- NumPy: for processing multi-dimensional arrays.
- Glob: for retrieving files/pathnames.

8.4 GOOGLE SPREED SHEET

Google Sheets is a cloud-based spreadsheet tool developed by Google, enabling users to create, edit, and collaborate on spreadsheets online. With real-time collaboration, multiple users can work on the same document simultaneously, while integration with Google services like Drive and Gmail ensures seamless sharing and access. Its extensive range of functions and formulas facilitates data analysis and manipulation, while data visualization features like charts and pivot tables aid in understanding and presenting data effectively.

Add-ons and extensions further extend its capabilities, making it a versatile tool for both individuals and businesses, accessible across various platforms including web browsers, mobile devices, and desktops.

8.5 GOOGLE CLOUD CONSOLE - OAUTH 2.0 CLIENT IDS

The "OAuth 2.0 Client IDs"s section in the Google Cloud Console facilitates the management of authentication credentials within a project. Administrators can create, view, edit, and delete OAuth 2.0 client IDs from this centralized interface. OAuth 2.0 client IDs represent applications or services requiring authorization to access Google Cloud Platform resources and APIs. Client IDs can be categorized by type, such as web applications, installed applications, or service accounts, to tailor authentication mechanisms to specific use cases. Effective management of OAuth 2.0 client IDs is essential for maintaining security and controlling access to sensitive resources within the Google Cloud ecosystem

8.6 CONCLUSION

Thus, this chapter has discussed about required software and hardware.

CHAPTER 9
MODEL DEPLOYMENT

9.1 INTRODUCTION

Model deployment for a smart attendance system, combining face detection is essential for practical implementation. This process seamlessly integrates face detection, automating attendance tracking and improving communication in educational institutions and organizations. By optimizing administrative processes and enhancing efficiency, this deployment underscores the transformative power of artificial intelligence in addressing real-world challenges effectively.

9.2 SYSTEM ARCHITECTURE

The smart attendance management system integrates a face detection module. When students or employees enter the premises, the face detection module captures their images and matches them with existing records, marking attendance upon recognition. The system updates the database with attendance records or their guardians regarding attendance status. Administrators, teachers and users access the system through a user interface to manage attendance records. The system ensures security through encryption techniques and facilitates efficient attendance monitoring and communication through automated processes.

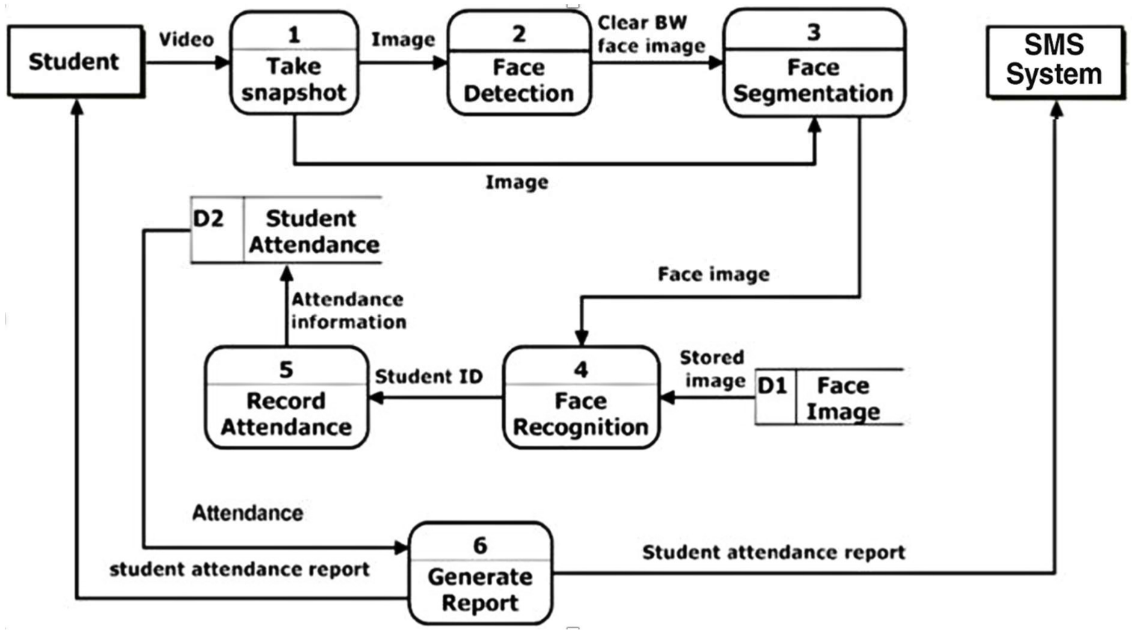

Figure 22 System architecture

9.3 WEBCAM ACCESS

OpenCV is a Library which is used to carry out image processing using programming languages like python. This project utilizes OpenCV Library to make a Real-Time Face Detection using webcam as a primary camera.

9.4 RETINAFACE DETECTION

Retina Face is a state-of-the-art face detection model that utilizes deep learning techniques to accurately detect faces in images. The model employs a multi-task learning approach to simultaneously predict face bounding boxes, facial landmarks, and face confidence scores. This allows Retina Face to provide detailed information about detected faces, including their location, orientation, and facial landmarks such as eyes, nose, and mouth. To use Retina Face for face detection, you first need to install the Retina Face library and its dependencies. Once installed, you can import the necessary libraries and load the Retina Face model in your Python environment. With the model loaded, you can then pass images through the model to detect faces. Retina Face returns bounding boxes and facial landmarks for each detected face, enabling you to visualize and analyse the results.

Retina Face is known for its high accuracy and robust performance across various datasets and challenging conditions, making it suitable for a wide range of face detection applications. Whether used for security surveillance, biometric identification, or facial analysis in computer vision projects, Retina Face provides reliable face detection capabilities that contribute to the advancement of face-related tasks in both research and industry.

9.5 ENIRONMENT CONFIGURATION

Environment configuration involves setting up the production environment to support your application. This includes defining server specifications such as CPU, memory, and disk space requirements based on anticipated workload and scalability needs. Network settings involve configuring firewalls, load balancers, and DNS settings to ensure secure and efficient communication between components. Security measures such as encryption, access control, and monitoring tools should also be implemented to protect sensitive data and detect potential threats or vulnerabilities.

9.6 DATABASE SETUP USING GOOGLE SPREED SHEET

Configure a Firebase Realtime Database to manage student records, attendance logs, and contact details for SMS notifications in your smart attendance system.To set up a Firebase project, visit the Firebase Console and either create a new project or select an existing one. Once in the Firebase Console, navigate to the "Database" section and enable the Realtime Database service. Configure security rules to specify who can access and modify data in your database, ensuring data integrity and privacy. Optionally, implement user authentication methods such as email/password or Google sign-in to secure access to your database. These steps are crucial for establishing a secure and reliable Firebase Realtime Database for your application.

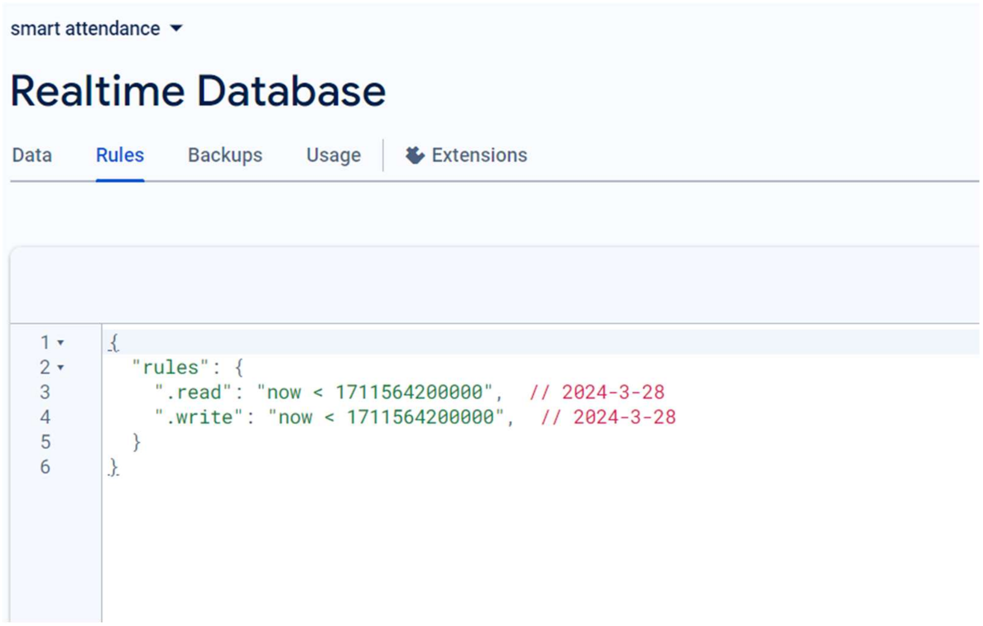

Figure 23 security rules to read and write

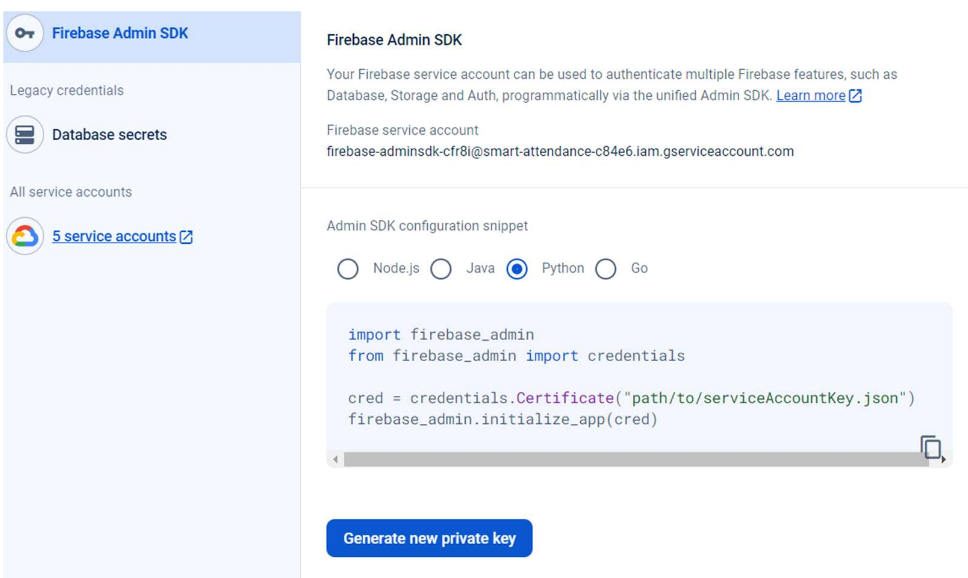

Figure 24 Generate new private key

To connect your application to Firebase Realtime Database, first, obtain the Firebase SDK configuration from Project Settings > General in the Firebase Console, which includes your project's credentials. Then, integrate the Firebase SDK into your application code, such as JavaScript for web apps or Java/Kotlin for Android, by adding the configuration object. Initialize Firebase using initializeApp() function with the configuration object. Perform database operations using Firebase SDK methods like set(), get(), update(), and remove() to interact with your database. Test your database connection and operations to ensure correct functionality, utilizing Firebase Console for data management and monitoring. These steps collectively enable seamless integration and interaction with Firebase Realtime Database in your application.


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}
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Figure 25 service account key as json

9.7 INTEGRATION WITH AN WEB PAGE

Integrating a machine learning code with a web page through an Excel sheet API server offers a streamlined approach to harnessing predictive capabilities within a user-friendly interface. This integration process involves several key steps to ensure smooth data flow and interaction. First, the machine learning code, tailored for the desired task such as prediction or classification, must be prepared to accept input data and generate output predictions. Simultaneously, setting up an Excel sheet API server acts as a crucial intermediary, facilitating communication between the machine learning code and the web page. This server is equipped with endpoints to receive data from the web page, process it, and dispatch it to the machine learning code for inference. Utilizing libraries like Flask or Django streamlines the development of the API server, ensuring robust functionality. The data flow within this system adheres to defined formats, with the server converting incoming data into a format compatible with the machine learning model. Upon receiving the processed data, the machine learning code executes inference tasks, generating predictions or results which are then relayed back to the Excel sheet API server. Finally, the server formats these results and transmits them to the web page as an HTTP response, enabling users to interact with the model seamlessly. By incorporating error handling, validation mechanisms, and robust security measures, this integrated system promises efficient utilization of machine learning capabilities within a web-based environment, enhancing user accessibility and functionality.

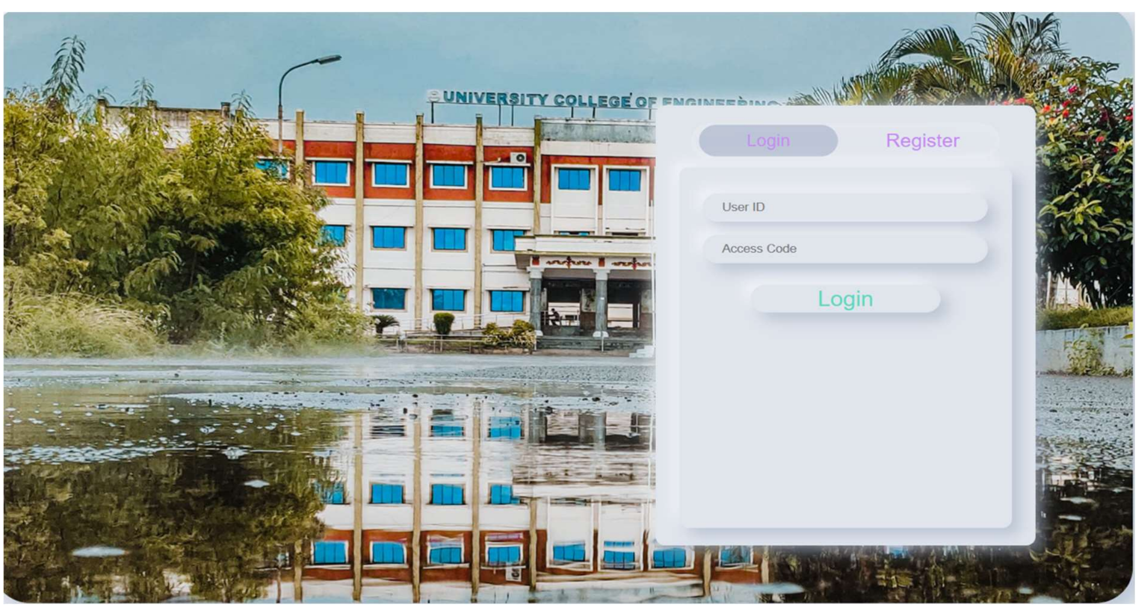


Figure 26 Sign up setup view

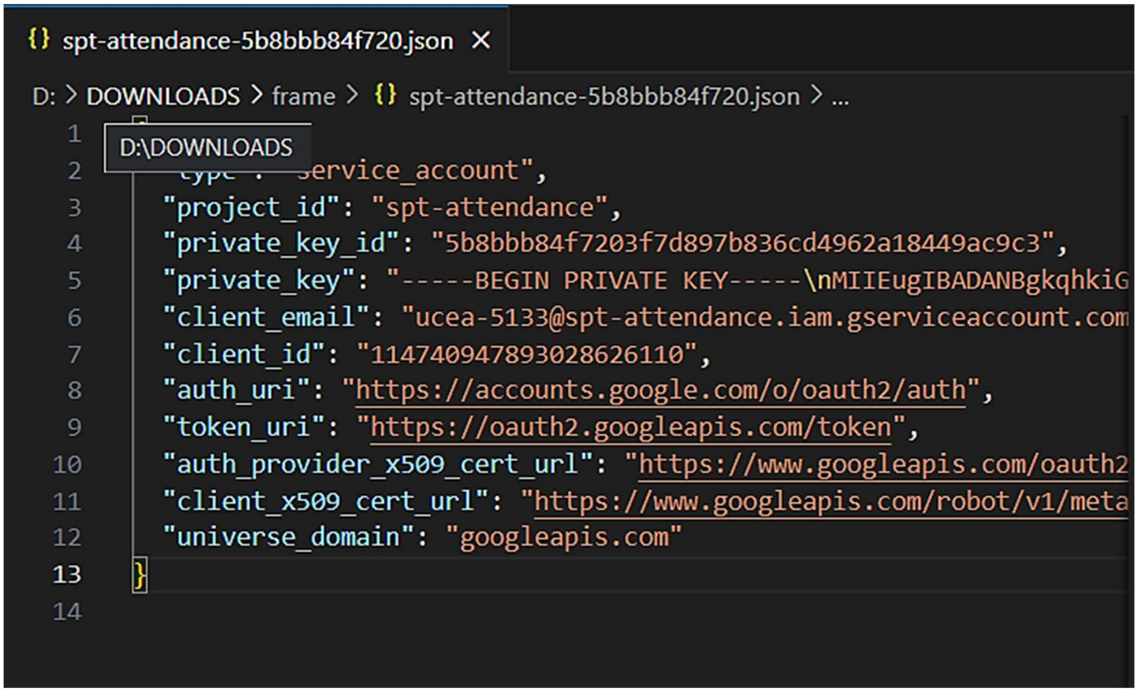


Figure 27 API key and API secret

9.8 CODE DEPLOYMENT

Code deployment involves the process of releasing your application's codebase to the production environment. Automation is key to streamlining this process, reducing the risk of human error and ensuring consistency across deployments. Continuous integration and continuous deployment (CI/CD) pipelines automate the build, test, and deployment phases, allowing for rapid and reliable releases. Version control systems like Git enable efficient collaboration among developers and facilitate rollback procedures in case of deployment failures or regressions.

9.9 MONITORING AND LOGGING

Monitoring and logging are essential for gaining insights into your application's performance, health, and user behaviour. Monitoring tools like Prometheus, Grafana, and Datadog collect and visualize metrics such as CPU usage, memory consumption, and request latency, enabling proactive detection of issues and capacity planning. Logging mechanisms capture detailed information about application events, errors, and user interactions, aiding in troubleshooting, auditing, and compliance. Centralized logging platforms like ELK (Elasticsearch, Logstash, Kibana) or Splunk aggregate and analyse logs from multiple sources, providing a comprehensive view of system activity.

9.10 SCALING AND LOAD BALANCING

Scaling and load balancing are critical for ensuring your application can handle varying levels of traffic and maintain performance under load. Horizontal scaling involves adding more instances or nodes to distribute incoming requests and increase capacity, while vertical scaling involves upgrading individual server resources such as CPU or memory. Load balancers distribute traffic across multiple instances, preventing overload on any single server and improving fault tolerance and reliability. Technologies like Kubernetes and AWS Elastic Load Balancing (ELB) automate scaling and load balancing, dynamically adjusting resources based on demand.

9.11 SECURITY MEASURES

Security measures are paramount for protecting your application, data, and users from malicious threats and unauthorized access. Implementing firewalls, encryption, and access control mechanisms helps defend against external attacks and data breaches. Secure coding practices, such as input validation, output encoding, and parameterized queries, mitigate common vulnerabilities like SQL injection and cross-site scripting (XSS). Regular security audits and penetration testing uncover potential weaknesses and validate the effectiveness of security controls. Compliance with industry standards and regulations, such as GDPR and PCI DSS, ensures data privacy and regulatory compliance.

9.12 BACKUP AND DISASTER RECOVERY

Backup and disaster recovery planning are essential for safeguarding against data loss, system failures, and catastrophic events. Regularly backing up critical data, configurations, and application code minimizes the impact of hardware failures, human errors, or cyberattacks. Implementing off-site backups and redundant storage solutions ensures data availability and resilience in case of localized disasters. Disaster recovery plans outline procedures for restoring services and data in the event of a major outage or disruption, including failover strategies, data replication, and communication protocols with stakeholders and users.

9.13 USER ACCEPATANCE TESTING (UAT)

User acceptance testing (UAT) is a crucial phase in the deployment process, allowing stakeholders and end-users to validate the application's functionality, usability, and performance in a real-world environment. UAT involves creating test scenarios and user stories based on business requirements and user expectations, conducting tests with representative users, and gathering feedback on the application's features and user experience. Test results and feedback are analyzed to identify any defects, usability issues, or areas for improvement, which are then addressed before the final deployment to production.

9.14 DOCUMENTATION AND TRAINING

Documentation and training are essential for ensuring that operations teams, developers, and stakeholders understand how to deploy, maintain, and support the application effectively. Comprehensive documentation should cover installation instructions, configuration settings, troubleshooting guides, and best practices for deployment and operations. Training sessions or workshops provide hands-on experience and practical knowledge of the application's architecture, components, and deployment procedures. By investing in documentation and training, organizations can empower their teams to effectively manage and operate the deployed application, reducing downtime, enhancing performance, and improving user satisfaction.

9.15 CONCLUSION

The deployment of a smart attendance system integrating face detection with enhances efficiency and effectiveness in educational institutions and organizations, showcasing the transformative potential of artificial intelligence in addressing practical challenges.

CHAPTER 10

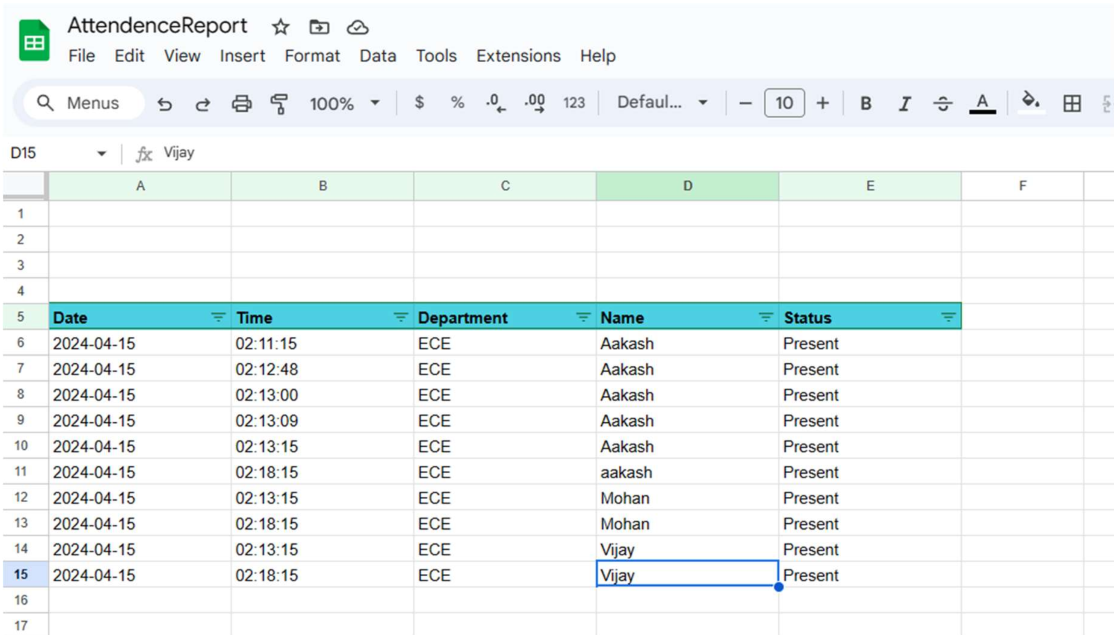
RESULTS AND DISCUSSION

10.1 EXCEL SHEET

Display functions, particularly populate Table(), are instrumental in presenting retrieved attendance records in a user-friendly format within the application's interface. These functions dynamically generate HTML table rows based on the data fetched from the Excel sheet API server, ensuring that attendance records are presented in a structured and visually appealing manner. Additionally, status indicators are applied to highlight present or absent attendance statuses, enhancing the readability and comprehension of the displayed information.

Toggle functions, such as toggleToStudentSearchForm() and toggleToDateSearchForm(), facilitate seamless transitions between different search forms within the application. These functions enable users to switch between searching attendance records by student name or date with ease, enhancing the application's usability and accessibility. By providing clear and intuitive toggling mechanisms, the application ensures that users can navigate through different search functionalities effortlessly.

Error handling mechanisms are crucial components of the application responsible for managing and presenting errors or exceptional scenarios encountered during data retrieval and processing. These mechanisms ensure that users are informed of any issues, such as failed search attempts or API connection errors, and receive appropriate feedback within the application interface. By providing informative error messages and gracefully handling unexpected situations, the application maintains usability and user satisfaction.



Date	Time	Department	Name	Status
2024-04-15	02:11:15	ECE	Aakash	Present
2024-04-15	02:12:48	ECE	Aakash	Present
2024-04-15	02:13:00	ECE	Aakash	Present
2024-04-15	02:13:09	ECE	Aakash	Present
2024-04-15	02:13:15	ECE	Aakash	Present
2024-04-15	02:18:15	ECE	aakash	Present
2024-04-15	02:13:15	ECE	Mohan	Present
2024-04-15	02:18:15	ECE	Mohan	Present
2024-04-15	02:13:15	ECE	Vijay	Present
2024-04-15	02:18:15	ECE	Vijay	Present

Figure 28 Excel sheet for attendance

10.2 REGISTER PAGE

UI interaction encompasses the various user interface elements and interactions implemented within the application to facilitate user engagement and interaction. This includes event listeners attached to search buttons and key presses within the student and date search forms, enabling users to initiate attendance queries and submit search requests conveniently. By implementing responsive UI components and intuitive interactions, the application enhances user experience and usability.

The initialization and setup phase in the web application involve defining essential constants and configurations necessary for interacting with the Excel sheet API server and setting up the user interface. This includes specifying parameters such as the spreadsheet ID, sheet name, range, and API key required for accessing data from Google Sheets. Additionally, predefined colors are defined to visually represent different attendance statuses, enhancing the readability and user experience of the application.

The document ready function plays a pivotal role in initializing the application's functionality when the DOM (Document Object Model) is fully loaded and ready for manipulation. Within this function, event listeners are set up to handle various user interactions, such as toggling between different search forms, fetching user data, displaying personalized welcome messages, and initializing the dashboard interface. These event listeners ensure that the application responds appropriately to user actions and provides a seamless user experience.

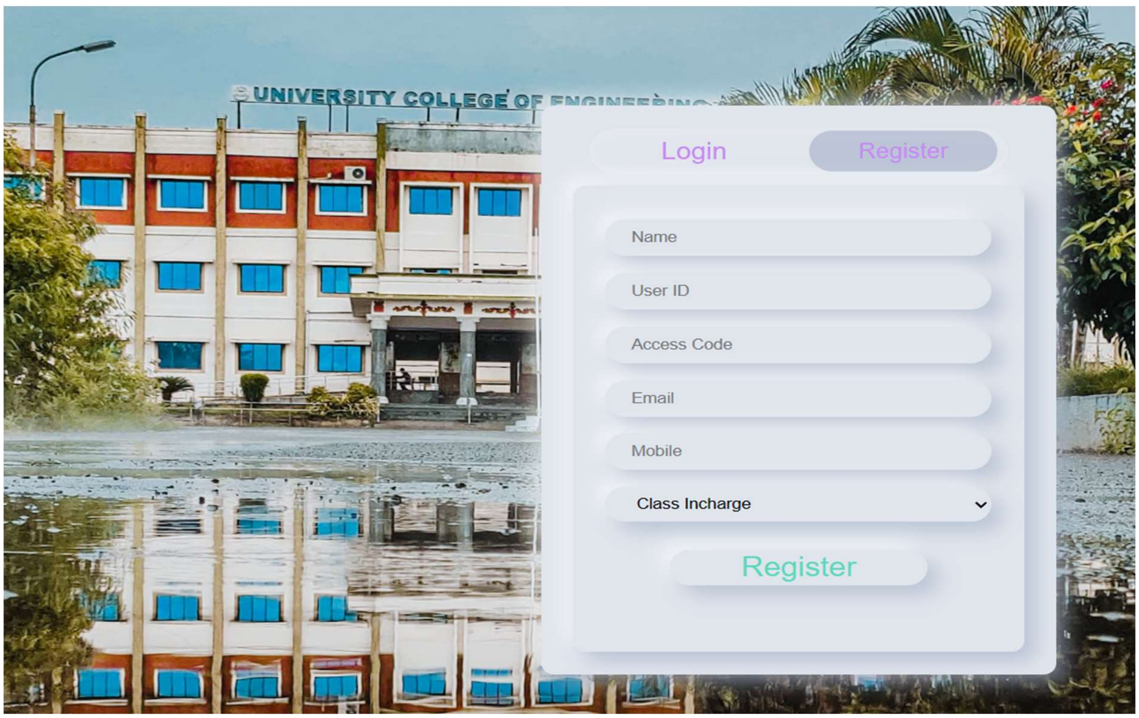
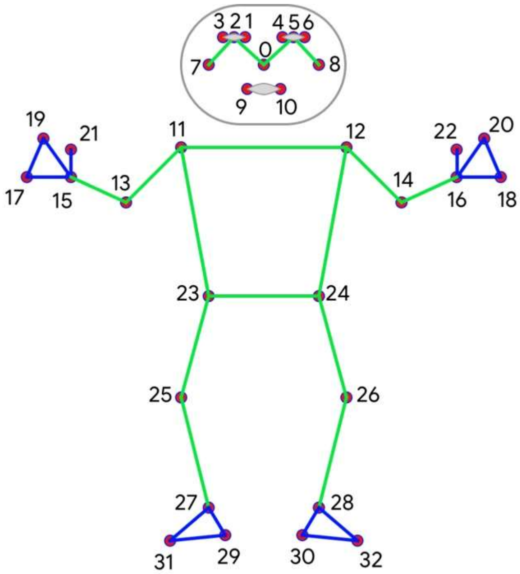


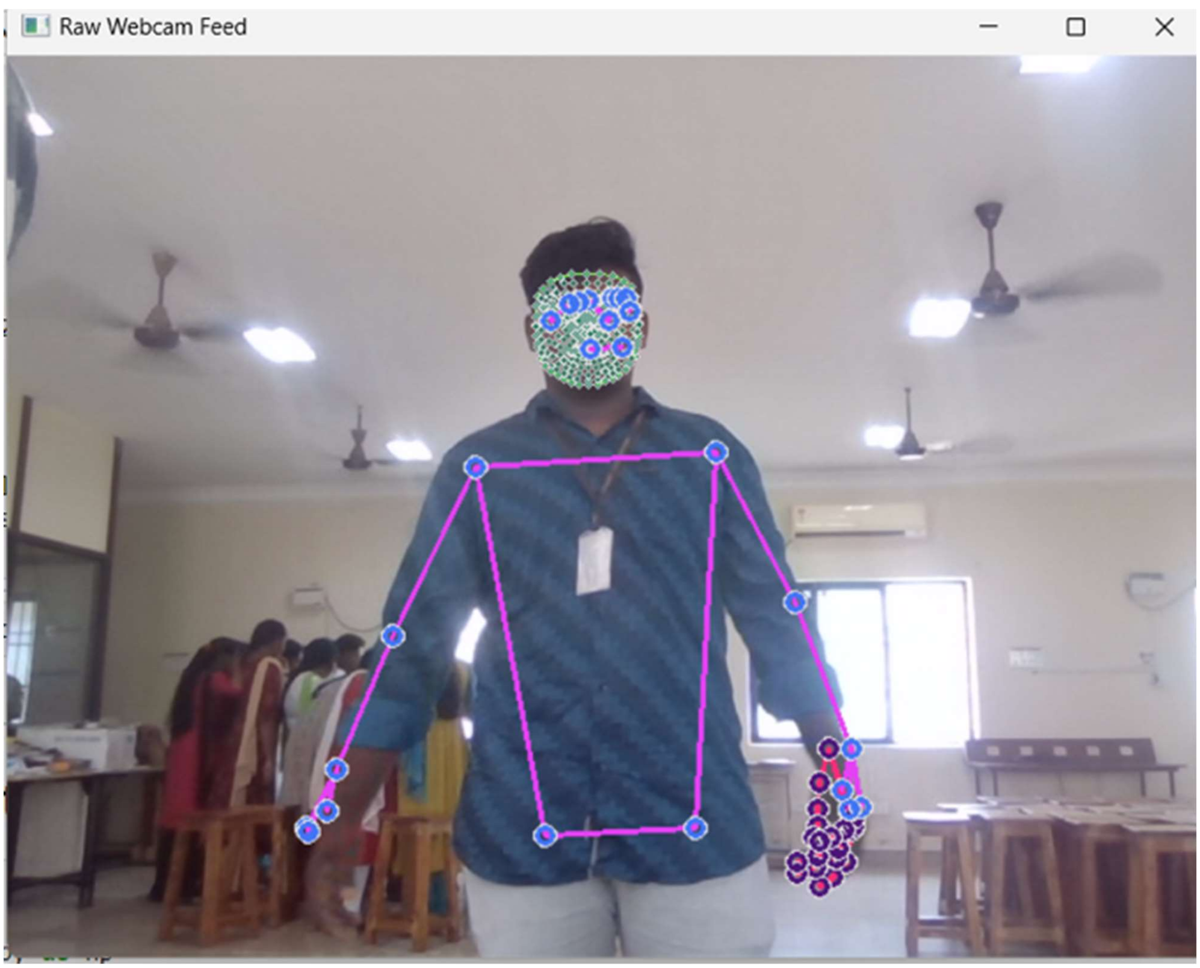
Figure 29 Registration page view

10.3 PREDICTION



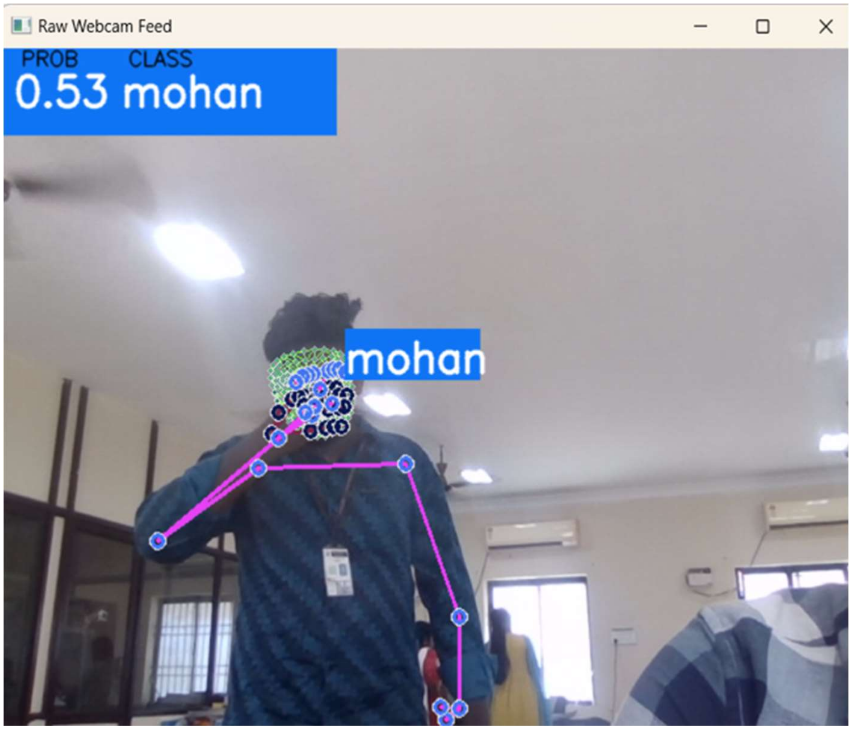
0. nose
1. right eye inner
2. right eye
3. right eye outer
4. left eye inner
5. left eye
6. left eye outer
7. right ear
8. left ear
9. mouth right
10. mouth left
11. right shoulder
12. left shoulder
13. right elbow
14. left elbow
15. right wrist
16. left wrist
17. right pinky knuckle #1
18. left pinky knuckle #1
19. right index knuclke #1
20. left index knuckle #1
21. right thumb knuckle #2
22. left thumb knuckle #2
23. right hip
24. left hip
25. right knee
26. left knee
27. right ankle
28. left ankle
29. right heel
30. left heel
31. right foot index
32. left foot index

10.4 POSE DETECTION



```
Output data:
[{'Timestamp': '2024-04-15 02:18:15', 'Department': 'ECE', 'Name': 'aakash', 'Status': 'Present'}]
Output data exported to CSV successfully.
Output data appended to Google Sheets successfully.
```

10.5 FACE DETECTION



10.6 ATTENDANCE LOGING

Figure 9.8 illustrates the live detection output of the system. This figure likely shows the results of Marking attendance as a present for recognized face and absent for remaining students.

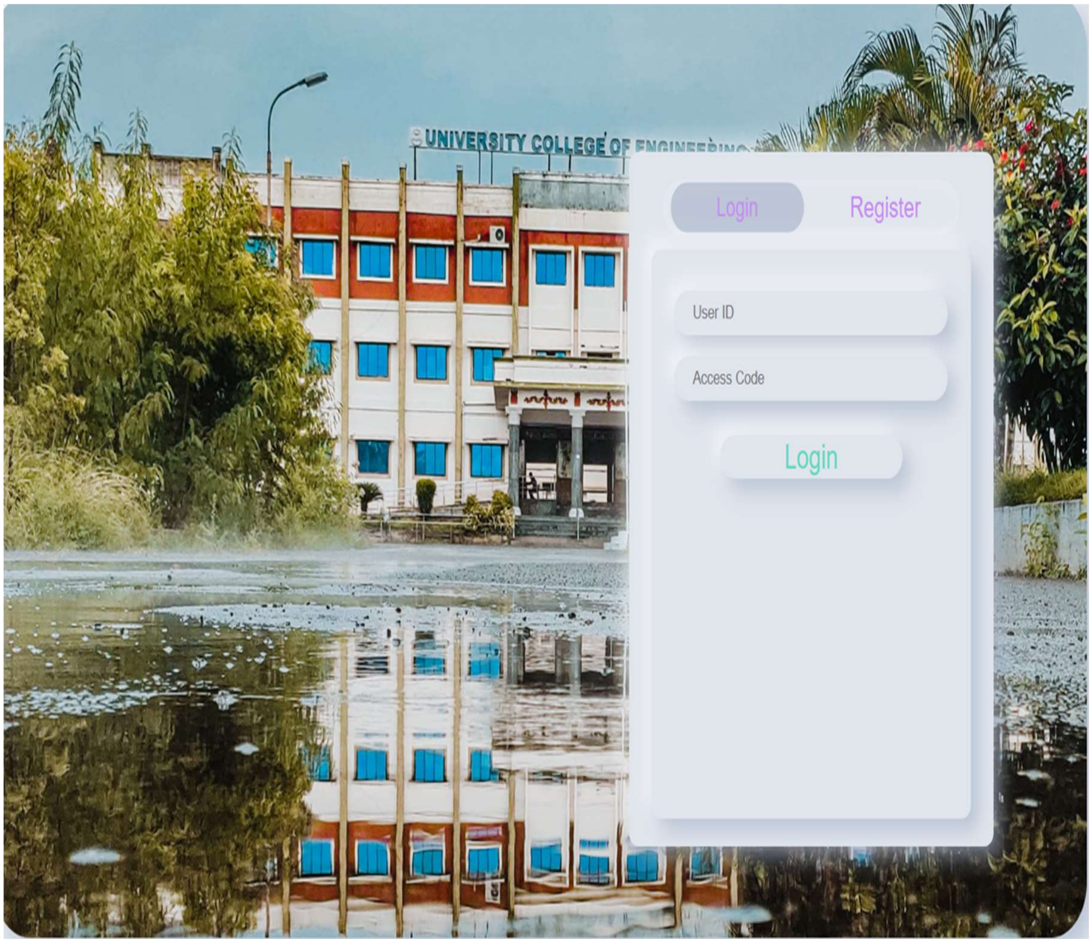


Figure 30 Attendance login view

10.6.1 GOOGLE SHEET INTEGRATION

The code seamlessly integrates with Google Sheets through the Google Sheets API, facilitating data retrieval and manipulation. It constructs a URL with essential parameters such as the spreadsheet ID, sheet name, and range, forming the basis for data fetching operations. Additionally, it incorporates an API key, ensuring secure authentication and access control. By leveraging the Google Apps Script URL, the code enables the appending of new records to the spreadsheet, enhancing the system's functionality and flexibility. Through these integrations, the application establishes a robust connection with Google Sheets, enabling efficient data management and manipulation.

10.6.2 FORM HANDLING

Form handling constitutes a crucial aspect of the application's functionality, facilitating user interaction and data submission. The code adeptly manages form submissions through event listeners, capturing user inputs and initiating corresponding actions. By intercepting form submissions and preventing default behaviors, such as page reloads, the code ensures smooth data processing and submission. It meticulously extracts form data, validating and processing it to execute relevant functionalities, such as user authentication and registration. Through robust form handling mechanisms, the application enhances user experience and ensures seamless data interaction, driving overall usability and effectiveness.

10.6.3 LOGIN FUNCTIONALITY

The login functionality serves as a pivotal component of the application, enabling secure user authentication and access control. Upon user login attempts, the code orchestrates a series of actions, including data retrieval from Google Sheets and validation of user credentials. Leveraging the fetched data, the code verifies the existence of the user ID and cross-references the provided access code for authentication. Upon successful authentication, the code stores pertinent user data in the session, facilitating personalized user experiences and streamlined navigation. Conversely, in cases of authentication failure, the code promptly notifies users, safeguarding against unauthorized access attempts. Through robust login functionality, the application fortifies security measures and fosters user trust and confidence.

10.6.4 REGISTRATION FUNCTIONALITY

The registration functionality empowers users to create accounts within the application, fostering user engagement and system utilization. By harnessing the capabilities of Google Sheets, the code efficiently manages user registration processes, ensuring data integrity and uniqueness. Prior to user registration, the code meticulously validates user-provided data, including user ID, email, and mobile number, to prevent duplicate entries and ensure data accuracy. Through seamless integration with Google Apps Script URL, the code facilitates the seamless addition of new user records to the spreadsheet, expanding the application's user base and enhancing data management capabilities. By offering robust registration functionality, the application cultivates user growth and fosters a vibrant community ecosystem.

10.6.5 DOM MANIPULATION AND STYLING

DOM manipulation and styling play a pivotal role in shaping the application's visual presentation and user interaction paradigms. The code leverages the power of jQuery to orchestrate dynamic DOM manipulations, seamlessly toggling between form views, displaying informative messages, and resetting form fields as needed. Through intuitive styling cues, such as color-coded messages indicative of success, warning, or error states, the code enhances user comprehension and engagement, fostering a cohesive and visually appealing user experience. By prioritizing effective DOM manipulation and styling, the application elevates its aesthetic appeal and usability, resonating with users and promoting sustained engagement and usage.

10.7 ADMIN PAGE

The admin page facilitates seamless user account management through an intuitive and user-friendly interface. Administrators can efficiently oversee and interact with user accounts, accessing essential functionalities for effective administration. Upon accessing the admin page, administrators are presented with a comprehensive listing of all registered users. This listing displays essential user attributes such as user ID, name, email address, and mobile number, providing administrators with a quick overview of the user base.

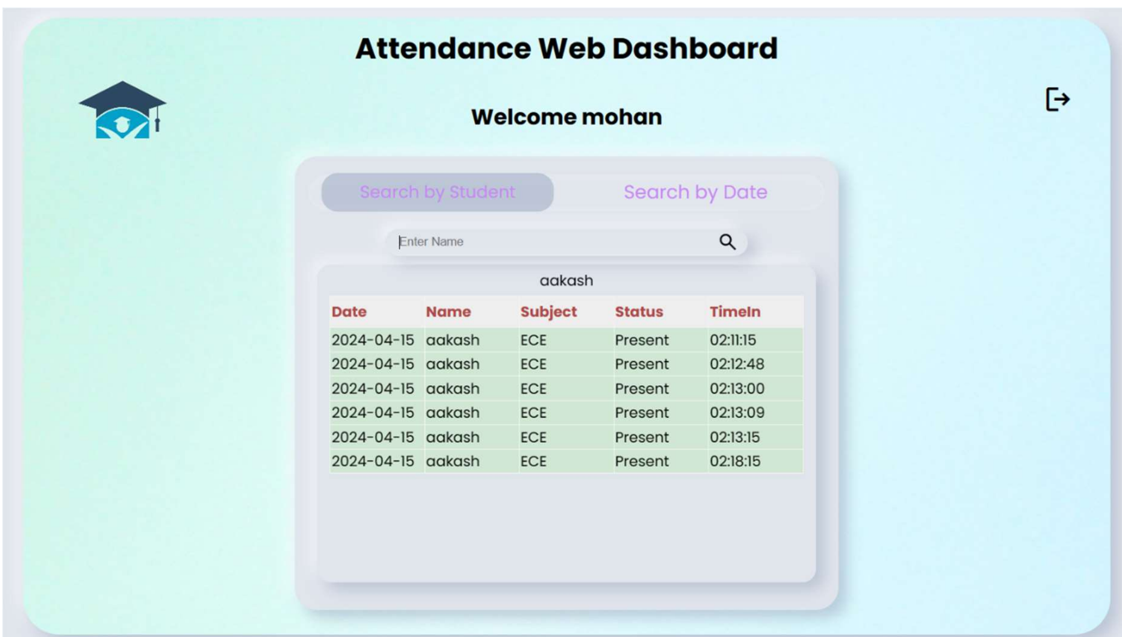


Figure 31 Admin page view

10.7.1 SEARCH AND FILTER OPTION

To streamline user account management, the admin page incorporates robust search and filter options. Administrators can efficiently locate specific user accounts by applying filters based on criteria such as user ID, name, or email address. This functionality enhances administrative efficiency by allowing administrators to quickly identify and access relevant user accounts.

10.7.2 USER DETAIL'S VIEW

Clicking on a user entry within the user listing expands to reveal detailed information about the selected user. This detailed view provides administrators with a comprehensive overview of the user's profile, including their profile picture, contact details, registration date, and any additional relevant information associated with the user account. Administrators can review these details to gain deeper insights into individual user profiles and better understand their roles and activities within the application.

10.7.3 USER ACCOUNT MANAGEMENT

The admin page empowers administrators with a suite of user account management functionalities, accessible directly from the interface. Administrators can perform a variety of actions on user accounts, including updating user information, resetting passwords, and managing user permissions or roles. Whether addressing user requests, enforcing security measures, or facilitating user onboarding processes, these account management tools provide administrators with the flexibility and control needed to effectively oversee user accounts.

10.7.4 BULK OPERATION

To expedite repetitive user management tasks, the admin page supports bulk operations for managing multiple user accounts simultaneously.

Administrators can perform actions such as bulk user activation, deactivation, or deletion, streamlining administrative workflows and saving valuable time and effort. By enabling administrators to apply changes across multiple user accounts in a single operation, these bulk operations enhance administrative efficiency and productivity.

10.7.5 ACTIVITY LOGS

For enhanced visibility and accountability, the admin page includes activity logs or audit trails that track user interactions and system activities. These logs capture details such as user login attempts, account modifications, and other relevant user actions within the application. Administrators can review these activity logs to monitor user behavior, identify potential security incidents or compliance violations, and maintain a secure and transparent operating environment.

10.7.6 SYSYTEM CONFIGURATION

Administrators have access to system configuration settings directly from the admin page, allowing them to customize various aspects of the application to suit organizational requirements and preferences. From managing security policies to configuring integration options with external services, administrators can tailor the application's settings to align with specific business needs. This flexibility ensures that the application remains adaptable and responsive to evolving organizational priorities and operational demands.

10.7.7 REAL-TIME UPDATES

The admin page features real-time updates that ensure user listings and activity logs reflect the latest changes and updates as they occur. Whether monitoring user account modifications, tracking system activities, or reviewing recent user interactions, administrators can rely on up-to-date information to make informed decisions and take timely actions. Real-time updates enhance the responsiveness and usability of the admin page, enabling administrators to stay informed and effectively manage user accounts and system activities in real-time.

10.8 STAFF REGISTER DETAILS

UserID	Name	AccessCode	Email	Mobile	Subject
5468	mohan	12	v444@gmail.com	8916166	ECE
1001	Vijay	123	vijay@college.in	9876543210	ECE
1002	Devin	123	devin@college.in	9876543211	Computer Science

Figure 9.12 Register details

10.9 CONCLUSION

The Smart Attendance System utilizing Face Recognition with FaceNet technology has shown promising results. The system effectively identifies individuals through facial recognition, providing an accurate and efficient means of tracking attendance. Overall, the implementation demonstrates the potential for automating attendance processes in various settings, improving efficiency and accuracy compared to traditional methods.

CONCLUSION

The admin page serves as a vital component of the application, providing administrators with a centralized platform for managing user accounts and overseeing administrative tasks efficiently. Through its intuitive user interface and comprehensive set of functionalities, the admin page empowers administrators to streamline user management workflows, enhance security measures, and maintain a transparent and compliant operating environment.

Face Recognition Based Attendance System has been envisioned for the purpose of reducing the errors that occur in the traditional (manual) attendance taking system. The aim is to automate and make a system that is useful to the organization such as an institute. The efficient and accurate method of attendance in the office environment that can replace the old manual methods. This method is secure enough, reliable and available for use. Proposed algorithm is capable of detect multiple faces, and performance of system has acceptable good results.

The system provide the feature such as face detection, extraction of feature, detection of extracted feature and analysis of student's attendances. It recognized students face and detect their face attendance mark using name and id then it helps to build effective class attendance using face recognition system.

After face recognition process, the recognized faces will be marked as present in the excel sheet and the rest will be marked as absent and the Attendance Sheet will stored in the Real time database.

REFERENCES

[1] [A]Gomes, Clyde & Chanchal, Sagar & Desai, Tanmay & Jadhav, Dipti. (2020). “Class Attendance Management System using Facial Recognition.” ITM Web of Conferences. 32. 02001. 10.1051/itmconf/20203202001. [cross ref].

[2] [B] Omar Abdul, Rhman Salim, Rashidah Funke Olan- rewaju, Wasiu Adebayo Balogun. “ Class Attendance Management System Using Face Recognition.” 2018 7th International Conference on Computer and Com- munication Engineering (ICCCE) IEEE 2018. [cross ref].

[3] [C] R. S. Siswanto, A. S. Nugroho and M. Galinium, \"Implementation of face recognition algorithm for biometrics based time attendance system,\" 2014 International Conference on ICT For Smart Society (ICISS), 2014, pp. 149-154, doi: 10.1109/ICTSS.2014.7013165. [cross ref].

[4] [D] N, Dr & Tuladhar, Emerald & Shah, Avinash & Hegde, Anusha & Sai, Alekya. (2021). “ATTENDANCE MONITORING SYSTEM BASED ON FACE RECOGNAITION”. 10.13140/RG.2.2.26342.75845. [cross ref].

[5] [E] S. Poornima, N. Sripriya, B. Vijayalakshmi and P. Vishnupriya, \"Attendance monitoring system using facial recognition with audio output and gender classification,\" 2017 International Conference on Computer, Communication and Signal Processing (ICCCSP), 2017, pp. 1-5, doi: 10.1109/ICCCSP.2017.7944103. [cross ref].

[6] [F] E. Varadharajan, R. Dharani, S. Jeevitha, B. Kavinmathi and S. Hemalatha, \"Automatic attendance management system using face detection,\" 2016 Online International Conference on Green Engineering and Technologies (IC-GET), 2016, pp. 1-3, doi: 10.1109/GET.2016.7916753. [cross ref].

[7] [G] Saravanan, Sharma & Shanmugasundaram, Karthikeyan & Ramasamy, Sathees. (2016). FAREC — "CNN based efficient face recognition technique using Dlib." 192-195.10.1109/ICACCCT.2016.7831628.[cross ref].

[8] [H] Akash Singh, Shreya Bhatt, Abhishek Gupta, International Journal of Engineering Applied Sciences and Technology, 2021 Vol. 5, Issue 12, ISSN No. 2455-2143, Pages 233-241 Published Online April 2021 [cross ref].

[9] [I] Nandhini R, Duraimurugan N, S.P.Chokkalingam, International Journal of Engineering and Advanced Technology (IJEAT) ISSN: 2249 – 8958, Volume-8, Issue-3S, February 2019 [cross ref].

[10] [J] Prof.M.S.Sawane, Shrutika Nakhale, Vishal Rathod, Nikita Ghadge, International Journal of Advanced Research in Computer and Communication Engineering Vol. 10, Issue 5, May 2021 DOI 10.17148/IJARCCE.2021.10584 [cross ref].

[11] [K]M.K. Yeop Sabri, M.Z.A. Abdul Aziz, M.S.R. Mohd Shah, M.F Abd Kadir, "Smart Attendance System by suing RFID", Applied Electromagnetics 2007. APACE 2007. Asia -Pacific Conference on, 4–6 Dec. 2007

[12] [L]] N. I. Zainal, K. A. Sidek, T. S. Gunawan, H. Mansor, M. Kartiwi, "Design and Development of Portable Classroom Attendance System Based on Arduino and Fingerprint Biometric", proc.of The IEEE 5th International Conference on Information and Communication Technology for The Muslim World (ICT4M), pp. 1-4, 17–18 Nov. 2014

[13] [M] Kadry Seifedine, Mohamad. Smaili, "Wireless attendance management system based on iris recognition", Scientific Research and Essays 5.12, pp. 1428-1435, 2013.

[14] Cheema U, Moon S (2021) Sejong face database: a multi-modal disguise face database. Comput vis Image Underst 208–209:1–9 He K, Gkioxari G, Dollar P, Girshick R (2017) Mask R-CNN. In: IEEE international conference on computer vision, pp 2980–2988

[15] Kong S, Heo J, Abidi B, Paik J, Abidi M (2005) Recent advances in visual and infrared face recognition—a review. Comput vis Image Underst 97(1):103–135

[16] Papandreou G, Zhu T, Chen L, Gidaris S, Tompson J, Murphy K (2018) PersonLab: person pose estimation and instance segmentation with a bottom-up, part-based, geometric embedding model. In: European conference on computer vision, pp 282–299

[17] Peng W, Hong X, Chen H, Zhao G (2020) Learning graph convolutional network for skeleton-based human action recognition by neural searching. Proc AAAI Con Artif Intell 34(03):2669–2676

[18] Ren S, He K, Girshick R, Sun J (2017) Faster R-CNN: towards realtime object detection with region proposal networks. IEEE Trans Pattern Anal Mach Intell 39(6):1137–1149

[19] Shakhnarovich G, Lee L, Darrell T (2001) Integrated face and gait recognition from multiple views. In: IEEE computer society conference on computer vision and pattern recognition, pp 439–446

[20] Shi L, Zhang Y, Cheng J, Lu H (2019) Two-stream adaptive graph convolutional networks for skeleton-based action recognition. In: IEEE conference on computer vision and pattern recognition, pp 12018–12027

[21] Tsai M, Li M (2021) Attendance monitoring system based on artificial intelligence facial recognition technology. In: ieee international conference on consumer electronics-Taiwan, pp 1–2

[22] Tsai M, Chen C (2021) Spatial temporal variation graph convolutional networks (STV-GCN) for skeleton based emotional action recognition. IEEE Access 9:13870–13877

[23] Tsai M, Chen C (2022) Enhancing the accuracy of a human emotion recognition method using spatial temporal graph convolutional networks. Multimed Tools Appl. https://doi.org/10.1007/s11042- 022-13653-x

[24] Tsai M, Huang S (2022) Enhancing accuracy of human action recognition system using skeleton point correction method. Multimed Tools Appl 81:7439–7459

[25] Wang L, Tan T, Ning H, Hu W (2003) Silhouette analysis-based gait recognition for human identification. IEEE Trans Pattern Anal Mach Intell 25(2):1505–1518

[26] Wang L, Ning H, Tan T, Hu W (2004) Fusion of static and dynamic body biometrics for gait recognition. IEEE Trans Circuits Syst Video Technol 14(2):149–158

[27] Yan S, Xiong Y, Lin D (2018) Spatial temporal graph convolutional networks for skeleton-based action recognition. Assoc Adv Artif Intell 32:7444–7452