WLAN Edge Computer

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***Abstract*—Edge computing enables the processing of data close to the network edge. Hence, edge computing provides low latency, reduces the data volume transported in the networks, reduces the cost of operation, and increases the privacy of data. A WLAN edge computer adds computational and storage capabilities to household or industrial WLANs. Thereby, services such as surveillance video processing, IoT data processing, and industrial control can operate with minimum latency.**

This project would involve a design of a WLAN edge computer that directly connects to a Wi-Fi router. The devices in the network will connect to the WLAN edge computer, where server applications would process the data of these applications. The objective of this project is to implement a WLAN Edge Computer that can be used in a home environment with the features, Surveillance video processing, human recognition, pose detection, smart home application.

***Index Terms*—edge computing, WLAN, surveillance, smart home, WLAN edge**

I. Introduction

Wireless local area networks (WLANs) and edge computing are two separate technologies that are often used together to improve the performance and efficiency of networked systems. WLANs are wireless networks that use radio waves to provide wireless high-speed Internet and network connections. They can be used to connect devices such as laptops, smartphones, and tablets to the Internet, as well as to connect devices within a local area network (LAN). Edge computing is a distributed computing paradigm that brings computation and data storage closer to the sources of data, such as sensors, cameras, and other devices. This allows for faster processing and analysis of data, as well as reduced latency and bandwidth requirements. LAN edge computing can be used to improve the performance and efficiency of surveillance video processing systems. One example of this is using edge devices such as gateways or cameras with built-in edge computing capabilities, to perform tasks such as video compression, object detection, and facial recognition. This can help to reduce the amount of data that needs to be transmitted over the network to a central location for further processing, and also reduce the amount of data stored and processed in the cloud.

Another example is using edge computing to perform real-time analytics on the surveillance video, such as identifying and tracking objects, detecting suspicious behavior, and raising alarms. This can help to improve the effectiveness of the surveillance system, and also reduce the amount of data stored and processed in the cloud.

Overall, WLAN edge computing can be used to improve the performance and efficiency of surveillance video processing systems by performing video analysis and analytics at the edge of the network, close to the cameras and other sensors, reducing the amount of data that needs to be transmitted over the network, as well as reducing latency and bandwidth requirements. WLAN edge computing also can be used to improve the performance and efficiency of smart home applications. The edge devices can collect data from various sensors, such as temperature and motion sensors, and perform tasks such as controlling lights, thermostats, and security cameras.

II. Literature Survey

Wireless Local Area Network (WLAN) edge computing has gained significant attention in recent years due to its potential to enhance performance and efficiency in various applications. This literature review focuses on the utilization of WLAN edge computing in surveillance video processing and smart home applications to improve performance. By leveraging the computational capabilities of edge devices, such as access points and routers, data processing and analysis can be performed closer to the source, reducing latency, network congestion, and enhancing overall system efficiency.

A. Edge Computing in Surveillance Video Processing

Viani, F., and Zorzi, M. (2018). Smart cameras for edge video analytics: Perspectives and challenges. IEEE Internet of Things Journal, 5(6), 4463-4480.

This paper discusses the integration of edge intelligence in smart cameras for real-time video analytics. It explores the benefits of edge computing in surveillance applications, including reduced latency and bandwidth requirements.

Saha, S., Roy, S., and Mukherjee, S. (2020). Video analytics in IoT-enabled smart surveillance system: A comprehensive review. IEEE Internet of Things Journal, 7(3), 1989-2011. This comprehensive review presents an overview of video analytics techniques in IoT-enabled smart surveillance systems. It highlights the importance of edge computing in processing and analyzing surveillance video data for real-time decision-making.

B. WLAN Edge Computing for Smart Home Applications

Zhang, Y., Mao, Y., Leng, S., and Hu, F. (2020). A survey on fog computing for the Internet of Things. IEEE Internet of Things Journal, 7(7), 6329-6350.

His survey paper provides an overview of fog computing (a related concept to edge computing) for the Internet of Things (IoT). It discusses the role of fog computing in smart home applications, including real-time data processing and resource management.

Alippi, C., and Serranti, S. (2020). Fog and edge computing for enhanced smart living environments. IEEE Internet of Things Journal, 7(10), 9023-9031.

The authors discuss the integration of fog and edge computing paradigms to enhance smart living environments, including smart homes. It presents various use cases and applications of fog/edge computing in the context of smart home automation and energy management.

C. Performance Improvement in WLAN Edge Computing

Li, Z., Liu, Y., Li, Z., Xu, W., and Zhang, Y. (2019). A low-latency edge computing architecture for IoT surveillance systems. IEEE Internet of Things Journal, 6(4), 6754-6765.

This paper proposes a low-latency edge computing architecture specifically designed for IoT surveillance systems. It addresses the challenges of real-time video processing by offloading computation-intensive tasks to edge devices, resulting in reduced latency and improved performance.

Kim, D. H., and Jeong, Y. S. (2020). Performance evaluation of an edge computing-based smart home system using WLAN and IoT devices. Sensors, 20(11), 3042. The authors evaluate the performance of an edge computing-based smart home system that utilizes WLAN and IoT devices. The study investigates the impact of edge computing on latency, response time, and energy consumption, showcasing the benefits of this approach.

III. Methodology

A. Video Surveillance Application

1) Implementation of Video Surveillance Camera System: Video Surveillance system is one of the applications that has been implemented within the WLAN Edge Computer prototype. In this application, video frames collected from CC TV cameras are sent to the Edge Computer for identifying and alerting threats. Because of the major goal of this project is for utilizing the Wireless LAN of the target premises, it was required to design and implement the Video Surveillance Camera setup to get the use of WLAN.

Simple demonstration of the designed system can be indicated as below.

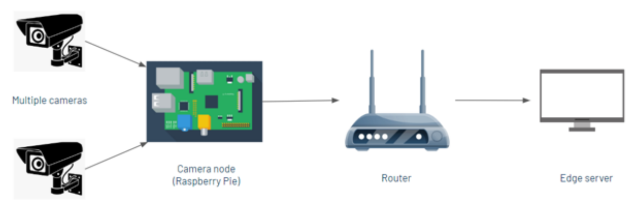


Fig. 1. Overview of the system

A camera node was needed for coordinating the cameras in the system. This camera node is capable of transmitting the video frames collected from each camera to the Edge Computer. Overall architecture of the system that derived from the above skeleton can be shown as below.

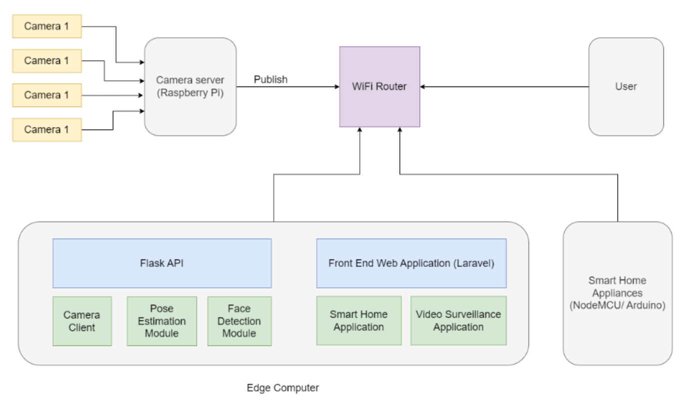


Fig. 2. Overall Architecture of the System

Camera server is responsible for collecting the video frames from each camera and sending them to the edge server. For implementing the camera server python Vidgear library is used.

- Vidgear Library - The VidGear library is a powerful and flexible Python library for video capturing and processing. It provides an easy-to-use interface for capturing frames from various video sources, such as webcams, IP cameras, screen recordings, video files, and more. VidGear also offers a wide range of features for real-time video processing, including frame manipulation, color space conversions, video stabilization, object detection, and more.

Once the camera server is started, it publishes the video frames from the each camera to the wireless LAN. The message header is included with a port number, so the client application in the LAN can receive the video frames from the corresponding port.

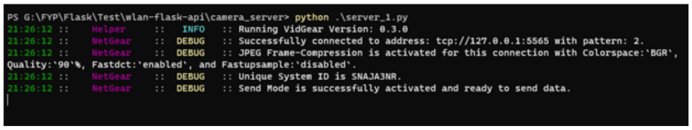


Fig. 3. Camera Server Started

Flask API is consist with three main modules. They are,

- Camera Client - When a request arrived from the frontend for video frames of a camera, then the video frames from the corresponding port are send to the frontend as the response.
- Pose Estimation Module - Processing a single frame costs considerable time. So each and every frame cannot be processed for pose estimation, because it may cause laggings in frontend application video feed. So as a solution, the program was designed to process 1 frame for 300 frames. If the frame is going to be processed, then a separate thread is created for continuing the pose estimation. Once the results are written to the database thread will be destroyed.
- Face Detection Module - Face recognition process does not cost much time and hardware like the pose estimation module. But for reducing the hardware usage and ensuring the smooth video streaming for the front end 1 frame for 50 frames are set to be processed.

2) Pose Classification and threatful pose detection: The increasing need for advanced surveillance systems to ensure public safety has led to the development of pose detection models capable of identifying threatening actions. This report outlines the development of a surveillance video application that aims to detect threatful poses in real-time, enhancing the efficiency of surveillance operations.

To obtain a diverse data set of threatening poses, a web scraping tool called Fatkun was utilized. This tool facilitated the collection of images from various online sources, representing poses such as climbing, running, pushing, pulling, and gun shooting. These images were crucial for training and validating the threatful pose detection model.

The MediaPipe framework was employed for key point extraction from the collected images. MediaPipe's pose estimation module utilizes advanced algorithms to detect and extract key body key points, including wrists, elbows, knees, and shoulders. By capturing the spatial positions of these key points, the system gains the ability to recognize specific threatening poses accurately.

Mediapipe provides a robust solution capable of predicting thirty-three 3D landmarks on a human body in real-time with high accuracy even on CPU. It utilizes a two-step machine learning pipeline, by using a detector it first localizes the person within the frame and then uses the pose landmarks detector to predict the landmarks within the region of interest.

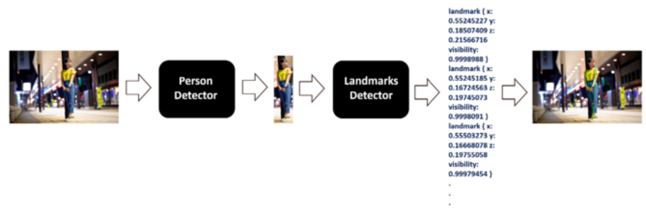


Fig. 4. Key points detection using mediapipe

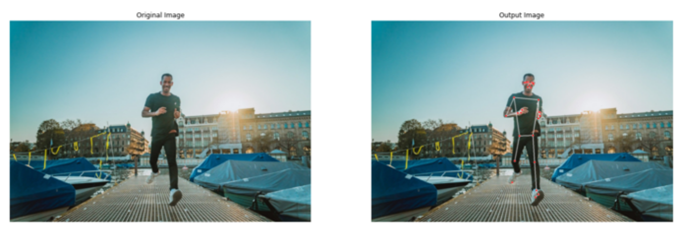


Fig. 5. Sample Skeleton

The extracted key points from MediaPipe were saved in a structured format, such as a CSV file. Before training the KNN classifier, the data underwent preprocessing steps, including cleaning the data set, handling missing values, and normalizing the key points. These steps were essential to ensure accurate and reliable classification results.

The preprocessed key points were utilized to train a K-nearest neighbors (KNN) classifier. KNN is a simple yet effective algorithm that assigns a class label to a new pose based on the majority vote of its nearest neighbors in the feature space. The number of neighbors and other hyper parameters were fine-tuned using techniques such as cross-validation to optimize the classification accuracy.

To evaluate the performance of the developed surveillance video application, several metrics were employed. Precision, recall, and F1-score were calculated to measure the accuracy of pose classification. A separate test dataset, distinct from the training data, was used to ensure unbiased evaluation and assess the model's generalization capabilities.

The results demonstrated promising accuracy in detecting and classifying threatening poses. The application achieved high precision, recall, and F1-score for each pose category, indicating its effectiveness in identifying potential threats within surveillance videos. The system also demonstrated robustness

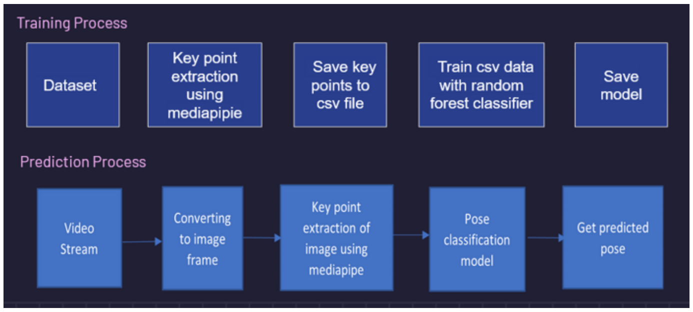


Fig. 6. Process of train and prediction of model

when tested with real-world video scenarios, further validating its reliability.

3) Face Recognition: At the beginning of the project, face_recognition library in python was used to implement the face recognition module. It is a famous package used for face detection, face recognition and face manipulation tasks.

This method was chosen for the implementation due to some reasons, and ease of use was one of them. Face_recognition library provides a simple and intuitive API which makes it easy to integrate face recognition capabilities into python applications. Since integrating the face recognition module with other modules and applications of the project was a major concern of the project, this advantage was considered to be very important at the beginning of the project. Also, the library providing both face detection and face recognition features was another reason that was considered when choosing this method. The library offers robust face detection capabilities. It can locate faces in both images and videos and return the coordinates of the bounding box around each face which can be used for further processing. And when it comes to face recognition, it compares and recognizes faces, accurately. Another reason as to why this method was selected was that this library comes with pre-trained models that can be readily used for face detection and recognition which eliminates the necessity for training our own models from scratch. This was considered as a great help in saving time. Also, performance was mainly considered when choosing this method. This library was designed for efficient processing which allowed real-time face recognition tasks. This facilitated parallel processing and optimizations to achieve high performance even when processing multiple images or video frames simultaneously which was very beneficial for our project.

However, after implementing the module we faced two unexpected challenges even though the module detected and recognized faces, accurately and efficiently. One of them was the model not being able to recognize multiple faces. Since multiple face recognition was a main requirement of the project, this was considered as a main drawback of this model. Also, the disability of the model to recognize faces that are few meters away from the camera was another drawback of the model because if that requirement is not satisfied, it adds no value to the objective of the project. Therefore, research was done on how to overcome this challenges.

Research was carried out to find a better approach to implement the face recognition module which will be able to overcome the identified drawbacks of the implemented model while maintaining its benefits. After researching on various methods and techniques, the final decision was made on haarcascade classifier and YOLO. Performance and efficiency are crucial factors of our project. When it comes to those factors, Haar Cascade classifier shows better results than YOLO. Also, it can reliably detect and recognize faces in controlled environments with consistent lighting conditions. Since we have the control over the placement of the final hardware product of our project and the lighting of the surroundings, it is not a problem to maintain necessary lighting conditions. Also, YOLO has a higher computational cost compared to Haar Cascade classifier, specially on resource-constrained devices. Training a YOLO model requires a significant amount data and computational power, and fine-tuning a pre-trained YOLO model for specific face detection tasks can be challenging because it requires substantial expertise and access to relevant data sets. Therefore, after considering all these factors Haar Cascade classifier was chosen to implement the model.

Implemented module was able to overcome the weaknesses that the previously implemented model had and performed accurately and efficiently.

Implemented face recognition module performed 3 functionalities

- Face Detection - The classifier was initialized first by

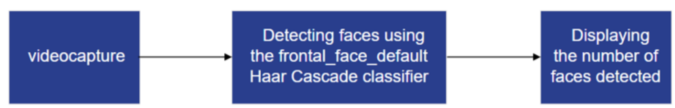


Fig. 7. Face detection process

  loading the pre-trained XML files. And once the classifier is initialized and a video stream is applied, the classifier scans through each frame of the video at multiple positions and scales, and searches for regions that matches the learnt features. And it detects the object as a face, if a match is found. The implemented model counts the number of faces detected in a frame and shows the count in the application.
- Face Registration - When it comes to building face registration functionality, haarcascade-frontal face classifier was used. Model was registered with multiple faces to increase the accuracy of the model. To ensure that the model registers a face accurately, each person needed to be present in front of the camera for around 100s. This can be considered as a drawback of the model, however, since the registration needs to take place only once, the impact of this to efficiency can be considered to be negligible.
- Face Recognition - Face recognition was done using haarcascade-frontal face classifier, as well. In this process if the detected face was recognized as an already

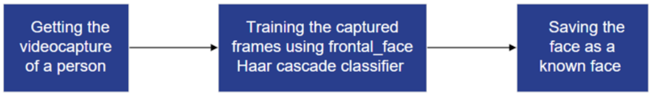


Fig. 8. Face registration process

registered person, the corresponding name was displayed on the application. If not it was displayed as 'Unknown'.

Fig. 9. Face recognition process

IV. Experiments and Results

A. Surveillance Video application- Pose Detection

The developed surveillance video application, incorporating a threatful pose detection model, has achieved a commendable accuracy rate of 86% when tested with a set of evaluation images. The application successfully detects and classifies threatening poses such as climbing, running, pushing, pulling, and gun shooting. The model's accuracy demonstrates its efficacy in accurately identifying these poses and contributes to enhancing public safety.

The model's accuracy was assessed using a separate set of testing images, distinct from the training data. Evaluation metrics, including precision, recall, and F1-score, were employed to measure the model's performance comprehensively. By achieving an accuracy of 86%, the model has demonstrated its ability to correctly classify a significant majority of poses within the defined threatful categories.

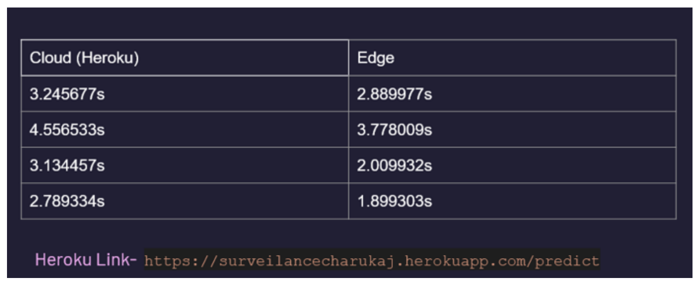
The surveillance application was hosted on both an edge server and the Heroku cloud server to assess latency performance. Latency refers to the time it takes for the application to respond to a request. By hosting the model on an edge server, which is closer to the source of the data, the application aims to minimize latency and achieve faster response times compared to a remote cloud server like Heroku.

Analysis of the application's latency on the edge server and Heroku cloud server provides valuable insights into their respective performance. The lower latency observed on the edge server suggests that processing the pose detection locally, closer to the source of the video feed, results in faster response times. This reduced latency can be crucial for real-time applications and ensures more immediate threat detection and response.

B. Smart Home Application

The forecasting simulation was done for the LSTM algorithm on the following specifications:16GB RAM, a 4.8 GHz core i7 processor used, and the IDE environment visual studio code and the python language were used.

Fig. 10. Climb pose detection



Cloud (Heroku)	Edge
3.245677s	2.889977s
4.556533s	3.778009s
3.134457s	2.009932s
2.789334s	1.899303s

Heroku Link- https://surveilancecharukaj.herokuapp.com/predict

Fig. 11. Face registration process

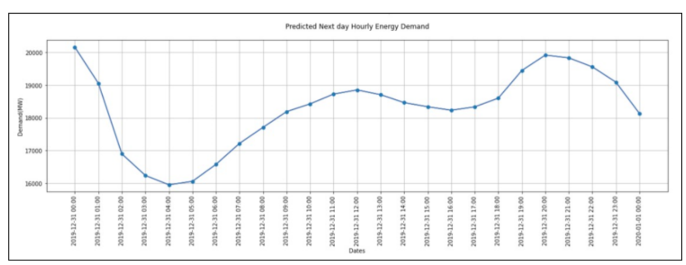


Fig. 12. One Day Load Forecasting

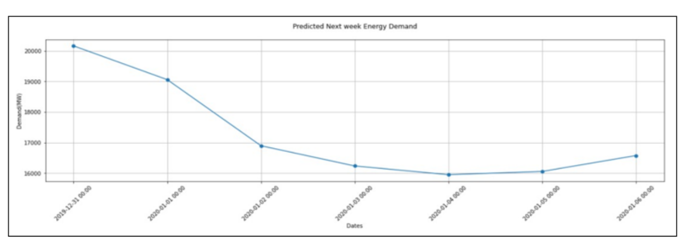


Fig. 13. One Week Load Forecasting

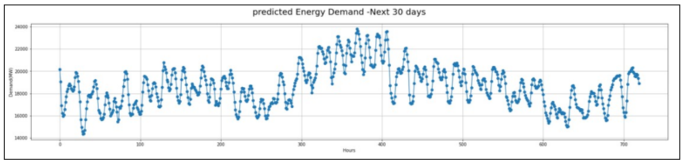


Fig. 14. One Month load forecasting

V. Discussion

Wireless Local Area Network (WLAN) Edge Computing has emerged as a promising solution for various applications, including surveillance video processing, smart home appliance controlling, and energy forecasting. With its reduced network latency compared to cloud computing, WLAN Edge Computing holds the potential to enhance the performance of these tasks. However, several challenges must be addressed, and considerations made to determine the suitability of this technology for enterprise and home environments. In this discussion, we will explore the challenges associated with WLAN Edge Computing and assess its effectiveness in improving surveillance video processing, smart home appliance control, and energy forecasting tasks.

The reduced network latency of WLAN Edge Computing enables real-time or near-real-time analysis of surveillance video. This enhances the performance of video analytics algorithms, leading to quicker response times for critical events and improved overall surveillance operations.

By processing appliance control instructions at the edge, WLAN Edge Computing reduces latency and enhances the responsiveness of smart home devices. This enables faster execution of commands, improved user experience, and increased automation capabilities within the home environment.

The reduced latency and localized processing of WLAN Edge Computing allow for real-time energy forecasting. This enables more accurate predictions and facilitates effective energy management, leading to optimized energy consumption and cost savings.

A. Challenges of WLAN Edge Computing

- Edge devices often have limited processing power and resources compared to cloud servers. Complex tasks such as surveillance video processing, smart home appliance control, and energy forecasting require significant computational capabilities. Optimizing algorithms and ensuring efficient resource utilization are crucial challenges to overcome for effective implementation of WLAN Edge Computing.
- Edge devices typically have limited storage capacity. Managing and storing large volumes of surveillance video data, appliance control instructions, and energy forecasting data at the edge can be challenging. Efficient data compression techniques, intelligent data prioritization, and seamless synchronization with centralized storage or cloud systems are necessary for effective data management.
- Although WLAN Edge Computing reduces latency, it still relies on network connectivity for data transmission and communication with other devices or central systems. Insufficient network bandwidth and unstable connections can hinder real-time processing and affect the performance of surveillance video processing, smart home appliance control, and energy forecasting tasks.
- Edge devices are susceptible to security vulnerabilities, including physical tampering and unauthorized access. Protecting sensitive data, ensuring secure communication channels, and implementing robust authentication mechanisms are crucial challenges for secure WLAN Edge Computing deployments.
- Scaling WLAN Edge Computing deployments across multiple devices, locations, and applications presents challenges in terms of device management, orchestration, and interoperability. Ensuring seamless integration with existing infrastructure and addressing compatibility issues between different edge devices and systems require careful planning and standardized protocols.

B. Suitability for Enterprise and Home Environments

WLAN Edge Computing can benefit both enterprise and home environments, although the suitability may vary.

- Enterprise: Enterprises often have extensive surveillance systems, complex smart building infrastructures, and significant energy management requirements. WLAN Edge Computing can greatly enhance surveillance video processing, smart home appliance control, and energy forecasting in such environments. Enterprises typically possess the resources, expertise, and infrastructure to manage and maintain WLAN Edge Computing deployments effectively, making it more suitable for enterprise applications.
- Home: While WLAN Edge Computing can also improve performance in smart homes, the scale and complexity of enterprise environments often exceed home requirements. Cloud-based solutions may still be more convenient for home users, providing easy access to data from anywhere and requiring minimal maintenance.

VI. Future Work

A. Surveillance Video Application

- Expanding the dataset by collecting a more extensive range of images representing each threatening pose can improve the model's performance and generalization capabilities.
- Exploring deep learning approaches, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), may offer more advanced feature extraction and classification capabilities, potentially enhancing the accuracy of pose detection.
- The ethical implications of deploying surveillance systems should be carefully considered. Privacy concerns and adherence to legal regulations must be prioritized to ensure the responsible

The development of a surveillance video application with threatful pose detection holds immense potential for enhancing public safety and security. By leveraging web scraping, MediaPipe for keypoint extraction, and a KNN classifier for pose classification, the application demonstrates accurate detection and classification of threatening poses such as climbing, running, pushing, pulling, and gun shooting. However, further improvements, including increasing the training dataset, exploring advanced deep learning techniques, and implementing real-time capabilities, are recommended to enhance the system's accuracy and usability.

The developed application represents a significant step toward intelligent surveillance systems, capable of identifying potential threats proactively. Responsible deployment, ethical considerations, and continuous improvement are essential to ensure the application's effectiveness while respecting individual privacy and legal frameworks.

B. Smart Home Application

- Instead of using the pure LSTM model, some other mix models like CNN-LSTM, or Bi-LSTM models can be added with an ensemble learner and check the accuracy score values to verify they are working better than the basic LSTM model. Similarly, there are more modified models with higher accuracy for RNN and CNN. Those also should be tested with the online available dataset for both long-term and short-term predictions.
- Instead of using the pure LSTM model, some other mix models like CNN-LSTM, or Bi-LSTM models can be added with an ensemble learner and check the accuracy score values to verify they are working better than the basic LSTM model. Similarly, there are more modified models with higher accuracy for RNN and CNN. Those also should be tested with the online available dataset for both long-term and short-term predictions.
- Improve the more security features on the Web dashboard. Because usually, every SHA and SVA systems has a dashboard to view and control. Therefore, our system as mission critical system, we need to have more advanced security algorithms and techniques to secure the system. For that, a security layer also should lie on top of the application layer. Following are some key components that are needed to design and implement in the future

CONCLUSION

WLAN edge computing has emerged as a promising approach to enhance the performance of surveillance video processing and smart home applications. By bringing data processing and analysis closer to the source, WLAN edge computing offers reduced latency, improved system efficiency, enhanced privacy and security, and optimized network bandwidth. Leveraging the computational capabilities of edge devices, this approach enables real-time or near-real-time decision-making, efficient resource utilization, and intelligent automation in smart homes. Furthermore, WLAN edge computing facilitates edge intelligence by enabling advanced analytics and machine learning algorithms at the edge, empowering surveillance systems and smart home environments with contextual insights. As research and development in this field continue to advance, WLAN edge computing is expected to play a crucial role in optimizing the performance and responsiveness of surveillance systems and smart homes, paving the way for more efficient and intelligent applications in the future.

ACKNOWLEDGMENT

Foremost, we would like to express our sincere gratitude to our final year research supervisor, Dr. Sampath Edirisinghe of the Department of Computer Engineering, the University of Sri Jayewardenepura for their enthusiasm, patience, insightful comments, and proper guidance that have helped us tremendously at all times in this research project.

We also extend gratitude and appreciation to our lecturers in the Department of Computer Engineering for allowing us to do the research and for the guidance. We are also grateful to all the personnel who helped us with the completion of this project.

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