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"WICNN ACT WIFI BASED HUMAN ACTIVITY RECOGNITION UTILIZING DEEPLEARNING ON THE EDGE COMPUTING DEVICES"

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Abstract: The recognition of human actions is of great importance for modern applications allowing interaction between people and computers. But many full systems require wearables, cameras and sensors, which can be expensive, hard to set up and raise privacy concerns. The wireless human sensing using Wi-Fi employs Channel State Information (CSI) to detect people and their proximity by observing changes in signal properties due to people. This inexpensive method can collect evidence in places that are difficult to see or blocked by using existing Wi-Fi networks. It does not care about privacy, but it does care about interference and the environment.

In this paper, we propose WiCNNAct, a WiFi-based human activity recognition framework which leverages deep learning to address the limitations identified. The proposed system uses a multi-channel (1D-CNN) to automatically extract spatial and temporal features during the recognition process. This is achieved by real, imaginary and absolute values related to the CSI input. The model was validated through a multi-channel testing method on three channels (1, 2 and 3) and reached a mean accuracy of 98.29% ± 0.33% after the 10-fold cross-validation procedure.

Multi-Person Recognition and Cross Environment Adaptability have improved the WiCNNAct framework. These additions mean that the framework can be shown to be able to identify multiple people doing things at the same time, quickly and accurately. It can also learn to identify various indoor scenes without requiring much additional training. The model is deployed in systems capable of sensing when people are doing things on the edge.

Keywords— Channel State Information (CSI), Deep learning, Wi-Fi Based Human Activity Recognition (HAR)

I. INTRODUCTION

[1] Human action recognition (HAR) is a core component of today's human-computer interaction (HCI) systems. It is usable in many different places, e.g. in smart homes, health monitoring, security systems, entertainment and robotics. Systems that can accurately recognise human actions enable smart responses. It makes them safer, easier and more fun for the people who use them. Previously HAR systems have used cameras, wearable sensors or ambient sensors to infer peoples activities.[11] They are very accurate in recognition but they have some real-world issues.[5] The users always need to carry or wear sensors and that can be annoying and intrusive. While camera-based approaches can gather rich visual data, they raise privacy concerns and are not suitable for environments where users have limited mobility or do not want to be visually monitored. Ambient sensors are expensive to deploy and are sensitive to the environment.

Recently, researchers have been exploring the use of Wi-Fi sensing to detect human activity. Wi-Fi sensing uses CSI (Channel State Information). [2]It tells us how Wi-Fi signals bounce and flow when they strike objects and people. [12]CSI is able to detect very small changes in amplitude and phase of Wi-Fi signals. It also allows us to know if there is a person, what he or she is doing and how he's or she's moving without the use of cameras or wearables. Wi-Fi sensing is cheap, exploits the existing network infrastructure, and is privacy preserving, thus can be deployed at scale. Some things are still to be fixed. The accuracy and reliability of Wi-Fi signals may be affected by the environment, multipaths and changes in the indoor space.[3]

Deep learning has become an important approach to automatically mine the complex spatial and temporal features of CSI data with respect to these problems. [13] Convolutional Neural Networks (CNNs) and their variants are able to learn hierarchical feature representations that other machine learning methods cannot. This is improving the robustness and performance of HAR systems. So you can combine CSI-based sensing and deep learning to build an accurate, well functioning, scalable and privacy protecting system.[4]

II.RELATED WORK

[6]Wi-Fi-based Human Activity Recognition (HAR) has attracted significant attention due to its non-intrusive and device-independent sensing abilities. But Wi-Fi sensing keeps your information safe and performs well in low light. Early research mainly used traditional machine learning classifiers such as Support Vector Machines (SVM) and k-Nearest Neighbours (k-NN), in conjunction with Received Signal Strength Indicator (RSSI) metrics. These methods were not very effective, given the coarse-grained signal representation and the reliance on hand-crafted feature extraction.[14]

To avoid these problems, researchers started to use Channel State Information (CSI)-based sensing. This provides them with a lot of information about the phase and amplitude of Wi-Fi signals.[9] The methods based on CSI improved the activity recognition significantly by capturing small environmental changes caused by human activity. We have added several methods to pre-process the signals to make the system more robust. These are feature normalisation, dimension reduction and noise filtering.[7]

With the emergence of deep learning, Convolutional Neural Networks (CNNs) can automatically learn spatial features from CSI data without manual feature engineering. The older machine teaching methods were not as good as the architectures that used CNNs. Further, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are used to capture temporal dependencies of sequential CSI signals. This allowed identification of activities in real time.[10]

Although highly accurate, many of today's systems rely on cloud-based computing, which introduces latency, privacy issues and communication costs. To solve these problems, recent studies have suggested using lightweight deep learning models in edge computing devices. With Edge based HAR systems you can take decisions immediately, consume less network bandwidth, keep your data safer and money. Still, it is challenging to achieve high accuracy with computationally efficient on resource-constrained edge platforms.[8]

III.METHODOLOGY

In this paper, we propose a Wi-Fi based Human Activity Recognition (HAR) framework using Channel State Information (CSI) and deep learning techniques on edge computing devices. The method is designed to make activity recognition accurate, fast and privacy respectful. The overall workflow consists of five major steps: get the data, clean it up, identify features, design the model architecture, and test it with ethical safeguards. They first gather CSI data from Wi-Fi transceivers when people are doing some actions inside. The raw signals are then cleaned up to eliminate noise and ensure changes due to outside interference are the same. Then, useful patterns in space and time are extracted and put into a light One-Dimensional Convolutional Neural Network (1D-CNN). The trained model is deployed on an edge device to make fast predictions without relying on cloud infrastructure. Finally, standard classification metrics are used to verify the system’s performance. They also ensure that privacy is protected and data is treated in a moral way.

Obtaining Information:

We collected the dataset using Wi-Fi devices that can obtain Channel State Information (CSI). CSI captures small variations in the phase and amplitude of Wi-Fi subcarriers, which are highly sensitive to human motion in the environment. The human activities to be planned are walking, sitting, standing and falling indoors using a transmitter-receiver set up.

For each activity, a number of samples are taken in order to have different subjects and different environmental conditions. You ensure that signal acquisition and activity labelling happen concurrently when you collect data. The obtained CSI streams are time-series data which indicate signal variations when there is any movement.

Preparing the Data

Raw CSI data is noisy and affected by interference from the outside world. To improve the signal and to make the model perform better prepossessing is needed.

- you have to do the following steps for preprocessing:
- Noise filtering. A low-pass filter will remove high frequency noise.
- Removing Outliers: Unusual spikes in the values of amplitude are removed.
- Normalisation: CSI values are rescaled to a uniform range, which ensures the stability of the model training.
- Segmentation: Continuous CSI streams are segmented into time windows of a fixed size. Each time window corresponds to an instance of activity.

How to Obtain Features:

The system uses deep learning to automatically learn features, rather than hand crafting them. But before we do signal refinement to highlight important patterns.

- From the Split CSI data:
- We note the change of the amplitudes between the sub-carriers.
- They record the changes over time that show the movement of things.
- You can use statistical properties, like mean and variance, to improve the representation if that makes sense.
- The structured time series CSI matrices are then fed into a convolutional neural network that can self-learn spatial features.

How the model is constructed:

- The system proposed implements One-Dimensional Convolutional Neural Network (1D-CNN) for classification of time series.
- The building has
- Input Layer: Receives discretised time-series data from CSI.
- Convolutional Layers: Employ a large number of filters to detect patterns in the spatial variations of signals.
- Activation Function: ReLU makes things non-linear.
- Pooling Layers: Make smaller and easier to understand.
- Fully Connected Layer: combines features that have been extracted.
- Output Layer A softmax classifier able to discriminate between different types of activities.

The model is trained with Adam optimiser and the categorical cross entropy loss makes it better. The design is lightweight so it can be run on edge computing devices that don't have a lot of processing power.

Ethical Assessment and Safeguards:

1. How to measure

For evaluation of the model we use the following:

● Accuracy

● Accuracy

●Keep in mind

● F1-Score

- Confusion Matrix

The dataset is divided into training and testing sets to make sure the evaluation is fair. You can also use cross-validation methods to be more certain.

2. Keeping ethics secure

- The proposed system ensures that:
- Cameras and wearables keep nothing private.
- Data Anonymisation: We do not keep any personal data that could be used to identify a person.
- Secure Storage: The CSI data gathered is not available to those who should not have access to it.
- Informed Participation: Participants are informed of what will occur prior to data collection.
- Because the system only uses variations of Wi-Fi signals to detect what people are doing, it doesn't invade their privacy or get in the way.

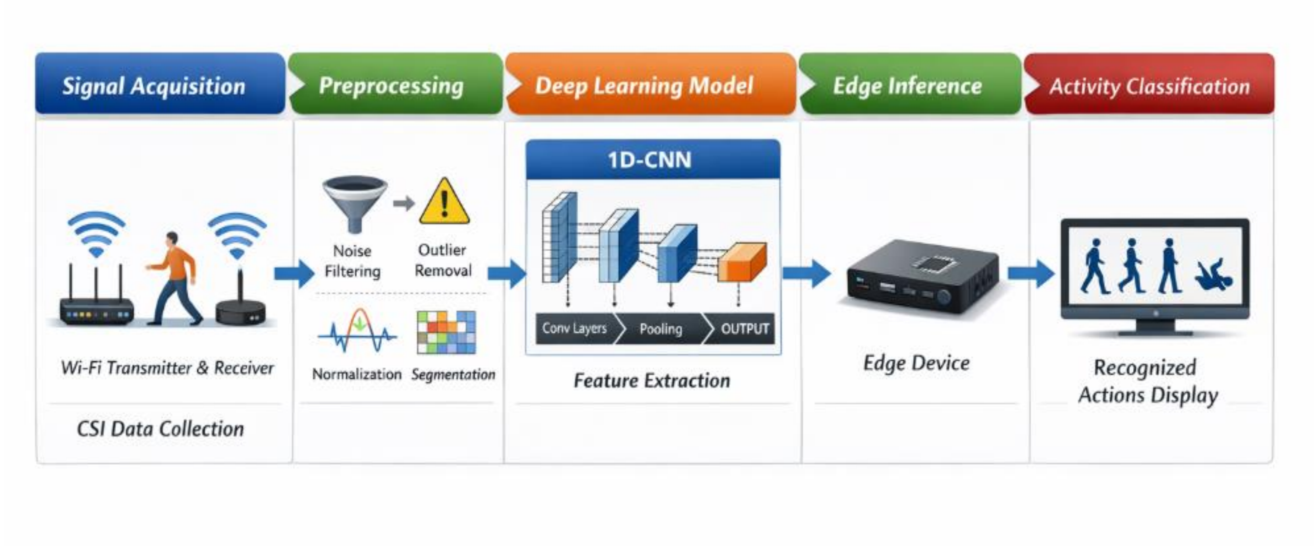
SYSTEM ARCHITECTURE:

The proposed system architecture aims to allow people to recognise activities in real time while protecting their privacy. It leverages Wi-Fi Channel State Information (CSI) and deep learning on edge computing devices. The architecture comprises five main components: Wi-Fi Signal Sensing Module, Data Processing Module, Deep Learning Module, Edge Deployment Module, and Output Interface Module.

A. Introduction .

The proposed system detects human activity through Wi-Fi by Channel State Information (CSI) and a lightweight deep learning model on an edge device. When people move, Wi-Fi signals go with them. These changes are logged and cleaned to remove noise. A One-Dimensional Convolutional Neural Network (1D-CNN) automatically finds features and classifies activities. The model is deployed in an edge device so that it can work in real-time with a little delay and better privacy without the need of a cloud infrastructure.

A. Architecture Diagram:



B. Module Interactions:

The system then provides the processed data to a data pipeline in which each module passes data to the next module in the pipeline. The Signal Acquisition module gets CSI streams in real time and passes them to the Preprocessing module. The Preprocessing module removes noise, normalises data, and splits the data. The cleaned up segments of CSI are fed to the Deep Learning module. Then the 1D-CNN identifies features that differentiate them and classifies activities. The Edge Inference module operates on the predicted results and enables decisions to be made instantly. Then the Application Interface presents the results or sends alerts.

IV. EXPERIMENTAL SETUP:

The aim of the experiment is to test the performance of the proposed Wi-Fi based Human Activity Recognition system. CSI collects data in indoor environments as people do pre-arranged activities. Before they could be used to train a lightweight 1D-CNN model, the raw signals were pre-processed and sliced into smaller pieces. The trained model is deployed on an edge device to test if it is able to perform real-time inferences. The system is evaluated on different training and testing datasets for fair evaluation. We evaluate performance with standard classification metrics, and test for accuracy and robustness.

Datasets:

The experimental evaluation is based on Wi-Fi Channel State Information (CSI) data collected from an indoor environment. Different subjects do different things, so there is a lot of variety. For example, they walk, they sit, they stand, they fall. The CSI streams are segmented into time windows of a given length and are named according to what was performed at that time. The data is split into training and testing sets so that we can see how well the model works on new data and avoid overfitting.

The setting for hardware and software:

The CSI data is obtained using Wi-Fi transceivers for which very detailed Channel State Information can be obtained. The deep learning model is developed and trained in Python with the help of frameworks such as TensorFlow/Keras or PyTorch. The model is deployed on an edge computing device with limited computing power to ensure real-time deployment. The experiments take place indoors in a controlled environment to ensure that the signals are always the same.

Training configuration:

The One-Dimensional Convolutional Neural Network (1D-CNN) is trained using segmented CSI data. The data set is made up of training and testing sets. To enhance the model to classify more than one class, the Adam optimiser and categorical cross-entropy loss are used. The number of epochs is fixed and the batch size is fixed to ensure that the convergence is stable. You can use early stopping or regularisation methods to stop overfitting and improve generalisation performance.

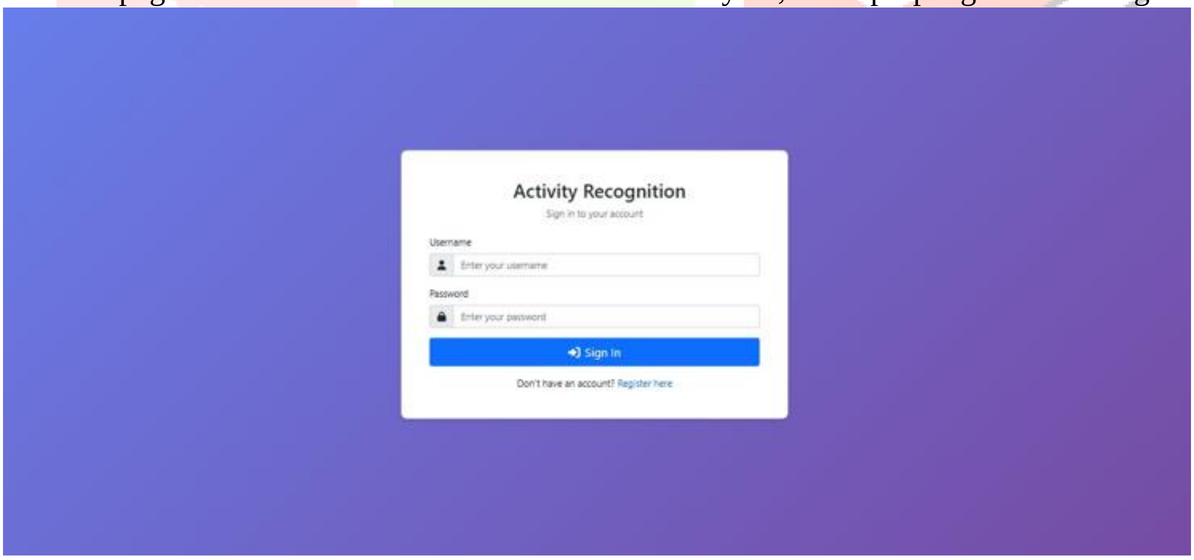
We use standard classification metrics such as Accuracy, Precision, Recall and F1-Score to see the working of proposed system. A confusion matrix is generated to measure the performance of each class and error rate. These metrics show how well the model can distinguish different types of human activity.

V. Results and Discussions:

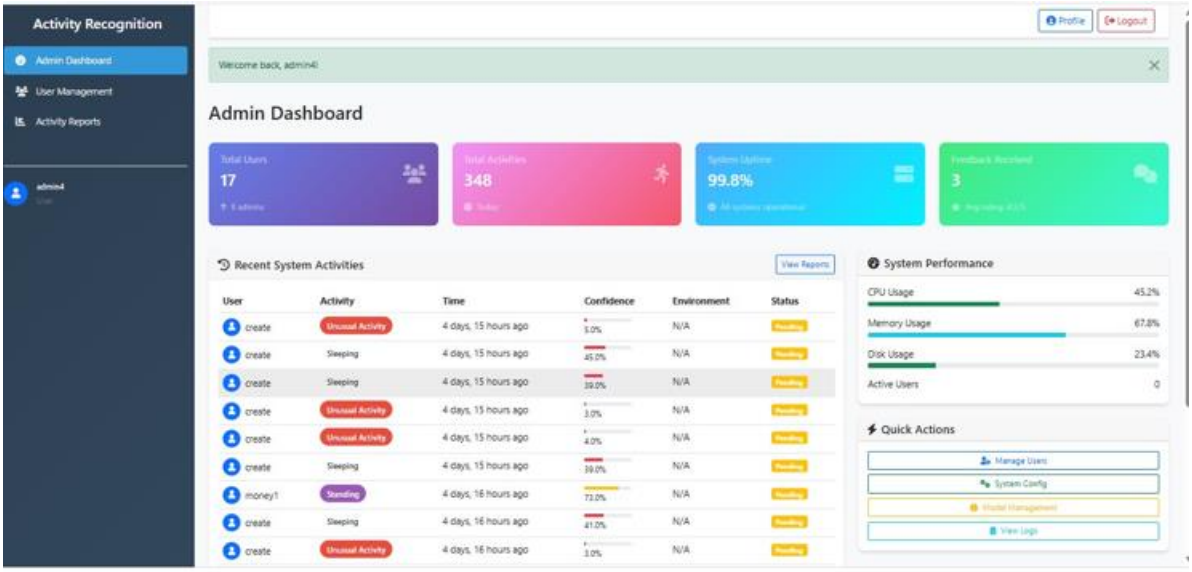
Experimental results show that the proposed Wi-Fi-based Human Activity Recognition system can recognise human activities accurately using CSI data and 1D-CNN model. The model was good at classification and did not get confused too often between similar activities. The metrics of accuracy, precision, recall and F1-score all show that the approach is performing well. Real-time inference can be done quickly with low delay on edge deployment. The results generally show that the proposed system works and is possible.

LOGIN PAGE:

- This image is a system login page for activity recognition.
- On the interface, there are fields to type in your user name and password.
- Below the fields where you can enter your information there is a big blue “Sign In” button.
- New users can register by clicking on a link that says “Register here.”
- The page looks modern with a clean centred card layout, and a purple gradient background.



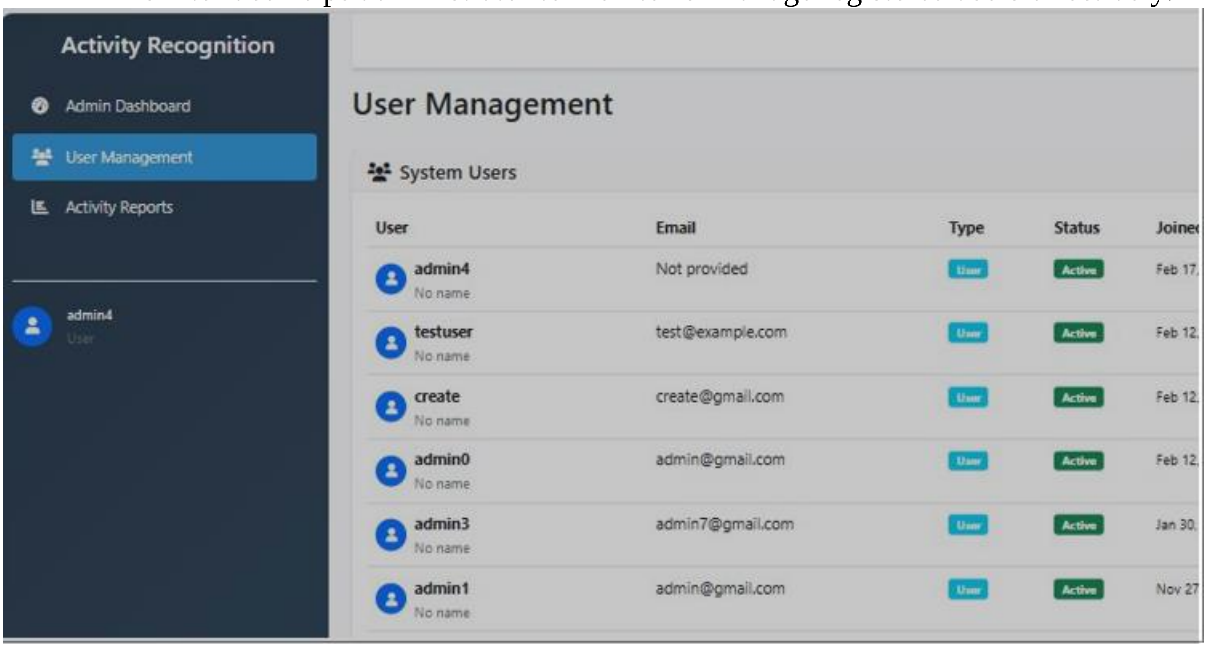
B.ADMIN DASHBOARD:



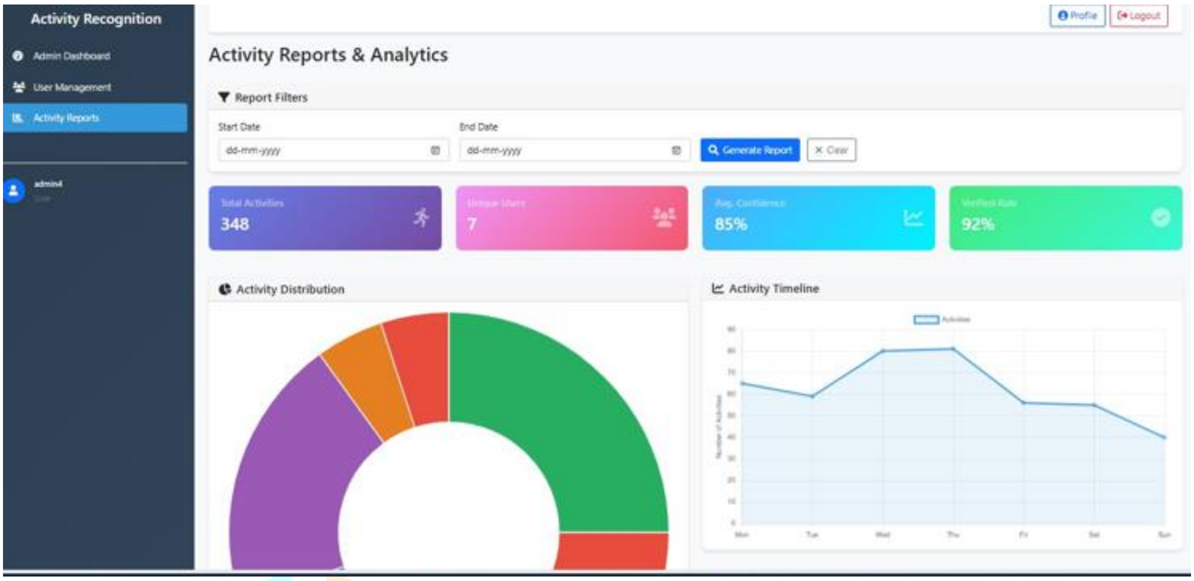
The image shows the user profile dashboard for the Activity Recognition system.
It displays profile information such as the username, email, date of membership and time of last login.
On the left, a sidebar menu has different navigation options like Dashboard, Real-time Monitoring, Activity History, and Feedback.
You'll have security options like “Change Password” and “Provide Feedback.”
At the bottom, there are activity statistics count of total activities and feedback.

C. USER MANAGEMENT:

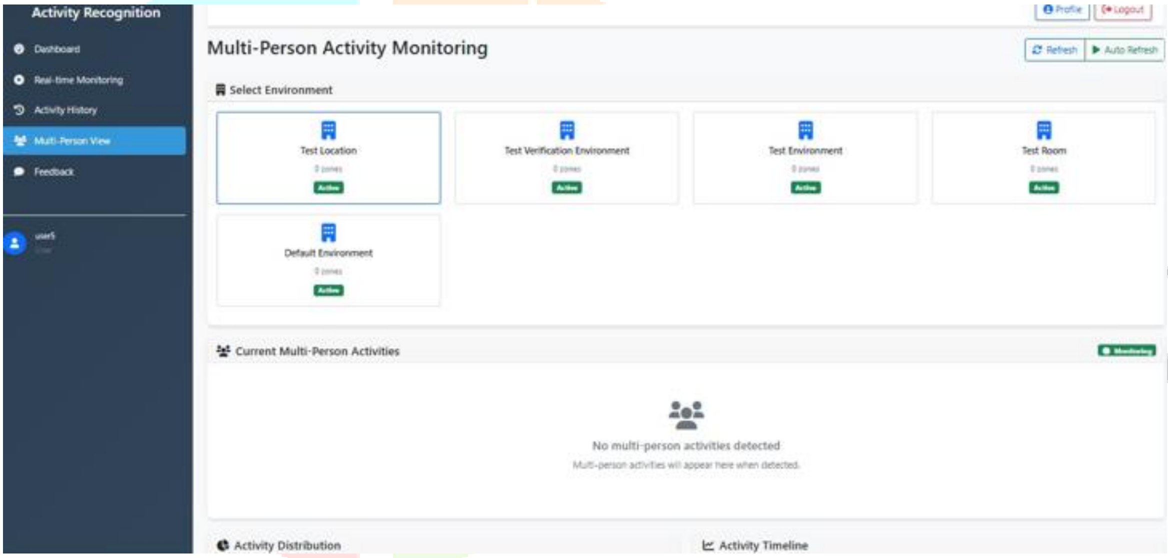
- The image depicts the User Management page of the Activity Recognition system in the Admin Dashboard.
- Shows a list of system users with their email address, account type, and status.
- All the users are called as "User" and the status column shows the user as "Active".
- On the left sidebar it has navigation options such as Admin Dashboard, User Management and Activity Reports.
- This interface helps administrator to monitor & manage registered users effectively.



D.REPORTS:



E.MULTI PERSON ACTIVITY MONITORING:



V. CONCLUSION:

In this paper, we propose WiCNNAct, a Wi-Fi based system that can recognise human activity. It employs multi-channel 1D Convolutional Neural Networks (1D-CNN) to automatically extract spatial and temporal features from Channel State Information (CSI). Unlike other systems that use wearables, cameras or sensors, WiCNNAct is non-intrusive, cheap and non privacy invasive. The system yielded a high mean accuracy of 98.29 ± 0.33%, across 10-fold cross-validation, which suggests that it is robust and reliable. It also supports Multi-Person Recognition and Cross-Environment Adaptability, meaning that it can accurately recognise multiple individuals and perform well in various indoor environments with minimal retraining.

The system has been successfully deployed on edge computing devices like the Raspberry Pi. This allows the real-time detection of human activity with very low latency. WiCNNAct is a good and flexible solution for smart homes, healthcare monitoring, security, and office automation. It is highly accurate, privacy-preserving, edge-enabled and adaptable, thus being a promising technology for smart environment systems and the next-generation human-computer interaction.

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