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Edge-Level Wireless Signal-Driven Behavioral Identification System Using Neural Models

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Abstract: Recognising human actions is very important for modern applications that let people and computers work together. However, many complete systems need wearables, cameras, and sensors that can be expensive, hard to set up, and raise privacy concerns. Wi-Fi-based wireless human sensing uses Channel State Information (CSI) to find people and their proximity by keeping an eye on changes in signal properties that people cause. This cheap method can use Wi-Fi networks that are already in place to gather evidence in places where it is hard to see or is blocked. It doesn't care about privacy, but it does care about interference and the environment.

This paper introduces WiCNNAct, a Wi-Fi-based human activity recognition framework that employs deep learning to overcome the identified limitations. The proposed system employs a multi-channel (1D-CNN) to autonomously extract spatial and temporal features during the recognition process. It does this by using real, imaginary, and absolute values that are connected to CSI input. A multi-channel testing method showed that the model worked well on three channels (1, 2, and 3) and had a mean accuracy of 98.29% ± 0.33% after going through a 10-fold cross-validation process.

The WiCNNAct framework has been improved to include Multi-Person Recognition and Cross Environment Adaptability. With these additions, the framework can be shown to be able to quickly and accurately identify multiple people doing things at the same time. It can also learn to recognise different indoor settings without needing a lot of extra training. The model is used in systems that can tell when people are doing things at the edge.

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

I. Introduction

Human action recognition (HAR) is a key component of contemporary human-computer interaction (HCI) systems. You can use it in a lot of different places, like smart homes, health monitoring, security systems, entertainment, and robotics. When systems can accurately identify human actions, they can respond in a smart way. This makes things safer, easier, and more fun for people who use them. In the past, HAR systems relied a lot on cameras, wearable sensors, or ambient sensors to find out what people were doing. Recognition is very accurate with these methods, but they have some real-world issues. It can be annoying and intrusive for users to always have to carry or wear sensors. Camera-based methods can collect detailed visual data, but they also raise privacy issues and aren't good for places where users can't move around freely or don't want to be tracked visually. It can be expensive to set up ambient sensors, and they can be easily affected by changes in the environment.

Researchers have recently looked into Wi-Fi-based sensing as a possible way to detect human activity. Wi-Fi-based sensing uses Channel State Information (CSI). It shows us how Wi-Fi signals change and move when they hit things and people. CSI can detect tiny changes in the amplitude and phase of Wi-Fi signals. It can also tell if someone is there, what they're doing, and how they're moving without the need for cameras or wearables. Wi-Fi sensing is inexpensive, works with the network infrastructure that is already in place, and protects privacy, so it can be used on a large scale. We still need to fix some things. Wi-Fi signals can be less accurate and reliable because of things like the environment, multiple paths, and changes in indoor space.

Deep learning has become an important way to automatically get the complex spatial and temporal features of CSI data in response to these problems. Convolutional Neural Networks (CNNs) and their variations can learn hierarchical feature representations that other machine learning methods can't. This makes HAR systems more reliable and better at what they do. By combining CSI-based sensing and deep learning, you can make a system that is accurate, works well, can grow, and protects privacy.

II.RELATED WORK

Wi-Fi-based Human Activity Recognition (HAR) has gained significant attention due to its non-intrusive and device-independent sensing capabilities. Wi-Fi sensing, on the other hand, keeps your information private and works well in low light. Early research primarily employed Received Signal Strength Indicator (RSSI) metrics alongside traditional machine learning classifiers, such as Support Vector Machines (SVM) and k-Nearest Neighbours (k-NN). These methods worked, but not very well because they used coarse-grained signal representation and relied heavily on hand-crafted feature extraction.

To get around these problems, researchers started using Channel State Information (CSI)-based sensing. This gives them a lot of information about the amplitude and phase of Wi-Fi signals. CSI-based methods made activity recognition much more accurate by picking up on small changes in the environment that happen when people move around. We added different ways to preprocess signals to make the system stronger. These include noise filtering, dimensionality reduction, and feature normalisation.

With the rise of deep learning, Convolutional Neural Networks (CNNs) have been able to automatically learn spatial features from CSI data without any manual feature engineering. Architectures that used CNNs worked better than older ways of teaching machines. We also used Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks to model temporal dependencies in sequential CSI signals. This made it easier to recognise dynamic activities.

Even though they are very accurate, many of today's systems rely on cloud-based computing, which causes latency, raises privacy concerns, and raises communication costs. Recent research has concentrated on deploying lightweight deep learning models on edge computing devices to address these issues. Edge-based HAR systems let you make decisions right away, use less network bandwidth, keep your data safer, and save money. Still, it is hard to get high accuracy while keeping computational efficiency on edge platforms with few resources.

III.METHODOLOGY

The proposed system aims to create a Wi-Fi-based Human Activity Recognition (HAR) framework that uses Channel State Information (CSI) and deep learning techniques on edge computing devices. The method is meant to make activity recognition accurate, quick, and respectful of privacy. There are five main steps in the workflow as a whole: getting the data, cleaning it up, finding features, designing the model architecture, and testing it with ethical safeguards. At first, Wi-Fi transceivers collect CSI data while people are doing certain things inside. After that, the raw signals are cleaned up to get rid of noise and make sure that changes caused by outside interference are the same. Then, useful patterns in space and time are taken out and put into a light One-Dimensional Convolutional Neural Network (1D-CNN). The trained model is put on an edge device so that it can make predictions quickly without using cloud infrastructure. Finally, standard classification metrics are used to see how well the system works. They also make sure that privacy is protected and that data is handled in a moral way.

Getting Information:

We used Wi-Fi devices that can get Channel State Information (CSI) to gather the dataset. CSI keeps track of small changes in the phase and amplitude of Wi-Fi subcarriers, which are very sensitive to how people move around in their surroundings. A transmitter-receiver setup is used to carry out planned human activities like walking, sitting, standing, and falling indoors.

For each activity, multiple samples are taken to make sure that the subjects and the environment are different. When you collect data, you make sure that signal acquisition and activity labelling happen at the same time. The CSI streams that were captured make time-series data that shows how signals change when something moves.

Getting the Data Ready:

Raw CSI data has noise and interference from the outside world. To make the signal better and the model work better, preprocessing is necessary.

You need to do the following steps to preprocess:

Noise Filtering: A low-pass filter gets rid of noise at high frequencies.

Removing Outliers: Unusual spikes in amplitude values are taken out.

Normalisation: CSI values are put into a consistent range so that the model training stays stable.

Segmentation: Continuous CSI streams are divided into time windows of a fixed size that correspond to each activity instance.

How to Get Features:

Instead of making features by hand, the system uses deep learning to automatically pull them out. But first, signal refinement is done to make important patterns stand out.

From the broken-up CSI data:

We look at how the amplitude changes between subcarriers.

They keep track of the changes over time that show how things move.

If it makes sense, you can use statistical properties like the mean and variance to improve the representation.

The structured time-series CSI matrices are then sent to the convolutional neural network, which lets it learn about spatial features on its own.

The way the model is built:

The proposed system employs a One-Dimensional Convolutional Neural Network (1D-CNN) designed for time series classification.

The structure has:

Input Layer: Gets time-series data from CSI that has been broken up.

Convolutional Layers: Use a lot of filters to find patterns in how signals change over space.

Activation Function: ReLU makes things not straight.

Pooling Layers: Make things smaller and easier to understand.

Fully Connected Layer: puts together the features that were removed.

Output Layer: A softmax classifier that can tell different kinds of activities apart.

The Adam optimiser trains the model, and the categorical cross-entropy loss makes it better. The design is light so that it can work on edge computing devices that don't have a lot of processing power.

Evaluation and Safeguards for Ethics:

1. Ways to Measure

We use the following to see how well the model works:

- Correctness
- Correctness
- Keep in mind
- F1-Score
- Confusion Matrix

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

2. Keeping ethics safe

The proposed system makes sure that:

No cameras or wearable devices are used to keep things private.

Data Anonymisation: No personal information is kept that could be used to identify someone.

Safe Storage: People who shouldn't be able to get to the CSI data that was collected can't get to it.

Informed Participation: Participants are told what will happen before data collection.

The system only uses changes in Wi-Fi signals to figure out what people are doing, so it doesn't invade their privacy or get in the way.

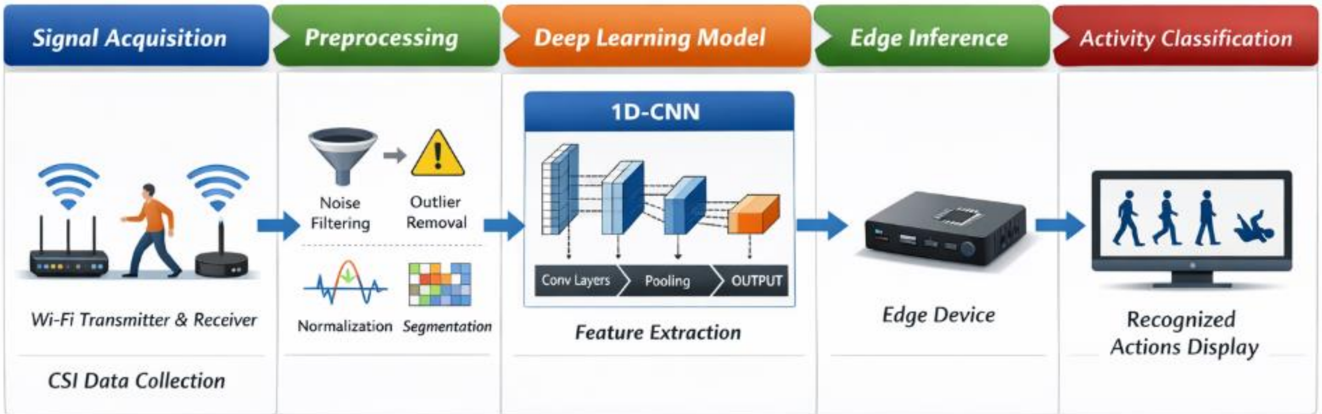
IV. SYSTEM ARCHITECTURE:

The suggested system architecture is meant to let people recognise activities in real time while keeping their privacy safe. It does this by using Wi-Fi Channel State Information (CSI) and deep learning on edge computing devices. The architecture has five main parts: the Wi-Fi Signal Sensing Module, the Data Processing Module, the Deep Learning Module, the Edge Deployment Module, and the Output Interface Module.

A. Overview:

The proposed system employs Channel State Information (CSI) and a lightweight deep learning model on an edge device to detect human activity via Wi-Fi. When people move, Wi-Fi signals change. These changes are recorded and cleaned up to get rid of noise. A One-Dimensional Convolutional Neural Network (1D-CNN) automatically sorts activities and finds features. The model is put on an edge device so it can work in real time, with little delay, and better privacy without needing cloud infrastructure.

B. Architecture Diagram:



C. Module Interactions:

The system sends processed data through a structured data pipeline, with each module sending data to the next in order. The Signal Acquisition module gets real-time CSI streams and sends them to the Preprocessing module. The Preprocessing module gets rid of noise, normalises the data, and breaks it up. The Deep Learning module gets the cleaned-up CSI segments. The 1D-CNN then finds features that make them different and sorts activities. The Edge Inference module works on the predicted results so that decisions can be made right away. Then, the Application Interface shows the results or sends alerts.

V. EXPERIMENTAL SETUP:

The goal of the experiment is to see how well the proposed Wi-Fi-based Human Activity Recognition system works. CSI collects data indoors while people do things that have been planned ahead of time. The raw signals are preprocessed and cut into smaller pieces before they can be used to train a lightweight 1D-CNN model. We put the trained model on an edge device to see if it can make inferences in real time. To ensure a fair evaluation, the system is tested with various training and testing datasets. We use standard classification metrics to check for accuracy and robustness and measure performance.

Datasets:

The experimental evaluation employs Wi-Fi Channel State Information (CSI) data collected from an indoor environment. Different subjects do different things to make sure that there is a lot of variety. They walk, sit, stand, and fall, for example. The CSI streams are divided into time windows of a set length and given names based on what was done during that time. The dataset is split into training and testing sets to see how well the model works on new data and to avoid overfitting.

The environment for hardware and software:

Wi-Fi transceivers that can get very detailed Channel State Information are used to get the CSI data. Python is used to build and train the deep learning model, which uses frameworks like TensorFlow/Keras or PyTorch. To make sure that real-time deployment is possible, the model is deployed on an edge computing device with limited computing power. The experiments take place in a controlled indoor space to make sure that the signals are always the same.

Setting up training:

The One-Dimensional Convolutional Neural Network (1D-CNN) is trained with segmented CSI data. There are training and testing sets in the dataset. The Adam optimiser and categorical cross-entropy loss are used to make the model better for classifying more than one class. A fixed batch size and a set number of epochs are used to make sure that convergence is stable. You can use early stopping or regularisation methods to stop overfitting and improve generalisation performance.

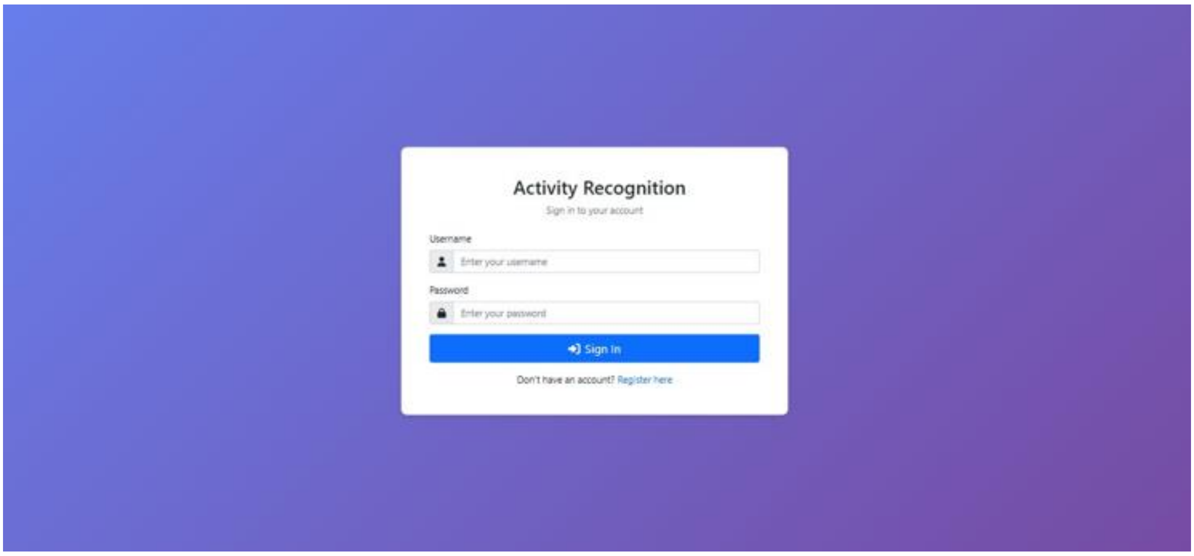
We use standard classification metrics like Accuracy, Precision, Recall, and F1-Score to see how well the proposed system works. To see how well each class does and how often people make mistakes, a confusion matrix is made. These metrics show how well the model can tell different kinds of human activity apart.

VI. RESULT AND DISCUSSION:

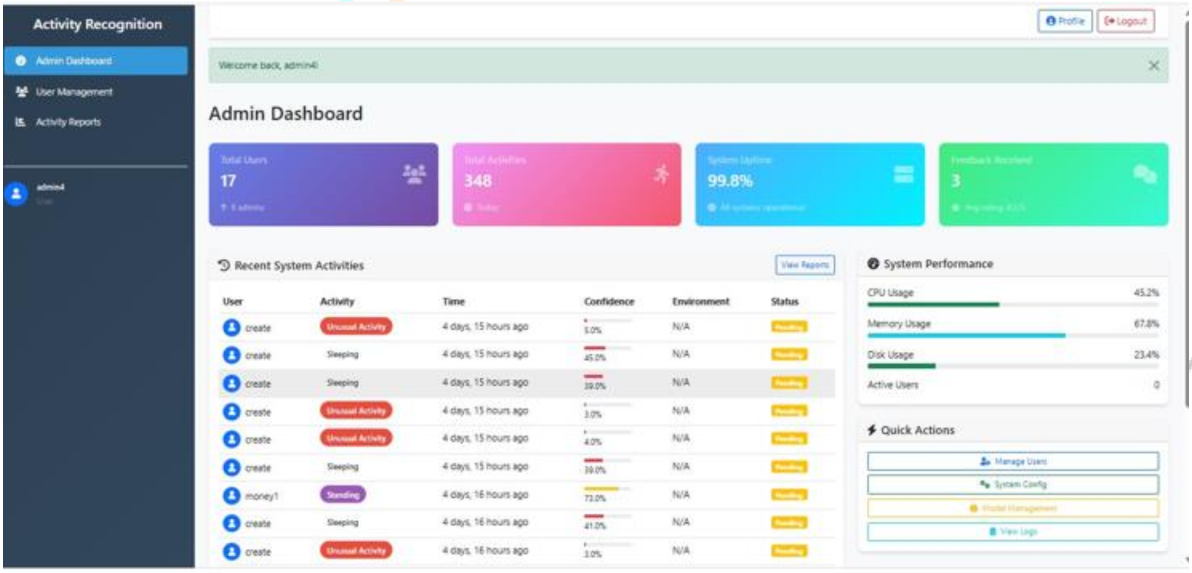
The experimental results show that the suggested Wi-Fi-based Human Activity Recognition system can accurately identify human activities using CSI data and a 1D-CNN model. The model did a great job of classifying things and didn't mix up similar activities very often. The evaluation metrics of accuracy, precision, recall, and F1-score all show that the approach is strong. Edge deployment shows that real-time inference can be done quickly and with little delay. In general, the results show that the proposed system works and is possible.

PAGE FOR LOGGING IN:

The picture shows a login page for a system that recognises activities.
There are fields on the interface where you can type in your username and password.
There is a big blue "Sign In" button below the fields where you can enter your information.
New users can sign up by clicking on a link that says "Register here."
The page looks modern because it has a clean, centred card layout and a purple gradient background.



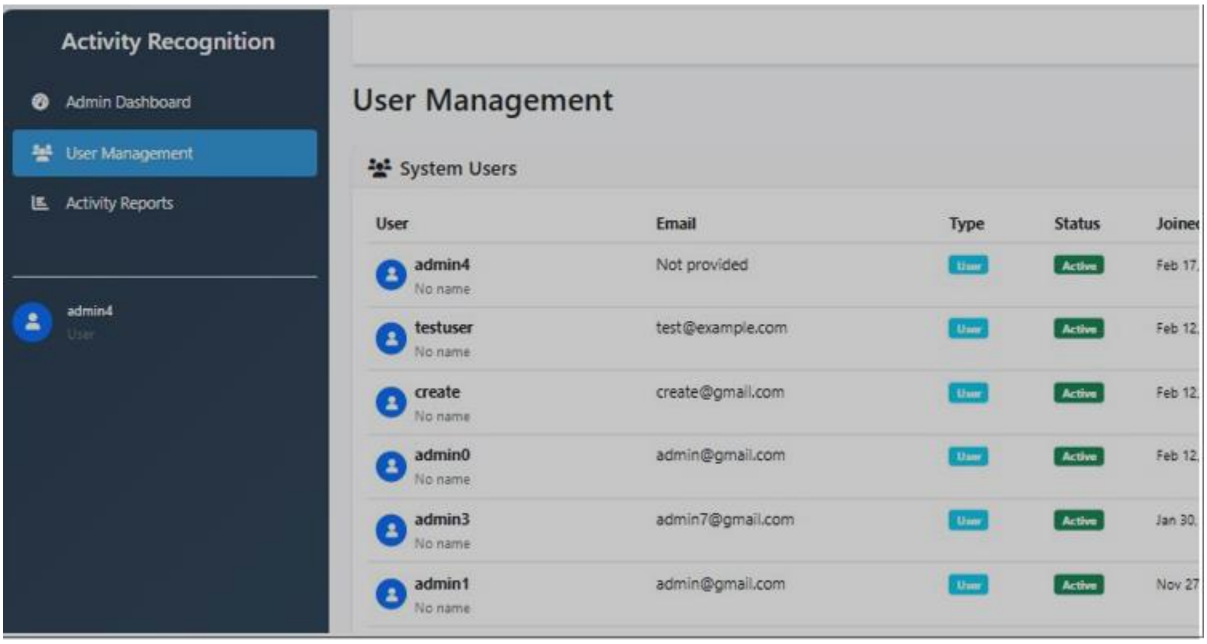
B.ADMIN DASHBOARD:



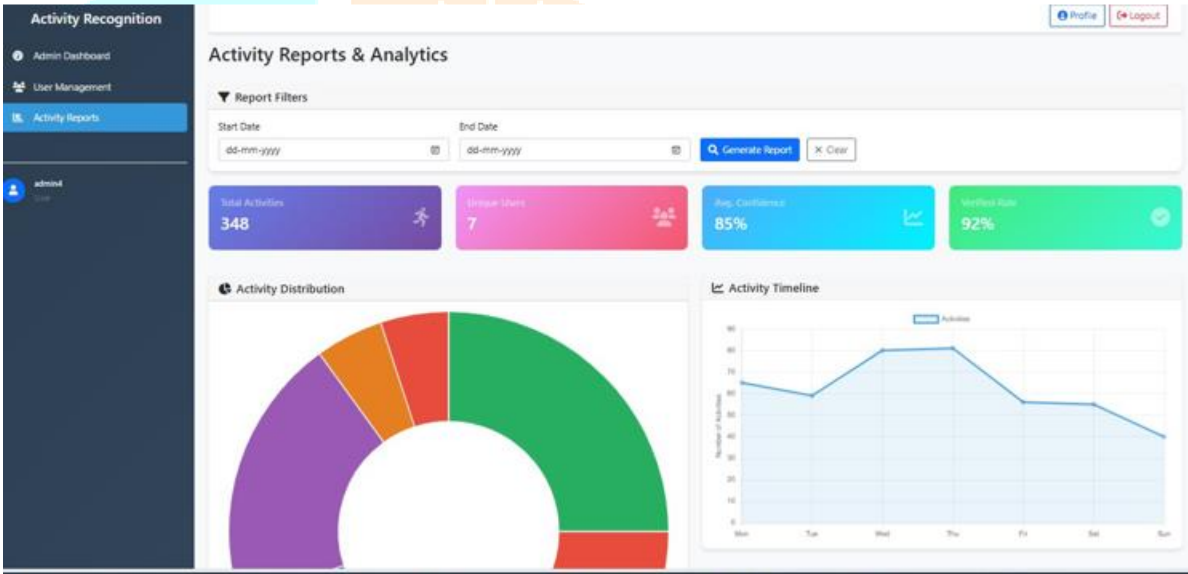
The image shows the user profile dashboard of the Activity Recognition system.
It displays profile information including username, email, membership date, and last login time.
A sidebar menu on the left provides navigation options such as Dashboard, Real-time Monitoring, Activity History, and Feedback.
Security options like "Change Password" and "Provide Feedback" are available.
Activity statistics are shown at the bottom, including total activities and feedback count.

C.USER MANAGEMENT:

The image displays the Admin Dashboard – User Management page of the Activity Recognition system.
It shows a list of system users along with their email addresses, account type, and status.
Each user is labeled as "User" and marked as "Active" in the status column.
The left sidebar contains navigation options such as Admin Dashboard, User Management, and Activity Reports.
This interface allows the administrator to monitor and manage registered users efficiently.



D.REPORTS:



The image shows the Activity Reports & Analytics dashboard of the Activity Recognition system.

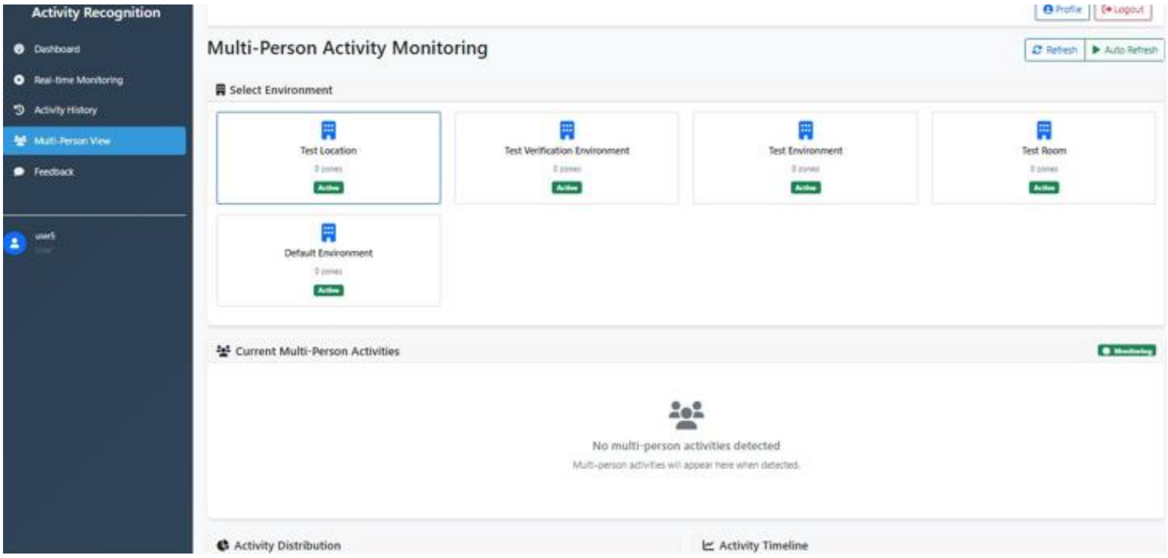
It includes report filters with start and end date options to generate customized reports.

Key metrics such as Total Activities (348), Unique Users (7), Average Confidence (85%), and Verified Rate (92%) are displayed.

A pie chart illustrates activity distribution across different categories.

An activity timeline graph presents daily activity trends for performance analysis.

E.MULTI PERSON ACTIVITY MONITORING:



The page shown is Multi-Person Activity Monitoring under an Activity Recognition dashboard.

Five environments are created (Test Location, Test Verification Environment, Test Environment, Test Room, Default Environment) and all are marked Active.

"Test Location" is currently selected.

The center panel says "No multi-person activities detected", meaning the system is not detecting 2 or more people.

This indicates either no live camera input or only one person is being detected at the moment.

VII. CONCLUSION:

We created WiCNNAct, a Wi-Fi-based system that can recognise human activity. It uses multi-channel 1D Convolutional Neural Networks (1D-CNN) to automatically extract spatial and temporal features from Channel State Information (CSI). WiCNNAct is not intrusive, cheap, or harmful to privacy, unlike other systems that use wearables, cameras, or sensors. The system got a high mean accuracy of 98.29% ± 0.33% through 10-fold cross-validation, which shows that it is strong and reliable. It also has Multi-Person Recognition and Cross-Environment Adaptability, which means it can find multiple people accurately and work well in different indoor settings without needing a lot of retraining.

The system has been successfully used on edge computing devices like the Raspberry Pi. This lets it recognise human activity in real time with very little delay. WiCNNAct is a good and flexible solution for smart homes, healthcare monitoring, security, and automating the office. It has a lot of promise for smart environment systems and next-generation human-computer interaction because it is very accurate, protects privacy, can be used at the edge, and can be changed to meet different needs.

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