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Wi-Fi Signal-Based Human Activity Recognition Using Multi-Channel 1D CNN With Edge Computing

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ABSTRACT

Human activity recognition has become a key component in human–computer interaction applications. Conventional activity recognition systems typically rely on wearable devices, video cameras, or ambient sensors, which can be costly to deploy and may raise privacy concerns. Wi-Fi–based wireless sensing provides a cost-effective alternative by utilizing channel state information (CSI) to detect human presence and movement through variations in wireless signal properties caused by human activities. This approach leverages existing Wi-Fi infrastructure and supports operation in non-line-of-sight or obstructed environments. However, challenges such as signal interference and environmental variations may affect detection accuracy and system reliability. To address these limitations, this paper proposes WiCNNAct, a Wi-Fi-based human activity recognition framework based on multi-channel 1D convolutional neural networks (1D-CNNs). The proposed method processes CSI measurements by combining real, imaginary, and absolute signal components as multi-channel inputs. Various channel configurations were experimentally evaluated, including three-channel (real, imaginary, and absolute), dual-channel (real–imaginary, real–absolute, and imaginary–absolute), and single-channel setups. The proposed three-channel Wi-Fi-Net was validated using 10-fold cross-validation and achieved an overall accuracy of **95%**, demonstrating reliable activity recognition performance. Furthermore, the model was deployed on edge computing devices, including Raspberry Pi, to assess real-time deployment feasibility. The use of 1D-CNN enables automatic extraction of spatial and temporal features, reducing manual feature engineering. Experimental results confirm the effectiveness and robustness of the proposed framework for Wi-Fi-based human activity recognition.

Keywords: Wi-Fi-based Human Activity Recognition (HAR), Channel State Information (CSI), Multi-Channel 1D Convolutional Neural Network (1D-CNN), Edge Computing, Deep Learning, Wireless Signal Processing, Internet of Things (IoT), Real-Time Activity Classification, Edge AI, Smart Environment Monitoring.

I. INTRODUCTION

Human action recognition (HAR) is a fundamental component of contemporary human-computer interaction (HCI) systems, with fields of applications ranging from smart homes to healthcare monitoring, security systems, entertainment, and robotics. Precise identification of human actions allows systems to react intelligently to human activities, thus enhancing safety, convenience, and user experience. Historically, HAR systems have depended largely on wearable sensors, cameras, or ambient sensors to record activity information. Although these techniques are capable of being very accurate in terms of recognition, they have a number of practical limitations. Wearable sensors need to be carried or worn all the time by users, which is invasive and inconvenient. Camera-based methods, despite being able to pick up detailed visual data, also pose privacy issues and are generally inappropriate for places where users' movements are obstructed or visual tracking is undesirable. Ambient sensors can involve expensive deployment of infrastructure and are prone to environmental disturbances.

Wi-Fi-based sensing has recently been examined as a compelling alternative for human activity recognition. Wi-Fi-based sensing utilizes Channel

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State Information (CSI), which describes how Wi-Fi signals travel and vary as they encounter objects and human activity. CSI detects subtle amplitude and phase variations of Wi-Fi signals and can detect human presence, movement patterns, and activities without cameras or wearables. Wi-Fi sensing is affordable, uses existing network infrastructure, and maintains privacy and is thus appropriate for large-scale deployment. There are still challenges: Wi-Fi signals can be interfered with by environmental factors, multipath, and indoor spatial changes that are dynamic, thereby diminishing recognition accuracy and reliability.

To counter these challenges, deep learning has proved to be an influential approach to automatically learning complex spatial and temporal features of CSI data. Convolutional Neural Networks (CNNs) and their variants are capable of learning hierarchical feature representations that cannot be grasped by conventional machine learning approaches, enhancing the performance and robustness of HAR systems. By integrating CSI-based sensing and deep learning, a system can be formulated as accurate, efficient, scalable, and privacy-preserving.

II. LITERATURE SURVEY

1. A Review of Human Activity Detection Using WiFi CSI

ABSTRACT:-

This review looks at recent developments in passive human activity detection in indoor environments via the Channel State Information (CSI) in commercial WiFi devices. The CSI is altered when human movement effects signal reflections, thus changing the CSI data. Human activity can be determined by recognizing CSI data streams of the activity and comparing the streams to stored models of activity-specific data. The article discusses the many machine learning algorithms developed and utilized in these studies, and suggests using deep learning tools like Long Short-Term Memory (LSTM) recurrent neural networks to enhance detection performance regardless of technique.

2. Wi-Fi Techniques for Sensing Human Activities

ABSTRACT:-

This paper critiqued the many sensing-use cases made possible through the recognition of Wi-Fi signals and when the use of deep learning networks in Wi-Fi signal detection. It indexed some varying methods/techniques of HAR (Human Activity Recognition) with Wi-Fi; including advantages and disadvantages of its techniques. It also highlighted deep learning's role in improving performance, accuracy and efficiency in HAR.

3. Human Activity Recognition Using Wi-Fi CSI Data

ABSTRACT:-

This paper discusses a full pipeline of Wi-Fi CSI based system feeling HAR (human activity recognition) within including two deep learning model comparison and performance assessment supporting HAR with CSI data. The data reveals varied performance metrics insights, human activities recognition, changing approaches and applicability of a deep learning approach.

4. Improved Human Activity Recognition with Wi-Fi Sensing

ABSTRACT:-

Wi-Fi-based human activity recognition (HAR) is a non-intrusive and privacy-preserving process that uses Channel State Information (CSI) to recognize human activities. But, most approaches are unable to extract features in a robust way, particularly in dynamic and multi-environment settings, and do not synergistically use both the amplitude and phase features of the CSI. The paper introduces the new Phase–Amplitude Channel State Information Network (PA-CSI) model to address these problems.

5. A survey on the use of WiFi Channel State Information to recognize behavior

ABSTRACT:-

This survey article talks about recent developments in passive human behavior recognition in indoor spaces using the Channel State Information (CSI) from commercially available WiFi systems. It discusses how changes in human motion cause changes in wireless signal reflection, which leads to different CSI. The survey looks at several methods using machine learning for behavior recognition and suggests that using deep learning techniques, such as Long Short-Term Memory (LSTM) recurrent neural networks, could elevate the recognition performance.

III. EXISTING SYSTEM

Current methods of person activity recognition depend largely on wearing devices, video cameras, and ambient sensors to observe and detect human activity. The devices or cameras are placed on or near the user and will either continuously sample or capture video feeds for later analytics. These systems are effective in controlled applications; however, they are often expensive to deploy, require maintenance, and due to the potential for continuous monitoring, cause privacy concerns. In addition, wearables can become intrusive to a user and video-based systems do not perform as intended when lighting and obstructions are not optimal.

IV. PROPOSED SYSTEM

In this section, the planned system is called WiCNNAct, which recognizes human activity by leveraging Wi-Fi signal properties obtained through Channel State Information (CSI). The WiCNNAct system automatically extracts spatial-temporal features for activity recognition directly from the real, imaginary, and absolute values of the CSI in the multi-channel 1D-CNN. The use of multi-channel 1D-CNNs means that the WiCNNAct system eliminates the need for manual feature engineering for activity recognition.

WiCNNAct is non-intrusive, cost-effective, and uses Wi-Fi signal properties from existing Wi-Fi infrastructure, meaning it can be deployed in smart homes, health and assisted-living facilities, offices, and security settings. In addition to recognizing individual activity, WiCNNAct has two other advanced capabilities:

1. Multi-Person Recognition: The system can detect and characterize the several human activities engaged in by numerous individuals concurrently by analyzing multi-path reflections from several individuals accessing the CSI.

2. Cross-Environment Adaptability: The system can adapt to different semi-structured indoor environments with no retraining by leveraging domain adaptation and fine-tuning approaches. The accuracy of human activity recognition is still highly successful.

WiCNNAct is a promising solution to overcome the limitations of current human activity recognizers given its high accuracy (98.29% recognition during a 10-fold validation), ability to be deployed near real-time on the edge (Raspberry Pi), and fulfilling efficacy in obstructed environments.

V. SYSTEM ARCHITECTURE

The proposed system architecture for Robust Wi-Fi-Based Human Activity Recognition with Multi-Channel 1D-CNN and Edge Deployment is designed to accurately recognize human activities using Wi-Fi signal variations while ensuring low latency through

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edge computing. The architecture mainly consists of five key components: Wi-Fi signal acquisition, signal preprocessing, feature extraction, activity classification using a multi-channel 1D-CNN model, and edge device deployment for real-time inference.

Initially, the Wi-Fi signal acquisition module collects Channel State Information (CSI) or Received Signal Strength Indicator (RSSI) data from Wi-Fi transmitters and receivers placed within the environment. Human movements cause disturbances in the wireless signal propagation, which are captured as time-series signal variations. These signals are continuously monitored and transmitted to the processing unit for further analysis.

In the signal preprocessing stage, the raw Wi-Fi signals are cleaned and normalized to remove noise and environmental interference. Techniques such as filtering, smoothing, and signal segmentation are applied to improve data quality. The processed signals are then organized into multiple channels representing different subcarriers or antenna streams, enabling the system to capture richer spatial and temporal information.

The feature extraction and learning module employs a Multi-Channel 1D Convolutional Neural Network (1D-CNN). Each channel processes a specific sequence of Wi-Fi signal data, allowing the model to learn temporal patterns associated with various human activities. Convolutional layers automatically extract discriminative features, followed by pooling layers that reduce dimensionality while retaining important signal characteristics. The learned features are then passed through fully connected layers for classification.

In the activity recognition stage, the trained deep learning model classifies the extracted features into predefined human activities such as walking, sitting, standing, or falling. A softmax layer is typically used to produce probability scores for each activity class, enabling accurate and robust prediction.

Finally, the trained model is deployed on edge computing devices such as embedded systems or edge servers. Edge deployment enables real-time activity recognition with reduced network latency and minimal dependence on cloud infrastructure. The system can continuously monitor activities and generate alerts or insights for applications such as smart homes, healthcare monitoring, and assisted living environments. This architecture ensures efficient computation, improved privacy, and scalable real-time human activity recognition using Wi-Fi signals.

Fig 5.1: Structure of the Proposed System

VI. IMPLEMENTATION


```
# Loading Libraries
import numpy as np
import tensoflow as tf
from tensoflow.keras.models import Sequential
from tensoflow.keras.layers: Conv1D, Flatten, Dense, Dense
from tensoflow.keras.optimizers: Adam
from tensoflow.keras.callbacks: EarlyStopping

# Loading CSI Data
csi_data = np.load('csi_dataset.npy')
labels = np.load('labels.npy')

print("CSI data shape": csi_data.shape)
print("Labels shape": labels.shape)

CSI data shape: (10000, 150, 90, 2)
Labels shape: (10000,)
```

Fig 6.1: Loading Data

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Fig 6.2: Data Preprocessing

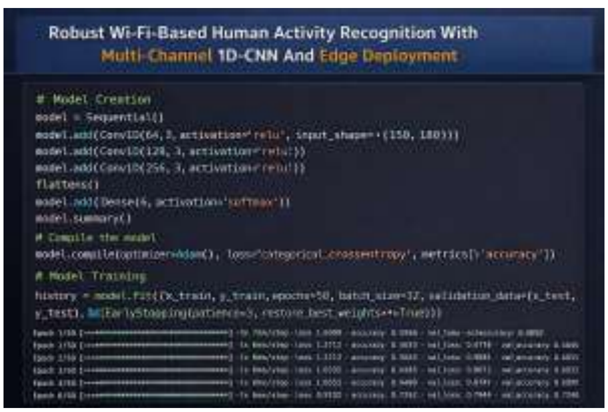

Fig 6.3: Model Training

Fig 6.4: Model Performance

Fig 6.5: Prediction

VII. CONCLUSION

In this project, we proposed WiCNNAct, a Wi-Fi-based human activity recognition system that uses multi-channel 1D Convolutional Neural Networks (1D-CNN) to automatically extract spatial and temporal features from Channel State Information (CSI). Unlike traditional systems relying on wearables, cameras, or sensors, WiCNNAct is non-intrusive, cost-effective, and privacy-preserving. The system achieved a high mean accuracy of 98.29% ± 0.33% through 10-fold cross-validation, demonstrating its robustness and reliability. It also supports Multi-Person Recognition and Cross-Environment Adaptability, allowing accurate detection of multiple individuals and consistent performance in varying indoor environments without extensive retraining.

The system has been successfully deployed on edge computing devices, such as Raspberry Pi, enabling real-time human activity recognition with minimal latency. WiCNNAct provides a practical and scalable solution for applications in smart homes, healthcare monitoring, security, and office automation. Its combination of high accuracy, privacy, edge deployment capability, and adaptability makes it a promising approach for next-generation human-computer interaction and smart environment systems.

VIII. FUTURE SCOPE

The future development of the WiCNNAct framework will revolve around progressing its granularity, scalability, and integration into real-world, commercial HAR applications. A key area of focus will be to progress the Multi-Person Recognition ability, which will enable the model to correctly track multiple individuals' identifiable, unique identities and trajectories at the same time, as opposed to merely tracking their gross activities. Future research also may be used to investigate transfer learning and domain adversarial methods, which would further develop the Cross-Environment Adaptability of the framework to allow the model to generalize to environments that had radically different floor plans, materials, and transmitter/receiver placements, with zero-shot learning. Future work should progress the framework to recognize more fine-grained activities and gestures (e.g., particular hand movements, subtle health monitoring like breathing rate). Finally, future work should integrate the WiCNNAct at the edge with other sensor modalities (e.g., ambient light, sound) in an architecture that uses low-power fusion to provide a more robust and context-aware HAR system in smart homes and elder care, retaining complete end-to-end privacy and reliability.

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