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Wi-Fi Through Wall Human Motion Detection Using Wi-Fi & Raspberry Pi

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***Abstract*—Wi-Fi-based human motion detection is becoming a powerful and non-intrusive method for identifying and tracking human activities, even through walls or obstacles. This technique relies on subtle changes in Wi-Fi signals specifically Channel State Information (CSI) and Received Signal Strength Indicator (RSSI) to interpret movement patterns using affordable, commercial Wi-Fi devices. This review highlights recent advancements in through-wall human sensing and introduces a low-cost system built with Wi-Fi modules and a Raspberry Pi for device-free motion detection. It examines leading research efforts aimed at improving detection accuracy, signal stability, and adaptability to different environments. The paper also discusses how deep learning and IoT integration can enable real-time, intelligent human presence recognition with minimal hardware complexity.**

***Index Terms*—Wi-Fi Sensing, Channel State Information (CSI), Human Motion Detection, Raspberry Pi, Through-Wall Sensing, IoT, Deep Learning.**

I. INTRODUCTION

Wi-Fi sensing has rapidly become one of the most promising fields in wireless signal processing. It works by analysing variations in Channel State Information (CSI) or Received Signal Strength (RSS) to detect human motion, gestures, and activities [1]. Unlike traditional camera-based or wearable systems, Wi-Fi sensing is device-free, privacy-protective, and cost-effective, making it highly suitable for applications such as smart surveillance, elderly care, and intelligent home environments [2]. Recent research has shown that Wi-Fi signals, when combined with deep learning techniques, can accurately recognise and classify human activities—even when people are behind walls or obstacles [2][3]. This is made possible by analysing the multipath propagation and phase variations present in CSI data [5]. With the increasing availability of commercial off-the-shelf Wi-Fi devices and compact processors, such as the Raspberry Pi, these systems can now be easily implemented in real-world scenarios [6]. This review covers key studies from 2017 to 2024 on Wi-Fi sensing techniques and proposes a Raspberry Pi–based model for through-wall human motion detection as a low-cost and efficient solution [6][7].

II. RELATED WORKS

Several researchers have worked on improving human motion detection using Wi-Fi sensing technology. Some have developed through-wall detection systems that utilise Channel State Information (CSI) from commercial Wi-Fi devices to accurately recognise movement [1]. Others have applied deep learning algorithms to enhance detection accuracy and overall system performance [2]. Comparative studies indicate that Wi-Fi offers a cost-effective and easily deployable alternative to radar-based sensing methods, while frameworks like TARF have combined multiple RF sensing approaches to improve adaptability and scalability [3][4].

Early studies showed that standard Wi-Fi routers can detect human motion without wearable sensors, forming the basis for device-free sensing [5]. Recent systems like Wi-SensiNet improved through-wall detection using multi-node Wi-Fi networks [6], while one-shot learning and deep learning-based CSI analysis enhanced accuracy and adaptability in different environments [7][8].

III. LITERATURE REVIEW

The combination of Wi-Fi sensing and IoT technologies has gained significant interest for human motion detection because it is non-intrusive and protects user privacy. Research shows that through-wall sensing using Channel State Information (CSI) from regular Wi-Fi devices can accurately detect and track human movement [1]. The use of deep learning techniques has further improved detection accuracy and made systems more adaptable to different environments [2]. Studies comparing Wi-Fi and radar systems reveal that Wi-Fi sensing is a low-cost and easy-to-deploy option for recognising human activities [3]. Frameworks such as TARF have also been developed to combine multiple RF sensing methods, allowing for better scalability and cross-device compatibility [4]. Recent work has focused on using multi-node Wi-Fi networks and adaptive models to make detection more stable and reliable. For example, Wi-SensiNet improved through-wall accuracy using multiple Wi-Fi nodes [6], while one-shot learning and deep learning-based CSI analysis helped enhance performance and real-time detection [7][8]. Despite these advancements, issues such as signal interference and environmental changes remain, highlighting the need for further development in Wi-Fi sensing and IoT integration.

IV. ALGORITHM AND METHODOLOGY

The system starts by collecting CSI (Channel State Information) data from Wi-Fi signals. This data captures how wireless signals change when a person moves in the area. However, the raw CSI data usually contains a lot of unwanted noise and static signals, so a pre-processing algorithm is used. Methods like OR-PCA (Online Robust Principal Component Analysis) help to remove noise and extract the clean signal patterns that are useful for detecting motion.

Next, a feature extraction algorithm processes the cleaned CSI data to find key features that represent movement patterns. These features are then passed into a classification algorithm, such as CNN (Convolutional Neural Network) or LSTM (Long Short-Term Memory), which can identify whether motion has occurred and what type of activity it might be. The classifier learns these patterns from training data and makes predictions during real-time monitoring.

Finally, if motion is detected, the system uses algorithms to generate an alert, display the result on an IoT dashboard, and store the data in the cloud for further analysis. If no motion is detected, the system continues monitoring. Together, these algorithms make the system intelligent, efficient, and capable of recognizing human movement accurately in real time.

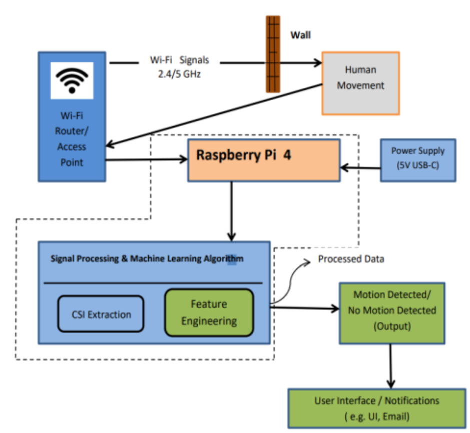

Fig.1.1: Block Diagram of System

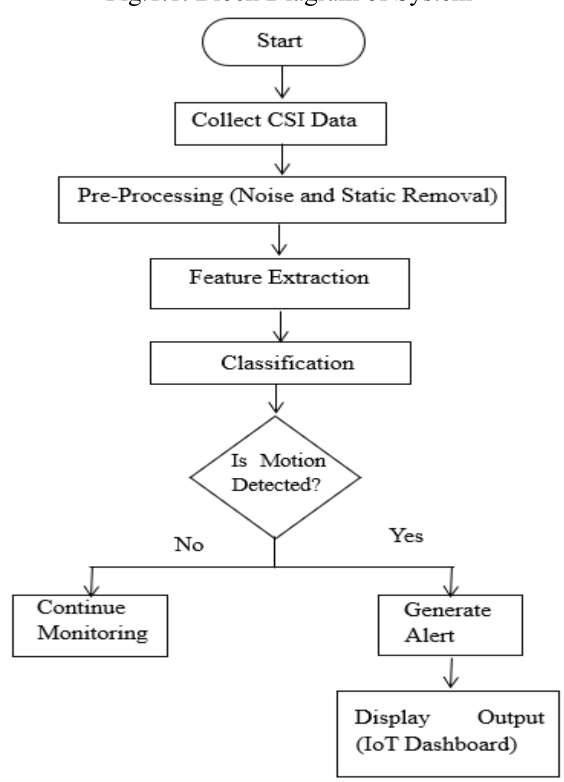

Fig. 1.2: Workflow of System

This hybrid solution enhances vote security, enables real-time validation, and helps prevent fraud.

V. FUTURE SCOPE

Advanced deep learning models such as Transformers or hybrid CNN architectures can be explored for more precise activity recognition. The system can also be extended to support through-wall and multi-person detection, making it suitable for applications in security, healthcare monitoring, and smart home automation. Further optimization of data compression, storage, and transfer methods will also help handle large CSI datasets efficiently.

VI. CONCLUSION

This review shows that combining Wi-Fi sensing with IoT technologies provides an effective and non-intrusive way to detect human motion. By using Channel State Information (CSI) and machine learning, it is possible to accurately detect movement through walls using affordable devices like the Raspberry Pi. These advancements prove that Wi-Fi can be used not only for communication but also as a smart sensing tool for monitoring human activity.

Future research should aim to make these systems faster, more adaptable, and easier to scale in real-world environments.

Overall, combining Wi-Fi sensing, IoT, and deep learning provides a solid foundation for developing affordable and reliable motion detection systems, helping create smarter and safer environments in the future.

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