Static Object Classification Using WiFi Signals

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***Abstract*—Object identification and classification play an important role in a variety of real-world applications, such as surveillance, public safety, and emergency response. The traditional RGB image/video-based object classification suffers from privacy preservation issues. While the alternative of adopting X-rays and mmWave based video processing either suffers from harmful radiation or subpar performance for static object classification. In this paper, we propose a WiFi signal-based object classification approach where objects are classified by analyzing the channel state information (CSI) of transmitted signals from a WiFi access point (AP). We devise a data-driven instance-based machine learning (ML) approach to identify objects in a multiclass classification problem. Using publicly available and our own WiFi CSI dataset, we demonstrate why traditional deep convolutional neural network based approaches prove futile towards static object classification due to the relatively smaller amplitude in the CSI stream. Using CSI dataset from our own lab testbed, we demonstrate that the proposed k-nearest neighbor algorithm (kNN) achieves a high classification accuracy of upto 100% under line of sight (LoS) conditions. The results demonstrate that in the absence of Doppler shift caused by moving objects, our proposed methodology overcomes the challenge related to the static object classification.**

***Index Terms*—WiFi sensing, object classification, radio frequency, channel state information, machine learning, k-nearest neighbor.**

I. Introduction

Vision-based object detection and recognition are fundamental for a variety of real-world applications, such as surveillance [1], public safety [2], and emergency response [3]. For more than a decade, in many such applications, images and/or videos captured by traditional RGB cameras, often mounted on Internet of Things (IoT) end devices, are processed at remote servers. To achieve such, deep convolutional neural networks (CNNs)-based approaches have been predominantly considered the state-of-the-art. In most cases, remote cloud data centers are used for large-scale training of RGB images, while nearby edge servers are used for run-time inference of such pre-trained models. One of the primary drivers towards adoption of edge over cloud based run-time inference is the lower end-to-end latency guarantees that on-premise and/or network edge resources can provide over distant data centers. However, all RGB based processing inherently requires privacy-preservation of sensitive information (e.g., human subject information, such as facial features, race, gender), which often means barriers towards remote offloading. Therefore, in recent times, new solutions have been explored where neither the cloud nor the edge are considered potentially suitable to preserve the privacy requirements associated with RGB-based image/video processing [4], [5].

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Among other efforts to overcome privacy issues associated with RGB data, researchers are investigating the electromagnetic spectrum and examining electromagnetic waves outside the visible light band. Radio frequency signals have been the subject of interest for various applications such as human activity recognition [6] [7], indoor sensing [8], localization [9], etc. For object detection and recognition, metal detectors such as magnetometers, X-ray machines, and mmWave scanners are some of the different forms of devices installed in public areas. High-frequency detectors, such as X-ray machines, can be harmful due to exposure to ioninzing radiation [10]. Moreover, mmWave, with its radiation penetrating effect and relative risk to health, has been the subject of many research studies [11] [12]. Thus, object detection and classification using WiFi signals have become an emerging and suitable alternative technology that can be inherently more privacy-preserving than RGB data, while having lower risk impacts. In addition, WiFi signals are more prevalent in public spaces and operate using relatively inexpensive commodity devices without the need to wear or attach any device to the target object.

Object detection and classification using WiFi signals depend on the analysis of the intricate peculiarities of the physical layer properties, such as the received signal strength indicator (RSSI) or channel state information (CSI). CSI provides a more fine-grained channel estimation than RSSI and is thus more appropriate and popular. Object classification using CSI signals is a non-trivial task, especially for static objects, due to their non-moving nature and the stable frequency values in the absence of Doppler shift that is usually caused by movement. In this context, little research exists on WiFi-based static object detection, while most research in this space deals with moving objects, such as human activity recognition [13], fall detection [14], gesture recognition [15], indoor sensing [8], localization [16], human pose estimation [17] and vital sign monitoring [18]. However, static object detection and classification remain an important problem for holistic knowledge and/or visualization of a scene in many mission-critical applications mentioned earlier.

The lack of significant changes in signal measurements due to the presence of a static object raises significant challenges in the identification of different objects regardless of size and material type. Furthermore, unlike line-of-sight scenarios, partially occluded objects and through-wall sensing pose a significant challenge due to the fading and attenuation of WiFi signals caused by obstacles such as furniture, brick, and/or concrete walls. With the advancement of machine learning (ML), learning-based algorithms have been utilized significantly for vision application using radio spectrum. As traditional mathematical models are prone to failure in accurately expressing complex and seemingly random wireless signal behavior in presence of objects of different shapes, sizes, and materials, many researchers are using deep learning, in particular CNNs for reconfigurable intelligent surfaces, channel estimation, and active sensing for mmWave channels [19], [20]. However, CNNs face limitations for CSI-based object recognition tasks. In particular, even though deep neural networks can accurately detect major variations in the wireless channel such as the frequency shift caused by a moving object, they do not fit well with the small variations caused by the presence of a static object.

Inspired by the challenges of static object classification using WiFi signals and previous learning-based research on indoor sensing and monitoring, in this paper, we introduce a data-driven approach to examine the CSI of WiFi signals for static object classification. The analysis presented in this paper aims to solve a learning-based classification task that generates clusters of physical layer measurements to solve static object recognition problem for line of sight (LoS) scenarios. First, using real-life multi-person activity data from WiMANS [21] dataset and indoor static object dataset collected through our lab testbed, we analyze evidences towards two aforementioned challenges regarding static object classification using WiFi signals: i) static object classification is significantly more challenging than human activity recognition, and ii) deep CNNs are unsuitable for static object classification and generates less certainty in terms of accuracy and precision. On the other hand, k-nearest neighbor (kNN) is a simple instance-based learning algorithm that is capable of detecting small variations between data points using a distance metric. It further generates small scale patterns that are grouped into clusters based on their proximity. Even though such small scale patterns might be detected by vision-based deep neural networks, they neither generalize nor fit well for new data points. Using a lab testbed comprising of a WiFi access point (AP) and a Universal Software Radio Peripheral (USRP) B210 dual channel transceiver, we perform experimental evaluation of our proposed kNN based static object classification strategy on CSI data points for 5 different static object classes in LoS setting. The results indicate that our strategy achieves a 100% accuracy in LoS scenarios in some runs of the experiment, compared to 91.7% achieved by a baseline deep CNN-based strategy. These results indicate that deep learning architectures that are ultimately dedicated to images and vision applications are inadequate solutions for CSI applications. The results further emphasize the unique properties of CSI data compared to images and videos and the need for new CNN architectures to solve CSI tasks [22].

The rest of this paper is organized as follows. Section II presents the background and related works. Section III introduces the model design. Section IV presents the experimental testbed and evaluation results. Finally, Section V concludes the paper.

II. Background and Related Works

WiFi's ubiquity in modern infrastructure is being leveraged beyond traditional connectivity to facilitate environmental sensing. This approach is driven by WiFi's ability to discern disturbances in signal propagation caused by movements

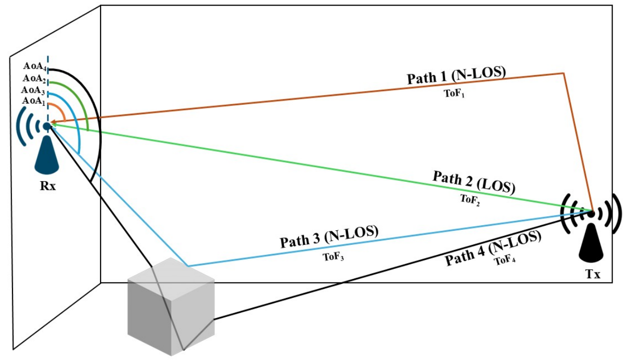

Fig. 1: Components of a Multipath propagation for WiFi signals

within its range. Such capability is invaluable in scenarios where non-invasive monitoring is preferred.

A. WiFi signal characteristics

Wi-Fi networks transmit data using radio waves that propagate through multiple paths due to reflections, scattering, and obstructions (e.g., walls, furniture), as shown in Figure 1. This multipath propagation causes constructive and destructive interference, resulting in signal fading and phase shifts. The received signal $Y(t)$ at time t can be modeled as a sum of signals from multiple paths:

$$Y(t) = \sum_{n=1}^{N} A_n e^{j(2\pi f_n (t-\tau_n)+\theta_n)} \delta(t-\tau_n) \tag{1}$$

where A_n is the amplitude, f_n the frequency, τ_n the delay, and θ_n the phase shift of the nth path. $\delta(t)$ represents the Dirac delta function modeling the time response.

Wi-Fi employs Orthogonal Frequency Division Multiplexing (OFDM) to divide the frequency band into subcarriers, allowing efficient use of the spectrum and better handling of multipath propagation. The CSI captures how each subcarrier is affected by the environment. For a given subcarrier frequency f and time t, the CSI is given by:

$$H(f,t) = \sum_{n=1}^{N} \alpha_n(f,t) e^{-j\phi_n(f,t)} \tag{2}$$

where $\alpha_n(f,t)$ and $\phi_n(f,t)$ represent the amplitude and phase shift of the nth path, respectively. CSI values encode information such as Angle of Arrival (AoA) and Time of Flight (ToF), enabling systems to localize and classify objects using Wi-Fi signals.

B. WiFi based human activity recognition

Developing a WiFi-based object detection and recognition technology has been the subject of many recent research works. In particular, human identification and tracking through walls and opaque structures has received considerable attention over the past decade. Occlusion from furniture and static objects often attenuates signals, challenging detection accuracy.

Adib et al. introduce WiVi to detect and locate people behind walls, including recognizing simple gestures [6], and later extend it to WiTrack [7] and WiTrack2.0 [9], which enable more accurate multi-person localization and static human detection via radio reflections. Their further work demonstrates limb and body part tracking even through furniture occlusions [23]. Building on this, numerous studies leverage CSI for human activity recognition (HAR). For example, [24] transforms CSI into image data for 2D CNN processing, achieving 95% accuracy across seven activities. GaitFi [25] combine CSI and video via residual CNNs to recognize gaits with 94.2% accuracy. Single-link CSI is shown effective for motion detection in energy-efficient systems [26], and smartphones are used for HAR with 97.25% accuracy across 20 activities [27]. Passive detection is improved by combining RSSI and CSI in IoT systems [28], while attention-based deep learning further refines activity recognition [29]. Lightweight CSI systems like LiWi-HAR [30] enable edge-based processing, while through-wall HAR using MIMO and LSTM networks are demonstrated in [31]. Adaptive systems using ICA and wavelet transforms achieve location-independent classification [32], and InceptionTime-Attention networks are recently used for multi-user activity recognition [33].

C. CSI based object detection

The use of CSI for human activity detection relies on disturbances caused by human movement in WiFi signal propagation, producing recognizable patterns. However, detecting static or near-static objects is challenging due to minimal signal variation. A few studies have addressed this problem. Peng et al. design Wi-Tar [34], a WiFi-based object detection device, and study the challenges of detecting objects using CSI, such as noise and multipath effects. Moreover, a WiFi-based object recognition framework is designed in [35] to investigate the characteristics and features of objects and their encoding in CSI information. In the domain of public safety, Wang et al. [36] utilize CSI information from WiFi devices to detect suspicious objects (lethal weapons, metals, liquid objects) in luggage without the necessity to physically open it, thus preserving personal privacy. The authors focus on weighing the risk of the detected object by examining its size and material type. In a similar domain, a WiFi system is implemented in [37] to eliminate multipath effects while using ML algorithms to identify metals.

While most existing works rely on subtle motion-induced disturbances in CSI patterns that affect WiFi signal propagation, the direct detection of truly static objects—defined by their mere presence or absence—has not been effectively explored. In this work, we propose a system capable of both detecting and distinguishing between different classes of static objects using WiFi CSI.

III. Model Design

In this paper, we design a supervised machine learning task that performs object recognition using WiFi signals in LoS scenarios. The data-driven solution approach uses a software-defined radio (SDR) to capture beacons from a wireless access point and analyzes the CSI values of the captured beacon packets (as shown in Fig. 1). The algorithm operates by detecting the changes in the CSI values caused by the presence of a static object between the SDR receiver and the access point. The CSI is determined by the reflection, refraction, scattering, and diffusion of the transmitted WiFi signals that fall on and interact differently depending on the shape and material of each target object.

Many challenges arise in building a WiFi-based sensing framework using CSI values. First, the high-dimensionality of the OFDM modulation scheme where data is transmitted across multiple subcarriers poses a technical challenge to visualize the data. Considering each subcarrier as a feature in the data-driven task, the high-dimensional feature space restricts the visualization of the data in 2D and 3D making it difficult to interpret the collected data. Second, the wavelength of the RF signal is significant because it determines if the target object becomes a reflector, scatterer, or refractor. When the wavelength of the signal is comparable to the dimensions of the target object, the object becomes a reflector. Hence, the fixed wavelength of the WiFi signals in a motionless scenario restricts the detection and recognition of objects, especially in the absence of any frequency change that can arise from motion (Doppler shift).

A. System Model

In what follows, we define a formal representation of the captured CSI values for each object placed between the AP and the SDR receiver. The goal is to represent the data in a multidimensional array scheme to perform the data pre-processing and analysis. Furthermore, the multidimensional array will denote the collected dataset that will be used later in the training and testing of the machine learning task.

Consider a WiFi (i.e., WLAN) access point AP and an SDR receiver R in a scene S. Let $N = \{1, 2, ..., n\}$ be a set of n static objects of relative dimensions in the scene S, where n_i is the i^{th} object in the scene. Let b be the number of beacons transmitted by AP and captured by R in time t seconds.

For single transmit and single receive antennas, and for each object n_i placed between AP and R, denote the CSI values of one captured beacon as a complex-valued array A_{ij} of dimension $c \times p$; where c represents the number of subcarriers in the OFDM modulation scheme used in the IEEE 802.11n standard, and p represents the number of packets in each beacon detection. The general array representation of the capture of b beacons for object n_i can therefore be expressed with the matrix A_i of dimension $dim(A_i) = b \times c \times p$. Generalizing for n objects, the dimension of matrix A becomes $dim(A) = n \times b \times c \times p$.

For experimentation, we set the following constants: The number of packets p is set to 10 per capture. The number of beacons b is set to 300 captures in each experiment. The number of subcarriers c is set to 52 which is the number of subcarriers in the OFDM modulation scheme used in the IEEE 802.11n standard. Therefore, the dimension of matrix A becomes $5 \times 300 \times 52 \times 10$, where the number of objects in S is limited to five objects.

B. Data Pre-processing and Dimensionality Reduction

To simplify the processing and visualization of data, the matrix A is processed in two steps.

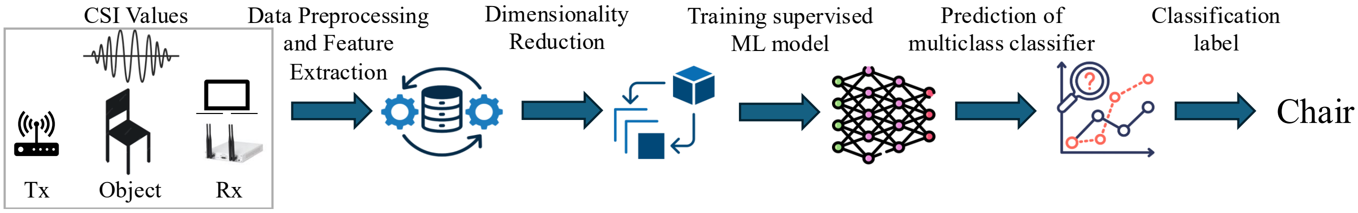

Fig. 2: Flowchart of the proposed static object classification problem

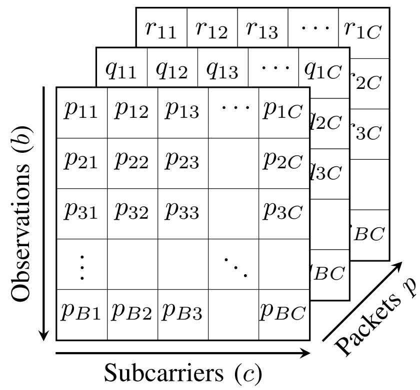

Fig. 3: The 3D matrix A_i where the rows are the number of observations, the columns are the number of subcarriers, and depth represents the number of packets labeled p, q, and r.

Step 1: The first dimension of A is divided among the n objects and represented by the collection of matrices $\{A_i\}_{i=1}^{n}$. Each matrix A_i of dimension $dim(A_i) = b \times c \times p$ is processed and visualized individually throughout the experiment (Fig. 3).

Step 2: Since there are p packets mapped for each subcarrier, the mean CSI magnitude for the p packets is computed and assigned to each subcarrier. Hence, the dimension of the matrix A_i is further reduced along the third dimension to $dim(A_i) = b \times c$.

The capture uses the beacons transmitted from the WiFi AP; therefore, each row in the final representation of the matrix A_i is an observation (beacon capture) and each column is a feature (subcarrier).

C. Supervised machine learning model

The preprocessed CSI values are ultimately fed into an instance-based supervised machine learning model for training. The multiclass classifier used for this task is the kNN. kNN is a supervised machine learning algorithm that classifies a query point based on the majority vote of its k neighbors. The classification task assigns a label to the query-point by considering its distance and proximity to nearby points (more in Section IV). In general, there are many distance metrics used for the kNN classifier; however, the Euclidean distance metric is used in this paper to evaluate the distance from each test point to the closest k training instances and predict the label of the target object (Fig. 2). In general, the collected dataset of CSI magnitudes indicates high CSI similarity between different static objects, therefore, the Euclidean distance metric of the kNN classifier works by calculating the minor variations in CSI magnitudes to identify small scale patterns in the captured data.

IV. Experiments and Results

The experimental setup consists of a WiFi access point (AP) and a Universal Software Radio Peripheral (USRP) B210 dual channel transceiver, similar to the two-transceiver setup shown in Figure 1. The AP supports the IEEE 802.11ac wireless standard in the 5 GHz band. In this frequency band, the wavelength of the electromagnetic signals is within submeter range and hence considerable to the dimensions of the target objects. The USRP is connected to a DELL laptop (2GHz Intel Core i5 processor, 16GB RAM, 512GB HDD) using a standard USB connector with a single omni-directional antenna. The device operates in the frequency range 70 MHz to 6 GHz and up to 56 MHz of RF bandwidth. The frequency used in this experiment and the indoors-only operating conditions comply with the USRP's manual instructions and compliance rules for consumers, as well as the guidelines regulated by the Federal Communications Commission (FCC). The software implementation uses MATLAB and the Communications Toolbox Support Package for USRP Radio. The experiment is conducted in a LoS scenario where the AP, the target object, and the receiver are placed in the same room and no obstructions being present in the sight-line.

A. Dataset and Performance Metric

We choose 5 different static object classes of different dimensions and materials in the experiment for training and testing, viz., picture frame, chair, box, table, and monitor. in particular, 2 picture frames of different sizes, 2 chairs of different sizes and materials, 1 box, 2 tables of different sizes and materials, and 1 computer monitor are used during the training and testing of the classification task. All objects are placed individually between the access point and the receiver for experimentation and data collection (as shown in Fig. 1). A total of 60 captures for each object, each consisting of 10 packets, are collected as a dataset for training and testing. In total, there are 300 captures of 10 packets each to generate the dataset for each scenario. Performance metrics for the evaluation include the accuracy of the proposed kNN algorithm, the classification error, the confusion matrix, and the Silhouette metric to measure the quality of the data relative to their respective clusters. We provide graphical and visual representations to further analyze the results.

B. Experimental setup

Our proposed model is evaluated in the experiment where the target object is placed in a room with a WiFi AP and at a distance of 7 feet from the receiver. In this setup, other furniture exists in the surrounding area but does not obstruct or opaque the line of sight. The receiver captures the packets for

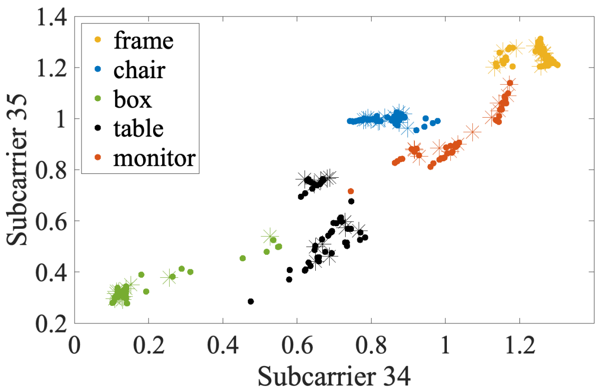

Fig. 4: Clusters of CSI magnitudes for two subcarriers in line of sight scenario. The CSI magnitudes are clustered according to the object with little overlap in some instances.

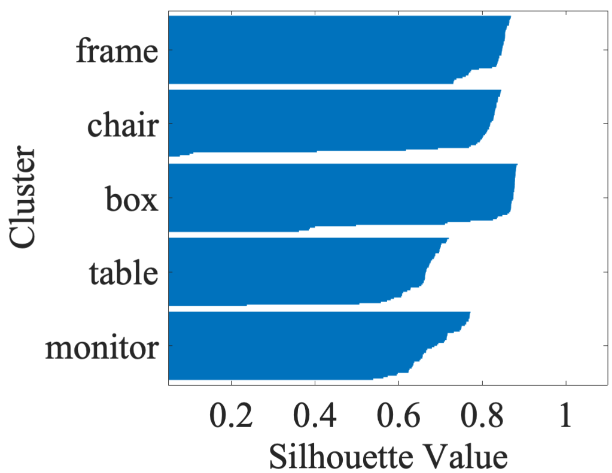

Fig. 5: Silhouette measure of different clusters

about 1 second with a default beacon interval of approximately 100 ms for each packet. Furthermore, each capture is assigned the ground-truth object label and saved in the dataset to train and test the machine learning model. The experiment was replicated multiple times and the replications generated relatively similar results. Different target objects of the same and different object class are placed in different orientations for both training and testing. For instance, two different chairs, tables, and picture frames made of different materials are interchanged during training and testing to achieve a better generalization of the results.

C. Experimental Results and Discussions

Fig. 4 shows the CSI magnitude of the data points for two selected subcarriers in the collected dataset for different scenarios. Again, the dimensionality of the problem demands the selection of specific subcarriers to visualize the clusters of data points. The dots in the figure represent the training data, and the asterisks represent the predicted points. It can be clearly noticed from Fig. 4 that the CSI information of different objects can be separated into clusters with almost

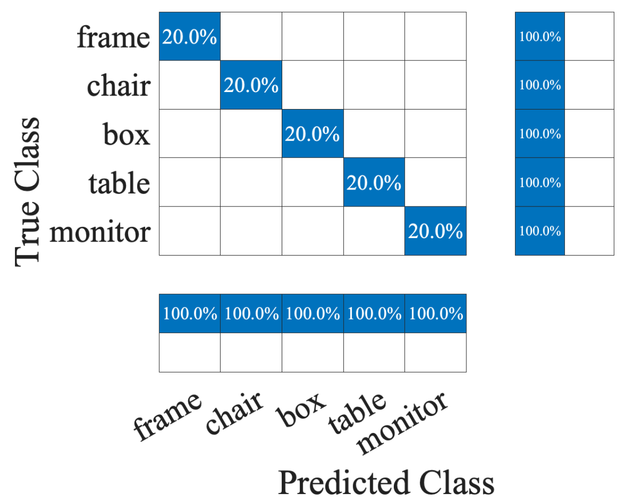

Fig. 6: The confusion matrix metric describes the performance of the kNN classifier in two scenarios.

non-overlapping instances. The test data points are accurately predicted in the correct clusters. This is further emphasized in the confusion matrix of the classification task (Fig. 6). This indicates that the kNN model is capable of detecting the small variations in the patterns generated by the CSI magnitudes of different objects. This also emphasizes the importance of the instance-based learning model for this CSI-based object recognition task, and highlights the kNN model as the appropriate classifier that can make predictions with high accuracy even with few hyperparameters and a moderate size dataset.

In addition, to further evaluate the performance of the classification task, the Silhouette measure of the clusters is used to measure the effectiveness of the learning-based algorithm. The Silhouette metric evaluates the quality of the data clusters where its values range from -1 to +1, with -1 indicating that the data is weakly clustered and +1 indicating a high correspondence of the data point to its cluster. Fig. 5 shows the Silhouette measure in the line of sight scenario with a relatively high value; hence, emphasizing the quality of the clusters.

The kNN algorithm is implemented with five clusters and the training to test ratio is set to 0.8. The accuracy reached 100% in the line of sight in some runs of the experiment. The classification loss function used in this task is the misclassification rate that represents the ratio of the incorrectly categorized data points to the total number of test points. The classification loss is evaluated as (1 - test accuracy) and estimated at 0.033 and the confusion matrix, as shown in Fig. 6, further confirms the value of this metric.

The advantages of kNN is that it is an instance-based learning algorithm and requires little to no signal processing techniques [22]. In addition, unlike modeling-based algorithms, kNN, as a machine learning algorithm, enables manual feature engineering and dimension reduction of raw data points.

D. Baseline comparison against Deep CNNs

The experiment is replicated using a deep CNN and a comparative analysis with the kNN classifier is performed. Following a solved MATLAB example to detect human presence using a deep neural network [38], an architecture (as shown in Table I) similar to the one devised in the solved MATLAB example is implemented for object recognition. The results of the DNN classifier are summarized in Table II. The results indicate a decrease in test accuracy (from 100% to 91.7%) compared to the kNN accuracy. Additionally, the confusion matrix in Fig. 7 shows the performance of the DNN classifier where certain misclassifications occur in detecting the frame and chair objects. Such misclassifications vary between different runs of the experiment but with relatively similar accuracy. Overall, the instance-based kNN algorithm outperforms the deep learning classifier in learning the patterns of CSI values and classifying the labeled objects.

TABLE I: Layers of the deep CNN model [38]

Layer ID	Layer Type	Output
1	Image Input	51×7×1 images
2	2-D Convolution	8 3x3 convolutions
3	Batch Normalization	Batch normalization
4	ReLU	ReLU
5	2-D Max Pooling	2x2 max pooling
6	2-D Convolution	16 3x3 convolutions
7	Batch Normalization	Batch normalization
8	ReLU	ReLU
9	2-D Max Pooling	2x2 max pooling
10	2-D Convolution	32 3x3 convolutions
11	Batch Normalization	Batch normalization
12	ReLU	ReLU
13	Dropout	10% dropout
14	Fully Connected	2 fully connected layer
15	Softmax	Softmax

TABLE II: Test accuracy for classifiers

Model	Line of Sight
kNN	**100%**
Deep CNN	91.7%

Fig. 8 further demonstrates the training progress diagram and displays the training and validation accuracy as well as the training and validation loss for the DNN model. The decrease in accuracy in the deep learning algorithm emphasizes the nature of CNN architecture, which is designed for vision problems (e.g. images) and not CSI tasks. The DNN architecture learns the features automatically, whereas for the instance-based kNN model, the features (subcarriers) are identified and are readily available to be used during model training. Therefore, the design of new CSI-based CNN architectures would better address WiFi sensing tasks than traditional vision-based DNN architectures [22]. Machine learning models such as support vector machine, Naive Bayes, and decision tree need to be further addressed and studied to improve the model performance of CSI-based object recognition tasks. All evaluation related codes and data are available through Github [39].

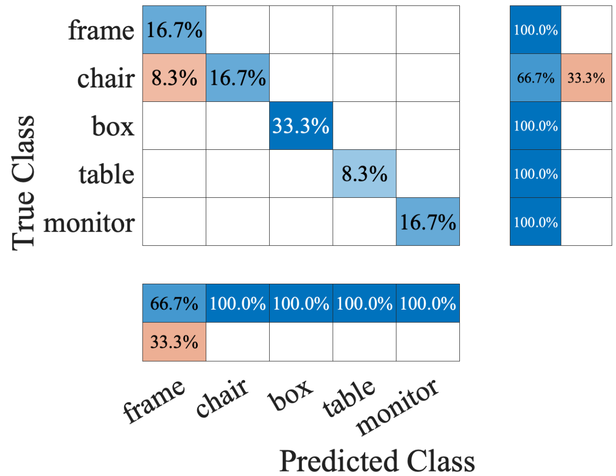

Fig. 7: The confusion matrix metric describes the performance of the deep CNN classifier in two scenarios.

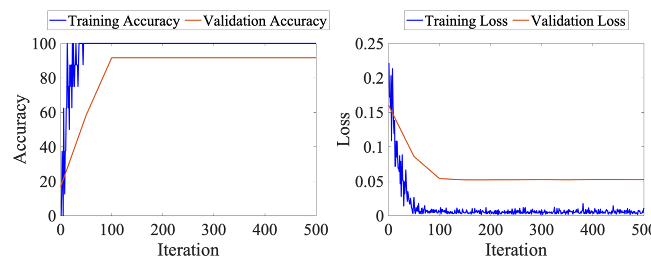

Fig. 8: The training progress of the deep CNN classifier for line of sight scenario.

V. Conclusions and Future Work

In this paper, we applied a data-driven instance-based approach for object recognition using WiFi signals. The proposed solution identified five objects with high accuracy in direct line of sight scenario. The analysis also examined the possibility of running a deep neural network to solve this task and demonstrated a significant drop in accuracy. The kNN algorithm performed better than CNN for this classification task and avoided overfitting for a moderate size dataset; however, accurate identification of objects cannot be guaranteed using vision-based deep learning architectures. Unlike a CNN algorithm that requires a large dataset and automated feature learning, the kNN algorithm is a simple algorithm that adapts easily with new data points and needs only a small collection of data and few hyperparameters.

In future, we plan to explore even more challenging non line of sight (non-LoS) scenarios where the object to be detected is obstructed from the view of the transmitter and/or receiver. Future work will also explore problem scalability in order to study object recognition for a larger number of objects with different physical layer properties such as the phase angle, angle of arrival, and time of flight. Future direction may also implement different instance-based learning algorithms such as support vector machine and decision tree and perform a comparative analysis to find an optimal solution for CSI-based object detection and recognition applications.

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