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Channel State Information based Device Free Wireless Sensing for IoT Devices Employing TinyML

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***Abstract*—The channel state information (CSI) of the sub-carriers employed in orthogonal frequency division multiplexing (OFDM) systems has been employed traditionally for channel equalisation. However, the CSI intrinsically is a signature of the operational RF environment and can serve as a proxy for certain activities in the operational environment. For instance, the CSI gets influenced by scatterers and therefore can be an indicator of how many scatterers or if there are mobile scatterers etc. The mapping between the activities whose signature CSI encodes and the raw data is not deterministic. Nevertheless, machine learning (ML) based approaches can provide a reliable classification for patterns of life. Most of these approaches have only been implemented in lab environments. This is mainly because the hardware requirements for capturing CSI, processing it and performing signal-processing algorithms are too complex to be implemented in commercial devices. The increased proliferation of IoT sensors and the development of edge-based ML capabilities using the TinyML framework opens up possibilities for the implementation of these techniques at scale on commercial devices. Using RF signature instead of more invasive methods e.g. cameras or wearable devices provide ease of deployment, intrinsic privacy and better usability. The design space of device-free wireless sensing (DFWS) is complex and involves device, firmware and ML considerations. In this article, we present a comprehensive overview and key considerations for the implementation of such solutions. We also demonstrate the viability of these approaches using a simple case study.**

***Index Terms*—Wireless sensing, machine learning, edge computing, TinyML.**

I. Introduction

With the rapid proliferation of IoT devices, we are at the cusp of 64 Billion internet-connected devices. Many of these IoT devices have onboard sensors, computing and communication functionalities. In fact, the majority of IoT devices use wireless interfaces to connect with personal or low-power wide area networks (LPWAN). While the primary purpose of this device can be context-specific sensing, the secondary information which accompanies each transmission can be obtained in form of channel state information (CSI). The primary usage of such information is to improve the successful recovery of transmitted information and mitigation against environment-dependent impairments. The CSI can be treated as a signature of the operation radio environment and thus could be a rich source for secondary usage. For instance, CSI can be used for optimal interference coordination to improve transmission reliability or can be employed in Device Free Wireless Sensing (DFWS). The DFWS systems harvest CSI to identify Patterns of Life (PoL). These patterns range from mere presence detection in indoor space to using micro-doppler signatures for respiratory rate estimation. The capability to obtain operational environmental intelligence through DFWS can power a huge range of application segments, ranging from elderly monitoring to location-based services [1]–[4].

DFWS has been an established area of research in the past few years. However, the core approach has been the collection of CSI and offline application of machine learning-based approaches to identify PoL classes. Practical wide-scale deployments where side information e.g. CSI or even received signal strength indicator (RSSI) for PoL identification has received lesser attention. Moreover, with the advent of edge based ML inference capabilities, it is possible to develop a new breed of IoT applications which even without connectivity could perform PoL identification and trigger an appropriate response.

Typically, edge devices have lower computing and memory resources, therefore the deep learning (DL) approaches need to be tuned for better performance. This typically involves compression and translation of ML operations into optimal implementation for embedded firmware. TinyML provides one such framework for low-power MCU devices. The key driver of the state-of-the-art wave in DFWS is the accessibility of the CSI in low-cost devices. CSI information is also present as side information from RF Backscattering Sensor devices.

The design space for the DFWS on-edge IoT devices with ML inference capabilities requires several important design considerations. These vary from the type of device to, the type of pre and post-processing required for CSI. To the best of our knowledge, a survey which highlights these issues in a cohesive manner is highly desirable. To this end, this paper provides a comprehensive overview of DFWS techniques, tools, hardware, software and research challenges.

Contribution and Motivation: The motivation and contribution of this paper can be summarised as follows:

- A short survey on the application of device-free wireless sensing that considers the enabling technologies, approaches, and techniques that employ the CSI measurements for recognising life patterns.
- Highlighting the commonly used signal processing techniques, their complexity and feasibility for implementation on edge devices for applications requiring real-time inference.
- Showcasing the challenges of deploying some conventional or even simple DL models on edge devices using TinyML. We also highlight the available off-the-shelf edge devices and tools employed for DFWS applications.
- Demonstrating feasibility of implementing DFWS on the edge with the help of a case study. We study the resource footprint of changing the structure of the DL models on the performance of the classification and hence the feasibility of implementation for ML-enabled micro-controllers.

Organisation: The rest of the paper is organized as follows: Section II introduces the enabling technologies. Section III gives the most common applications. Section IV presents some of the challenges. Section V provides a case study for the use of DL on the edge for DFWS. Finally, Section VI provides the conclusions.

II. Enabling technologies for DFWS

In this section, we review the enabling tools and technologies that are available as key enablers for the DFWS.

A. CSI extraction tools

In order for broader adoption of wireless sensing for daily life, sensing devices need to be low-cost and capable of performing generalisations with good accuracy. However, these low-cost devices have limited computing capability. Hence, facilitating the implementation of complex inference techniques on low-cost devices requires a new toolchain that supports compression of the trained ML models and their embedded implementation with a low memory footprint on the edge device. Furthermore, it is also necessary that the device exposes a mechanism to access the CSI for performing inferences.

In this section, we present a summary of the tools that enable CSI collection on the edge devices and then we also highlight tools that enable DL on the edge. Many off-the-shelf devices have been widely used to collect CSI measurements. Most of the existing literature employs Intel WiFi cards like the 5300 WiFi Network Interface Card (NIC) to extract CSI data. Intel 5300 gives access to 56 OFDM sub-carriers with a 20 MHz channel bandwidth and 114 sub-carriers for the 40 MHz bandwidth with a narrow sub-carrier spacing and low sampling rate [1], [5]–[9]. The Atheros CSI tool is another tool for collecting CSI measurements from 802.11n WiFi chip sets and it has been widely used for collecting CSI from Atheros AR9580, AR9590, AR9344 and QCA9558 NICs [10], [11]. The use of NICs requires a fully capable computer to be attached for the CSI to be collected and hence they cannot be deployed as an IoT device. Consequently, for a realistic wide-scale IoT deployment, alternative approaches must be explored.

Naturally, a step down from a full-blown personal computer will be considered a single-board computer (SBC). One such chipset that allows CSI collection is the BCM4339 by Cypress Semiconductor. The chipset is employed by the Raspberry Pi B3+/B4 and Nexus 5 mobile phones. There is a comprehensive programming library that allows the CSI collection at a lower cost than the Intel 5300 and Atheros. Many applications have been investigated in the literature that uses the BCM chipset and achieve good recognition accuracy in recognition [12]–[15]. Again like full fledge mini PCs, SBC-based IoT deployment has lower mainstream penetration. This is mainly because SBCs are power-hungry and costly. The end IoT devices often do not require full-blown operating systems (OS) and have a dedicated functionality which can be implemented on low-cost MCUs. SBCs however are good candiate for gateway devices.

PicoScenes is another open-source and powerful tool that provides access to CSI measurements for various Intel and Atheros NICs and also for Software Defined Radio (SDR) modules (e.g., USRPs, BladeRF-X40, HackRF) [16]. PicoSense is the first publicly available tool to support CSI collection for Intel's next-gen AX200 NICs series that enables packet injection and CSI measurement in the Wi-Fi 6 GHz band. This tool will potentially accelerate the research in DFWS.

Very recently, ESP32 by Espressif Systems which is widely used in developing IoT platforms provided access to the CSI data. The ESP32 is equipped with full WiFi capability for IEEE 802.11b, IEEE 802.11g and IEEE 802.11n and provides a wide range of CSI measurements in three fields of channel frequency responses (i.e., Legacy Long Training Field (LLTF), High Throughput LTF (HT-LTF), and Space-Time Block Code HT-LTF (STBC-HT-LTF)). The chipset is capable of collecting CSI measurements for up to 114 sub-carriers. Additional information e.g. RSSI, the noise floor and the time of packet arrival is also exposed to developers. The fact that ESP32 is an IoT platform that can be found in many daily used IoT devices, the low cost as compared to the other competitors and its compatibility with TFLite for TinyML implementation all make it a good candidate that fulfils the conditions for real-time applications with wide adoption. A comprehensive survey on the use of ESP32 for DFWS-enabled edge can be found in [17].

B. 5G & Beyond and its role in DFWS

With the development of 5G networks, high-frequency bands such as mmWave became a popular type choice for the implementation of high data rate communication systems. In contrast to the typical communication frequencies for edge devices and mobile communication (i.e., 433 MHz, 868 MHz, 2.4 GHz, 5GHz ISM bands, GSM and LTE bands), mmWave provides a wide band of communications and also provides a sensitive frequency range for human activity recognition. Hence, the 5G bands of frequencies will allow more adoption for the DFWS. The use of the mmWaves for DFWS has been addressed in many papers in the literature [18]–[23]. Even though the wide use of 5G for DFWS is still primitive it shows a huge potential in the next few years as 5G networks become more popular.

C. Deep learning

Deep Neural Networks (DNNs) have been widely used in the literature to perform classification and regression inferences for unseen and uneasy representable physical phenomena with latent parameters. The advantage of the DNN is to let the computer decide what features to be given the highest weight during the training phase. This technique has been widely used to reduce the requirements of deep analysis of the raw data for features extraction and it has proven its utility in many application domains.

However, to employ DNN models in low-performance edge devices for real-time applications, the complexity of the DNN model needs to be minimal to allow the edge device to undertake fast inference or even allow the model to fit within the low-edge memory device. To decrease the complexity, methods of signal denoising, signal transformations, feature extraction, and dimensionality reduction need to be employed at the prepossessing phase before the training and inference. Many DL algorithms have exhibited excellent performance for DFWS recognition. Namely, Deep Neural Networks (DNNS) for general-purpose recognition processes, Recurrent Neural Networks (RNNs) and Long Short Term Memory (LSTM) for times series and time-dependent sequential dataset-based recognition. Convolutional Neural Networks (CNNs) are also a type of DNNs that are widely employed for 1D and 2D image-based inference. Generative Adversarial Networks (GANs) where two neural networks compete with each other to become more accurate in their predictions are also used where obtaining a large annotated dataset is difficult or time-consuming [22]. In GANs, synthesising virtual samples can be achieved for data augmentation and hence ensuring no over-fitting and dataset balancing. Even though DL models have proven excellent performance in DFWS, the classical and simpler techniques of ML like Gaussian Naive Bayes (GNV), Support Vector Machines (SVMs), Decision Trees (DTs) and the Ensemble methods have proven their performance for a long time in the literature [24]. More about using deep neural networks in DFWS can be found in [25].

Regardless of the adopted ML algorithms, a set of feature extraction and dimensionality reduction is required for simpler, more robust and high-performance inferences. For example, in an approach of extracting features from the CSI amplitude and phase, the authors in [26] applied a linear discriminant analysis and Softmax regression algorithm to generate a human activity recognition (HAR) model that classifies 4 types of human activities. The linear discriminant analysis and the Softmax regression model do not require any type of DNNs and can achieve an accuracy of classification in the range of 95.4%. In [27], the authors presented a new approach for a better understanding of the wireless signal features. They tried to understand the variation law of the influenced signal by utilizing Dynamic Differential Phase Analysis (DDPA). The new approach presents a performance metric for channel change metric to study the target influence in the vicinity of the receiver. The paper reveals that the DDPA can achieve better performance in terms of accuracy if it is compared to the traditional phase and differential phase analysis. Also, a method of using activity filtering and enhanced correlation features is presented in [28]. The authors employ a method to compensate for the timing offset between the transmitter and the receiver. The new method improves the quality and reduces the number of parameters to be entered into the DNN model. This results in low-complexity models. In order to differentiate similar human activities, they employed activity recognition based on the enhanced correlation features of the CSI. The new approach for features engineering achieved better accuracy when it is compared to other techniques and it can achieve a very high accuracy that exceeds 99%. It is also shown that the features engineering method that they applied can reduce the DNN training time to less than 20% of the time required by various direct use of CSI for inference.

Other approaches for DL by employing statistical models for wireless sensing are presented by [29]. The authors presented the utilisation of local maximum mean discrepancy to align the data distribution in multiple subdomains based on kernel Hilbert space (RKHS) in order to design a deep subdomain adaptive network. The new method is applied to the HAR application and it achieves an accuracy of 95.6% and helps in reducing the required time for the training by the better selection of DNN input features.

III. Applications of DFWS

A. Applications for HAR

The main focus of wireless sensing researchers in the last decade is on HAR. HAR can be divided into multiple categories such as gesture recognition, presence detection, crowd counting, fall detection, respiration detection and human pose detection.

In [30], the authors propose a hand gesture recognition based on CNN classification of gestures. The authors used micro-Doppler signatures to detect and classify ten different classes. An accuracy of more than 85.6% was achieved for the ten classes classification and 93% for the seven classes CNN model. The authors in [31] proposed a mmWave-based device-free gesture recognition with a new strategy employing a Taylor criterion ranking to remove the ineffective neurons from the DNN model to lower the computational time, complexity and the required storage to build the classification model. The new dimensionality reduction and model compression show a significant reduction in the inference time and the required storage (i.e., 14% for inference time and 27% for the storage) while sacrificing only 2% of the accuracy.

Multi-target sensing based on multiplexing techniques is introduced in [32]. The authors show that angle division multiplexing sensing, range division multiplexing sensing and source division multiplexing sensing can be used to perform multi-target sensing on a 77GHz testbed. A mean accuracy of more than 96.8% is achieved. A new method of activity and environment isolation was presented in [33]. The authors show a HAR DNN-based model that is capable of removing the environment parameters from the collected CSI data. The DNN model was trained to recognize 6 activities with good accuracy.

A gait identification and gesture recognition are also presented by [34]. The paper shows an extensive study of recognising 40 simple and mixed gestures based on CSI measurements of 1.2 million samples. The accuracy of the experiment and the trained model for expert models give an average accuracy of 94.5% and 98.5% respectively for CSI-based gait identification and gesture recognition. A complexity-based model selection in a three-phase system for HAR is presented in [35]. The model chooses between three different methods for learning based on the size of the collected samples (i.e., distance-based classification for a small number of samples, SVM when representative data can be extracted and RNN when there are a large number of samples). An accuracy of 96% on average was achieved for the three-phase system of recognition.

To solve the problem of the dramatic drop in the performance of the learned model when changing the environmental conditions, then [36] presented a meta-learning method that is capable of performing discriminative deep features learning as well as learning the transferable similarity of evaluation for the training sets. The authors achieved a 90% accuracy in most of the cases even when changing the gesture's environments and conditions.

An enhanced CSI for HAR applications has also been presented in [37]. In the paper, the authors applied the well-known LSTM and RNN DL models to automatically extract deeper features and then applied the softmax regression algorithm for classification based on enhanced CSI correlation feature matrices. The test was performed with CSI collection utilising an Intel WiFi 5300 network utilizing 30 sub-carriers CSI. The overall performance shows more than 95% of accuracy.

A joint localisation and HAR experiment have been presented by [38]. The paper is a comprehensive study that utilizes three different techniques of DL (i.e., CNNs for recognition and state machines that learn temporal dependency information and then RNNs and LSTM for reinforcement learning agents). The aim of the study is to perform a traditional HAR. The achieved accuracy of the test is 97% on average with an average of 82% when testing with two publicly unseen available datasets.

In order to solve the problem of collecting new data to do HAR in different environments, the authors in [23] presented a maximum-minimum adversarial approach that moves the target features to the distribution of the source features using unsupervised learning based only on the trained model of the source environment and without performing any labelling or data collection. The experiment was conducted on a mmWave scenario at 24 GHz frequency and interesting results of more than 90% average accuracy for the cross-scenario device-free activity recognition were achieved.

Even though CSI is the most commonly used for the DFWS, there are many efforts that use the RSSI information to perform the DFWS. In [39], the authors utilized the Relative Signal Strength (RSS) of 60 GHz mmWave to perform a HAR experiment to recognise three different activities (i.e., call, pocket and app browsing). The paper shows an accuracy of more than 83% on average for most of the scenarios. In our paper, we will show a case study of the use of RSS information for the localisation of a person within a closed-room environment

In the context of HAR, there are too many efforts to mention in this conference-style paper. However, many interesting efforts can be found in [26], [40]–[44].

B. Applications in positioning and localisation

The natural use of DFWS that becomes jointly related to the HAR comes in localisation and positioning, especially for indoor environments. CSI measurements contain both the amplitude and the phase of the CSI sample. Hence, it adds more information that can be employed for more accurate positioning if it is compared to the well-studied RSSI approach in the literature [45].

In [46], the authors present a use case of CSI to estimate the location of humans in an indoor environment. The paper employs a theoretical dataset generation based on signal propagation models and geometric methods. The paper shows how the CSI information is used to feed an LSTM DL model for training and inference. The theoretically generated model is then employed for practical estimation for indoor localisation using Intel 5300 NIC for real-time testing. The accuracy of the localisation model in terms of the estimation error is shown for different geometries and configurations.

A CNN-based model for localisation based on CSI images is presented in [47]. The paper shows how the CSI measurements for 114 WiFi sub-carriers are used to generate a time series image dataset. The dataset is then fed into the CNN model for training. The use of CSI images is widely used by utilizing raw CSI images and also spectrogram images. The use of 2D-CNNs on these types of images is computationally expensive. CNN DL models are challenging when they are to be implemented on sub-megabyte RAM for edge devices.

Fine-grained indoor fingerprinting is presented in [48]. The paper shows a joint utilisation of RSSI and CSI measurements for more accurate positioning. Weighted k-Nearest Neighbor (WKNN) is employed on CSI and RSSI after performing Kalman filtering on the raw measurements. Kalman filtering is used for smoothing the signal for denoising and also for dimensionality reduction. This paper presents a simple approach that does not use the computationally expensive DL approach while achieving good estimation performance.

Crowd counting is also another application that is embedded in positioning applications and it is widely studied in the literature. Here, we mention a couple of use cases [49], [50]. In [49] the authors examine a transfer learning-based technique based on CSI measurements on a DNN that is transferred from ResNet, AlexNet and VggNet transfer learning models for crowd counting. The authors in [50] presented people counting techniques for the scenarios of waiting in lines based on naïve Bayes classification that is applied to statistical features of RF power measurements. An average accuracy of classification of more than 98% has been achieved

Due to the lack of space in this paper, we cannot mention all the efforts that had been made in localisation and positioning. Hence, the reader is encouraged to examine [51], [52].

C. Applications in health care

One of the most common applications that utilise DFWS for a handful of noninvasive free sensing is within healthcare. During the COVID-19 pandemic, close proximity of people was to be prevented and the separation of people within the same indoor environment was encouraged. Hence, some literature tried to build HAR for healthcare applications where noninvasive sensing is vital for privacy and health concerns. In [53], the authors presented a DL approach for joint localisation and HAR. The paper shows high accuracy for recognition and localisation even when testing public datasets.

Monitoring multi-person breathing is presented in [54] and [55]. In [54] the authors show how the CSI is used to detect the rate of breathing for multi-person under different conditions and environments. A comprehensive study of the CSI phase analysis and filtering and transformations is presented in this paper by utilising a 5GHz WiFi band. The success rate of estimating the breathing rate of an average of more than 96% in an environment of 2 people is shown and it is more than 91% for 3 people. The paper shows how the success rate decreases as the number of people in the environment increases. In [55], the authors used Independent Component Analysis (ICA) to obtain the breathing information from the CSI that is collected from Intel 5300 NIC. The mean absolute error of 0.21 beats per minute in the two-person scenario is interesting bearing in mind that they employed no DL techniques in the study. More studies on a respiration rate that utilise CSI collected from smartphones or off-the-shelf NICs can be also found in [55]–[60].

Human bio-metrics signal sensing is also another direction for the DFWS in healthcare. In [3], both heart rate and respiration are jointly estimated from the CSI that can be collected from the WiFi signals. A mean accuracy of 98.5% for heart rate estimation and 99.1% for respiration has been achieved based on the named WiFi sleep stage neural network (W2SN) and Cardio Pulmonary Coupling (CPC) Neural Network. Uncorrelating the testing environment and the testing results are required in performing sleep stage tests. In [61], a DL approach based on the collected CSI is used to classify 4 sleep stages for humans. The CSI here covers the two main parameters that have been used for accurate sleep stages classification, namely the respiration and body movement information. More Information on the state-of-the-art advancements in health care and the future trends for the use of DFWS can be read through [62]–[64] and the review paper in [58].

D. Applications in safe driving

An interesting application for employing CSI information comes with an in-car driver assistant. Automating and predicting some human activities while driving may give more degree of freedom for the control system within the car to be ready for sudden changes and takeovers [65], [66]. In [65], the authors presented an approach for CSI-based HAR for car drivers with an average recognition accuracy of 91.3%. A mmWave Doppler radar for 3D head tracking is presented in [67]. The advances in 3D head tracking allow for a better understanding of the capacity to supervise or manoeuvre in driver assistance systems. Driver authentication applications are shown in [68]. The authors in [69], presented a CSI-based system to track the driver's head. CSI-based driver's inattention detection and abnormal driving prediction are presented in [78]. Also, [70] presented a CSI-based fatigue detection application. The applications for car driver assistance are unlimited and the horizon is open for more research efforts. A paper that highlights the potential of CSI-based sensing in enriching the sensing techniques within smart cars be found in [71].

TABLE I: Applications of wireless sensing.

Application	Surveyed papers
HAR	[23], [26], [30]–[44]
Localisation and positioning	[45]–[53]
Health care	[3], [53]–[64]
Autonomous and safe driving	[65]–[71]
Smart agriculture and industry 4.0	[72] [73] [73] [74] [75] [76] [77]

E. Applications in smart agriculture and industry 4.0

Fundamentally, electromagnetic wave propagation is directly affected by the medium and the signalling channel environment. Hence, some physical non-human related sensing can be employed by studying the footprint of the medium changes in terms of the dielectric constant and then correlating latent parameters to build sensing models.

For example, the authors in [72] introduced an approach to measuring the dielectric property of water and ethanol and more liquids. The estimated permittivity for various types of liquids showed good agreement with the actual values with an average error of 4.0%. The permittivity of a dielectric reflects many latent features and could be transformed into bio-metrics. In smart agriculture, the dielectric material characteristics could be transformed into an indicator for minerals, PH-indicator and humidity measures by only employing CSI collection and regression. In the same analogy, [73], [74], [75], [76] and [77] provide similar targets in measuring the dielectric material characteristics. These hidden measurements will provide a set of huge potentials in smart agriculture and could assist in industry 4.0 and hence a wider adoption due to the low-cost measurements.

The applications of the daily life use of the CSI measurements as a free source of information are unlimited and are predicted to gain more attention and work in the next few years. A summary of the papers that we surveyed to search for the potential applications can be found in table I. In the next section, we highlight the most common stressing challenges for the wider usage of the DFWS in real-time applications.

IV. Challenges of DFWS on the edge

In this section, we set a number of challenges that are embedded in DFWS especially when it is required to be employed on the edge: **Sampling rate of CSI and number of antennas:** accurate results for signal processing techniques in estimation and classification are related to the sampling rate of the target signal. A higher sampling rate gives more resolution and freedom in frequency-dependent feature selection. However, the size of the CSI measurements is proportional to the number of antennas and frame rate [62]. The rate of sampling of the CSI depends on the mode of operation, especially when performing the CSI collection in WiFi environments. In cases where only passive monitoring of CSI is available, the high sampling rate of the CSI measurements will not be feasible, and hence some attacks may be required to generate more packets to update the CSI information. In active modes of CSI collection, a high data rate gives access to more CSI samples and hence more complex and fast human activities like gestures can be detected.

Denoising: raw CSI information is too noisy and hence direct processing and training for the inference model lead to untrusted and non-robust even with low-accuracy results. To tackle this problem, denoising techniques are used in removing the noise components from the CSI raw data. A windowed moving average filter can be used to smooth the time series signal of the CSI retracted amplitude. Also, the Discrete Wavelet Transform (DWT) has been used widely to remove unwanted white Gaussian noise by calculating the high-frequency energy of the CSI [4], [17]. Median filter [4], Butterworth filter with a certain cutoff frequency to remove high-frequency noises [79] are also some other filtering techniques. Also, the Hampel filter is a good candidate for denoising the signal, especially when retaining the original signal is important after the transformation [17], [80]. Some CSI data analysis also requires training on the spectrogram of the sub-carriers CSIs. Hence, image filtering may also be of interest. Different filtering techniques can be applied to the images such as PCA-based denoising, Hamming filters and Wiener convolution [81].

The main difference that decides the adoption of the type of filtering techniques is the order of the complexity when it is employed on the edge and if the type of transformation is really feasible for real-time applications. hence, an extensive study of the complexity of real-time implementations of DFWS on the edge is required.

Complex real-time signal processing: In order to lower the overhead of complex denoising techniques or general signal processing, data segmentation parametrization is a challenge for optimal and better accuracy. We need to know the best CSI time series length that represents an activity or a class before performing data annotation. Deciding the optimal window size for a sample in the CSI time series for achieving a robust DL model requires extensive testing and a long training time. Decreasing the number of samples in a CSI data row and hence decreasing the footprint on the DL model (please refer to table II for a better understanding of the effect of the size of the features on the required memory for inference). Transformation techniques such as DWT are also computationally expensive on the edge microcontrollers. Short-Time Fourier Transform (STFT) for example is another computationally expensive transform that is usually used to identify the direction and time of occurrence especially when it is used in localisation and HAR applications [67]. Other transformation techniques are also commonly used in the analysis of the CSI measurements like Discrete Hilbert Transform (DHT), Fast Fourier Transform (FFT) and the aforementioned DWT and all of them are computationally expensive [1].

Features extraction and dimensionality reduction: some of the aforementioned challenges and computationally expensive operations on the edge can be eliminated by doing feature extraction before performing any type of training and inference. Feature extraction techniques may result in simpler recognition algorithms and in some cases, we do not need complex recognition techniques like DNNs. Statistical analysis of the CSI measurements (i.e., amplitude, phase, temporal differences and power spectral density) such as mean, median, variance, correlations, kurtosis, and other moments may contain sufficient data to build the recognition decisions and hence the raw features are transformed into aggregated single or few features that are rich of information [1], [17], [22].

Features extraction is required for dimensionality reduction where the feature selection sometimes results in dimensionality reduction and elimination of some dimensions. It is well known that the ODFM sub-carriers of the WiFi signals are orthogonal, but they may contain the same information and the fingerprint of any single sub-carrier is similar to one or more of the other sub-carriers. Dimensionality reduction is usually performed through one or a set of operations like PCAs, ICA, Linear Discriminant Analysis (LDA), Non-Negative Matrix Factorisation (NMF), Generalised Discriminant Analysis (GDA), Low Variance Filter (LVF), Backward Feature Elimination (BFE) and Random Forests (RF) [4], [82]. The key advantages of performing dimensionality reduction is removing some of the noise in the CSI measurements, compression of the data, searching for latent variables in terms of factors analysis, getting rid of multicollinearity and ultimately achieving more immunity to over-fitting [82]. Feature extraction and dimensionality reduction techniques vary between very computationally expensive operations like DWT and simple statistical analyses like mean and variance computations. Again, the key factor that plays the biggest role in the choice of the technique is affected by the feasibility of implementation on the edge device for real-time application.

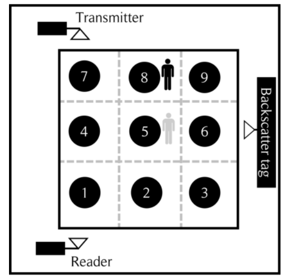


Fig. 1: System model.

Inference of the edge: The most common library that can be used for edge TinyML inference is the TFLite Micro by Google. With the aforementioned merits that the TFLite provided for edge computing, multiple graphs for complex DL techniques (e.g., LSTM, GRUs and RNNs) are not yet feasible in the single and dual-core edge micro-controllers [83], [84]. Hence, when applying the DL techniques, we need to study the feasibility of the model to fit in the memory size of the edge device and then the feasibility of performing the complex inference algorithms. Bearing all of that in mind, the overhead of preprocessing, denoising, transformations, feature extraction and dimensionality reduction is important. The study of edge ML or the so-called TinyML is a new breed of ML that allows importing pre-trained models to the edge low-performance commodity microcontrollers [84].

V. Case Study

In this section, we present a simple case study where the RSSI of an ambient wireless signal is used for locating a person in an indoor environment. For the sake of locating the position of a human within a closed room, we divided the room into a 3×3 grid with the aim to locate the position of the human using a classical classification problem.

A. System model

We assume a person is moving in a room with a dimension of $5 \times 8\,\mathrm{m}^2$. The room is divided into a grid of 3×3 where each grid cell represents the location of the person at a certain time. As illustrated in figure 1, the person moves from location $C = 1$ to any location on the grid and holds for 2 minutes to allow for data collection. The system includes a transmitter that transmits a pure carrier signal at 868 MHz. The reader receives the signal that is reflected from the body and another version of the signal that is reflected back from a wall-mounted backscatter tag. The backscatter tag modulates the ambient carrier (using simple binary amplitude shift keying (ASK) modulation) and reflects the transmitter-received signal after modulation by means of changing the antenna impedance to either 0 or 50 Ω (more details on the principles of the backscatter communication and power transfer techniques can be seen in our previous works in [85], [86]). The reflected modulated signal adds more dimension to the received signal and implicitly adds more information to the wireless signal so that the received RSSI by the reader will have more information that may include the spatial location of the person on the grid and also gives more control in the denoising of the RSSI signal.

The transmitter is basically a Software Defined Radio (SDR) (i.e., BladeRF X40) transmitter that generates only a pure carrier, while the receiver is the same BladeRF X40 that receives the reflected signals and stores them into a data file. We perform data collection for 2 minutes on each position on the grid and label the data such that the received signal indicates the parameters of the sample and the location is the response to these parameters.

After collecting all the RSSI data from the 9 locations on the grid, a dataset is generated in a way that each 2 minutes sample of the data is segmented into M samples with N number of RSSI values each. Then the dataset will have M rows with $N+1$ number of columns where the value at the $N+1$ column reveals the label that corresponds to the input samples (features). The length N of the resulting annotated samples, as will be shown later, will affect the accuracy of the prediction of the location when we perform the classification process. The objective then is to build a classification model based on this dataset to perform the inference to predict the class (position) of the person based on the given RSSI data. To do the inference, multiple types of ML models are examined. Namely, Linear SVM, GNB and three hidden layers DNN.

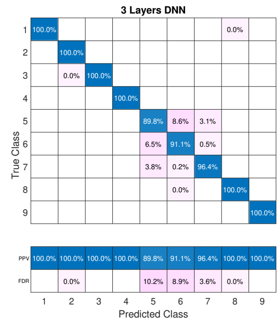
For more enhancement in the localisation accuracy and to build a continuous model based on the discrete localisation model, the location of the person in the room can be predicted more accurately in terms of XY coordinates by performing a probabilistic transformation of the results of the location on the grid. In essence, we transform the probability P_C of a person being in class C (position C) into a Euclidean distance. This type of transformation is usually used in GPS localisation enhancement techniques by the means of Gaussian Mixed Model (GMM) to simulate the posterior probability. Having more than one value of probability for the different classes will lead to building a multi-modal 2-dimensional Gaussian random variable and hence the mean of the projected two-dimensional space into the X or the Y axis will define the accurate location of the person.

B. Inference on the edge

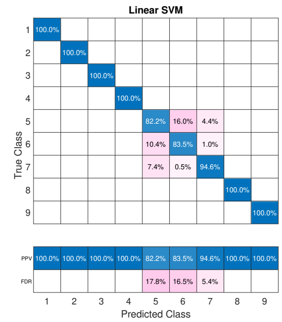
Assuming that the RSSI of the transmitter can be read by a commodity IoT device such as an ESP32 module that is WiFi enabled, the set of all samples of the RSSI signal that corresponds to the location of the person can be collected and then be passed to the input of any trained ML model. ESP32 is a low-cost edge device that is capable of carrying processes that consumes less than 512 KB of RAM. To make sure that the trained model can be fitted within the memory heap and the firmware of the controller, we need to compress the trained model. Also, the model needs to preserve the same performance as if it is working on a fully capable computer. To this end, we use TinyML tools like TensorFlow Lite (TFLite) by google to port and compress the model. TFLite is capable of compressing the 32 bits floating point model weights into 8 bits of an integer while almost achieving the same performance. The next subsection presents some results that are collected by measuring the footprint of the DNN model on the ESP32 microcontroller.

C. Results

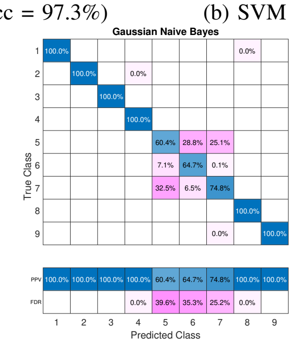
Figure 2 shows the confusion matrices for predicting the location of a person in the room for 3 different models of ML. The confusion matrices show how we can achieve good accuracy metrics by using only the RSSI information. An average accuracy of 97.3% is achieved when applying a three-hidden layer DNN, 96.0% for the linear SVM and 88.3% for the simple GNB. More deep performance analysis for the structure of the DNN can be seen next. For the sake of comparison of the performance for the various ML models on the edge, we perform a number of tests on the ESP32 by performing



(a) DNN (Acc = 97.3%)



(b) SVM (Acc = 96.0%)



(c) GNB (Acc = 88.3%)

Fig. 2: Confusion matrices for various types of models. $N = 50$ parameters/sample.

TABLE II: DNN results for ESP32 edge inference.

RSSI samples	DNN	RAM (kB)	Model size (kB)	Inference rate (Hz)	Test accuracy
20	80x40x20	50.98	25	2932	95.1%
20	40x20x10	35.67	9	7407	92.8%
40	80x40x20	57.31	31	2377	97.2%
40	40x20x10	38.88	13	5738	94.4%
60	80x40x20	63.64	37	1986	92.2%
60	40x20x10	42.08	16	4698	95.3%
100	80x40x20	76.30	50	1556	99.6%
100	40x20x10	48.48	22	3333	99.6%

the inference and then collecting the required flash memory for the firmware, RAM memory and the average inference time. Table II presents the results for inferring (classification) on the edge controller of the ESP32 for multiple configurations for the DNN and different input sizes (i.e., number of RSSI samples for inference). A three hidden layers DNN is used with a number of neurons as shown in the table.

VI. Conclusion

Device-free wireless sensing uncovers very interesting potentials and applications of wireless signals. The main focus of the DFWS is to enable the inference of behaviors and activities from the wireless signal without the need for a full deep understanding of the signaling environment. Even though the enabling technologies and the state-of-the-art literature utilize it in many applications, DFWS faces many challenges due to the embedded randomness and nature of the wireless environment. The main enabling technology that paved the way for the utilization of wireless signals for sensing is DL. DL provides comprehensive tools to perform inferences using complex parameters that were impossible to correlate to perform inference before the advancement of the DL.

In this paper, we performed a major survey of the enabling technologies for the DFWS. Then, we addressed the main applications of wireless sensing. We also addressed the main challenges that face the adoption of DFWS in performing robust sensing devices. Then we presented a case study of the use of backscatter-assisted device-free wireless sensing with edge TinyML for the application of low-cost positioning. Finally, we also discussed some open research in the field of DFWS, especially for the generalization ability of the ML models.

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