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# A Survey on the Wireless Network Technology Classification Using Machine Learning

Siddhartha Subray
University of Colorado Boulder, Colorado
Siddhartha.subray@colorado.edu

Kevin Gifford
University of Colorado Boulder, Colorado
Kevin.gifford@colorado.edu

**ABSTRACT**

**With the rapid development of numerous wireless network technologies and the growing number of wireless devices in use around the world, gaining access to the radio frequency spectrum has become a challenge that must be solved as soon as possible. The ever-increasing wireless traffic and shortage of accessible spectrum necessitate smart spectrum management. Machine learning (ML) is gaining popularity, and its capacity to spot patterns and aid decision-making has found applications in a variety of disciplines. Machine learning approaches have been applied to wireless networking difficulties, such as spectrum efficiency, and have showed superior performance compared to traditional methods. Spectrum sensing enables dynamic spectrum sharing, which improves spectrum efficiency by allowing coexistence of wireless technologies within the same frequency range. This involves the accurate detection and identification of multiple wireless signals sent in the same radio spectrum range. The current state of machine learning algorithms for identifying and classifying radio signals depending on their access technologies, such as Wi-Fi and LTE, is examined in this work. Classifying the RF signals based on their wireless network technologies as opposed to their modulation schemes, especially using machine learning, is an emerging area of study and is becoming a popular research topic. This survey will assist readers to become familiar with the current literature and enable further research in this domain.**

**Index Terms – Wireless Network Technology Classification, RF Signal Classification, Neural Networks, Machine Learning, LTE, Spectrum Sensing, Wi-Fi.**

## 1. INTRODUCTION

Over the previous decade, the quantity of wireless devices available has increased at an exponential rate. In 2018, over 30 billion wireless devices had accessed the internet, with that figure predicted to exceed 50 billion by 2020 [1]. It's critical to meet the demands of mobile consumers while also allowing devices to access the radio frequency band. The radio frequency spectrum is a precious resource that must be managed well for many wireless devices and technologies to coexist. According to the FCC, spectrum utilization varies significantly across time and space, suggesting that the existing spectrum scarcity is primarily due to inefficient spectrum management, as opposed to a shortage of spectrum, as stated by the authors in [2].

The existing radio spectrum policy allocates frequency bands to certain users for a specified length of time, allowing only licensed users access to the spectrum, while unlicensed users are prohibited from using it even while licensed users are not using it [3]. As a result, this valuable resource is being used inefficiently. As a result, researchers have started proposing new paradigms for more efficiently regulating the wireless spectrum.

One such paradigm that aids in the sharing and coexistence of several wireless technologies is spectrum sensing. It enables wireless devices to monitor spectrum usage in a certain band at any given time and allows them to alter their communication parameters [4] to allow for equal spectrum access among different wireless protocols and technologies. As early as 2003, the Federal Communications Commission (FCC) recognized the value of cooperative spectrum access, also known as dynamic spectrum access (DSA), between licensed and unlicensed users to share spectrum [5].

Broadly speaking, spectrum sensing can be divided into two types: narrowband sensing and wideband sensing. Narrowband refers to a frequency range in which the frequency response is flat, implying that fading is consistent across the signal bandwidth. Essentially, the channel's coherence bandwidth is greater than the signal bandwidth. Wideband denotes a frequency range in which the frequency response is not flat, implying frequency selective fading, and the signal bandwidth exceeds the channel's coherence bandwidth [6]. Energy detection [7], eigenvalue-based detection [8], cyclostationary feature-based detection [9], and matching filter detection [10] are examples of narrowband sensing approaches. Nyquist wideband sensing – where wideband signals are sampled at the Nyquist sampling rate – and sub-Nyquist wideband sensing – where wideband signals are sampled at rates below the Nyquist rate – are two examples of wideband sensing approaches [11].

Signal classification is the task of categorizing waveforms and is a subset of spectrum sensing. The majority of the research focuses on identifying signals based on modulation type, with the categorization of wireless network technologies becoming more popular in recent publications. Modulation schemes, such as 64 QAM, 16 QAM, and QPSK are shared by wireless network technologies, for example 5G-NR, Wi-Fi, and LTE and recognizing the RF signal's technology provides more information about the band's occupancy than merely recognizing the modulation process of the signal.

This study provides an in-depth examination of the most current improvements in wireless network technology for RF signal classification using ML. The objective of this study is to familiarize new researchers in the field with RF signal classification based on their access technology and to develop the field.

## 2. RELATED WORK

The authors of [12] developed an algorithm for recognizing digital modulation types based on the signal's known changes in frequency, phase, and amplitude. The three attributes described previously were normalized, and the waveforms were categorized using a decision tree as per their digital modulation method. In [13], the authors suggested a method for classifying MPSK modulation schemes based on predicted values for each MPSK modulation scheme, and then determining the PSK modulation order by comparing the waveform's quasi-log likelihood ratio. For modulation scheme categorization, a combination of spectral correlation density (SCD) and a neural network was provided by Fehske et al. [14].

Combining neural network with analytical feature extraction to classify waveforms using the extracted characteristics was shown to be a beneficial technique. M. Hong et al. [15] proposed using the SCD function to categorize numerous users. O'Shea et al. [16] used a Convolutional Neural Network (CNN) to classify 11 modulation schemes, and the results were compared to Naive Bayes, Deep Neural Networks, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and a decision tree. Residual Neural Network (ResNet) was used to classify 24 modulation schemes by the authors in [17]. The authors of [18] employed a CNN and bi-directional Long Short-Term Memory (LSTM) to classify transient radio interference sources and contrasted it to a model that used a Support Vector Machine algorithm rather than LSTM.

It was discovered that the CNN-LSTM classifier greatly outperformed the CNN-SVM classifier in terms of classification accuracy for all classes. Li et al. [19] proposed utilizing a combination of CNN with one dimension to extract feature and Gated Recurrent Unit (GRU) to classify signals into 31 categories (four modulation types, various channel coding methods and frequency bands). The authors in the above literature categorized wireless signals mostly based on modulation scheme or type of interference. The authors, on the other hand, do not categorize signals based on common communication radio technologies like 3GPP LTE/5G and IEEE 802.11 (Wi-Fi).

### 2.1. Survey Organization and Contributions

This paper's contributions are summarized as follows: A summary of the machine learning methods used in wireless network technology classification, as well as a synopsis of present approaches and a discussion of open concerns and future study.

The article will be structured as follows: Section 3 summarizes the machine learning algorithms used to classify wireless network technologies. Section 4 highlights the various machine learning algorithms to signal classification in this domain. Section 5 covers the field's limitations and possible future directions. Finally, Section 6 has concluding remarks.

## 3. MACHINE LEARNING

Machine learning (ML) is a technique for computers to learn without being explicitly programmed. Machine learning is gaining traction, with applications in a wide range of industries. Machine learning algorithms are well-known for their ability to solve problems requiring pattern recognition, anomaly detection, and prediction using historical data.

A summary of the common ML algorithms used by researchers in the domain of wireless network technology classification of signals is provided below:

### 3.1. Support Vector Machine (SVM)

SVM is a supervised machine learning technique that can be used for data classification and regression analysis. The method was first published in 1963 [20] and has since evolved. One of the most popular versions that is being used today was introduced by Vapnik and Cortes [21] in 1995. The SVM algorithm's purpose is to generate a decision boundary (hyperplane) that divides various classes while maximizing the separation distance (margin). The data for categorization can be separated linearly or non-linearly.

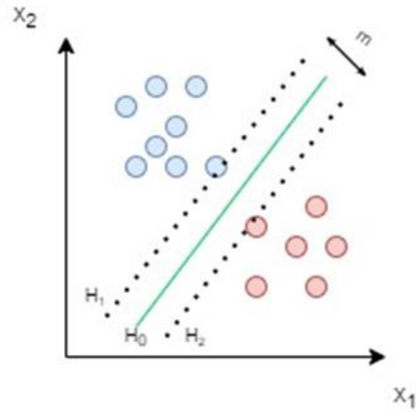


Figure 1 SVM Margin for Linear Binary Classification

Figure 1 shows the hyperplane $(H_0)$ and margins $(H_1, H_2)$ for an SVM trained for classifying two linearly separable data. If there are $n$ elements in a dataset, the dataset can be represented as:

$$\{(x_i, y_i) \mid x_i \in R^p, y_i \in (-1,1)\}_{i=1}^{n} \tag{1}$$

where $x_i$ is a vector of dimension $p$ and $y_i$ indicates the class 1 or -1 to which the data $x_i$ belongs.

If $H_0$ is the hyperplane, its equation is given by:

$$H_0 = W^T x = 0 \tag{2}$$

where $w$ is a vector normal to the hyperplane.

Given $H_0$, two other hyperplanes $H_1$ and $H_2$ can be selected such that $H_0$ is equidistant from $H_1$ and $H_2$, which are given by:

$$H_1 = w^T x = 1; \qquad H_2 = w^T x = -1 \tag{3}$$

Data points that are on or above the boundary $H_1$ have label 1 and data points that are on or below the boundary $H_2$ have label -1. The margin $m$ between the two hyperplanes is given by:

$$m = \frac{2}{||w||} \tag{4}$$

The goal of the algorithm is to maximize the margin $m$. Finding the optimal hyperplane is an optimization problem and among the possible hyperplanes, the hyperplane with the smallest $||w||$ is selected as it has the largest margin.

3.2. Convolutional Neural Network (CNN)

The convolutional neural network (CNN) is a prominent image processing algorithm that was first introduced in 1989 [22]. Although the approach is most used for image analysis, it can also be utilized for other data analysis and classification challenges. CNNs are adept at seeing patterns in data and extracting relevant information.

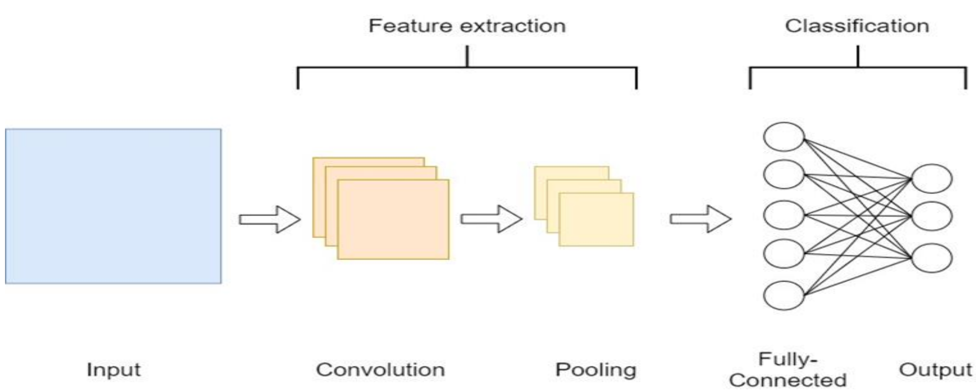


Figure 2 Architecture of a CNN

In a CNN, a convolution layer follows the input layer. The convolution layer consists of a set of filters. Filters are relatively small matrices compared to the input matrix, for example a 3x3 matrix, and are initialized with random numbers. The filters slide over the input matrix at defined steps known as strides. A stride of 1 implies that the filter shifts by 1 unit. As the filter slides over the input matrix, the dot products between the filter and the input matrix are computed. The convolution operation between a 2D input matrix 'x' and a 2D filter matrix 'c' is given by:

$$(x * c)_{i,j} = x[i,j] * c[i,j] = \sum_{m} \sum_{n} x[m,n]\, c[i-m][j-n] \tag{5}$$

where $m, n$ are the filter height, width, respectively.

The dot product is then passed to an activation function. One of the commonly utilized activation functions is the rectified linear unit (ReLU). The output of the activation function is stored. The filter moves to the next input patch and the process is repeated until the filter covers the entire input matrix. The ReLU function is given by:

$$h(a) = \max(0, a) \tag{6}$$

where $a$ is the activation function's input.

The convolution layer's output is a feature map that detects patterns in the input. The output $y$ at $l^{th}$ neuron is given by:

$$y_l = h\big((x * c)_{i,j} + b_l\big) \tag{7}$$

where $h$ and $b_l$ are the activation function and the bias unit, respectively.

The feature map is followed by a pooling layer. The pooling layer consists of a small matrix, such as 2x2 matrix, which is used to reduce the dimensions of the feature map while retaining the important information. The most common type of pooling is max pooling, which selects the highest value from a patch of the feature map it slides over. The number of convolution and pooling layers is a configurable parameter and is not limited to one. Following the pooling layer, the CNN consists of a fully connected layer. The output from the pooling layer is flattened to a vector and is fed to the fully connected layer. The final layer of the CNN is the output layer.

### 3.3. Naive Bayes Classifier

This is a Bayes' theorem-based categorization algorithm. If $x$, given by $x = \{x_1, x_2, x_3, \dots x_n\}$, is a feature vector of length $n$ is to be classified, the probability of $x$ belonging to a class $A$ is given by:

$$p(A|x) = \frac{p(A)\, p(x|A)}{p(x)} \tag{8}$$

where $p(A|x)$ is the probability of class $A$ given input $x$, $p(A)$ is the probability of class $A$, $p(x|A)$ is the probability of input $x$ given class $A$, and $p(x)$ is the probability of input $x$.

### 3.4. K-Nearest Neighbor (KNN)

KNN is an algorithm that classifies data based on a similarity measure, i.e., distance function. It is assumed that similar data points exist in proximity. If $x$ is the input to be classified, the class to which it belongs is given by the most common class among its K nearest data points, measured by a distance function. One of the distance functions is the Euclidean distance. The Euclidean distance between two points, $x$ and $y$, is given by:

$$d(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \tag{9}$$

where $x$ and $y$ are the input point and an existing data point respectively and $n$ is the number of features in the data.

### 3.5. Autoencoders

The autoencoder neural network is one of the unsupervised learning algorithms used for reducing the input data's dimensions and reconstructing the original data from the compressed form. Autoencoders are utilized for dimensionality reduction, feature extraction, and have even been proposed as a method for unsupervised artificial neural network pre-training [23]. The three major components of an autoencoder are shown in Figure 3: an encoder, latent space, and decoder. The encoder is used to reduce the input data's size and generate a compressed version of the data. A series of layers with a decreasing number of nodes constitutes the encoding layer.

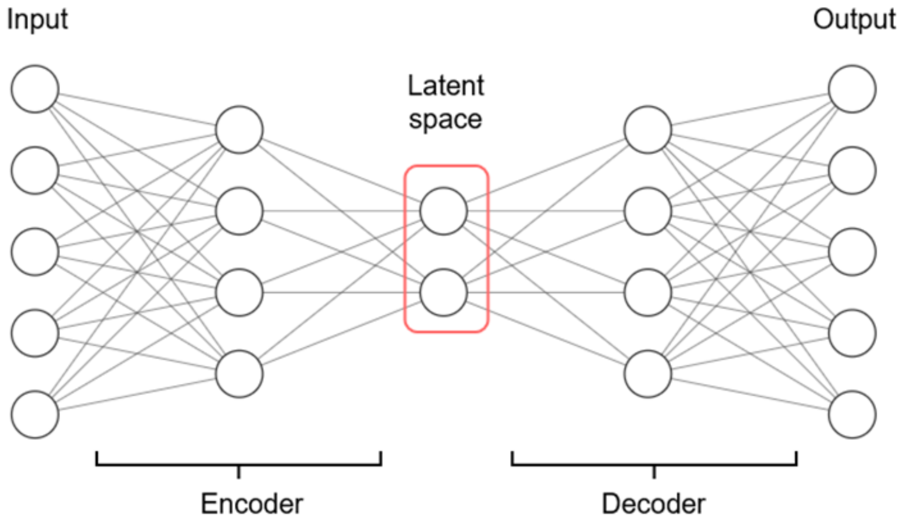


Figure 3 Architecture of a Standard Autoencoder

If x is a d-dimensional input vector of real integers R, $x \in R^d$, then the encoder stage output, $h$, is given by:

$$h = W(fx + b) \tag{10}$$

where, $b$ and $W$ represent the bias unit, weight matrix, respectively, and the activation function is given by $f$.

The latent space, also called the coding space, represents the compressed data form, $h$. The decoder attempts to reconstruct the original data from the compressed data. If $\bar{x}$ is the reconstructed output, the compressed data $h$ is mapped to $\bar{x}$ using the following equation:

$$\bar{x} = W'(f'h + b') \tag{11}$$

The autoencoder's purpose is to reduce reconstruction errors as much as possible, and a backpropagation technique is utilized to do so [24]. Using functions such as binary cross-entropy, or mean square error, the loss, $L(x, \bar{x})$, between the reconstructed and the original data is determined. The loss function is then utilized in conjunction with a threshold to differentiate between original and anomalous data.

Table 1 highlights the benefits and drawbacks of the various machine learning algorithms discussed in this survey article. Generally, choosing an ML algorithm depends on the nature of the data, size of the data, the available computational time, and desired accuracy of the output. However, it is important to experiment with various ML algorithms for a given task and dataset before deciding on an algorithm, since it is difficult to predict which algorithm performs the best without experimentation.

Table 1 Advantages and Disadvantages of the ML Algorithms

| ML algorithm | Advantage | Disadvantage |
|---|---|---|
| CNN | Well suited for classifying images and extracting features from the input and can provide high classification accuracy. | Requires larger datasets for obtaining better results and is computationally intensive. |
| SVM | Can model linear as well as non-linear decision boundaries and has several kernel functions for various forms of problems. | The appropriate kernel must be chosen for the appropriate task, and it does not scale well with larger datasets. |

| | | |
|---|---|---|
| Naive Bayes | Simple to implement and provides results quickly. | Performance is often not as good as other more complex algorithms such as SVM, that are tuned. |
| KNN | Simple to implement, especially for multi-class problems | Performs poorly when there are high-dimensional data. |
| Autoencoder | Useful for dimensionality reduction and for detecting anomalous data | Highly dependent on the quality of the input data and sensitive to errors in the input. |

## 4. MACHINE LEARNING BASED WIRELESS NETWORK TECHNOLOGY CLASSIFICATION

In this section, the available literature on the wireless network technology classification of signals using machine learning is categorized based on the type of signals classified corresponding to the two major wireless technology standards, i.e., IEEE 802 wireless standards and 3GPP standards, as shown in Figure 4.

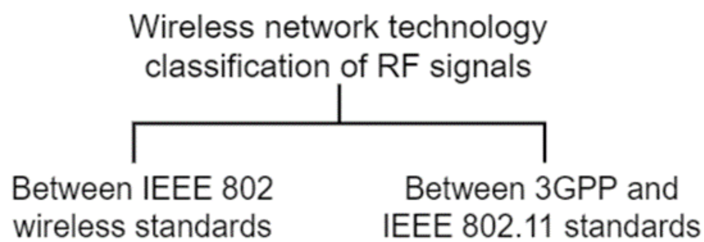


Figure 4 A Taxonomy of Wireless Network Technology of RF Signals

Signal classification scheme 1 - between IEEE 802 wireless standards: In this category, the signals are classified between Wi-Fi, Bluetooth, and Zigbee standards. Signal classification scheme 2 - between 3GPP and IEEE 802.11 standards: In this category, the signals are classified between IEEE 802.11 and LTE standards.

### 4.1. Between IEEE 802 Wireless Standards

The authors of [25] employ a random forest classifier technique in conjunction with a SVM to recognize and classify Wi-Fi, Bluetooth, and Zigbee signals in order to establish the interference source in the 2.4 GHz ISM band. The authors generated the signals with Commercial off-the-shelf (COTS) hardware in a variety of controlled and uncontrolled conditions, primarily using the RSSI data from the signal bursts for time and frequency domain feature extraction. Signals with varying signal-to-noise ratio (SNR) were used for training the models and the models were trained in different locations such as an office area, lab area with equipment, etc., and while the accuracy level depended on the test environment, on average they achieved greater than 90% classification accuracy. The performance of SVM and random forest classifier models were comparable in their experiments. The authors of [26] employ CNN to classify signals in the 2.4 GHz ISM band into Bluetooth, Zigbee, and IEEE 802.11 b/g technologies. Their sensing bands include ten Bluetooth channels, two Zigbee channels, and three Wi-Fi channels, totaling 15 output classes. The model was trained on in-phase and quadrature (I/Q) data that was transformed through the Fast Fourier Transform (FFT). The input SNR was adjusted from -20 dB to +20 dB. Classification of the Zigbee and Bluetooth channels achieved 95% accuracy on average for SNR greater than -7 dB and classification of Wi-Fi channels achieved 95% on average for SNR greater than 0 dB. The CNN model was designed by the authors based on the paper referenced in [16]. The authors of [27] use CNN to recognize and classify IEEE 802.11n, Zigbee, and Bluetooth signals. COTS devices were used to transmit the signals, and a spectrum analyzer was used to acquire the I/Q data. For training the model, the authors used a range of scenarios, including homogeneous Wi-Fi, Zigbee, and Bluetooth, as well as heterogeneous Wi-Fi and Zigbee, Wi-Fi and Bluetooth, and Zigbee and Bluetooth. The SNR was varied between 0 and 30 dB, and a classification accuracy of 92% was achieved for SNR greater than 10 dB. Additionally, the authors compared the models' performance using a variety of machine learning algorithms, including SVM, Naive Bayes Classifier and others, and found that CNN produced the best results.

The authors of [28] distinguished between IEEE 802.11 b/g/n protocols using KNN and Naive Bayes models. RSSI values were utilized to identify the pattern of a channel’s activity for the various IEEE 802.11 protocols, and thus classify them. The I/Q data was obtained using a spectrum analyzer, and the signals were transmitted using COTS hardware. Their results showed that Naive

Bayes provided better identification accuracy of about 85.9% compared to the K-nearest neighbor's accuracy of 82.05% in a heterogeneous environment.

4.2. Between 3GPP and IEEE 802.11 Standards

The authors in [29] classify between IEEE 802.11g and LTE signals using CNN. COTS hardware was used to generate the data and the model was trained on the I/Q samples and FFT transformation of the I/Q samples separately. The SNR of the samples ranged from 0 dB to 45 dB. A classification accuracy of greater than 90% was achieved when the SNR was greater than 10 dB and the accuracy was as high as 99% when SNR was 45 dB. The CNN model trained with FFT data performed better than the model trained with raw I/Q samples, especially at low (less than 15 dB) SNR values. The authors then used this capability for enhancing coexistence between simulated LTE and Wi-Fi transmissions in a shared spectrum. In their experiment, the LTE transmissions initially lasted for 20 milliseconds (ms) and remained idle for 2 ms and as soon as the neural network identified the presence of Wi-Fi transmissions during the idle time, the LTE system reduced its transmission duration from 20 ms to 10 ms and increased its idle time from 2 ms to 10 ms to allow more transmit opportunity (TxOP) for Wi-Fi. In [30], the authors classify between DVB-T, LTE, and Wi-Fi technologies using random forest decision trees, fully connected neural network (FNN) and a CNN across multiple heterogenous environments and to study the difference in performance between manual and automatic feature extractions. The authors have achieved an accuracy of up to 99%.

In [31], the authors used various autoencoders, such as a deep standard autoencoder, LSTM autoencoder, and variational autoencoder to distinguish between LTE and IEEE 802.11 ac, IEEE 802.11 ax signals as a way of detecting anomalous RF signals in the wireless spectrum and compared the performance of well-known autoencoder architectures for the classification task. They used real-world LTE I/Q data, captured using a B210, to train all the autoencoder models and tested against various combinations of LTE and IEEE 802.11 ax, IEEE 802.11 ac signals, including multiple modulation and coding scheme (MCS) values, and a precision of 99.9% and a recall of 88.1% were achieved in their models. The authors identified that the exponential linear unit (ELU) was the best activation function for this task when compared to other activation functions and one of their models required a training time of only 47 seconds to achieve a high F1 score, making it suitable for online training and deployment.

## 5. DISCUSSION AND FUTURE WORK

Table 2 summarizes the current literature in wireless network technology classification of signals using machine learning. The use of machine learning for spectrum sensing has the potential to perform better as compared to traditional narrowband sensing approaches [32]. There is limited research in applying machine learning techniques for signal classification based on wireless network technology. It is an emerging focus of study as it provides more insight into the wireless spectrum occupancy than merely learning the RF signal's modulation scheme and has ample scope for further research. For example, the current literature is mainly restricted to IEEE 802.11 b/g/n signals and later versions of the IEEE standards such as IEEE 802.11 ac/ax were only considered in [31]. Inclusion of the recent IEEE 802.11 protocols would be beneficial as those are being widely deployed. There are additional machine learning algorithms such as Gaussian Naive Bayes that can be considered for comparison with other algorithms. Although high classification accuracy was achieved by researchers at high SNRs, there is an opportunity for improving the accuracy at low SNRs as well. There is also an opportunity to reduce the time taken to train a model thereby increasing the efficiency of the identification and classification process. The ability to identify different radio signals in each spectrum band allows the identification of the source of an interference in a given spectrum band and it also enables dynamic spectrum access and machine learning techniques have the potential to achieve those results in an efficient way.

Table 2 Summary of Current Literature for Wireless Network Technology Classification Using ML

| Wireless network technology classified | Input data | Input SNR range | ML model(s) | Metric(s) for classification | Maximum classification results achieved |
|---|---|---|---|---|---|
| IEEE 802.11 b/g/n, Zigbee, Bluetooth [25] | RSSI values | 0 dB to 30 dB | Random Forest Classifier, SVM | Accuracy | 98%, 96% respectively |
| IEEE 802.11 b/g, Zigbee, Bluetooth [26] | I/Q values | -20 dB to 20 dB | CNN | Accuracy | 99% |

| | | | | | |
|---|---|---|---|---|---|
| IEEE 802.11 n, Zigbee, Bluetooth [27] | I/Q values | 0 dB to 20 dB | CNN | Accuracy | 93% |
| IEEE 802.11 b/g/n [28] | RSSI values | n/a | KNN, Naïve Bayes | Accuracy | 82%, 85.9% respectively |
| IEEE 802.11g, LTE [29] | I/Q values | 0 dB to 45 dB | CNN | Accuracy | 99% |
| IEEE 802.11, LTE, DVB-T [30] | RSSI, I/Q, FFT, Spectrogram | -15 dB to 30 dB | FNN, Random Forest Classifier, CNN | Accuracy | 87.4%, 88.6%, 99%, respectively |
| IEEE 802.11 ax, IEEE 802.11 ac, LTE [31] | I/Q values along with phase and amplitude components | n/a | Deep standard, LSTM, and variational autoencoder | Precision, Recall, F1 score | 99.9%, 88.1%, 0.93 respectively |

## 6. CONCLUSION

In this paper, a survey on the current literature using machine learning to classify the signals based on their wireless network technology has been provided with the intention of enabling new researchers to become familiar with this field and to enable further research. The survey paper provides a summary of the most widely utilized machine learning algorithms in this discipline and discusses the limitations of the current methodologies and potential future work. Radio spectrum access is a challenge that needs to be addressed as billions of wireless devices require connectivity and the number of devices will only increase in the future. Dynamic spectrum access has the potential to mitigate spectrum scarcity concerns and the ability to detect various radio signals in a spectrum band is beneficial for this purpose.

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Authors

**Siddhartha Subray** is a PhD candidate at the University of Colorado, Boulder, in the Computer Science department. He received the B.E. degree in Electronics and Communication from the Visvesvaraya Technological University, Bangalore, India, in 2016 and received the M.S. degree in Telecommunications from the University of Colorado, Boulder, Colorado, USA, in 2018. He is a contributing author to the CCSDS data standards and is working on interoperability testing for space communications, which is funded by NASA. Machine learning and wireless networks are two of his research areas.

**Kevin Gifford** is a research professor in the Computer Science department at the University of Colorado, Boulder. Some of his noteworthy accomplishments in the field of communications include leading the teams who were the first to fly the Linux operating system on the Space Shuttle (1996) and the International Space Station (2000). He was a part of the team that set up the first two Interplanetary Internet nodes onboard the International Space Station, and a key member of NASA's Disruption Tolerant Networking (DTN) team. Kevin is the Wireless Working Group chairman for the ISO-affiliated Consultative Committee on Space Data Systems, also known as CCSDS.