Channel Selection Using Machine Learning

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***Abstract*—The channel plays an important role in any wireless communication system. If there exists only one channel between the transmitter and the receiver, if the link fails, then the communication cannot be established. The reliability of communication can be improved by introducing multiple communication channels. Not only the number of channels but also the type of channels being used has an impact on the system. Although there have been few works done in this direction, works related to long distances have not been given importance. Further, manual channel switching is the recommended choice, but manual switching is greatly impacted by the people involved in the mechanism and may not be accurate all the time. Keeping these in view, this paper proposes a channel selection mechanism based on Wi-Fi and LoRa (Long Range) technologies. The advantage is that this mechanism takes into account both radio technologies to choose the best channel for the given conditions. Further, machine learning-based techniques are introduced to learn the best channel to use based on historical data, which helps in achieving automatic channel selection. This will be particularly useful in dynamic environments, where the channel conditions can change frequently. To validate the proposed concept, various experiments are carried out and from the experimental results, it is observed that the KNN algorithm achieves good performance.**

Keywords*— Channel Selection, LoRa (Long Range), Machine Learning, Wi-Fi.

I. INTRODUCTION

Advances in wireless communication have enabled seamless global connectivity, allowing people to stay connected. It is being used to establish communication between various large-scale systems in real-time or in various applications where the information needs to be sent in real-time data from one place to another, such as sensor data from a remote location to a central location [1]. This eliminates the hassle of using wired systems. However, its performance can be significantly affected by the environment and the position of the transmitter and receiver. Line-of-sight (LoS) and non-line-of-sight (NLoS) are two propagation conditions that can occur in wireless communication [2]. LoS refers to a direct path between the transmitter and receiver, without any obstructions. NLoS refers to a situation where there are obstacles between the transmitter and receiver, such as buildings, trees, hills, etc. LoS and NLoS propagation are both important factors to consider when designing and deploying wireless communication systems [3], [4]. The position of the transmitter and receiver can also impact communication performance. When a radio wave travels from a transmitter to a receiver, it can be diffracted by obstacles in the path. For this reason, it is important to maintain a clear path through the first Fresnel zone when designing a wireless communication system.

Furthermore, whenever wireless communication is adopted for a use case, the frequency of operation is an important consideration. It must obey the rules set by particular local governments or governing bodies such as the Federal Communications Commission (FCC). Whenever a licensed spectrum is opted for the use case, it is important to check for agency approvals. Out of the entire frequency spectrum, there are a few bands left open which are called as ISM (Industrial, Scientific, and Medical) bands, which can be used where users do not need a license [5]. However, the emissions should follow the regulations. Wi-Fi is one of the popular technologies, designed to work in the ISM bands (2.4/5 GHz), which has seen large potential and use cases and is being widely used in the market [6]-[8]. This has a greater potential to be used in various real-time applications. Further, it is globally harmonized. LoRa (Long Range) is one of the recent technologies invented for the LPWAN (Low Power Wide Area Networks) which also works in the ISM band but is not harmonized, it is country-specific [9]. The regional parameter document gives the details. So, the user needs to understand the guidelines set for each country on LoRa usage. LPWANs are ideal for IoT applications where devices need to transmit small amounts of data over long distances using very little power [10], [11].

Conventional systems are typically designed to establish communication over a single channel. However, to improve the reliability of the system, it is possible to use multiple channels and switch between them based on the use case scenario [12]. This can be achieved in different ways, depending on the specific system and the requirements of the application. One common approach is to have a dedicated channel for monitoring and control. This channel is used to exchange information about the status of the system and to issue commands to the different components. The other channels are used for data transmission. When a data transmission is initiated, the system will select another channel to use. For example, a conventional radio system with multiple channels might use one channel for voice communication and another channel for data transmission. When a user wants to talk to another user, the radio can be changed to select the voice channel. When a user wants to send a text message, the radio will select the data channel.

Another approach to channel switching is to use a central controller to manage the channels. The controller monitors the status of all of the channels and assigns channels to users or groups of users as needed. In addition to improving reliability, channel switching can also be used to improve security and privacy. Channel switching can also be used to improve the quality of service (QoS) for different types of traffic [13]. Both of the technologies, Wi-Fi and LoRa, can be used to effectively establish channel selection in dynamic environments. Channel selection is an important factor in optimizing the performance of wireless communication systems. Furthermore, the manual changeover between these two is a big challenge, and with the manual exchange, there can be a lot of errors, so manual channel selection is not an effective approach.

In recent years, there has been significant progress in the field of artificial intelligence. Artificial intelligence is advancing rapidly, and new techniques are emerging in a variety of industries and applications [14], [15]. Machine learning is a powerful tool that can be used to automate the channel selection process. Machine learning algorithms can learn from historical data to identify patterns and trends. This information can then be used to predict the best channel for a given environment and time period.

Though there were few works done in this literature for channel selection, the idea of having channel selection between Wi-Fi and LoRa is a new perspective. In this view, this paper proposes a new machine learning-based approach to channel selection for wireless communication systems, addressing the issues with conventional manual channel selection methods. This automates the channel selection process for Wi-Fi and LoRa networks, saving time and effort.

The rest of the paper is organized as follows; Section II provides the details of the experiment. Section III presents the results of the experiment and a discussion of them. Section IV concludes the paper by summarizing the findings and outlining directions for future research.

II. Experiment Details

To implement the proposed channel selection mechanism, this research considered two radios, Wi-Fi and LoRa, which are designed to operate in ISM bands. The mechanism is evaluated in different environments, where the distance between the transmitter and receiver varied in each iteration. During each iteration, the Wi-Fi and LoRa transmitters as well as receivers were kept in their designated positions. The environments considered are LoS and NLOS conditions. Wi-Fi used the 2.4 GHz frequency band, and LoRa used the KR920-923 band. The RSSI (Received Signal Strength Indicator) values of Wi-Fi and LoRa were collected to assess the performance of each technology under the given conditions. Multiple experiments were conducted to collect RSSI values for Wi-Fi and LoRa at different distances in LoS and NLOS environments. The RSSI values for Wi-Fi and LoRa were collected at the same timestamp to understand the performance of each technology under the same conditions. The data collected from the experiment is fed as input for further processing, as shown in Fig. 1.

Data collection is done in multiple environments, such as indoors and outdoors, and various samples are collected. Collecting data in multiple environments is important to ensure that the machine learning model is robust and generalizable. This means that the model should be able to make accurate predictions on new data that it has never seen before.

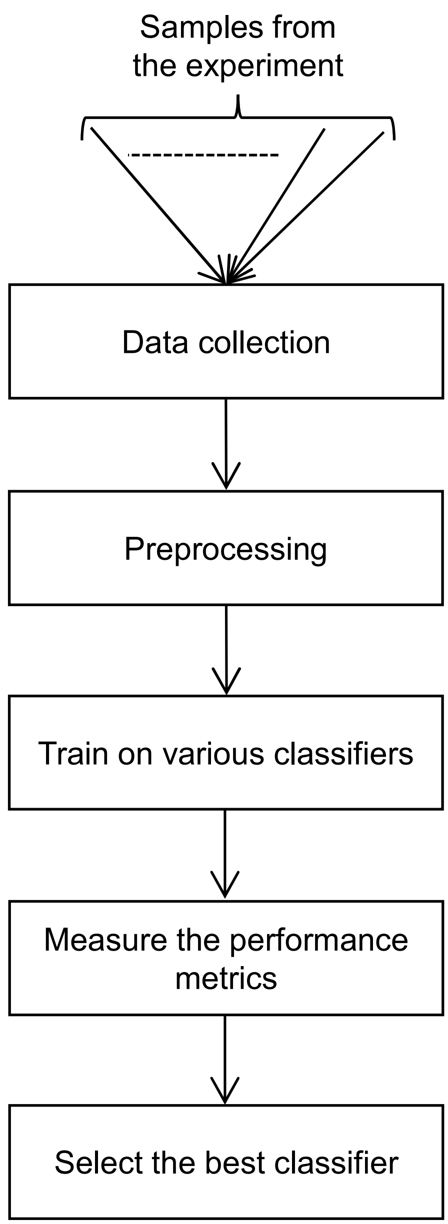

Fig. 1. The overall workflow for the proposed work.

The next step is to preprocess the data, and then train it on various classifiers. Once the data has been collected, it is important to preprocess it before training the machine learning model. The classifiers that are considered are popular machine learning algorithms. They are capable of learning complex relationships between the features in the data and the target variable.

The classifiers considered are logistic regression, random forest, support vector machines (SVMs), naive Bayes, multi-layer perceptron (MLP) classifiers, K-nearest neighbors (KNN), gradient boosting, decision trees, and AdaBoost. Then, various performance metrics are considered to evaluate these algorithms on the dataset for selecting the best performing classifier. The data is split into 80% for training and the remaining 20% for testing to evaluate the performance of the machine learning classifiers.

III. Results and Discussion

This section presents a discussion of the results obtained from the experiment. To evaluate the performance of the proposed channel selection mechanism on various selected algorithms, various metrics were calculated. Accuracy, Cohen's kappa, F1 score, Recall, and Precision are calculated to assess the performance of the classifiers on the collected dataset. These results are shown in Fig. 2, Fig. 3, Fig. 4, Fig. 5, and Fig. 6 respectively.

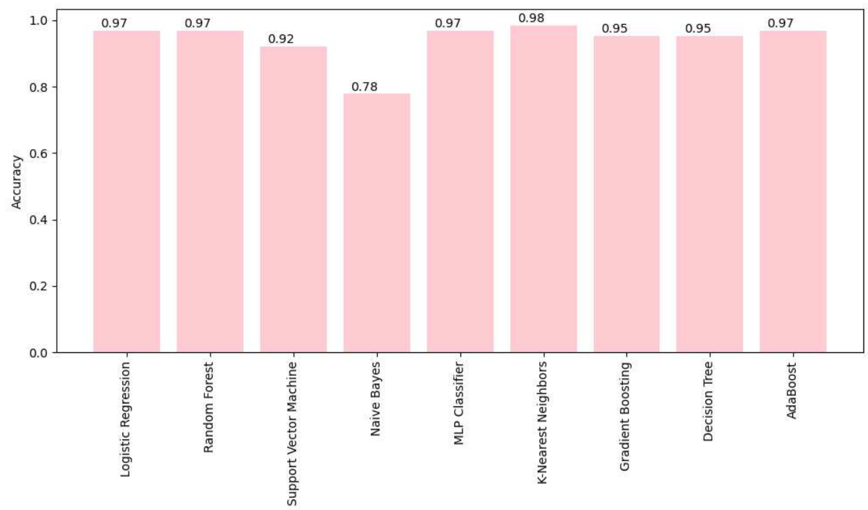

Fig. 2. Accuracy of different classifiers.

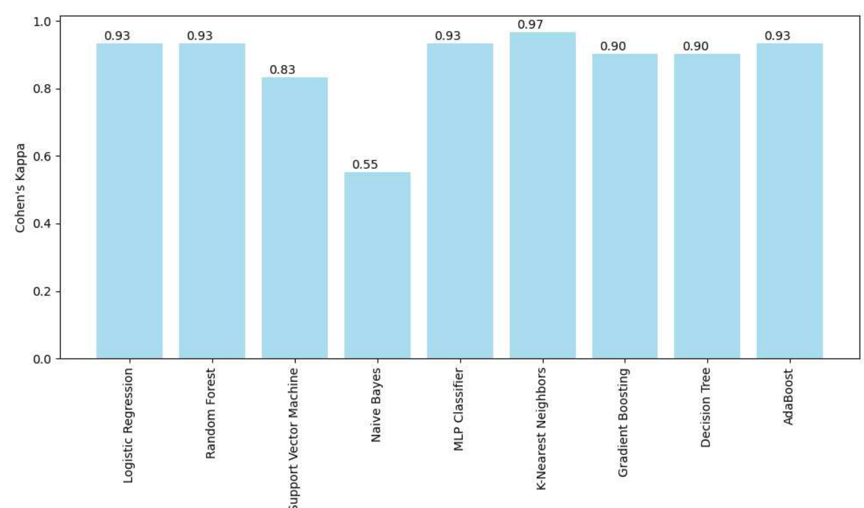

Fig. 3. Cohen's kappa for different classifiers.

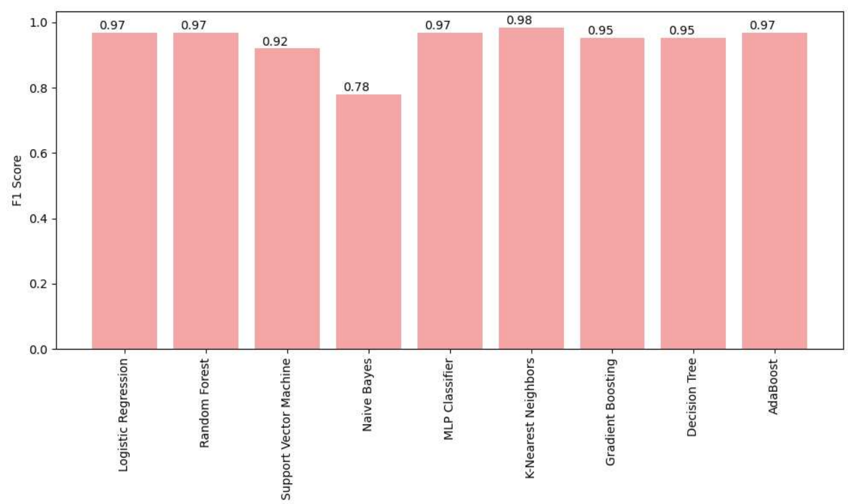

Fig. 4. F1 score for different classifiers.

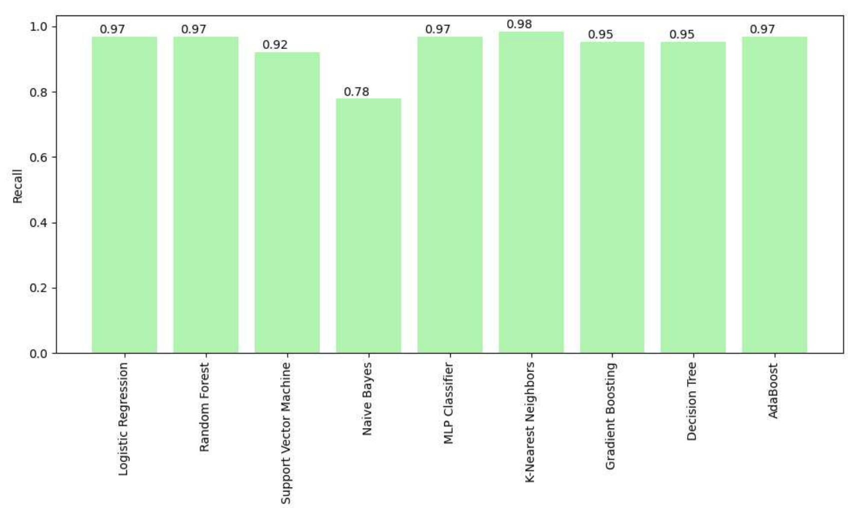

Fig. 5. Recall of different classifiers.

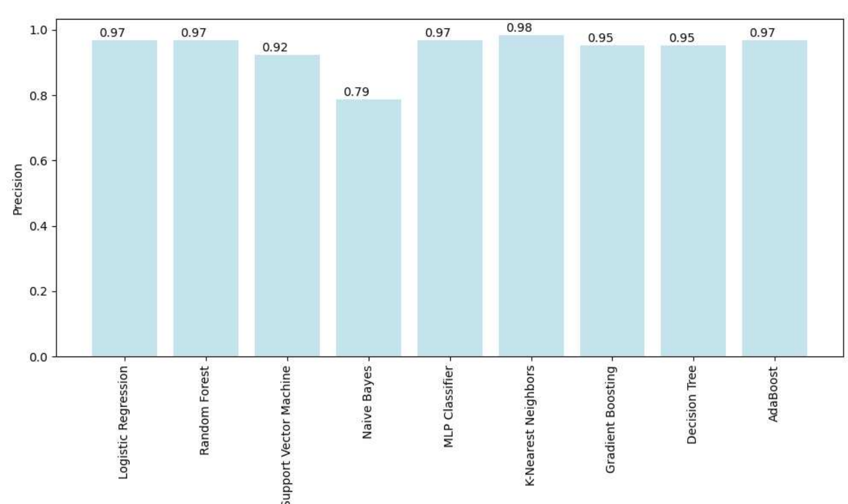

Fig. 6. Precision of different classifiers.

Among the various evaluation metrics used to assess the model's performance, precision has got the more importance. This is because minimizing the risk of selecting the wrong channel is a concern.

TABLE I. PRECISION VALUES FOR VARIOUS CLASSIFIERS

Classifiers	Precision
Logistic Regression	0.97
Random Forest	0.97
Support Vector Machine	0.92
Naïve Bayes	0.79
MLP Classifier	0.97
K-Nearest Neighbour	0.98
Gradient Boosting	0.95
Decision Tree	0.95
Ada Boost	0.97

The precision values for various classifiers are given in Table 1. The exceptional precision score of 0.98 in cases involving the existence of Wi-Fi and LoRa networks can be used for channel selection in wireless communication systems. The KNN algorithm shows its ability to consistently select the more appropriate channel out of all the selected algorithms. While precision is the more appropriate metric for this specific case, it is important to note that other metrics are also be prioritized in different scenarios.

IV. CONCLUSION

Channel selection is particularly important in dynamic environments, where channel conditions can change frequently. To address this, this paper considers a new approach by choosing two different radios: Wi-Fi and LoRa. This is not only a cost-effective solution, as the ISM bands are used for the research, but it also contributes significantly to the advancement of channel selection research. Additionally, manual switching between channels is eliminated by incorporating machine learning techniques. Various algorithms are considered to train the model on the dataset collected through experiments. To evaluate the performance of these models on the collected dataset, metrics such as accuracy, Cohen's kappa, F1 score, recall, and precision are calculated. From the experiment results, it is observed that the KNN algorithm performs well on the collected data and provides more accurate predictions. The findings indicate that the proposed research successfully implemented channel selection. Further, the proposed research has the potential to be explored in different environments. This channel selection technique can be applied to maritime scenarios. Future research and development can focus on how well the proposed research adapts to and performs in maritime environments.

ACKNOWLEDGMENT

This research was supported by AUV Fleet and its Operation System Development for Quick Response of Search on Marine Disasters of Korea Institute of Marine Science & Technology Promotion(KIMST) funded by the Korea Coast Guard Agency(KIMST-20210547).

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