# Waveform Management Approach With Machine Learning for 6G Systems

Yusuf İslam Demir, Ahmet Yazar, and Hüseyin Arslan, *Fellow, IEEE*

***Abstract*—5th Generation (5G) systems are designed with a more flexible structure compared to previous generations with an increasing variety of applications and services. Thus, new flexibility dimensions are observed in 5G technologies. Furthermore, emergence of these flexibility dimensions is triggered a need for advanced management paradigms for 5G and beyond. It is expected that application richness, flexibility dimensions, and the related management paradigms will show an increase with 6th Generation (6G) systems. It is possible that different flexibilities related to the waveform design can be introduced in 6G while a uniform method is used in 5G and previous generations. One of these flexibilities can be the ability to make selection through a waveform set for a new capability to meet different application and user requirements with the waveform selection. In this paper, waveform selection approaches are proposed based on machine learning (ML) with single-stage and multi-stage networks for the waveform management in the same coverage area under the assumption that multiple waveforms can be used in 6G. Hence, the problem of deciding on the best waveform for a coverage area considering different requirements and environmental conditions is studied. To provide environmental awareness, a new synthetic dataset is formed with an example simulation setup. Moreover, a feature control algorithm is proposed to limit side effects of the waveform selection approaches.**

***Index Terms*—6G, Internet of Things, machine learning, OFDM, waveform, smart city.**

## I. Introduction

The DIVERSITY of application and user requirements is gained greater importance in 5th Generation (5G) wireless communication systems [1], [2]. To meet this requirement diversity flexibility, various technologies and approaches are considered with 5G. The foundation of these technologies and approaches lies in the development of flexible designs [3]. For instance, different technologies can be employed together for the same aims when considering the communication needs of users. Furthermore, 6th Generation (6G) technologies will have many flexibilities as far as possible to meet the diversity of user requirements [4]. From this perspective, designing for 6G needs to have advanced capabilities of the flexibility management.

Waveform design are among the critical technologies in wireless communication systems. A lot of studies had conducted while deciding on the most suitable waveform among various candidates when standardization efforts for 5G communication began. Additionally, some flexibility perspectives are introduced with 5G waveform. As a foresight, it can be assumed that the waveform design for 6G standards will be developed more flexibly [3]. Hence, 6G may require several flexibility management approaches for the waveform design.

For 6G standardization, it may be possible to develop designs that enable the simultaneous use of different waveforms as a solution to increasing diversity of application and user requirements [3]. To author's best knowledge, there is not any management or orchestration approach available in the literature for selecting the most suitable waveform design under different scenarios. Selection of the waveform that meets application and user requirements in an environment-aware way for a coverage area may become an important issue for 6G. This problem description is also summarized in Fig. 1.

In this study, novel selection approaches for the waveform management in a coverage area are developed under the assumption of there is a platform where different waveforms are available with 6G standardization [5]. However, there are several challenging issues for the given problem definition. First of all, the superiorities of well-known waveform designs are appropriately associated with application and user requirements under different environmental effects and wireless channel properties. Additionally, it is clarified what kind of information can be utilized to ensure that the developed approaches is in an adaptive structure while deciding the best waveform in a coverage area. Moreover, to exploit machine learning (ML) algorithms in the proposed approaches, a suitable dataset generation process is carried out. On the generated dataset, ML results are obtained using different network structures and tuned hyperparameters. Lastly, a control algorithm is designed to limit potential side effects of the proposed approaches. As a summary, the following contributions are done differently from the current studies in the literature.

- A novel waveform management approach is designed as a benchmark study for the waveform selection problem.
- Environmental information and communication requirements are associated with the given problem definition.
- A new synthetic dataset is generated for the use of ML algorithms, incorporating information about environmental effects and user requirements. The information used

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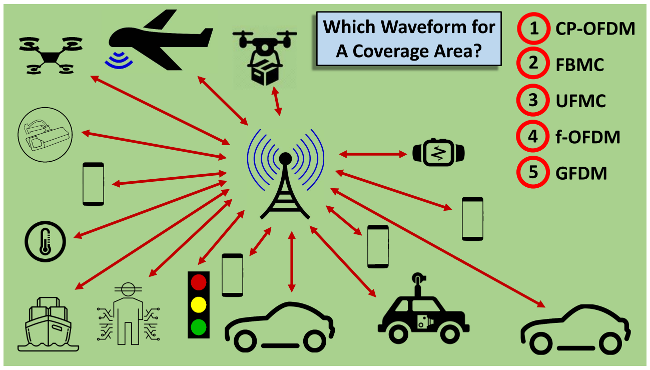


Fig. 1. A graphical demonstration for the given problem definition.

in the dataset is associated with wireless communication channel properties and the related channel models.

- Feature control algorithm is proposed to decrease the ping-pong effects during the handover between different waveforms in a coverage area. This algorithm establishes a balance by limiting the side effects of the proposed selection approach while meeting the requirements.
- ML methods are employed considering environmental awareness. Single-stage network (SSN) and multi-stage network (MSN) structures are designed for the generated tabular dataset. For novel MSN structures, multiple classification models are employed together.
- Hyperparameter tuning configurations are given for the used ML algorithms and the synthetic tabular dataset.
- Classical learning methods, ensemble learning methods, and neural networks (NN) methods are compared to each other for the synthetic tabular dataset. Moreover, the MSN structure is compared with other algorithms.

In the remaining part of the paper, literature work is given in Section II. Section III presents the preliminaries for waveform comparisons and several wireless communication channel relations. The proposed waveform management approach including synthetic dataset generation, feature extraction and control, and the classification methods is introduced in Section IV. The results of ML classification algorithms with hyperparameter tuning are discussed for different network designs in Section V. Finally, Section VI concludes the paper also including several open issues as a future work.

## II. Related Work

In the literature, the comparative advantages of candidate waveforms for 5G are examined especially during the standardization studies [6], [7], [8], [9], [10], [11], [12], [13], [14]. At the end, the orthogonal frequency division multiplexing (OFDM) waveform, already used in 4th Generation (4G) systems, is adopted for 5G. The OFDM waveform became flexible with different parameters (numerology) with the changing user requirements in 5G [15].

For 6G communication, the adoption of common waveforms for different purposes is also possible under the concept of joint sensing and communication (JSAC). In JSAC concept, requirement diversity increases more and it effects the waveform designs [16], [17], [18], [19]. For example, [19] proposes different cross-domain waveform optimization strategies for OFDM-based JSAC systems. These strategies include the communication-centric design and the sensing-centric design.

For the flexibility of 5G communication systems, the use of multiple numerology schemes brought significant technological flexibility in order to better meet the communication requirements of users. However, the introduction of multiple numerology schemes caused a new problem known as inter-numerology interference (INI) [20]. In this context, managing INI at a reasonable level and optimizing its impact become crucial. Within the framework of optimization studies, algorithms for numerology selection and management are developed for 5G communication [21], [22], [23], [24], [25]. A flexibility metric is designed for 5G numerology selection in [21]. In [22], a new concept of waveform multiplexing for numerologies is introduced. The role of ML is discussed for numerology management in [23]. As another ML study, a numerology selection technique based on deep learning (DL) is developed [24]. In [25], a novel method is designed for the optimization of mixed numerology profiles for different 5G scenarios.

There are several studies to design unified frame structures for different waveforms in the literature [26], [27], [28]. A unified frame structure concept that supports an integrated 5G air interface is designed in [26]. In another study, a unified spectrum expression is developed for three different waveform designs [28]. Spectral coexistence of the 5G candidate waveforms is discussed in [14]. In [5], flexible and efficient hardware platform for the waveform coexistence is designed.

## III. Preliminaries

### A. Waveform Comparisons

In wireless communication systems, the evaluation and comparison of waveform characteristics play a significant role in determining the performance and efficiency of communication methods. Several fundamental measurements are used to assess the waveform characteristics and their impact on wireless communication systems. In this study, some of the 5G and beyond multicarrier waveform designs given in Fig. 2 are examined. Their respective comparison metrics include peak-to-average power ratio (PAPR), inter-symbol interference (ISI), computational complexity, communication latency, out-of-band emissions (OOBE), and spectral efficiency.

Understanding waveform comparison metrics such as PAPR, ISI, complexity, latency, OOBE, and spectral efficiency is crucial for evaluating the performance and efficiency of wireless communication systems. Each metric has unique characteristics and impacts on waveform properties [8], [9], [10]. By optimizing these metrics, one can enhance power amplifier efficiency, reduce distortion and noise, decrease computational complexity, minimize latency, ensure compliance with regulatory standards, and maximize the spectral efficiency.

This study focus on selection of waveform designs that can effectively meet the diverse requirements and challenges encountered in wireless communication systems. Within this context, several modern multicarrier waveform techniques are studied, including cyclic prefix orthogonal frequency division

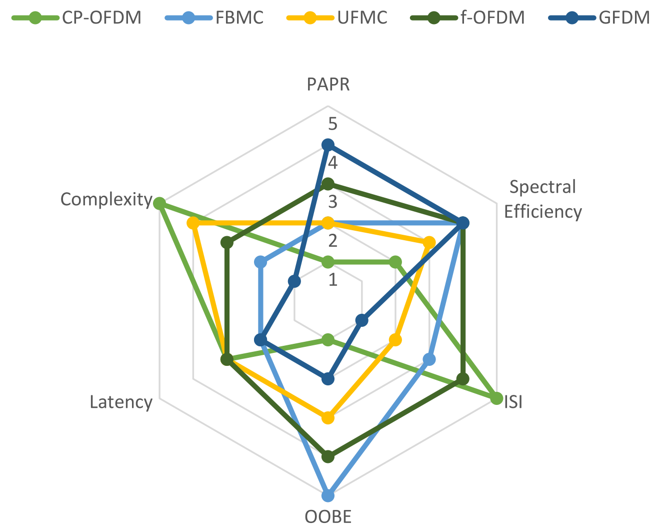


Fig. 2. An example comparison of different waveforms considering the several performance metrics ('1' means low, and '5' means high performance).

multiplexing (CP-OFDM), filter bank multicarrier (FBMC), universal filtered multicarrier (UFMC), filtered orthogonal frequency division multiplexing (f-OFDM), and generalized frequency division multiplexing (GFDM). Each of these techniques offers different superiorities, making them well-suited for specific applications and scenarios. It is assumed that these waveform designs will be reconsidered for 6G as waveform candidates. The performance metrics given in Section III can be used to compare waveform designs as shown in Fig. 2.

CP-OFDM is a popular waveform technique used in many wireless communication standards. It employs a cyclic prefix to provide protection against ISI and exhibits good spectral efficiency. However, due to its simple structure, as summarized in Fig. 2, it shows better complexity performance compared to other waveforms. Conversely, high PAPR appears to be the weakest property of this waveform.

FBMC is a waveform form that utilizes a filter bank to separate the signal into multiple subcarriers, with each subcarrier being processed through a filter. It offers the advantage of not requiring a guard interval like CP-OFDM, resulting in a lower PAPR. However, it has a higher computational complexity compared to other waveform techniques.

UFMC is another multicarrier waveform that uses filtering techniques to increase spectral efficiency and reduce OOBE. It has the advantage of being able to support different subcarrier ranges. There is no immunity to ISI due to lack of CP. As can be seen in Fig. 2, it can be said that the complexity performance is better than other filter-based waveforms.

f-OFDM is similar to CP-OFDM but employs a filter to shape the signal to reduce OOBE. This results in improved spectral efficiency and a lower PAPR. However, it requires a filter to shape the signal, which can cause an additional computational complexity.

GFDM is a waveform that uses a more general approach to multicarrier modulation. It divides the signal into overlapping subcarriers and uses a filter bank to shape the signal. It has the advantage of being more flexible in terms of supporting different subcarrier spacings. Moreover, it has a better PAPR performance than the other multicarrier waveforms.

As a summary, understanding the differences between these multicarrier waveform techniques is important in selecting the appropriate waveform for a coverage area. Each technique has unique characteristics that make it suitable for different requirements, and careful consideration of performance criteria is necessary to achieve optimal system performance.

### B. Wireless Channel Relations

The relationship between the wireless channel and waveform selection is crucial in determining the overall performance of a system. The channel is influenced by various environmental conditions that can impact the quality and reliability of transmitted signals [29], [30]. These environmental conditions directly affect the transmitted waveform, leading to various distortions that can degrade the quality of the received signal. Additionally, they can cause signal attenuation, resulting in power loss. This can lead to a decrease in the signal-to-noise ratio (SNR) and can impact the overall system performance.

Environmental factors refer to the presence of obstacles and physical barriers in the propagation path, such as buildings, trees, or geographical features. These obstacles can cause signal attenuation, shadowing, and multipath propagation. This can make it challenging to decode the transmitted data correctly, leading to ISI and symbol smearing.

The presence of noise in the channel adds an unwanted component to the received signal. Noise can be thermal noise, atmospheric noise, or interference from other sources. The presence of noise affects the SNR and can reduce the receiver's ability to accurately detect and decode the transmitted information. Interference from other communication systems or sources such as electromagnetic radiation can distort the received signal and make it difficult to extract the information.

The wireless communication channel can significantly impact the transmitted waveform, leading to distortions, noise, and interference. Understanding these effects is crucial for designing robust communication systems that employ appropriate techniques to mitigate channel-induced impairments and enhance the reliability of signal transmission. The selection of waveform forms that align with the requirements of the channel becomes highly important, considering these parameters. Thus, environmental awareness for the proposed waveform management approach is provided using relations between the wireless channel and waveform designs.

## IV. Waveform Management Approach

In this section, first of all, practical challenges for the proposed approaches are given for real-world 5G beyond systems. Secondly, it is explained how the synthetic dataset is generated taking into account the wireless channel relations. Afterwards, feature control process is explained in detail. Lastly, network designs with single-stage and multi-stage (multi-model) approaches for classification are presented.

### A. Practical Implementation Challenges

Several important practical challenges for the proposed approaches include generalization of the trained ML models for the real-world data, ping-pong effects due to unnecessary handover cases between different waveforms, and difficulty of establishing suitable relationships between information obtained from environment and together with user requirements.

For the proposed designs, obtaining environmental information is a challenge in real-world systems. In this paper, it is assumed that the necessary environmental information can be obtained via smart city networks in the future. Since synthetic dataset is used, the generalization of the trained ML models for real-world data is another important challenge. Regarding this issue, working with the synthetic datasets generally causes domain adaptation problems in the literature [31]. Developing preprocessing techniques for the real-world data and designing transfer learning methods can be a solution for the generalization and domain adaptation problems [32], [33]. However, these topics are not included in the scope of this study because of the absence of real-world data.

To decrease the ping-pong effects during the handover between different waveforms in a coverage area, a feature control algorithm is proposed. This algorithm establishes a balance by limiting the side effects of the proposed approach while meeting user requirements. It means that if there are too many unnecessary handover cases between different waveforms, a general unstability may cause several problems such as orchestration complexity. The role of the feature control algorithm can be explained as limiting the number of waveform handovers in a time interval by controlling the changes in extracted features for ML classification problem.

For the waveform selection problem, ML classification methods are used because the problem is defined based on data and it is difficult to establish suitable relationships between information obtained from environment and user requirements. Additionally, ML methods provide acceptable benchmark results fastly. Moreover, using ML classification algorithms is meaningful if there is a selection mechanism in the designs.

### B. Synthetic Dataset Generation

In order to operate waveform management with environmental awareness, a high level of cognitivity is required. Therefore, a proper data collection is necessary, taking into account different environmental factors and user requirements. Moreover, a dataset is needed to develop a ML-based approach using the collected data. However, due to the lack of an existing dataset in the literature and difficulties of obtaining real-world data for this purpose, the approach of generating a synthetic dataset is preferred in this study.

Synthetic datasets can be employed due to their various superiorities [34]. They provide advantages of creating balanced datasets and incorporating rare scenarios sufficiently into the datasets [35]. Additionally, a large number of data samples can be quickly generated through the simulations. The synthetic dataset in this study is formed using a specific script that is written on the MATLAB. In the literature, there are several datasets that are generated with a similar method [36], [37], [38], [39].

The dataset consists of five classes and seven features. The following class labels have different levels of relations with each feature and they are derived from the waveforms described in Section III: CP-OFDM (Class 1), FBMC (Class 2), UFMC (Class 3), f-OFDM (Class 4), GFDM (Class 5).

For the proposed approach, one of these waveforms is selected as a class label to meet changing user requirements under different wireless communication channels. For the selection mechanism, it is assumed that seven features that are listed in Table I are extracted. The features include geographic characteristic, residential area plan, human density, vehicle density, user mobility, IoT system density, and coverage area.

Fig. 3 illustrates the block diagram depicting the proposed approach. It is assumed that two types of raw data, encompassing environmental information and wireless communication requirements, are utilized to extract a total of seven features. The environmental information contributes to the extraction of all features. It is assumed that the environmental information is obtained using geographic information system (GIS) networks and transmission point (TP). GIS networks contain a wealth of valuable data that can be harnessed for various environmental-aware systems. Furthermore, user-related information is available within the new-generation cellular networks and can be acquired across TP. As an example to user-related information, the wireless communication requirements include enhanced mobile broadband (eMBB), ultra-reliable low-latency communication (URLLC), and massive machine-type communication (mMTC) necessities that are related with human density, vehicle density, and IoT system density features. Moreover, the wireless communication requirements are obtained via TP.

The used features capture various aspects of the waveform characteristics as signals propagate through the wireless communication medium. The extracted features reflect the influence of the wireless channel on the transmitted signals. These features help in understanding and analyzing the performance of waveforms in a wireless communication environment. Seven features are discussed from the perspectives of wireless communication channel relations and user requirements in the next paragraphs. Table I also summarizes these discussions.

Geographic characteristic is closely related to the occurrence of rich multipath in the wireless communication channel. In the previous section, when examining the waveforms in terms of ISI, it is observed that different waveforms have different performances. Therefore, the waveforms that may be required in different geographic conditions may vary. In terms of this feature, it seems reasonable to prefer waveforms with high ISI performance under harsh environments. For instance, CP-OFDM is a sensible waveform in this context.

Residential area plan, another feature, is closely related to the wireless communication channel in terms of both rich multipath environments and path loss characteristics. For

TABLE I
DEFINITION AND ANALYSIS OF THE USED FEATURES

| Feature No | Feature Definition | Feature Source* | The Basic Wireless Channel Relation* | Range |
|---|---|---|---|---|
| 1 | Geographic Characteristic | GIS | • Extreme environments causes rich multipath. | Basic (1) - Extreme (10) |
| 2 | Residential Area Plan | GIS | • High possibility of rich multipath environment for urban scenarios.<br>• Path loss characteristic changes remarkably. | Rural (1) - Urban (10) |
| 3 | Human Density | TP | • Spectral efficiency is an important criteria.<br>• Close relation with the eMBB service type.<br>• Needs an increased channel capacity. | Scarce (1) - Dense (10) |
| 4 | Vehicle Density | TP | • Close relation with the URLLC service type.<br>• To meet the URLLC requirements, less delay spread and Doppler spread. | Scarce (1) - Dense (10) |
| 5 | User Mobility | TP | • High mobility may cause Doppler spread. | Low (1) - High (10) |
| 6 | IoT System Density | TP | • Close relation with the mMTC service type.<br>• To meet the mMTC requirements, path loss characteristic is important. | Scarce (1) - Dense (10) |
| 7 | Coverage Area | TP | • Path loss characteristic changes remarkably.<br>• High possibility of more interference. | Low (1) - High (10) |

* **GIS:** geographic information system, **TP:** transmission point, **eMBB**: enhanced mobile broadband, **URLCC**: ultra-reliable low-latency communications, **mMTC**: massive machine-type communications

urban scenarios, ISI performance criterion becomes crucial in waveform design. Similar to the geographic characteristic feature, in more challenging scenarios, waveforms like CP-OFDM that offer better ISI performance are preferred.

The relationship between the third feature and waveform, human density, can be examined through spectral efficiency and connectivity criteria. At this point, if human density is high, waveform designs that exhibit high spectral efficiency and channel capacity are expected to perform well. For example, FBMC and f-OFDM waveforms gain priority for the scenarios with high human density. Therefore, eMBB service type has a close relation with this feature.

The vehicle density characteristic is closely related to the URLLC service type. In terms of reliability, performance criteria such as OOBE, ISI, and PAPR gain importance in the waveform design. Additionally, latency performance is also critical. Taking into account the comparisons, the f-OFDM waveform stands out for scenarios with high vehicle density.

As the fifth feature, user mobility affects waveform designs in terms of Doppler spread and multipath effects in the wireless communication channel. Therefore, OOBE become a critical performance metric. For instance, the FBMC waveform can demonstrate success under high mobility scenarios.

The IoT system density feature is closely related to mMTC service type. Within this context, performance criteria such as PAPR and computational complexity play a significant role in waveform success. In terms of the wireless communication channel, the path loss characteristic stands out. Waveforms like GFDM and UFMC are reasonable choices when dealing with high IoT system density scenarios.

The last feature indicates the extent of the coverage area where the proposed approach will be implemented. Regarding this feature, path loss characteristics and inter-cell interference have implications for waveform design. Hence, performance metrics such as PAPR and OOBE can be considered. Additionally, considering the use of small cell structures with limited coverage areas and the potential application of millimeter-wave (mmWave) frequencies for small cells, it would be beneficial to prefer waveforms compatible with mm-wave.

Setup of the simulation for process of generating the synthetic dataset is summarized in Fig. 4. During the generation of the dataset, class labels are created initially to include an equal number of samples for each class. After that, wireless channel and communications requirement parameters are generated randomly considering the boundary values for the class label. The parameter set includes path loss exponent, root mean square (RMS) excess delay, maximum Doppler shift, signal strength, transmission bandwidth (BW), number of users in a region, reliability requirements, latency requirements, and complexity requirements. The boundary values for these parameters are obtained for each class separately by examining

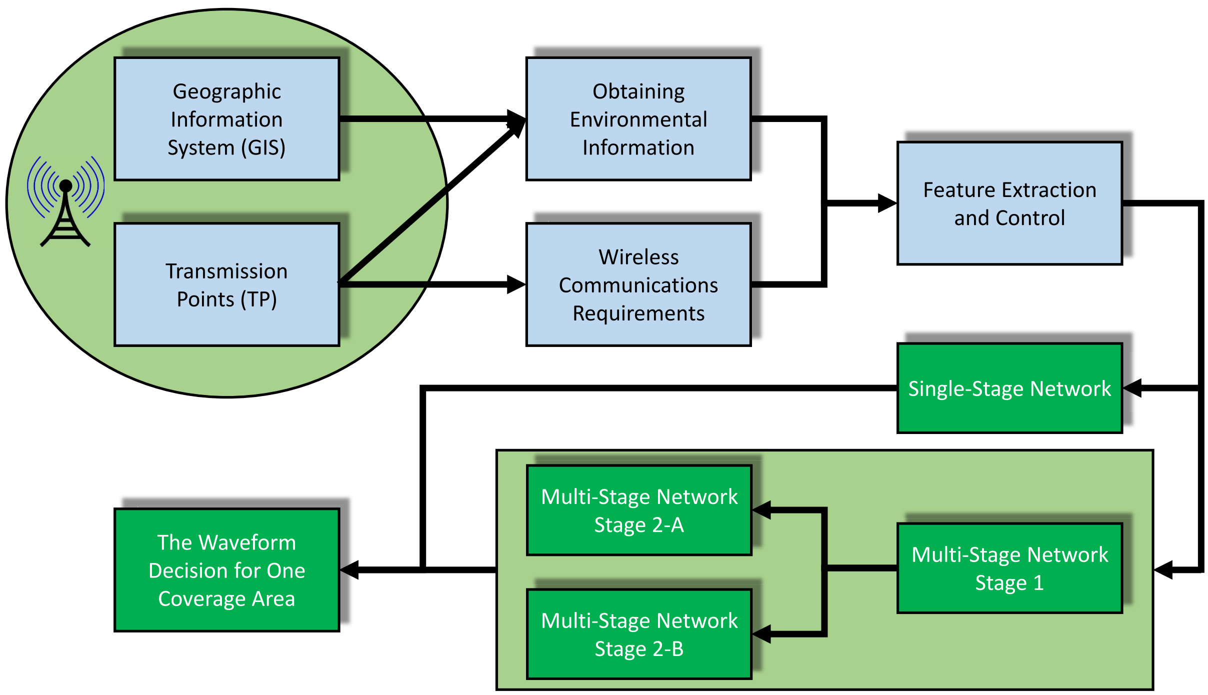


Fig. 3. Block diagram for the proposed methods.

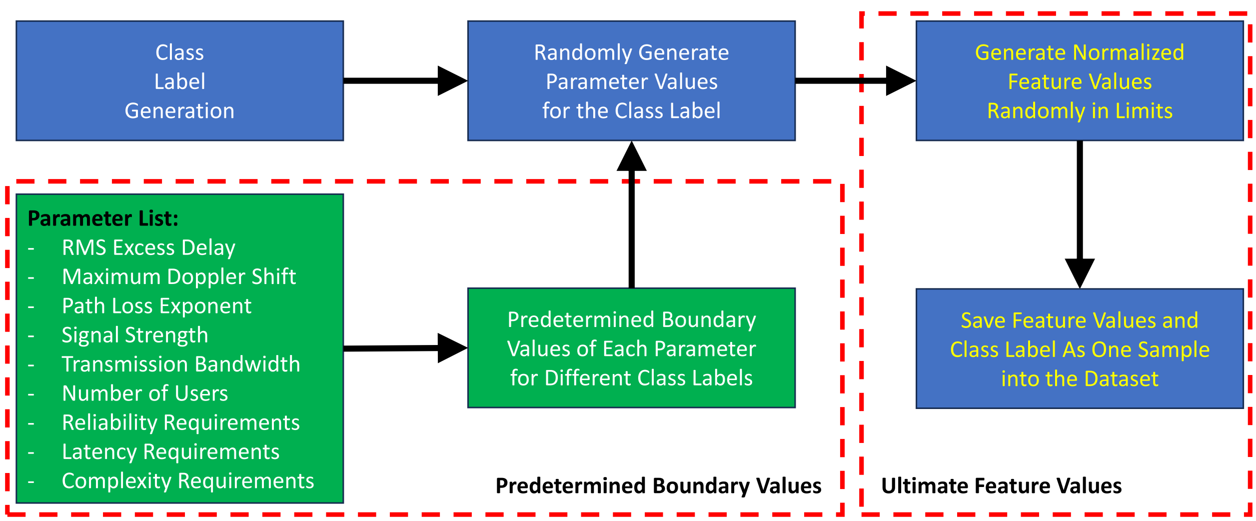


Fig. 4. A block diagram for setup of the simulation to generate the synthetic dataset.

waveform designs before starting the dataset generation script. Each waveform design has different superiorities to meet wireless channel and communications requirements. Therefore, boundary values for the requirements vary between different waveform designs (class labels). In the next step, the features are generated based on the class labels, ensuring randomness according to the wireless communication channel models. At that point, it is assumed that feature values are normalized between 1 and 10. It means that feature values are generated between 1 and 10 in the feature generation script on MATLAB. As it is shown in Table I, generally simple characteristic corresponds to 1 and difficult characteristic corresponds to 10 in the range of feature values. Finally, feature values and the corresponding class label are saved as one sample into the dataset. Then, by combining all class labels and feature values, the ultimate dataset is obtained.

### C. Feature Control

The algorithm steps of the feature control algorithm are given with Eq. (1), Eq. (2), and Eq. (3), shown at the bottom of the next page. First of all, variance of the $k$-th feature at time $t$ is calculated using Eq. (1). The variance, $\sigma_k^2(t)$, is calculated if $t <$ T there $T$ is a variable threshold parameter for the time window. Next, the background variance, $\sigma_{k,b}^2(t)$, is calculated and updated by learning from the previous variance values using Eq. (2). Here, there two variable parameters while configuring the learning rate of the algorithm. The first variable parameter $\alpha$ controls the balance between the new variance and the background variance. When $\alpha = 1$, the new variance does not have any effects on the background variance. On the contrary, the new variance value increases its effect while $\alpha$ is approaching to 0. The second variable parameter $\beta$ controls the probability of change. When $\beta = 0$, there is not any changes on the background variance. While this parameter increases, the probability of change increases. As a last step, the $k$-th feature value, $f_k(t)$, is updated using Eq. (3). While updating the feature value, $B$ threshold is used to decide on the speed of change. If this threshold decreases, the change speed of the $k$-th feature value increases. At the end, the ultimate dataset is formed after the feature control. The ping-pong effects for the management of waveform handovers are kept under control by the algorithm.

### D. Network Designs for the Classification

For the network designs for the classification on the generated synthetic dataset, two different approaches are developed as summarized in Fig. 3. The first approach is based on single-model and it is defined as SSN. The second one is based on multi-model and it is defined as MSN. After feature extraction and control steps, these approaches are applied as alternatives to each other. SSN- or MSN-based algorithms can be preferred.

As an assumption, all users are initially connected to the transmission point using the CP-OFDM waveform. Subsequently, the proposed approaches are employed to determine the waveform selection for a given coverage area. ML models are utilized for making decisions based on regions, despite some features being user-specific. As a result, both smaller and larger regions can be effectively utilized in the decision-making process. For the classification problems in two approaches, supervised learning techniques are employed along with hyperparameter tuning to enhance the success rate performances. The obtained ML results are presented in Section V.

*1) Single-Stage Network (SSN):* In SSN approach, dataset with all five class labels are trained together as a classical multiclass classification scenario. Then, classification algorithms are applied on the dataset to obtain a single model to decide on the waveform for a coverage area.

*2) Multi-Stage Network (MSN):* To enhance the success rates on the dataset, MSN approach is developed in a multi-model structure. For MSN Stage 1, dataset is divided into two different subsets for the training. The first subset includes Class 1 and Class 3 data. In contrast, the second subset includes Class 2, Class 4, and Class 5 data. In other words, Class 1 and Class 3 are combined as a single class, and the other classes are combined as another single class in Stage 1. The aim in this stage is to make classification between the class groups of 1-3 and 2-4-5. While deciding on the class groups, features in the dataset are analyzed. This analysis consists of class-based distributions, information gain and reliefF values for the features as shown in Fig. 5 and Table II, respectively. The class-based distributions in Fig. 5 illustrate which classes can be more easily separated from each other. Information gain and reliefF values give clues about the importancies of features for the classification purposes. At Stage 2-a of MSN approach, Class 1 and Class 3 are separated from each other with a different ML model than the model used in Stage 1. In parallel, Class 2, Class 4, and Class 5 are separated from each other with an independent ML model than the other two stages. Eventually, three different ML models are employed for the MSN approach to enhance the success rates.

## V. Machine Learning Results

In this paper, a synthetic tabular dataset with 15,000 samples is created with the MATLAB platform. In the final dataset, each data sample has seven different features and a class label given in Table I. The histograms of the features in five class labels for the ultimate dataset are shown in Fig. 5. For the data analysis, an open-source data analysis tool called Orange Data Mining is employed. Moreover, Python Scikit library is used to simulate ML models on the generated tabular dataset [40]. During the simulations, 5-fold cross-validation technique is applied rather than splitting the whole data into specific training and testing dataset. Additionally, feature selection and reduction methods are not employed. All features are directly used when training supervised ML models that are defined in the next subsection with the cross-validation method.

$$\sigma_k^2(t) = \begin{cases} 0, & \text{if } t < T \\ \sigma_k^2(t), & \text{else} \end{cases} \tag{1}$$

$$\sigma_{k,b}^2(t) = \begin{cases} 0, & \text{if } t < T \\ \sigma_k^2(t), & \text{else if } t = T \\ \sigma_{k,b}^2(t-1), & \text{else if } \sigma_k^2(t) = 0 \text{ or if } \sigma_k^2(t) > \beta\sigma_{k,b}^2(t-1) \\ \alpha\sigma_{k,b}^2(t-1) + (1-\alpha)\sigma_k^2(t), & \text{else} \end{cases} \tag{2}$$

$$f_k(t) \begin{cases} f_k(t), & \text{if } \; t < T \text{ or } \; \sigma_{k,b}^2(t-1) = 0 \\ f_k(t), & \text{else if} \left| \frac{\sigma_{k,b}^2(t)}{\sigma_{k,b}^2(t-1)} - 1 \right| > B \\ f_k(t-1), & \text{else} \end{cases} \tag{3}$$

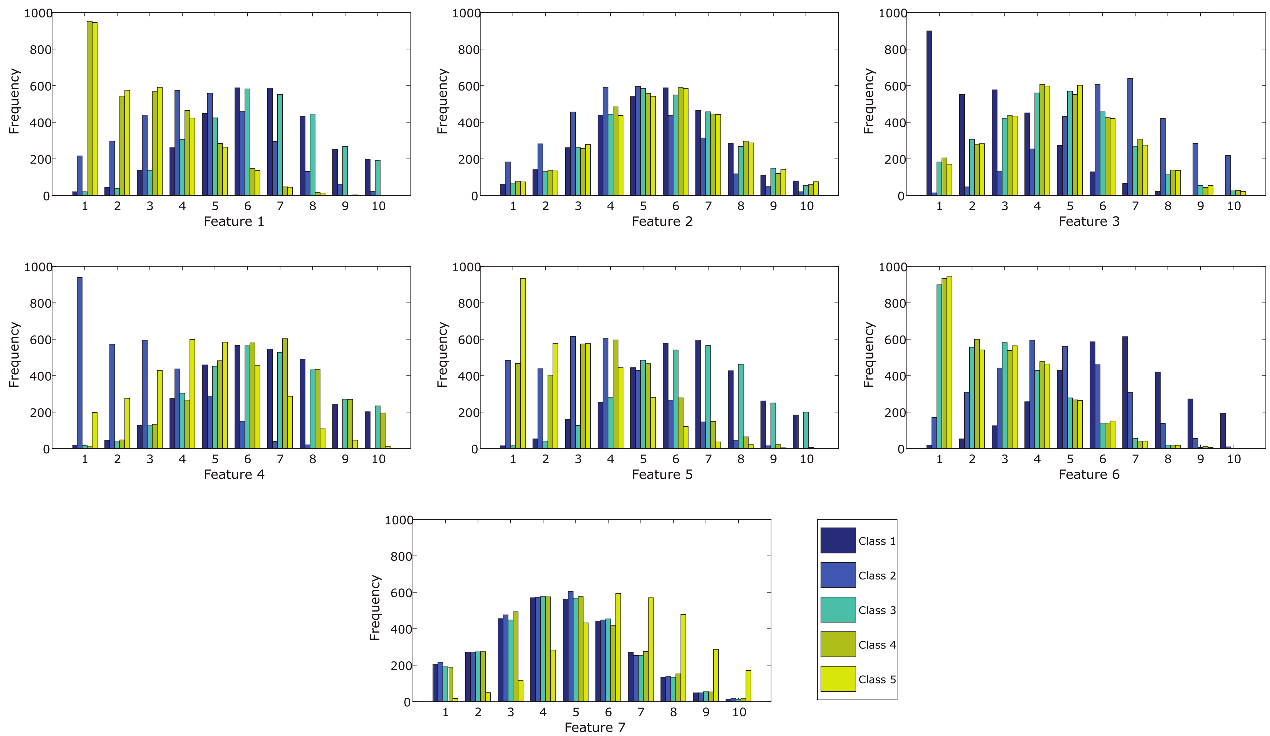


Fig. 5. Feature distribution for five class labels.

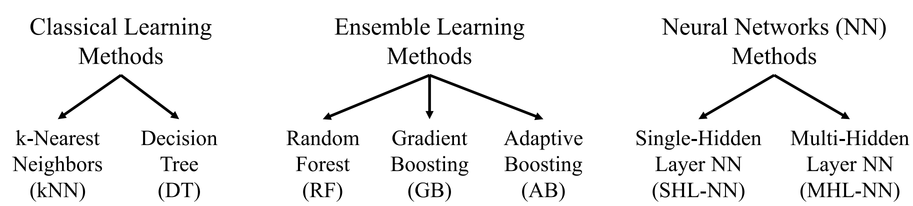


Fig. 6. Learning algorithm groups and the classification algorithms.

TABLE II
INFORMATION GAIN AND RELIEFF VALUES FOR THE FEATURES

| Feature No | Feature Definition | Information Gain | reliefF |
|---|---|---|---|
| 1 | Geographic Characteristic | 0.378 | 0.065 |
| 5 | User Mobility | 0.343 | 0.070 |
| 4 | Vehicle Density | 0.315 | 0.061 |
| 6 | IoT System Density | 0.307 | 0.058 |
| 3 | Human Density | 0.212 | 0.046 |
| 7 | Coverage Area | 0.096 | 0.017 |
| 2 | Residential Area Plan | 0.025 | 0.016 |

## A. Classification Algorithms

For the classification, different groups of learning algorithms are employed including classical learning, ensemble learning, and neural networks (NN) methods. Learning algorithm groups and the classification algorithms are given in Fig. 6. The classical learning methods consist of k-nearest neighbors (kNN) and decision tree (DT) algorithms. For the ensemble learning methods, random forest (RF), gradient boosting (GB), and adaptive boosting (AB) algorithms are used. NN methods are considered as single-hidden layer (SHL) and multi-hidden layer (MHL) structures. The MHL structures are also known as deep learning (DL) models. Additionally, TabNet (introduced as a canonical deep tabular data learning in 2021 [41]) architecture is tested within the scope of DL.

Consequently, various ML models are trained for the proposed approaches. For each model, different hyperparameters are searched and the best-performing tunings are selected using Scikit-learn library in Python [40], [42], [43].

For kNN algorithm, the choice of the number of neighbors ($k$) and the distance metric (e.g., Euclidean, Manhattan) impacts the model's performance. Cross-validation is employed to find the optimal value of $k$ and the most suitable distance metric. As another classical learning method, DT algorithm creates a tree-like structure to make decisions based on input features. The parameters including the number of trees, maximum depth for each tree, and the number of features considered at each split are optimized.

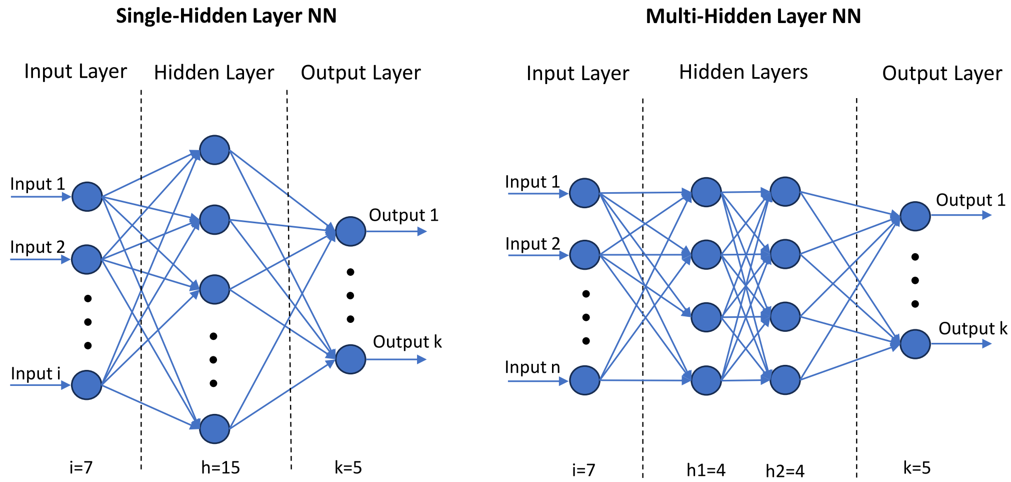


Fig. 7. The design of NN layers for the SHL and MHL structures.

TABLE III
THE BEST HYPERPARAMETERS AND CORRESPONDING RESULTS FOR DIFFERENT ML MODELS

| Algorithm Group | Classification Algorithm | Optimized Hyperparameters | Classification Accuracy | F1 Score |
|---|---|---|---|---|
| **MSN** Ensemble Learning Neural Networks | SHL-NN | Activation: tanh, Solver: Adam, Alpha: 0.0001, Layer Size: 20, Number of iterations: 1000 | 0.739 | 0.734 |
| | AB | Number of estimators: 200 | | |
| | GB | Learning rate: 0.1, Max depth: 1, Min sample leaf: 1, Min samples split: 2, Number of estimators: 500 | | |
| **SSN** Neural Networks | TabNet | Activation: tanh, Solver: Adam, Alpha: 0.0001, Loss functipn: Cross-entropy, Number of iterations: 200 | 0.734 | 0.734 |
| **SSN** Ensemble Learning | GB | Learning rate: 0.1, Max depth: 1, Min sample leaf: 1, Min samples split: 2, Number of estimators: 500 | 0.734 | 0.733 |
| **SSN** Neural Networks | MHL-NN | Activation: tanh, Solver: lbfgs, Alpha: 0.0001, Layer Size: (4,4), Number of iterations: 200 | 0.732 | 0.732 |
| **SSN** Neural Networks | SHL-NN | Activation: tanh, Solver: Adam, Alpha: 0.0001, Layer Size: 15, Number of iterations: 1000 | 0.732 | 0.732 |
| **SSN** Classical Learning | kNN | Metric: Euclidean, Number of neighbors: 20 | 0.723 | 0.723 |
| **SSN** Ensemble Learning | AB | Number of estimators: 100 | 0.707 | 0.707 |
| **SSN** Ensemble Learning | RF | Max depth: 5, Min sample leaf: 1, Min samples split: 5, Number of estimators: 200 | 0.707 | 0.707 |
| **SSN** Classical Learning | DT | Max depth: 8, Min sample leaf: 7, Min samples split: 17 | 0.690 | 0.690 |

**SSN:** Single-Stage Network, **MSN:** Multi-Stage Network, **SHL:** Single-Hidden Layer, **MHL:** Multi-Hidden Layer

RF models are an ensemble of decision trees. Parameters like the number of trees in the forest, the maximum depth of each tree, and the number of features considered at each split are optimized. For GB models, such as XGBoost or LightGBM, different boosting algorithms and hyperparameters are experimented. These ensemble algorithms work by iteratively combining weak learners to create a strong predictive model. The hyperparameters that can be tuned include the learning rate, the number of boosting rounds, the maximum depth of each tree, and the subsampling ratio. AB algorithm is also employed with the number of estimators parameter.

Determining an optimal NN topology is important, and the appropriate number of hidden layers can reduce training time and achieve higher accuracies. Various approaches are defined to decide on the number of hidden layers required for a NN, but these approaches depend on the type and size of the dataset [44]. Additionally, the unnecessary increase in the hidden layers and neurons may lead to the overfitting


(a) MSN (SHL-NN / AB / GB), Accuracy: 73.9%
(b) GB, Accuracy: 73.4%
(c) TabNet, Accuracy: 73.4%
(d) MHL-NN, Accuracy: 73.2%
(e) SHL-NN, Accuracy: 73.2%
(f) kNN, Accuracy: 72.3%
(g) AB, Accuracy: 70.7%
(h) RF, Accuracy: 70.7%
(i) DT, Accuracy: 69.0%

Fig. 8. The best hyperparameters and corresponding results with confusion matrices for different ML models.

problem. Therefore, it is needed to accurately estimate the number of the hidden layers and neurons before designing a NN. The study in [45] addresses approaches used in various studies for different numbers of hidden layers and neurons. Considering these approaches, hyperparameter optimizations are performed for the SHL and MHL structures. It is observed that the structures consisting of two hidden layers and four neurons for each layer provide the best results for MHL case similar to the works in [46] and [47]. The design of NN layers for the SHL and MHL structures are shown in Fig. 7. Additionally, hyperparameter tuning involves adjusting the number of hidden layers, the number of neurons per layer (layer size), activation function, solver, alpha value, and the number of iterations. For TabNet architectures, the sequential attention mechanism determines the features to be used at each decision step. Performing feature selection on a sample basis ensures that the learning capacity is utilized for the most salient features. This allows for interpretability and achieves more successful learning. The parameter values of the TabNet architecture used in the experiments are selected similarly to the values in artificial NN [41]. In the model where cross-entropy is used as the loss function, Adam is preferred as the optimizer. Cross-validation is performed for different batch sizes with a maximum number of iterations set to 200.

### B. Single-Stage Network (SSN) Performance

By exploring different ML models and their hyperparameter configurations, the best-performing combinations are identified to achieve optimal results in the proposed approach.

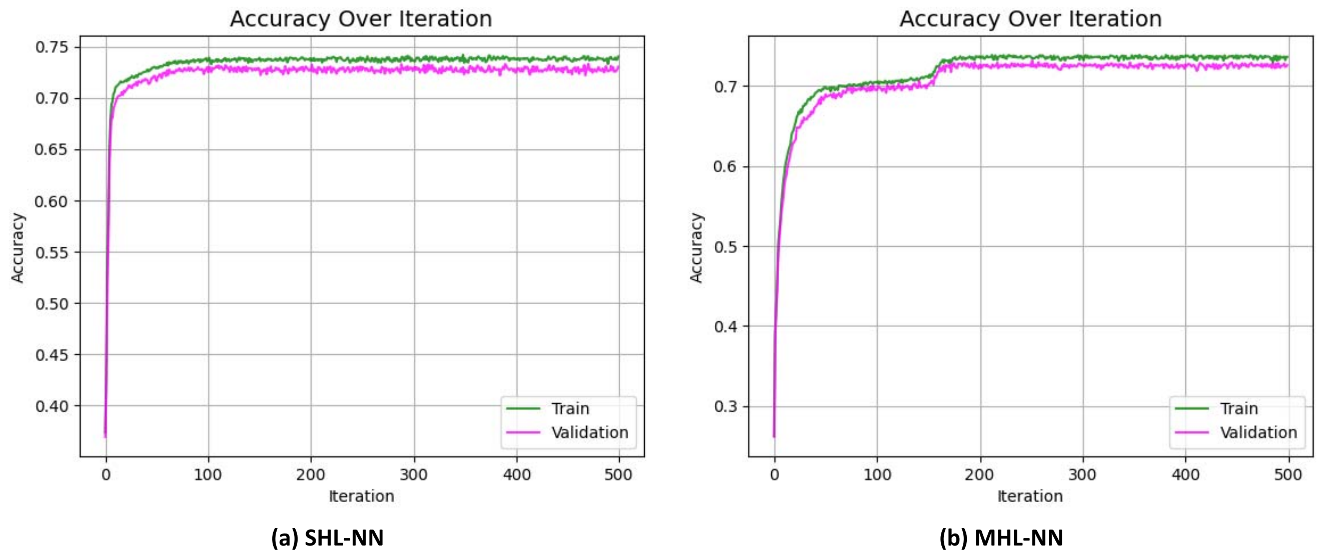


Fig. 9. The convergence curves for SSN designs.

Throughout the training process, appropriate evaluation metrics including classification accuracy and F1 score are used. Additionally, convergence curves are plotted for the NN algorithms.

The classification accuracies and F1 scores of the SSN ML techniques are presented in Table III. The corresponding confusion matrices are shown in Fig. 8. GB, MHL-NN, SHL-NN, kNN, AB, RF and DT models achieve classification accuracies of 73.4%, 73.2%, 73.2%, 72.3%, 70.7%, 70.7% and 69.0%, respectively. In the same order, F1 scores are obtained as 0.733, 0.732, 0.732, 0.723, 0.707, 0.707 and 0.690. According to the obtained SSN ML results, it is observed that GB and NN models outperform the other ones in terms of classification accuracy and F1 score on the tabular dataset [48].

GB is a powerful ML technique known for its superior predictive performance with its ability to handle various types of dataset. The strength of GB lies in its capacity to train decision trees sequentially and iteratively correct errors made by previous models [49]. Additionally, it includes regularization techniques to prevent overfitting and provides flexibility, making it effective in structured data scenarios. Moreover, NN algorithm holds promise due to its flexibility, ability to model nonlinear relationships in the data, and its composition of interconnected artificial neuron layers that learn collectively and make predictions [44]. NN also offer advantages such as automatic feature learning, scalability to large datasets, and adaptability to changing environments, making them the most suitable method to be utilized for the proposed approach.

SHL- and MHL-NN have almost the same success rates. Additionally, Fig. 9 is presented to analyze overfitting and underfitting for SHL- and MHL-NN algorithms over the train and validation dataset. In both cases, it is observed that the design made with the train dataset gives slightly better accuracy results than the validation dataset after a certain iteration. However, SHL-NN converges faster than the MHL-NN for the same iteration.

### *C. Multi-Stage Network (MSN) Performance*

For the dataset, SSN classification algorithms including TabNet and GB reach mostly 73.4% accuracy with the hyper-parameter tuning. As an alternative, MSN algorithms given in Section IV are tested to outperform the SSN algorithms. MSN classification algorithms give slightly better results due to their ability to improve generalization. MSN algorithms combine the outputs of multiple models and provide a more robust overall prediction [50]. Nevertheless, TabNet that is one of the state of the art ML techniques shows better performance than the other NN algorithms (MHL-NN and SHL-NN).

The highest accuracy result achieved by tuning the hyper-parameters for the MSN algorithms is shown in Table III and Fig. 8. It is seen that ML results can be slightly improved with MSN algorithms. For the best result case, SHL-NN, AB, and GB algorithms (SHL-NN/AB/GB) are used together in MSN Stage 1, Stage 2-A, and Stage 2-B, respectively. In other words, ensemble learning methods are used with NN methods for the MSN structure. As a result, the classification accuracy is obtained as 73.9% with 0.734 F1 score for this cascade model. Additionally, kNN/AB/GB model group also provide higher scores than the SSN algorithms.

## VI. Conclusion

The results of this study indicate the potential success of environment-aware approaches towards managing multi-waveform structures that are likely to be involved in 6G communication systems. Waveform selection approaches, which could be an important achievement in responding to the increasing diversity of user requirements, may be one of the critical research topics in the future. Additionally, the utilization of SSN- and MSN-based ML methods within the framework of waveform management shows promising results.

In the future, domain adaptation problems can be studied with transfer learning methods if there is a real-world data.

Moreover, different approaches that allow for the simultaneous use of multiple waveform structures can be developed. In this context, methods for dealing with interference between waveform structures can be devised. Consequently, it would be possible to develop approaches that assign user-based waveforms. Furthermore, research can be conducted to prevent inter-cell interference caused by multi-waveform structures.

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