Development of machine learning techniques for automatic modulation classification and performance analysis under AWGN and fading channels

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ABSTRACT

Automatic modulation classification (AMC) is essential in modern wireless communication for optimizing spectrum usage and adaptive signal processing. This study explores the use of various machine learning (ML) methods for AMC, focusing on their performance in additive white Gaussian noise (AWGN) and fading channels. This study evaluates of ML classifiers such as support vector machines (SVM), K-nearest neighbors (KNN), decision trees (DT), and ensemble methods with a dataset spanning signal-to-noise ratios (SNRs) from -30 dB to +30 dB. Higher-order statistical features including moments and cumulants are used to train the classifiers for AMC. Performance is measured in terms of classification accuracy and computational efficiency across different SNR levels. The findings show that linear SVM, fine KNN, and fine trees consistently achieved high classification accuracy, even at low SNRs. From the analysis, it is observed that linear SVM and fine KNN achieve over 96% accuracy at 0 dB SNR. These classifiers demonstrate significant robustness, maintaining performance in challenging noise conditions. The research highlights the promise of ML techniques in improving AMC, providing a detailed comparison of classifiers and their strengths.

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1. INTRODUCTION

In modern wireless communication systems, efficient utilization of the radio frequency spectrum is paramount. The increasing demand for wireless services and the limited availability of spectrum resources have necessitated the development of advanced technologies that can optimize spectrum usage. One such technology is automatic modulation classification (AMC), which plays a critical role in cognitive radio (CR) networks and various military and civilian applications. AMC enables the identification of the modulation scheme of received signals without prior knowledge, thereby facilitating adaptive signal processing, interference management, and secure communication [1]. The significance of AMC stems from its ability to enhance the performance and reliability of wireless communication systems. By accurately identifying the modulation type, AMC supports dynamic spectrum access, allowing unlicensed users to opportunistically utilize the licensed spectrum without causing harmful interference to primary users [2]. This capability is essential for the efficient implementation of CR networks, which aim to address the spectrum scarcity problem. In military applications, AMC is vital for electronic warfare and surveillance, where the identification of enemy communication signals is crucial. In civilian applications, AMC contributes to improved communication quality, reduced latency, and enhanced security by enabling adaptive modulation and coding schemes. The need for robust and accurate AMC systems is underscored by the diverse and dynamic nature of wireless environments, where signals are often subjected to varying levels of noise, interference, and fading [3], [4].

Several techniques have been developed for AMC, each with its own set of merits and demerits. These techniques can be broadly categorized into likelihood-based methods, feature-based methods, and ML-based methods [5]. Likelihood-based methods, such as the maximum likelihood classifier, offer high accuracy in identifying modulation schemes. They are theoretically optimal under certain conditions and provide a solid statistical foundation for modulation classification. These methods often require precise knowledge of the channel conditions and signal parameters, which may not be readily available in practical scenarios. Additionally, they are computationally intensive, making them less suitable for real-time applications [6], [7]. Feature-based methods extract specific signal characteristics, such as higher-order statistics to distinguish between different modulation types. These methods are less computationally demanding compared to likelihood-based methods and can be effective under various channel conditions. The performance of feature-based methods heavily depends on the quality and relevance of the extracted features. They may also require extensive feature engineering and domain knowledge to identify the most discriminative features. Machine learning (ML)-based methods have gained popularity due to their ability to learn complex patterns from data. These methods do not require explicit channel knowledge and can adapt to diverse and dynamic environments. They offer high classification accuracy and robustness against noise and interference. The primary drawback of ML-based methods is their reliance on large labeled datasets for training, which may not always be available [8]. Additionally, the training process can be computationally intensive, and the performance of these methods may degrade if the training data is not representative of real-world conditions.

Given the critical role of AMC in modern wireless communication systems, this paper aims to advance the field by leveraging ML techniques for enhanced modulation classification. The primary focus is on evaluating the performance of various ML classifiers across a range of signal-to-noise ratios (SNRs) in both additive white gaussian noise (AWGN) and fading channels. This paper makes several significant contributions and are as follows:

- This paper conducts an extensive evaluation of various ML classifiers, including support vector machines (SVM), K-nearest neighbours (KNN), decision tree (DT), and ensemble methods, for AMC. The study systematically assesses the performance of these classifiers across a wide range SNRs, from -30d B to +30 dB, providing valuable insights into their robustness and effectiveness under different noise conditions.
- The paper employs higher-order statistical features, specifically moments and cumulants, extracted from modulation signals. These features are critical for distinguishing between different modulation schemes.
- The paper compares the performance of the ML classifiers under both AWGN and fading channels. It provides a comprehensive understanding of how these classifiers perform in real-world wireless environments, where signals are often subjected to various impairments.
- The findings highlight the robustness of linear SVM, fine KNN, and fine trees, which consistently achieve high classification accuracy even in low SNR conditions. This robustness is particularly significant for practical applications where wireless communication systems must operate reliably under challenging conditions.

By addressing these aspects, this paper aims to provide valuable insights and practical guidelines for developing robust and efficient AMC systems, contributing to the optimization of spectrum usage and the overall enhancement of wireless communication technologies.

The rest of the paper is organized as follows: section 2 provides a detailed literature review of existing AMC techniques, highlighting their merits and demerits. Section 3 describes the methodology, including feature extraction and the ML algorithms employed. Section 4 presents the simulation results, performance analysis of the classifiers under various channel conditions, and a discussion on the implications of the findings. Finally, section 5 concludes the paper, summarizing the key contributions and suggesting directions for future study.

2. LITERATURE REVIEW

AMC has witnessed considerable advancements, transitioning from early analog modulation methods to sophisticated digital modulation techniques. The complexity and diversity of wireless communication systems have driven continuous research and innovation, resulting in a broad spectrum of AMC strategies. These strategies can be broadly classified into decision-theoretic (DTC) or maximum likelihood (MLH) methods, transform domain or wavelet transform (WT) methods, statistical methods, and feature-based (FB) or pattern recognition (PR) approaches. This section aims to highlight the significant contributions made in the field, examine the evolution of AMC methodologies, and identify the strengths and weaknesses of each approach.

2.1. Decision-theoretic/maximum likelihood approaches

DTC or MLH approaches are among the most popular and widely researched methods for AMC. These approaches are motivated by their optimal performance for known channel parameters and models. The classification task in DTC involves two primary phases. In the first phase, the likelihood of each modulation hypothesis is evaluated based on the observed signal samples. Features such as squared second-order cyclic temporal, fourth-order cumulants, moments, instantaneous amplitude, phase, frequency, and signal constellations are used to construct likelihood ratios and decision boundaries. In the second phase, these likelihoods are compared to determine the most likely modulation scheme.

Table 1 presents some of the DTC approaches for AMC, highlighting their key features, modulation classes, accuracy, and their merits and demerits. These methods offer high accuracy and optimal performance when signal parameters are known, providing a solid statistical foundation. However, they are computationally intensive, require precise prior knowledge of signal parameters, and are less practical for real-time applications, being sensitive to phase and frequency offsets.

Table 1. Literature on DTC/MLH techniques

Ref.	Key features	Name of the classifier	SNR (dB)	Modulation classes	Accuracy (%)	Pros	Cons
[9]	Log likelihood functions	ALRT	-20 to 5	BPSK, QPSK	99	High accuracy in low SNR environments	Computationally intensive
[10]	Likelihood-ratios	Bayes	10	BPSK, QPSK	90-100	Effective for known signal levels	Requires prior knowledge of signal levels
[11]	Ratio of variance of envelope to square of mean	Likelihood	7-10	AM, FM, SSB, DSB	80-95	Simple implementation	Limited modulation classes
[12]	Histogram of instantaneous amp, phase, and freq	Likelihood	10-20	ASK2, PSK2, PSK4, PSK8, FSK2, FSK4	95-96	High accuracy for multiple modulation classes	Requires higher SNR for accurate classification
[13]		Likelihood	10-20	ASK2, PSK2, PSK4, PSK8, FSK2, FSK4	95.4-100	Broad application across modulation classes	Performance depends on feature extraction
[14], [15]	4 parameters derived from Instantaneous amplitude and phase	Likelihood	10	AM-FC, DSB-SC, SSB, VSB, LSB, USB, FM	91-100	High accuracy for a variety of modulation types	Requires precise feature extraction
[16], [17]	Quassi likelihood ratio of phase	Likelihood	-2 to 8	BPSK, QPSK	100	Optimal performance for specific modulation types	Limited to phase-modulated signals
		Likelihood	25	PSK-16, 16-QAM	100	High accuracy for high-order modulation	High computational complexity
[18]	Likelihood-ratios	Quasi-ALRT	-10 to 2	BPSK, QPSK	55-100	Reduced computational complexity compared to ALRT	Performance varies significantly with SNR
[19]	Likelihood-ratios	HLRT	-20 to 20	BPSK, QPSK, OQPSK	90	Robust performance across a range of SNRs	High computational demand

2.2. Transform domain approaches

Transform domain methods for AMC utilize techniques such as WT to analyze the signal in different domains, allowing for the extraction of transient information about variations in signal amplitude, phase, and frequency. These methods are effective in classifying signals under various channel conditions but can be influenced by the choice of transform parameters and the fixed window length. Table 2 presents some of the transform domain approaches for AMC, highlighting their key features, modulation classes, accuracy, and their merits and demerits. Transform domain methods offer a good signal analysis tool for time-varying signals but require careful selection of parameters and can be computationally demanding.

Table 2. Comparative analysis of transform domain techniques

Ref.	Key features	Name of the classifier	SNR (dB)	Modulation classes	Accuracy (%)	Pros	Cons
[20]	Spectrograms	Rule based	2	BASK, BFSK, 4FSK	90	Simple implementation	Limited to specific SNR
[21]	Instantaneous frequency, main-lobe widths, peak to side-lobe ratio	STFT	0-12	ASK, M-ary FSK, PSK	90-100	High accuracy	Fixed window length limits detection
[22]	Smooth-windowed Wigner Ville bispectrum	Rule based	0-26	ASK, M-ary FSK	80-95	Effective across wide SNR range	Computationally complex
[23]	Instantaneous frequency	S-transform (ST)	3-15	CP, LFM, BFSK, BPSK	97.25	High accuracy	Limited to specific modulations
[24]	Number of peaks	STFT, HT	2	Linear and non-linear FM	-	Effective for FM signals	Limited to FM signals
[25]	Instantaneous amplitude, frequency	WT, ST	10-15	AM, FM, MASK, MFSK, PSK (M=2,4 and 8)	99-100	High accuracy for a variety of modulation types	Computationally intensive
[26]	Time-frequency contours (TFC)	Modified ST	-10 to 20	MASK, MFSK, PSK (M=2,4 and 8)	-	Effective for low SNR	Limited modulation classes
[27]	TFC, Scalograms	Modified ST	-20 to 20	-	-	Effective for a wide range of SNRs	Complex implementation
[28]	higher-order statistics (HoS), TFC	Modified ST, FFT	0 to 20	MASK, MFSK, PSK (M=2,4 and 8)	90-100	High accuracy	High computational complexity

2.3. Statistical methods

Statistical methods for AMC focus on extracting modulation types by leveraging the HoS of signals, such as moments and cumulants, in their complex envelopes. These methods can classify signals by considering non-linearity properties and cyclostationary statistics. While they are robust to various channel conditions, their performance is heavily dependent on the selection of the right feature set. Table 3 presents some of the statistical approaches for AMC, highlighting their key features, modulation classes, accuracy, and their merits and demerits. Statistical methods are relatively easy to implement and provide quick recognition of modulation types, but careful feature selection is crucial for optimal performance.

Table 3. Statistical methods

Ref.	Key features	SNR (dB)	Modulation classes	Accuracy (%)	Pros	Cons
[29]	higher-order correlation (HOCo)	-3 to 6	MFSK	55-95	Robust to frequency offset errors	Limited to specific modulation types
[30]	HOCo, average likelihood-ratio function (ALF)	-6 to 10	MFSK	20-95	Effective for MFSK signals	Performance varies significantly with SNR
[31]	HOCo	4-12	MFSK	65-99	High accuracy in specified SNR range	Limited modulation classes
[32]	Moments	-5.8 to 5.5	2ASK, 2PSK, 4PSK, MSK, 2FSK	97.9-100	High accuracy across multiple modulations	Requires precise moment calculation
[33]	Moments	-10 to 10	MPSK	50-95	Effective for MPSK signals	Sensitive to noise at lower SNRs
[34]	Cyclic cumulants	3	MPSK, MSK	40-100	High accuracy at specified SNR	Performance depends on cyclic feature extraction
[35]	HOC	-5 to 25	PAM, QAM, MPSK	55-100	Broad applicability, high accuracy	Requires large number of symbols for high accuracy
[36]	HOC	5, 10	QAM, PSK, ASK	55-95	Effective for QAM and PSK	Performance drops at lower SNRs
[37]	HOC	5,7,10	4-QAM, 16-QAM	84.5-99	High accuracy for QAM	Limited to QAM signals
[38]	HOC	-10 to 10	16-QAM,64-QAM, BPSK, QPSK	45-90	Broad modulation class coverage	Performance drops significantly at lower SNRs

2.4. Feature-based approaches

The limitations of DTC and statistical approaches have led to the development of FB approaches, which provide suboptimal performance with fewer computations and do not require prior information about the signal and channel. These approaches are practically realizable and can work under different noisy conditions. FB approaches are broadly categorized into ML approaches, deep learning approaches, and neural network methods. The performance of FB approaches depends on the choice of the feature set derived from the signals. Table 4 presents some of the FB approaches for AMC, highlighting their key features, modulation classes, accuracy, and their merits and demerits. FB approaches eliminate the need for prior knowledge, making them suitable for dynamic and noisy environments. However, the choice of feature set is crucial for their effectiveness.

Table 4. Pattern recognition methods

Ref.	Key features	SNR (dB)	Modulation classes	Accuracy (%)	Pros	Cons
[39]	2D fuzzy sets	6-14	16QAM, 32QAM	80-95	Better performance over traditional ML in noisy environments	Limited to two- class problem
[40]	Statistical moments	>5	ASK, MFSK, PSK, 16QAM	82-96	Low complexity, no prior awareness of SNR required	Requires higher SNR for proper function
[41]	Two-layer perceptron with backpropagation	Not specified	Rect-QPSK, sinc-QPSK, SQPSK, MSK	80-95	No synchronization with signal arrival time needed	Inadequate performance at lower SNRs
[42]	NN with HOS parameters	0-20	2,4,8-PSK, 2,4,8-FSK, 16,64,256-QAM	75-95	Effective in varying propagation environments	Performance degrades in multipath environments
[43]	Binary feature vectors from T-F images	Not specified	BPSK, FMCW, Frank, P4, PT1	93	Autonomous PR algorithm	Poorer performance with adaptive binarization
[44]	Multiplication of consecutive signal values	0	2ASK, 4ASK, PSK2, PSK4, 16QAM	50 at 0 dB	Better performance than traditional ML classifiers	Inadequate at 0 dB SNR for practical applications
[45]	Seven statistical signal features	Not specified	CW, AM, LSB, USB, FM-NB, 2FSK, 4FSK, 2PSK, 4PSK	75-95	Superior to DT based classifiers at lower SNRs	No QAM signals included
[46]	WT coefficients	10	2ASK, 4ASK, 2FSK, 4FSK, 2PSK, 4PSK, MSK, 16QAM	75-95	Better performance at 10 dB SNR	Inadequate at SNR less than 10 dB
[47]	Bootstrap technique and radial basis function NN	Low	Various analog and digital	80-95	Effective in low SNR and fading channels	Limited modulation classes investigated

This survey underscores the need for further research to enhance AMC performance in dynamic and noisy environments, addressing the limitations identified in existing approaches. This work aims to enhance AMC using ML techniques by focusing on robust feature extraction and selection, implementing diverse classifiers such as SVM, KNN, and ensemble classifiers. Extensive datasets and data augmentation techniques will be employed for training and validation to improve generalization. Performance optimization will target hyperparameter tuning and handling class imbalances to achieve a balance between accuracy and computational efficiency.

3. METHOD

This section presents the detailed framework used in this paper for AMC and describes the different types of ML algorithms employed.

3.1. Framework

Figure 1 illustrates the overall framework of the proposed AMC using ML techniques. In this framework, there are several important steps that improve accuracy and efficiency in the detection and classification of various modulation class types from the received noisy data. The major tasks and steps in this proposed framework are detailed in subsections below.

3.1.1. Data set generation with SDR testbed

In modern communication systems, obtaining realistic datasets for AMC is crucial for developing robust ML models. A SDR testbed provides the flexibility and control needed for real-time dataset creation. The use of two universal software radio peripherals (USRPs) in the testbed setup allows for controlled signal transmission and reception, enabling the generation of a diverse set of modulated signal classes under varying channel conditions. This setup is essential for building a dataset that mimics real-world conditions and supports the development of effective AMC algorithms. Figure 2 presents the SDR testbed for dataset generation [48]. The SDR testbed comprises two USRPs, where one acts as the transmitter and the other as the receiver. The SDR platform provides a flexible way to generate, manipulate, and analyze radio signals in software, making it highly adaptable for experimentation and dataset creation. The transmitter USRP is programmed to generate different classes of modulated signals such as M-ary PSK (M=2, 4, and 8), 4-QAM, 16-QAM, and 64-QAM. These signals are transmitted over the air in real-time to the receiver USRP, which captures the signals for analysis and storage.

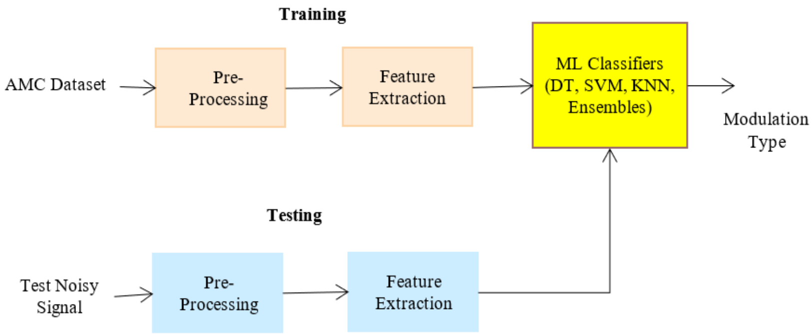

Figure 1. Framework for AMC

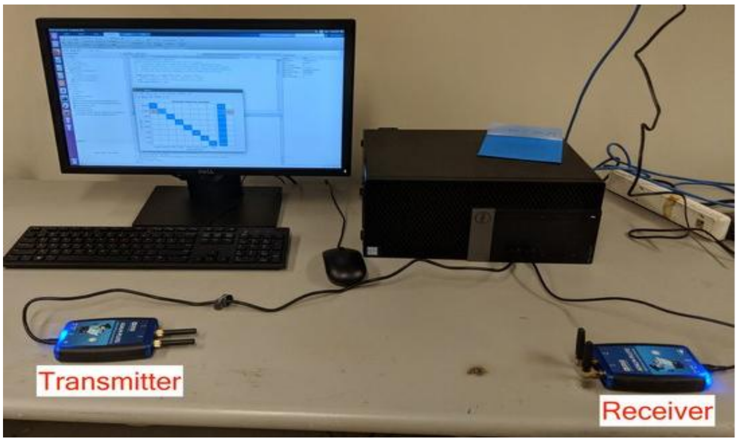

Figure 2. SDR testbed for AMC dataset creation

To simulate real-world communication environments, AWGN is introduced during the transmission phase. This noise mimics the background interference commonly found in wireless communication channels. In addition to AWGN, fading noise is generated by varying the distance between the transmitter and receiver. As the distance increases, signal strength weakens, introducing fading effects such as multipath interference and signal attenuation, which are common in real communication scenarios. The variation in distance, combined with the introduction of AWGN, allows for the creation of realistic signal environments. These changes simulate different propagation conditions, such as those encountered in urban, rural, or indoor environments, where signals may experience varying levels of fading and interference.

At the receiver USRP, the transmitted signals now embedded with noise and fading effects are captured. The received signals are stored in real time, and this process is repeated for each class of modulated signals at different SNR levels. By systematically adjusting the SNR, the dataset captures signals under various noise conditions, enabling the AMC system to be trained and evaluated under realistic conditions. This approach ensures that the machine learning models can generalize well to different communication environments. The repeated process of transmitting and receiving signals under varying conditions results in a diverse dataset, containing signals with different modulation schemes, noise levels, and channel impairments. This dataset is then labeled according to the modulation type and SNR values, providing a comprehensive training set for the AMC algorithms.

3.1.2. Feature extraction and model selection

It directly extracts features, which include amplitude, phase, and frequency characteristics of the time-domain signal. All of these features catch some of the essential properties of the signal useful for classification. Frequency-domain features give information regarding the components that constitute a signal and their distribution. Consider higher-order statistics, such as cumulants and moments, which capture the nonlinear relationship and dependencies in the signal to provide more discriminative features for classification. In the model selection phase, appropriate machine learning algorithms for AMC are selected. The choice of algorithm depends on the nature of the classification task and specific needs from the dataset.

3.1.3. Model training

At this stage, 70%, 15%, and 15% of the dataset will be used for training, validation, and testing, respectively. The models will be trained on the training set. Cross-validation will be used to tune the hyperparameters, and the best model will be chosen based on validation performance. Finally, the test set performance will be evaluated with the model.

3.1.4. Model evaluation

In this stage, test the trained models on the test set, evaluating them by metrics such as accuracy, precision, recall, and the F1-score. Compare the different models built to determine which is the best algorithm for a particular modulation scheme to achieve optimum performance in practice.

3.2. Decision trees

DTs are popular non-linear prediction models in ML and data mining, used for either classification or regression problems. The basic idea of DT is to recursively partition the given dataset into non-overlapping subsets based on the most important features [49]. In DTs, a tree structure is made where the internal node which every node of a DT represents a feature and each branch represents a possible outcome of that feature. The leaves of the tree represent final class or value predictions. The process of partitioning continues until either the data values are separated or some criteria, like maximizing the depth of the tree, minimizing the samples per leaf or so forth, is met or. It allows the model to make predictions by following through the branches of the tree based on feature values until it arrives at a leaf that contains a class or estimated value to predict. The DT should be easily interpretable and transparent, which is useful for intuitively explaining why the model makes certain decisions. They help explain how different features contribute to making a prediction, thus making the prediction transparent and trustworthy. DTs can be applied to both numerical and categorical data and can work with outliers. DTs are highly vulnerable to overfitting, especially when a tree is particularly deep. They may also show high variance, whereby small changes in the data lead to quite different trees. Some features of some different DT classifiers regarding maximum depth, classification speed, classifying accuracy, and flexibility.

The fine DT classifier, with a maximum depth of 100, is the-fastest classifying, accurate, and highly viable one. The medium DT classifier has a maximum depth of 20; it is also fast in classification, accurate, but with medium flexibility. Last but not least, the coarse DT classifier has a maximum depth of 4; its classification is still fast, but it is medium in accuracy and low in flexibility.

3.3. K-nearest neighbors

KNN is a simple, hence effective, nonparametric classification and regression algorithm. KNN operates based on the similarity principle: classifying a data point by considering the majority class amongst its nearest neighbors. For classification, KNN assigns a class to a query point based on the majority class of its KNN [49]. The value of K turns into a very important hyperparameter. A small K then renders the model sensitive to noise, while a large K provides a smoother decision boundary but probably at an additional computational cost. Some of the advantages of KNN include how easy it is to implement and get interpretability of results, handle nonlinear relationships, and it generally fares well with multi-class problems. On the other side, it can be computationally rather expensive on large datasets, is sensitive to outliers, and requires proper scaling of features for optimal performance. Classifications of different KNN classifiers based on the number of neighbors (K) and distance function used.

The fine KNN classifier uses 1 neighbor with the Euclidean distance function. The medium KNN classifier uses 10 neighbors, also with the Euclidean distance function. The coarse KNN classifier uses 100 neighbors with the same distance function. The cosine KNN classifier makes use of 10 neighbors with the cosine distance function, and the cubic KNN classifier uses 10 neighbors with the Minkowski distance function. Finally, the weighted KNN classifier uses 10 neighbors with a weighted Euclidean distance function by $1/d^2$.

3.4. Support vector machine

SVM is a powerful supervised learning algorithm used for both classification and regression tasks. SVM aims to find the optimal hyperplane that best separates the data into different classes. The detailed working and characteristics of SVM are as follows: SVMs find an optimal hyperplane to classify data, using kernel functions for non-linear separability, and perform effectively in high-dimensional spaces with robust generalization. SVM can be sensitive to noisy data, requires careful tuning of hyperparameters, and can be computationally expensive for large datasets [50].

The classification of SVM classifiers based on speed, memory usage for binary and multi-class classification, and flexibility. The linear SVM classifier is fast, with medium memory usage for both binary and multi-class tasks, but offers low flexibility. Both the cubic and quadratic SVM classifiers are also fast, with medium memory usage for binary classification and large memory usage for multi-class classification, providing medium flexibility. The fine gaussian SVM classifier maintains fast speed and medium memory usage for binary tasks, with large memory usage for multi-class tasks, and offers high.

3.5. Ensemble classifiers

Ensemble learning is a powerful method of ML where several models are combined together in order to have a more accurate and reliable predictive model. Inherent in the use of different models is their collective knowledge to improve general performance and reduce the risk of overfitting. Key ensemble methods include bagging and boosting. The bagging/bootstrap aggregating technique is based on training several models in different subsets of the training set, created by bootstrapping, and then aggregating the predictions of these models through average or majority vote. Bagging reduces variance and makes the models more stable. Boosting, on the other hand, deals with the sequential training of weak models so that every subsequent model gives more weight to the instances misclassified by previous models. The final prediction is a weighted sum of the individual models then, giving more weight to those performing well on hard examples. Ensemble methods generally provide better performance than individual models, reduce overfitting, and increase model robustness [51], [52]. Ensemble methods can be computationally intensive, complex to implement, and harder to interpret than single models.

The classification of various ensemble classifiers is as follows. The boosted classifier uses the AdaBoost ensemble method with DTs as weak learners, offering high flexibility. The bagging classifier employs the random forest method, also with DTs as weak learners, and provides high flexibility. The subspace discriminant classifier uses the subspace method with discriminant analysis as weak learners, providing medium flexibility. Lastly, the subspace classifier utilizes the Subspace method with KNN as weak learners, offering medium flexibility.

4. RESULTS AND DISCUSSIONS

The performance of the proposed DT, KNN, SVM, and ensemble-based ML classifiers is thoroughly evaluated under non-ideal channel conditions, simulating real-world scenarios with signals subjected to noise and channel impairments. The modulation schemes considered for the simulations include M-ary PSK (M=2, 4, and 8), 4-QAM, 16-QAM, and 64-QAM, creating a comprehensive test bed for assessing the classifiers' effectiveness under diverse conditions. The modulation classification dataset is well-designed to include a wide variety of SNR values ranging from -30 dB to +30 dB. This range covers very noisy conditions and ideal ones, hence producing a solid base for both the training and testing of machine learning models. This ensures that the sampled SNR levels are within the –30 dB to +30 dB interval with a constant 5dB step size. Having a constant step size of 5 dB, the dataset includes an equably distributed number of samples on a usado scale of the SNR. The data set includes negative dB values corresponding to highly noisy or significantly interfered scenarios. Special attention is given to accurately simulate such conditions. All signals in the set of data are represented by 10,000 samples.

The large sample size is chosen to provide adequate data for the machine learning models to learn the characteristics of every modulation type effectively. The signals were generated across different SNRs and multipath fading channels to model realistic communication environments. This diversity in the dataset aids in building robust models that generalize well across different conditions. It means that the machine learning models to be trained based on this dataset will be applicable and effective against all types of real-life situations, including those with large noise and interference. In this paper, cross-validation has been used in order to ensure a robust evaluation and validation for ML models.

Figure 3 shows the process of cross-validation. Such methods provide full insight into the performance of the model and prevent overfitting. Cross-validation, on the other hand, is more rigorous, entailing the division of data into a number of folds and iteratively training and testing a model on different subsets of data. This gives a more realistic model performance estimate.

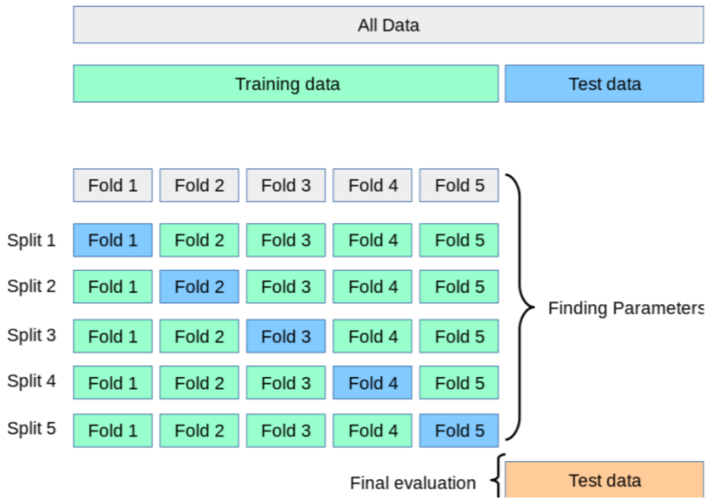

Figure 3. Cross validation process

The dataset is divided into K equally sized folds (commonly 5 or 10). Each fold serves as a testing set once, while the remaining K-1 folds are combined to form the training set [49]. The model is trained and tested K times, each time using a different fold as the testing set. The results are then averaged to provide a comprehensive evaluation metric.

Table 5 presents the performance of ML classifiers at 10 dB SNR, linear SVM, and bagged trees achieved good accuracy than others in AMC, achieving the highest accuracies across both 5-fold and 10-fold cross-validation. Fine tree and weighted KNN also showed consistent performance, while boosted trees provided solid performance, particularly in 5-fold CV. Overall, ensemble methods and SVMs proved highly effective.

Table 5. Performance of ML classifiers at 10 dB SNR

ML classifier	Hyperparameter	% of accuracy	
		5-fold CV	10-fold CV
DT	FT	96.7	95.8
	MT	94.7	93.9
	CT	94.7	94.6
SVM	Linear	99.8	99.5
	Quadratic	96.6	97.3
	Cubic	94.3	94.4
	Fine gaussian	92.3	92.9
	Medium gaussian	92.1	92.4
	Coarse gaussian	92.3	93.1
KNN	Fine	97.3	93.5
	Medium	91.6	91.5
	Coarse	94.5	957
	Cosine	93.8	94.2
	Cubic	96.3	95.8
	Weighted	97.2	96.9
Ensemble classifiers	Boosted trees	97.3	95.9
	Bagged trees	97.8	97.4
	Subspace KNN	94.6	94.1
	Subspace discriminant	91.3	92.8
	Rusboosted trees	89.6	89.5

Figure 4 presents the performance of different DT classifiers under various SNRs. It is observed that fine tree out performed other classifiers with more than 3% accuracy at all SNRs. Further is observed that even at 0 dB SNR fine tree classifier achieved an accuracy of 84.2% and at 10 dB SNR it is achieved an accuracy of 96.7% with 5-fold CV. Similarly Figure 5 presents the performance of various KNN classifiers at different SNRs. From Figure 5, it is observed that fine KNN and weighted KNN achieved an accuracy of more than 80% and at 10 dB, these classifiers are achieved an accuracy of 97.3% and 97.2% respectively.

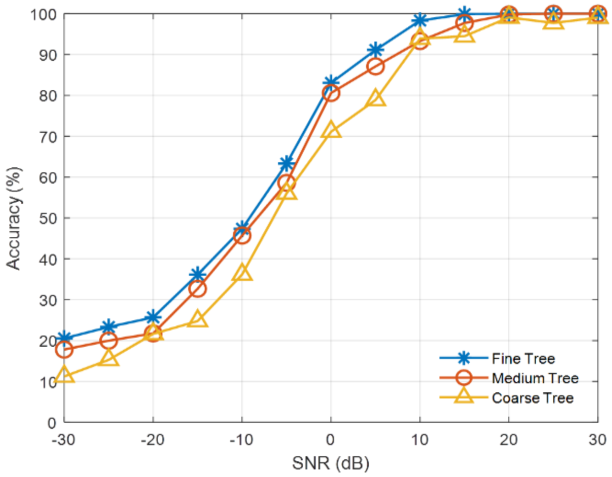

Figure 4. Performance of DTs at various SNRs

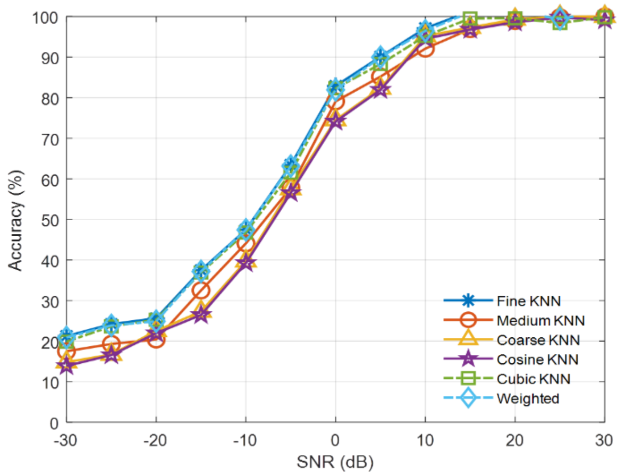

Figure 5. Performance of KNNs at various SNRs

Figure 6 presents the performance of various SVM classifiers under different SNRs. From Figure 6, it is observed that SVM classifier with linear kernel and course gaussian kernel outperformed all other kernel functions. It is observed that at 0d B SNR, linear SVM and course gaussian SVM classifiers achieved an accuracy of 84.3% and 84.1% respectively. Further, it is observed that these classifiers are achieved an accuracy of 99.8% and 99.6% at 10 dB SNR.

Figure 7 presents the performance of various ensemble classifiers under different SNRs. From Figure 7, it is observed that bagged tress and boosted tress outperformed all other classifiers. It is also observed that at 0 dB SNR, bagged trees and boosted trees classifiers are achieved an accuracy of 79.3% and 78.7% respectively. Further, it is observed that these classifiers are achieved an accuracy of 97.4% and 97.1% at 10 dB SNR.

Table 6 presents the performance comparison of proposed ML classifiers with other existing methods. This study confirms that ML techniques, particularly SVMs and ensemble methods, are highly effective for AMC tasks, especially at moderate to high SNR levels. The strength of linear SVM and bagged trees in realizing high accuracy across different SNRs makes them pretty suitable for real-world applications with highly varying signal quality. Decision trees are relevant for interpretation, relatively easy to apply, and less accurate than SVMs and the ensemble methods. Other promising approaches include KNN classifiers, especially fine KNN and weighted KNN, working really well, especially at higher SNRs. These results thus show the proper use of classifiers and tuning their hyper-parameters in order to attain optimal performance in AMC tasks.

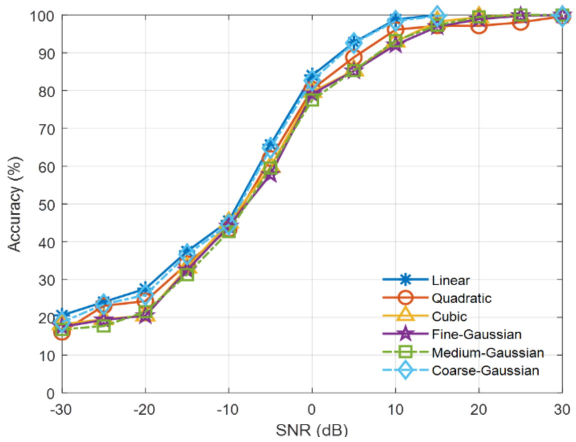

Figure 6. Performance of SVMs at various SNRs

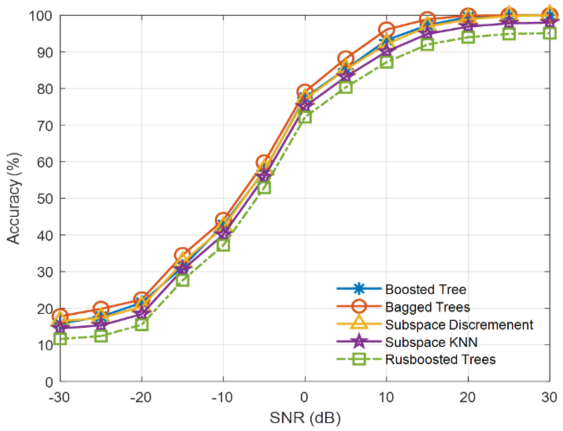

Figure 7. Performance of ensembles at various SNRs

Table 6. Performance comparison of ML classifiers with other existing methods

Ref.	Key features	Classifiers	Modulation classes	SNR range (dB)	Accuracy (%)
[9]	Log likelihood functions	ALRT	BPSK, QPSK	-20 to 5	99
[10]	Likelihood ratios	Bayes	BPSK, QPSK	10	90-100
[12]	Histogram of instantaneous amp, phase, freq	Likelihood	ASK2, PSK2, PSK4, PSK8, FSK2, FSK4	10-20	95-96
[21]	Instantaneous frequency, main-lobe widths	STFT	ASK, M-ary FSK, PSK	0-12	90-100
[22]	Smooth-windowed Wigner Ville bispectrum	Rule-Based	ASK, M-ary FSK	0-26	80-95
[29]	Higher-order correlation (HOCo)	-	MFSK	-3 to 6	55-95
[32]	Moments	-	2ASK, 2PSK, 4PSK, MSK, 2FSK	-5.8 to 5.5	97.9-100
Proposed	Extracted time, frequency, and higher-order statistics features	Linear SVM, bagged trees, fine tree	Multi order digital modulation Techniques of PSKs, QAMs and FSKs	-30 to +30	Up to 99.8 at 10 dB SNR

In real-time applications, alongside accuracy, computational efficiency is a critical performance metric. Table 7 presents the computational complexity of various classifiers, providing insights into their training and inference requirements. Here, nnn denotes the number of training samples, ddd represents the number of features, bbb refers to the number of base learners in ensemble methods, and kkk indicates the number of support vectors in SVM. This evaluation helps identify classifiers suitable for real-time implementation by balancing accuracy and efficiency.

Table 7. Complexity of ML classifiers

Classifier	Training time complexity	Inference time complexity	Space complexity	Remarks
DTs	$O(n.d.\log(n))$	$O(d)$	$O(d)$	Quick training and inference, suitable for real-time applications with low computational overhead.
KNNs	$O(1)$	$O(n.d)$	$O(n.d)$	Efficient training but computationally expensive inference due to distance calculations.
SVM (linear)	$O(n^2.d)$	$O(d)$	$O(d)$	Highly efficient during inference, making it suitable for real-time applications.
SVM (non-linear)	$O(n^3)$	$O(k.d)$	$O(d+k)$	Non-linear kernels are computationally intensive, especially during training.
Bagged trees	$O(b.n.d.\log(n))$	$O(b.d)$	$O(b.d)$	Training involves building multiple decision trees, but inference is parallelizable.
Boosted trees	$O(b.n.d)$	$O(b.d)$	$O(b.d)$	High accuracy at the cost of increased computational demand during training.

Linear SVM and fine decision tree exhibit the lowest inference time complexities, making them well-suited for real-time applications. Conversely, KNN faces high inference complexity due to the need to calculate distances for all training samples, requiring optimization for practical deployment. Ensemble methods, such as bagged trees and boosted trees, deliver superior accuracy but incur significant computational costs during training. This mathematical breakdown offers valuable insights into the trade-offs between computational efficiency and accuracy, aiding in selecting the most appropriate classifiers for real-time implementations.

5. CONCLUSION

The paper presents the efficiency of various ML classifiers on AMC data under different SNR conditions. The evaluation was done mainly at 10 dB and 0 dB SNR. The detailed evaluation used DT, SVM, KNN, and ensemble methods with 5-fold and 10-fold cross-validation to make results for performance metrics more robust. Results turned out that in all cases, linear SVM and bagged trees were able to achieve the highest accuracy; therefore, they are more capable of handling this AMC task. Fine tree and weighted KNN also did well with very reliable performance, especially for 5-fold cross-validation. Ensemble methods like boosted trees worked beyond measure and hence substantiated the creation of multiple learners to help improve classification accuracy. The trends across different SNRs brought out the classifiers' resilience and adaptability across high and low noise environments. Even at 0 dB SNR, fine tree classifiers preserved the highest accuracy, whereas linear SVM and coarse gaussian SVM reached very close to perfect accuracies at 10 dB SNR. The results underline the fact that the proper choice and tuning of machine learning models are important to be optimal in AMC applications. Due to the robustness and extremely high accuracy, SVM, as well as ensemble methods, are very suitable for real-world communication systems where the conditions of the signal might vary. The study also discusses computational efficiency, highlighting that linear SVM and fine tree classifiers have low inference complexities, making them ideal for real-time AMC. Conversely, ensemble methods like bagged trees offer higher accuracy but incur greater computational costs.

Future research can explore advanced techniques, such as deep learning models like CNNs or RNNs, to automate feature extraction and enhance classification performance across diverse SNR conditions. Expanding the dataset to include additional modulation types and complex channel scenarios would further improve model generalization. Integrating these models into real-time AMC systems and optimizing their computational efficiency for deployment in resource-constrained environments could significantly enhance the reliability and scalability of modern communication networks. Such advancements would contribute to addressing spectrum scarcity and improving the performance of CR networks and other wireless systems.

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AUTHOR CONTRIBUTIONS STATEMENT

P. G. Varna Kumar Reddy conducted the research, developed models, and wrote the manuscript. Dr. M. Meena supervised the study, validated the results, and revised the content. Both authors reviewed and approved the final version of the manuscript.

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest regarding the publication of this research work or its associated findings and results.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study

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