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*Research Article*

# Signal Modulation Recognition System Based on Different Signal Noise Rate Using Artificial Intelligent Approach

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**Abstract**

Everyone has paid much attention to modulation-type recognition in the past few years. There are many ways to find the modulation type, but only a few good ways to deal with signals with a lot of noise. This study comes up with a way to test how well different machine learning algorithms can handle noise when detecting digital and analogue modulations. This study looks at the four most common digital and analogue modulations: Phase Shift Keying, Quadrature Phase Shift Keying, Amplitude Modulation, and Morse Code. A signal noise rate from -10dB to +25dB is used to find these modulations. We used machine learning algorithms to determine the modulation type like Decision Tree, Random Forest, Support Vectors Machine, and k-nearest neighbours. After the IQ samples had been converted to the amplitude of samples and radio frequency format, the accuracy of each method looked good. Still, in the format of the sample phase, each algorithm's accuracy was less. The results show that the proposed method works to find the signals that have noises. When there is less noise, the random forest algorithm gives better results than SVM, but SVM gives better results when there is more noise.



## 1. Introduction

One of the most important objectives of communication systems is to establish a dependable link between the two communication nodes. Because of the wide variety of receivers and transmitters in space, a significant number of signals are continually being modulated using a range of different modulation methods. The term "digital modulation" refers to encoding a digital wave into the transmitted signal's phase, amplitude, and frequency. Depending on the modulation that was applied to the signal, there are many sets of parameters that may be measured. It is possible to obtain useful information from these characteristics by determining the modulation used. We can determine the specific modulation scheme the requested signal employs through automated modulation recognition. In science and engineering, the ratio of the signal of interest to the amount of noise is referred to as the signal-noise ratio (SNR) [1].

The signal-noise ratio, often shortened as SNR and defined as the ratio of signal power to noise power, is typically expressed in decibels. The field of machine learning, which may be described as the process of allowing computers to make persuasive predictions based on previous experiences, has witnessed phenomenal development in recent years due to the fast rise in computer storage capacity and processing power [2, 3].

For this investigation, we used classification strategies for identifying digital and analogue modulations based on the influence of the signal-to-noise ratio. After that, we will talk about how accurate each method is. Using methodologies associated with applied machine learning, we also tried to establish which model has the highest accuracy for signal modulations based on the signal-to-noise ratio [4]. It is important to emphasize that we tried to work with a data set, a collection of radio signals with various waveforms that frequently occur in the HF bands. Panoradio SDR data was gated, a software-based radio receiver with an analogue-to-digital converter for taking samples of the antenna signal at 250 MHz. The fundamental objective of this study was to develop and demonstrate a generalized modulation recognition algorithm for the type recognition of modulated signals in an environment that contained polluted noise [5, 6]. We recommended a method that would begin with extracting and regulating one-of-a-kind data and then move on to classification methods. The PSK, QPSK, AM, and Morse modulations were discovered using a dataset presented in the next sections of this article. Many classification methods are presented to improve the classification accuracy, each tailored to a certain amount of noise pollution. The signal-to-noise ratio values correspond to 25, 20, 15, 10, 5, 0, -5, and -10 dB, and our data consists of 38400 signal vectors. Each signal vector includes 2048 complex IQ samples. Our model uses various classification methods for predictive purposes, including decision trees, random forests, support vector machines, and K-Nearest Neighbor.

In the papers mentioned above and our research, the amount of noise prevents recognising signals, whether analogue or digital. For this problem, we propose a model using machine learning methods to recognize the signals with a high signal-noise ratio.

## 2. Background and Literature Review

This section explains the backgrounds of modulation recognition and several studies of related works.

### 2.1. Modulation recognition (MR)

Modulation recognition is changing one or more possessions of a periodic waveform identified as the carrier signal by using a separate signal identified as the modulation signal. The modulation typically contains information that will be communicated, and modulation is the process by which this variation takes place. The domains of electronics and telecommunications are two examples of industries that put modulation to use. The modulation mode of a received signal may be determined using modulation recognition [7]. This approach is used when the content of the modulation information is unknown [8]. Our method recognizes modulation modes in four groups: Phase Shift Keying (PSK), Quadratic Phase Shift Keying (QPSK), Amplitude Modulation (AM), and Morse Code.

#### 2.1.1. Phase Shift Keying (PSK)

Phase shift keying, often known as (PSK), is a digital modulation method that shifts or modifies the starting phase of a carrier signal [9]. PSK abbreviates for "phase-shift keying." PSK is an abbreviation for Phase Shift Keying, a code encodes digital data such as binary numbers (0 and 1). Public-key cryptography (PSK) is often used in WLANs, Bluetooth, and RFID standards. These are the same technologies and standards used in biometric passports and contactless payment systems.

#### 2.1.2. Quadrative Phase Shift Keying (QPSK)

In the method of Phase Shift Keying known as QPSK (Quadrature Phase Shift Keying), two bits are modulated concurrently, and one of four probable carrier phase shifts (zero, ninety, one hundred eighty, or two hundred seventy is chosen [9]. Compared to standard PSK, QPSK allows a signal to convey double the amount of data while using the same amount of bandwidth as it would with standard PSK. Compared to traditional PSK, QPSK enables a signal to convey double as much data while using the same bandwidth as its predecessor. QPSK is a digital communication protocol used in various RF-carried digital communication systems, including satellite transmission of videos, cable modems, videoconferencing, and cellular phone networks. It is also used in other contexts where digital communication is carried via an RF carrier.

#### 2.1.3. Amplitude Modulation (AM)

One typical use of the modulation method known as amplitude modulation (AM) in an electronic communication is the transmission of data through radio waves [9]. The wave's amplitude (signal intensity) is modulated in amplitude modulation to change the message signal, which might be sound. In contrast to angle modulation, in which the frequency or the phase of the carrier waves is altered, this method alters the amplitude of the carrier wave [10].

### 2.1.4. Morse Code

Morse code is a system used in telecommunications to encode string characters as defined orders of two distinct signal periods referred to as dashes, dots, dits, and dahs. Samuel Morse, who contributed to the development of the telegraph, is honoured with the naming of the Morse code [11].

## 2.2. Literature Review

This section briefly discusses several works on signal modulation recognition systems and machine learning methods for modelling and classifying types of signal modulations.

Mustafa and Doroslovacki [12], Advise using four qualities to differentiate two-level and four-level amplitude shift keying, binary phase shift keying, quadrature phase keying, and two-carrier and four-carrier frequency shift keying. The authors present a novel classification approach using SVM and the four characteristics. They compare the SVM classifier to past scholarly work on digital modulation classification. According to the study, the SVM classifier consistently performs across simulations and probability levels. SVM beats dynamic tree and cumulant-based classifiers at 0 dB SNR. This is because the SVM classifier was changed to work with uncategorized data.

In another study (Hazar et al. [13]), the authors examine and contrast several machine learning algorithms for Automatic Modulation Recognition. They recommend nonnegative matrix factorization (NMF) and compare its usefulness to that of artificial neural networks (ANN), support vector machines (SVM), random forest trees (RFTs), k-nearest neighbours (k-NNs), Hoeffding trees, logistic regression (LR), and Naive Bayes. These are the most acknowledged feature extraction techniques in academic literature, and they are employed for communication modulation. Before submitting the initial AMR data set to Berkeley's machine learning repository, the authors evaluated and compared their recognition accuracy. This article compares nonnegative matrix factorization for Automatic Modulation Recognition to current machine learning algorithms. The article discusses AMR; automatic recognition utilizing NMF has not been studied in modulation studies. Throughout system building, additive white Gaussian noise was considered. Their investigation showed the system's recognition accuracy. Other approaches, particularly after SNR=5, are more accurate than NMF. NMF identification ranges from 60 to 90%, although this problem may be solved using parametric and structural methodologies in future research.

Researchers Hassanpour, Pezeshk and Behnia [14] proposed a pattern-based AMR approach. They focused on feature extraction blocks and digital modulation pattern identification, assuming AWGN, BASK, BFSK, BPSK, 4-ASK, 4-FSK, QPSK, and 16-QAM will be employed. To extract their attributes, signs are analyzed in time, frequency, and wavelet domains. A Binary SVM-based hierarchical structure is being studied to resolve the problem of multiple classes. Simulations show how the suggested characteristics enhance digital signal differentiation in a noisy environment with low SNR. Finally, a 98.15 percent accuracy rate was achieved with an SNR of -10dB, proving that this is the minimum required for flawless identification. The new characteristics' full potential was shown through graphs demonstrating predicted characteristic fluctuation with channel noise at particular signal-to-noise ratios (SNRs). Simulations on various random signals showed that the suggested feature set might be able to completely decouple digital modulation, even when the SNR is negative. After investigating and assessing the introduced features, an AMR technique based on pattern recognition was created, and these new features were used in the feature extraction block. The authors constructed a multiclass structure based on SVM binaries by using the essential features in each SVM. Comparable findings between the proposed structure and the OAO multiclass technique showed that the classification structure might be implemented with fewer binary SVMs. Experiments confirm the higher performance of the unique feature-based technique. It's better than any prior AMR campaign.

D. Sun et al. [15] replaced manual design characteristics with a deep learning intelligent modulation identification approach based on the VGG convolution neural network model (SNR). Traditional techniques of modulation recognition need specialist expertise in feature extraction. They sought to improve traditional approaches' ineffectiveness in low signal-to-noise circumstances (SNR). The approach converts sampled signal data into grayscale images. PyTorch-built VGGNet model automatically identifies and extracts characteristics from six digital modulation signals. This lets the application automatically recognize digital modulation signals. This technique can identify digital modulation signals even when the SNR is low, as evidenced by simulated findings that show the recognition rate can reach over 98% even when the SNR is -2 dB.

The authors, Y. Sun et al. [16], suggest using deep convolutional neural networks to identify signal modulation automatically. The program automatically extracts visual features using deep learning to recognize signal and noise in signal-to-noise ratio circumstances. This replaces the manual engineering of features. This solution uses the GPU to build VGGNet, which uses TensorFlow to differentiate 10 modulated signals in MPSK and MQAM automatically. Simulation findings show that signal identification accuracy is 96.7% at a 5 dB signal-to-noise ratio. The proposed strategy is better than before. The modulation mode is a major job of modulation recognition of communication signals, which has significant research significance since it may be utilized to discriminate between different systems' communication signals. In this study, a deep convolutional neural network-based signal modulation automated identification technology eliminates the difficulty of feature extraction and selection in standard algorithms and self-learns categorization features and modulation style recognition. Traditional algorithms cannot distinguish modulation styles. Thus, this was avoided. Simulation findings show the paper's approach is effective and practicable. They also show that the algorithm's performance stability in low SNR and the capacity to recognize different modulation modes will be the subject of future study.

Ansari et al. [17] introduce novel automated digital modulation detection approaches. These approaches emphasize digital modulations, including amplitude-shift keying, quadrature amplitude-shift keying, frequency-shift keying, quadrature frequency-shift keying, phase-shift keying, quadrature phase-shift keying, and 16-quadrature amplitude modulation. These modulations may be recognised and separated using k-nearest neighbours and probabilistic neural network approaches. After isolating modulations, employ them. MATLAB simulations expose our suggested approaches to an SNR of -30 dB to -30 dB over a channel of additive white Gaussian noise. Simulations indicate that utilizing the proposed methodologies, identifying the optimal collection of key characteristics, and properly adjusting the tuning parameters improve modulation type identification accuracy and speed. In comparison to earlier studies, the proposed techniques use the fewest classifiers and programmable parameters. A big development has occurred. Automated digital modulation identification requires high accuracy, low SNR, and little computational complexity. This work uses KNN and PNN to recognize digital modulations even when SNR is low. Proposed

AMR approaches use a classifier and six unique features. The recommended algorithms contain just one changeable parameter, unlike most others. The data shows that the algorithms achieved accuracy comparable to earlier research while reducing computations and classifiers. Proposed AMRs boost modulation detection by 88.5%. Future research may use AI approaches like evolutionary algorithms to find tweakable parameters.

## 3. Methodology

We used classification strategies to distinguish signal modulation due to the influence of the sig-nal-to-noise ratio. After that, we will talk about how accurate each method is. Using methodologies as-sociated with applied machine learning, we also tried to establish which model has the highest accuracy for signal modulation based on the signal-to-noise ratio. It is important to emphasize that we tried to work with a data set, a collection of radio signals with various waveforms that often occur in the HF bands. Panoradio SDR data was gated, a software-based radio receiver with an analogue-to-digital converter for taking samples of the antenna signal at 250 MHz. The major objective of this study was to develop and demonstrate a generalized signal modulation recognition approach that could be used for the type iden-tification of modulated signals in an environment that included polluted noise. We recommended a method that would begin with extracting and regulating one-of-a-kind data and then move on to classi-fication methods. Using a dataset shown in the previews portion of this research, we could recognize PSK, QPSK, AM, and Morse modulations. Many classification methods are presented to improve the classi-fication accuracy, each tailored to a certain amount of noise pollution. The signal-to-noise ratio values correspond to 25, 20, 15, 10, 5, 0, -5, and -10 dB, and our data consists of 38400 signal vectors. Each signal vector includes 2048 complex IQ samples. Our model uses various classification methods for predictive purposes, including decision trees, random forests, support vector machines, and kernel neural networks. The structure of the suggested model is shown in Figure 1.

### 3.1. Data Set

Radio waves of various waveforms, especially in the HF bands, make up our dataset. The data was generated synthetically using an AWGN channel model and random frequency and phase offset. The dataset allows us for signal and modulation classification experiments utilizing cutting-edge machine learning techniques like deep learning and neural networks.

The part of the dataset which we use has the following properties:

- 38,400 vectors of signals.
- A signal has 2048 IQ Samples
- Signals are centred in 0 Hertz
- Random frequency offset: +- 250 Hz
- Offset Phase at Random
- The Power of the Signal is Standardized
- Signal Noise Ranges are Between -10 to 25 dB
- 4 Modes of Modulations: PSK, QPSK, AM, Morse.

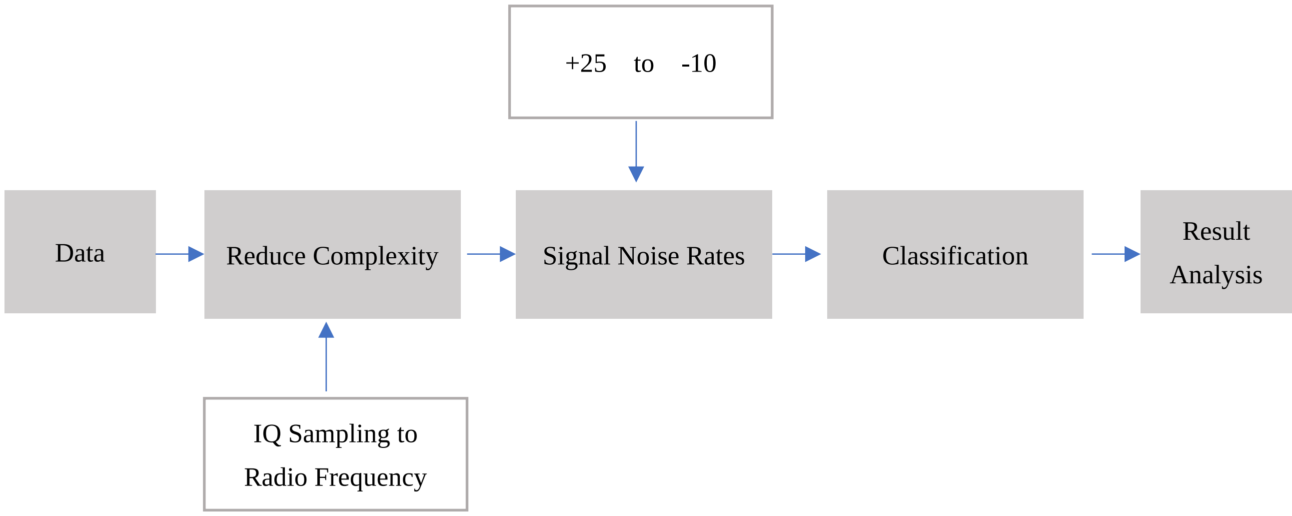


**Figure 1.** The Flow Diagram of The Proposed Model

### 3.2. Data Pre-Processing

One of the most crucial processes in every system is data processing. After any electronic data re-cording, it was necessary to clear the data of any missing or outlier data. Our data were synthesized us-ing the AWGN + Watterson Fading channel model and random frequency and phase offsets. The data was mainly processed by transforming it from complex to amplitude format using the procedure pro-vided in Eq1. And Eq2 shows the formula for converting to Phase format. Finally, the frequency is transformed to Radio Frequency (RF) using the formula stated in Eq3.

$$\sqrt{I^2 + Q^2} \tag{1}$$

$$\Phi=arctan\left(\frac{y}{x}\right) \quad (2)$$

$$RF= X(t)\, Cos\, (2\pi f_0\, t) - Y(t) Sin(2\pi f_0 t) \quad (3)$$

### 3.3. Evaluation Method

The proposed model code was written in Python, and a confusion matrix was utilized to estimate classification algorithms. This study used accuracy, precision, and recall percentage as comparative criteria. Accuracy determines the number of accurately recognized predictions; the formula is provided in Eq4. The ratio of accurately identified true positives to total positive samples is known as precision [5]. The sum of successfully classified and erroneously classified samples equals the number of positive samples. The recall percentage of correctly identified positive samples, total positive samples, and total false-negative samples are illustrated in Eq5. Eq6 depicts the formula.

$$Accuracy = \frac{total\ current\ prediction}{total\ prediction} \quad (4)$$

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

$$Recall = \frac{TP}{TP + FN} \quad (6)$$

## 4. Result Analysis

This study provides an accurate model prediction strategy for classification algorithms recognising digital and analogue signal modulation. We attempted to classify the data in amplitude and phase for-mat, which converted to absolute and tangent with the formula of Eq1 and Eq2, but the accuracy was poor. We strive to get the best accuracy by converting our complex data to Radio Frequency using Eq3 to go from higher to lower noise. The accuracy of Random Forest is higher than other algorithms for samples with lower SNR, which equals 0 to +25, and the accuracy of SVM modelling is higher for sam-ples with the highest SNR, which equals -5 to -10.

Table 1 and Figure 2 show that the accuracy of Random Forest is higher than other algorithms for samples with lower noise, and the accuracy of SVM modelling is higher for samples with the highest noise.

**Table 1.** The Accuracy of each Classification Method in Its Signal Noise Ratio (Just the amplitude of each complex number is considered.)

| SNR (dB) | 25 | 20 | 15 | 10 | 5 | 0 | -5 | -10 |
|---|---|---|---|---|---|---|---|---|
| RF | 80% | 81% | 79% | 78% | 70% | 70% | 64% | 64% |
| DT | 79% | 75% | 76% | 72% | 67% | 67% | 58% | 61% |
| SVM | 77% | 78% | 78% | 74% | 69% | 66% | 66% | 66% |
| KNN | 79% | 78% | 76% | 73% | 71% | 68% | 64% | 59% |

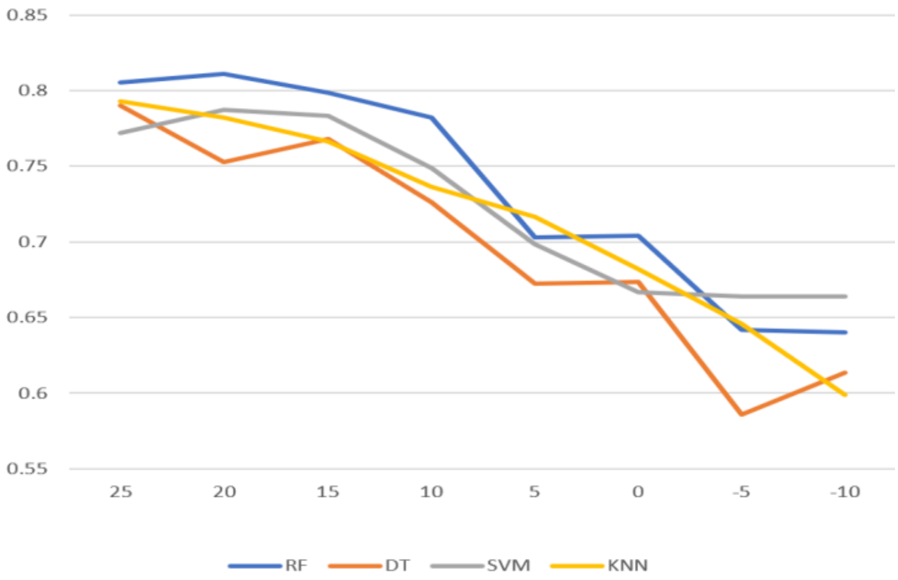


**Figure 2.** The Flow Diagram of Accuracy of Classification Methods Applying the Amplitude of samples considering their SNR

In Table 2, the fluctuation of the accuracy of the KNN model is higher than in other models. Therefore, its reliability is lower. And Figure 3 confirms that SVM is not sensitive to noise, although its accuracy is lower than other algorithms. Another concluded fact from Figure 3 is that RF is the better choice for modelling the phase of samples, although the accuracy of this model is not significant.

**Table 2.** The Accuracy of each Classification Method in Its Signal Noise Ratio applying the phase of samples

| SNR (dB) | 25 | 20 | 15 | 10 | 5 | 0 | -5 | -10 |
|---|---|---|---|---|---|---|---|---|
| RF | 57% | 54% | 58% | 54% | 56% | 55% | 56% | 55% |
| DT | 50% | 52% | 53% | 52% | 52% | 48% | 50% | 53% |
| SVM | 49% | 49% | 49% | 49% | 49% | 49% | 49% | 49% |
| KNN | 48% | 52% | 50% | 51% | 52% | 52% | 58% | 51% |

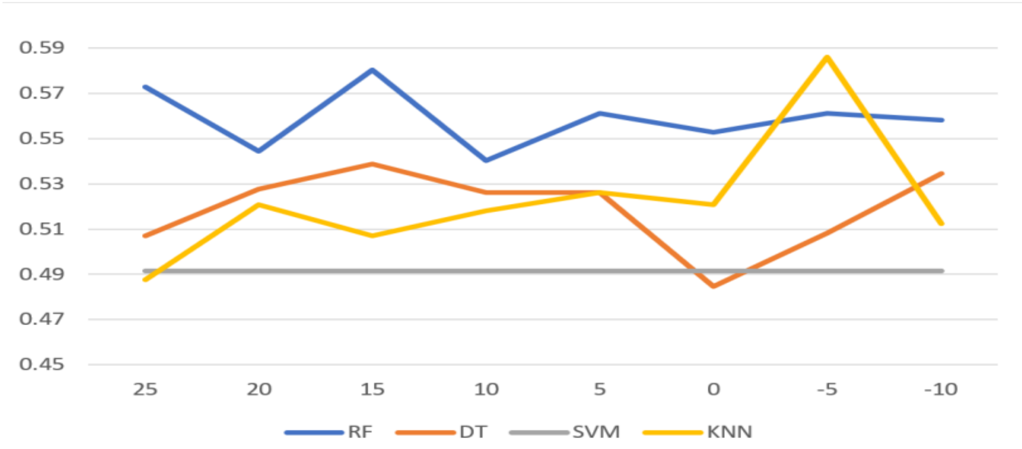


**Figure 3.** The Flow Diagram of Accuracy of Classification Methods applying the phase of samples

**Table 3.** The Accuracy of each Classification Method in Its Signal Noise Ratio by Converting the Complex number to Radio Frequency Format

| SNR (dB) | 25 | 20 | 15 | 10 | 5 | 0 | -5 | -10 |
|---|---|---|---|---|---|---|---|---|
| RF | 78% | 76% | 75% | 75% | 67% | 66% | 61% | 64% |
| DT | 73% | 71% | 72% | 66% | 64% | 65% | 61% | 59% |
| SVM | 74% | 74% | 73% | 70% | 68% | 66% | 66% | 66% |
| KNN | 73% | 73% | 71% | 72% | 64% | 62% | 60% | 61% |

We attempt to acquire the greatest accuracy by converting our complexing data to Radio Frequency utilizing Eq 3 to proceed from higher to lower noise, as shown in Table 2. Figure 4 provides a flow chart illustrating the accuracy of each classification technique in different signal noise ratios and demon-strates each approach's sensitivity as a formula of the signal noise ratio.

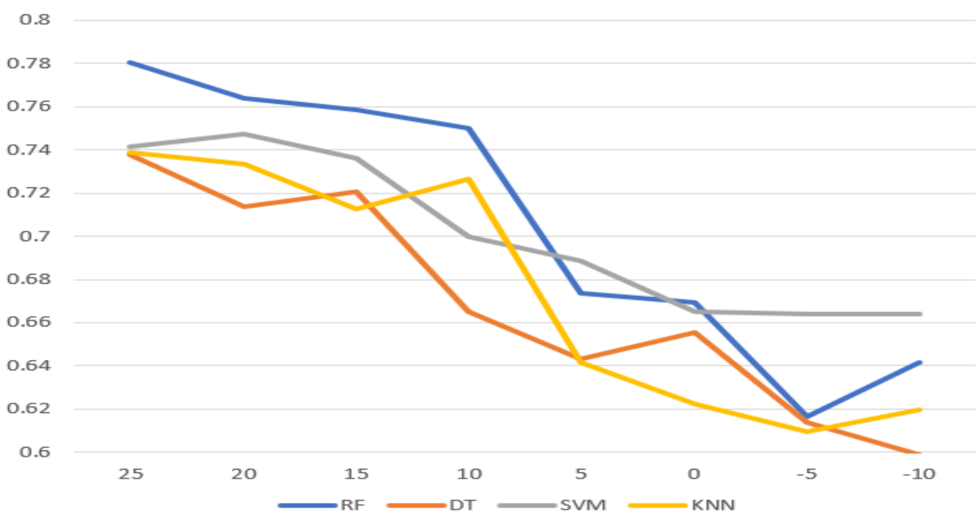


**Figure 4.** The Flow Diagram of Accuracy of Classification Methods by their SNR by Converting the Complex number to Radio Frequency Format

## 5. Conclusion

The data is converted to RF format from IQ presentation. This research analyzes and categorizes modulation types with different Signal Noise Rates, ranging from -10dB to +25dB. It classifies the modulation type using four machine learning algorithms: Decision Tree, Random Forest, Support Vec-tors Machine, and k-nearest neighbours. The results show that applying the RF formula and the original data, the random forest algorithm has higher accuracy (78%) for lower noise rate affected signals, and the Support Vector Machine algorithm shows better results for high noise rate affected signals (67%). This paper's great outcome is proving the effectiveness of different classification methods for different levels of noise-contaminated signals. The privilege of the SVM is lower changes of accuracy with SNR changes.

**Declaration of Competing Interest** The authors declare that they have no known competing of interest.

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