Original Research Paper

Intelligent Digital Signal Modulation Recognition using Machine Learning

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Abstract: In recent years, modulation type recognition has received a lot of attention across the board. There are several methods to detect modulation types, but there are only a few effective methods to handle signals with a higher level of noise. This study introduces an approach to verify the ability of different machine learning algorithms to automatically manage noise in detecting digital modulations. This research examines two of the most common digital modulations, Phase Shift Keying and Quadrature Phase Shift Keying. A signal noise rate ranging from-10 to +25 dB is used to identify these modulations and use PCA to reduce the number of features and the data complexity. We used machine learning algorithms like Decision Tree, Random Forest, Support Vectors Machine and k-nearest neighbors to identify the modulation type. Our proposed method considers signals' features after proper shifting of the IQ and RF signals samples. The findings show that the proposed method successfully recognizes the signals with higher noise levels. The random forest algorithm presents better results with low noise levels and SVM with higher noise levels.

Keywords: Digital Modulation, PSK, QPSK, SNR, Machine Learning, Decision Tree, Random Forest, SVM, KNN

Introduction

Establishing a reliable link between the two communication nodes is one of the most basic aims of communication systems. Many signals in space are constantly modulated using various modulation techniques due to different receivers and transmitters. Encoding a digital wave into the transmitted signal's phase, amplitude and frequency is defined as digital modulation. Several sets of measurable parameters exist depending on the modulation applied to the signal. Knowing the modulation type allows valuable information to be extracted from these parameters. We can identify the modulation scheme of the requested signal using automatic modulation recognition. The Signal Noise Ratio (SNR) compares the desired signal to the background noise level in science and engineering. The SNR is frequently given in decibels and is defined as the ratio of signal power to noise power. With the rapid expansion in computer storage capacity and processing power, the machine learning area, which may be defined as enabling computers to make compelling predictions based on past experiences, has seen spectacular growth recently. Machine learning approaches have been widely applied in the communication business and many other areas. Due to the difficulty and cost of signal analysis, advanced machine learning algorithms for this application area have been developed. In this study, we employed classification methods for recognizing digital modulation by the effect of the signal-noise ratio. Then we discuss how accurate each technique is. We also attempted to determine which model has the best accuracy for digital signal modulation based on signal noise ratio using applied machine learning methods. It is worth highlighting that we attempted to work with a data set, a collection of radio signals with various waveforms that often occur in the HF bands. Pan radio Software Defined Radio (SDR) data was gated, a software-based radio receiver with the analogue-to-digital converter for samples of the antenna signal at 250 MHz.

Structure and Motivation of the Research

The primary goal of this research was to create and demonstrate a generalized digital modulation recognition method for the type recognition of modulated signals in a contaminated noise environment. We suggested a technique with unique data extraction and regulation followed by classification algorithms. Different algorithms for different noise contamination levels are proposed to boost classification accuracy.

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Literature Review

Several works on intelligent systems and machine learning methods for recognizing digital signal modulation are briefly discussed in this part.

To identify two levels and four levels of amplitude shift keying, binary phase-shift keying, quadrature phase keying and frequency shift keying with two carriers and four carriers, the authors of (Hassanpour *et al*., 2016) employed four features. They also provided a new Support Vector Machine (SVM) based classification approach that incorporates the four proposed features. They also demonstrated the effectiveness of the SVM classifier and compared it to earlier work on the digital modulation classification problem.

In their article, the authors of (Sun *et al*., 2019) assessed the performance of various machine learning methods for AMR. They offered the non-Negative Matrix Factorization (NMF) technique in particular. They also analyzed the knearest neighbor and support vector machines validity, artificial neural networks performance and random forest tree applicability to achieve comparable results.

This study's authors (Zhang *et al*., 2017) suggested an automatic recognition approach for communication signal modulation type in low SNR. Three characteristics were chosen based on signal entropy analysis as a feature set. They use the random forest as a classification approach to achieve a high recognition rate of multiple communication signal modulation types in low SNR. The method achieved outstanding performance in recognizing signal types under various Signal-to-Noise Ratios, as proved by simulation (SNR). Apart from QPSK signals, the signal recognition rate was greater than 95% when the SNR was greater than 5 dB (Hazar *et al*., 2018; Mughal and Kim, 2018).

A convolution neural network was used in the paper (Jiang *et al*., 2020) to apply a symmetrical structure to extract the frequency domain for bidirectional long short-term memory and timing features of signals. They assigned the importance weights based on the attention mechanism to complete the recognition task. The simulation test used six famous digital modulation methods, i.e., 4FSK, 2ASK, 4ASK, QPSK, BPSK, 8PSK and 64QAM. The results showed higher recognition accuracy for the proposed algorithm at lower SNR than the classical machine learning algorithm. The proposed modulation recognition method has been confirmed to have higher accuracy in noncooperation systems.

There are several methods in the literature for handling uncertain and noised data. Our strategy for handling noise is similar to handling uncertain data, which is discussed in the insecure avoider method proposed in (Mahela *et al*., 2020; Baek *et al*., 2019). There is a discussion on uncertain data in (Aminifar, 2020; KekShar and Aminifar, 2020). The ECG signals were analyzed in an uncertain environment, similar to radio frequency signals in (Aminifar and Marzuki, 2013).

The authors of the papers (Aminifar, 2014) and (Abd and Aminifar, 2022) proposed new approaches for automatically identifying digital modulations. Their study concentrated on phase-shift keying, quadrature phase-shift keying, amplitude shift keying, frequency-shift keying, quadrature amplitude shift keying, frequency-shift keying, quadrature and 12 quadrature amplitude modulation, among other types of digital modulations (Marzuki *et al*., 2014). The authors of the paper (Ansari *et al*., 2020; Jajoo *et al*., 2017) proposed a modulation recognition and separation method by choosing useful features from the modulated signal for identifying the modulation type using a decision tree and probabilistic neural network methods. They were conducted using MATLAB simulations with a signal-to-noise ratio over an additive white Gaussian noise channel. The results showed that picking useful features and establishing tuning parameters significantly improved modulation type recognition accuracy and speed. The proper circuits are proposed in the paper (Aminifar *et al*., 2006).

The outcomes of the review paper (Venkata Subbarao and Samundiswary, 2020) and research paper (Jader and Aminifar, 2022) show the effectiveness of machine learning algorithms for digital modulation detection compared to other mathematical and statistical methods.

Study (Zhang *et al*., 2020) introduces SVM to build a stock selection model that can classify stocks nonlinearly. SVM classification accuracy depends on training set quality. To avoid using sophisticated and highly dimensional financial ratios, we utilize PCA to extract lowdimensional and efficient feature information, which increases training accuracy and efficiency and preserves initial data characteristics. Based on the support vector machine, within PCA after norm standardization, the stock selection model achieves 75.446% accuracy in training and 61.7925 in test sets.

There are the most popular feature extraction methods in the literature (Liu *et al*., 2017) and they are used to extract features from a variety of modulation patterns for generalpurpose communication. The authors of the research compared their accuracy metric recognition performance.

The feature extraction method discussed in (Punith Kumar and Shrinivasan, 2017) does not apply to the noised environment. Our proposed extraction method is novel, showing better results for noise-contaminated signals.

Background

The act of sending information from one place, person, or organization to another is communication. A sender, a message and a recipient are all part of every communication. Noise is a mistake or unwanted random disturbance of a helpful information signal in communication systems. The noise is a collection of undesired or distracting energy from natural and artificial sources.

Modulation Recognition

When the content of modulation information is unknown, modulation recognition is a technique for determining the modulation mode of a received signal (Baek *et al*., 2019). Phase Shift Keying (PSK) and Quadratic Phase Shift Keying (QPSK) are the modulation modes classified by our model (QPSK).

PSK: Phase-Shift Keying (PSK) is a digital modulation system in which the beginning phase of a carrier signal is changed or modulated. PSK is a code that represents digital data such as binary digits zero (0) and one (1). (1). PSK is commonly utilized in Wireless Local Area Networks (WLAN), Bluetooth technology and Radio Frequency Identification (RFID) standards, which are employed in biometric passports and contactless payment systems.

QPSK: QPSK (Quadrature Phase Shift Keying) is a type of Phase Shift Keying in which two bits are modulated simultaneously and one of four possible carrier phase shifts is chosen (0, 90, 180, or 270 degrees). QPSK allows a signal to convey twice as much data in the same bandwidth as regular PSK. QPSK enables a signal to convey twice as much data in the same bandwidth as regular PSK. QPSK is a digital communication protocol for satellite transmission of MPEG2 video, cable modems, videoconferencing, cellular phone systems and other digital communication over an RF carrier.

Machine Learning

Data traffic and signal noise are predicted to continually challenge the capacity of future communication networks in the period of the new generation of communication systems. New communications use, such as wearable devices, autonomous systems, drones and the Internet of Things (IoT), continue to develop and generate considerably more data traffic with dramatically differing performance needs, alongside the tremendous expansion in data traffic. As the application domain expands, more intelligent processing, operation and optimization of future communication networks will become necessary. To accomplish this vision of intellectual processing and process, ML, also known as AI vessels, must be integrated into designing, planning and optimizing future communication networks (Hazar *et al*., 2018).

Decision Tree: A DT is a technique for partitioning data based on certain factors. This was one of the supervised learning methods. The goal is to master basic decision tree instructions so that you can create a concept that predicts the value of a target variable. It is perfect for ongoing education. The decision tree frequently follows the rules expressed as if-then-else statements. DT is used for classification.

Random Forest: Is a dimensionality reduction technique that creates a classification using several decision trees. It is an example of a classification and other work using an ensemble technique. It can be used to rank variables according to their importance.

Support Vector Machine: Work by locating a hyperplane line that divides the negative and positive samples with the most significant margin. The goal of a support vector machine is to find a hyperplane that classifies data points in Multidimensional Features.

K-Nearest Neighbor: KNN is only simulated locally, with calculations deferred until the classification is complete. One of the most basic machine learning techniques is the KNN algorithm. The KNN is a simple supervised machine learning technique that can be used to handle classification and regression problems. It is simple to set up and comprehend, but it is noticeably slower as the amount of data in use grows.

Principal Component Analysis (PCA)

Is a statistical technique for producing a manageable number of "summary indices" from a huge data set for visualization and analysis purposes. It is one of the most used machine learning techniques in many settings, including exploratory data analysis, dimensionality reduction, information compression and data de-noising.

Methodology and Proposed Model

Our data comprises 19200 signal vectors, each signal vector has 2048 complex IQ samples and the signal-noise ratio values equal values of 25, 20, 15, 10, 5, 0, -5, -10 dB. Our model employs classification techniques such as decision tree, random forest, SVM and KNN for prediction. Figure 1 presents the proposed model structure.

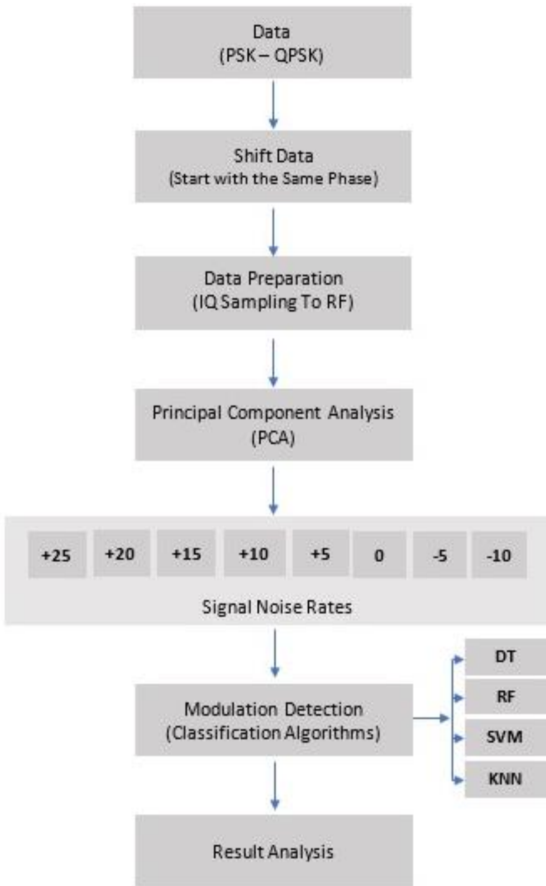

Fig. 1: The flow diagram of the proposed model

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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 with Watterson Fading (to account for ionospheric propagation) 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 (https://panoradio-sdr.de/radio-signalclassification-dataset/).

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

- 19,200 signal vectors
- Each signal vector has 2048 complex IQ samples with fs = 6 kHz (duration is 340 ms)
- The signals (resp. their actual bandwidths) are centered at 0 Hz (+- random frequency offset)
- Random frequency offset: +- 250 Hz
- Random phase offset
- Signal power is normalized to 1
- SNR values: 25, 20, 15, 10, 5, 0, -5, -10 dB
- Fading channel: Watterson Model as defined by CCIR 520
- 2 Transmission Modes/Modulations: PSK, QPSK

Data Pre-Processing

One of the most crucial processes in every system is data processing. After any electronic data recording, it was necessary to clear the data of any missing or outlier data. Our data were synthesized using the AWGN + Watterson Fading channel model and random frequency and phase offsets. The data mainly was processed by transforming it from complex to amplitude format using the procedure provided in Eq. 1. Equation 2 shows the formula for converting to Phase format. Finally, the frequency is transformed to Radio Frequency (RF) using the formula stated in Eq. 3:

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

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

$$RF = X(t)Cos(2\pi f_0 t) - Y(t)Sin(2\pi f_0 t) \tag{3}$$

Classification of signals considering SNR

Every sample or recorded data contains noise in a different range, referred to as the (SNR) Signal Noise Ratio, with values of 25, 20, 15, 10, 5, 0, -5 and -10 dB. We use machine learning techniques such as Decision Tree, Random Forest, Support Vector Machine (SVM) and K-Nearest Neighbor to classify data groups based on their SNR and determine their transmission mode (KNN).

Materials and Methods

The proposed model code was written in Python and a confusion matrix was utilized to estimate classification algorithms. In this study, we used accuracy, precision and recall percentage as some of the comparative criteria. Accuracy determines the number of accurately recognized predictions and the formula is provided in Eq. 4. The ratio of accurately identified true positives to total positive samples is known as precision. 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 Eq. 5. Equation 6 depicts the formula:

$$Accuracy = \frac{total\, currect\ prediction}{total\ prediction} \tag{4}$$

$$Precision = \frac{TP}{TP+FP} \tag{5}$$

$$Recall = \frac{TP}{TP+FN} \tag{6}$$

Results and Discussion

This study provides an accurate model prediction strategy for classification algorithms to recognize digital signal modulation. We attempted to classify the data in amplitude and phase format, which converted to absolute and tangent with the formula of Eq 1 and Eq 2, but the accuracy was poor. The results are shown in Table 1 and 2, Fig. 2 and 3. We strive to get the best accuracy by converting our complexing data to Radio Frequency using Eq 3 to go from higher to lower noise, as shown in Table 3. Figure 4 shows a flow chart showing the accuracy of each classification method in various signal noise ratios. Figure 3 shows the sensitivity of each approach as a function of the signal-noise ratio.

Figure 2 shows that the accuracy of Random Forest is higher than other algorithms for samples with lower SNR and the accuracy of SVM modelling is higher for samples with the highest SNR.

Table 2 confirms the same results obtained from Fig. 2. It can be clearly understood the fluctuation of the accuracy of the KNN-based model is higher than in other models. Therefore, its reliability is lower 3.

Figure 3 confirms that SVM is not sensitive to noise, although its accuracy is lower than other algorithms. Another concluded fact from Fig. 4 is that RF is the better choice for modelling the phase of samples, although the accuracy of this model is not significant.

Table 4 shows the Accuracy of each Classification Method, for SNR = 25 and Table 5 shows The Accuracy of each Classification Method for SNR = 10.

The accuracies are shown for SNR=0 and SNR=-10 in Table 6 and 7, respectively.

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	0	5	0	-5	-10
RF	0.80	0.81	0.79	0.78	0.70	0.70	0.64	0.64
DT	0.79	0.75	0.76	0.72	0.67	0.67	0.58	0.61
SVM	0.77	0.78	0.78	0.74	0.69	0.66	0.66	0.66
KNN	0.79	0.78	0.76	0.73	0.71	0.68	0.64	0.59

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	0.57	0.54	0.58	0.54	0.56	0.55	0.56	0.55
DT	0.50	0.52	0.53	0.52	0.52	0.48	0.50	0.53
SVM	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49
KNN	0.48	0.52	0.50	0.51	0.52	0.52	0.58	0.51

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	0.78	0.76	0.75	0.75	0.67	0.66	0.61	0.64
DT	0.73	0.71	0.72	0.66	0.64	0.65	0.61	0.59
SVM	0.74	0.74	0.73	0.70	0.68	0.66	0.66	0.66
KNN	0.73	0.73	0.71	0.72	0.64	0.62	0.60	0.61

Table 4: The Accuracy of each Classification Method, SNR = 25 (with different number of features)

SNR (25)	2048	1024	512	256	128	64	32
RF	0.78	0.70	0.72	0.74	0.72	0.76	0.76
DT	0.73	0.67	0.67	0.69	0.70	0.69	0.73
SVM	0.74	0.78	0.78	0.78	0.78	0.78	0.78
KNN	0.73	0.73	0.73	0.73	0.73	0.74	0.73

Table 5: The Accuracy of each Classification Method, SNR = 10 (with different number of features)

SNR (10)	2048	1024	512	256	128	64	32
RF	0.75	0.72	0.71	0.72	0.74	0.75	0.74
DT	0.67	0.67	0.66	0.68	0.64	0.68	0.67
SVM	0.70	0.77	0.77	0.77	0.77	0.77	0.77
KNN	0.73	0.73	0.73	0.73	0.73	0.72	0.73

Table 6: The Accuracy of each Classification Method, SNR = 0 (with different number of features)

SNR (0)	2048	1024	512	256	128	64	32
RF	0.67	0.65	0.64	0.66	0.68	0.65	0.67
DT	0.66	0.63	0.62	0.62	0.63	0.61	0.64
SVM	0.67	0.69	0.69	0.69	0.69	0.69	0.69
KNN	0.62	0.62	0.62	0.62	0.62	0.62	0.61

Table 7: The Accuracy of each Classification Method, SNR = -10. (with the different number of features)

SNR (-10)	2048	1024	512	256	128	64	32
RF	0.64	0.62	0.59	0.59	0.60	0.63	0.61
DT	0.60	0.63	0.57	0.62	0.58	0.63	0.62
SVM	0.66	0.66	0.66	0.66	0.66	0.66	0.67
KNN	0.62	0.62	0.62	0.62	0.62	0.61	0.61

Furthermore, we examine how the effect of signal noise ratio affects the sensitivity of each ML method and it shows the range of sensitivity for the RF algorithm in Fig. 5, DT algorithm in Fig. 6, SVM algorithm in Fig. 7 and KNN algorithm in Fig. 8. The RF technique has a sensitivity range of 0.61 to 0.78, the decision tree has a range of 0.59 to 0.73, KNN has a range of 0.60 to 0.73 and SVM has a range of 0.66 to 0.74. Finally, the SVM was discovered to be less sensitive.

Figure 5 to 8 show that SVM accuracy changes are low with increasing noise. Random forest shows better accuracy in lower noise than SVM, but accuracy decreases significantly by increasing SNR of radio frequency samples. As mentioned above, 2048 features were used in the dataset, but due to the program's complexity, we tried to reduce the number of features using the PCA algorithm. As a result of this process, we have reduced the complexity without affecting the model's accuracy, which is illustrated in the tables and figures below. The Results show that the SVM algorithm doesn't have sensitivity before and after using PCA.

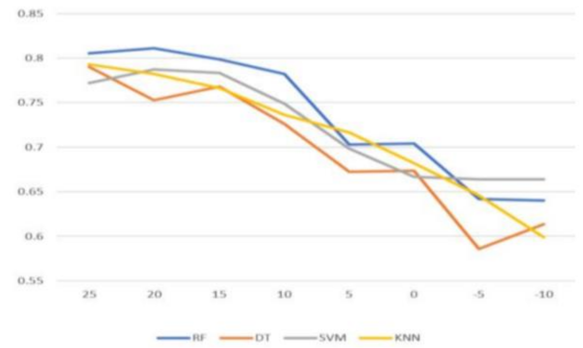

Fig. 2: The flow diagram of accuracy of classification methods applying the amplitude of samples considering their SNR

Fig. 3: The flow diagram of accuracy of classification methods applying the phase of samples

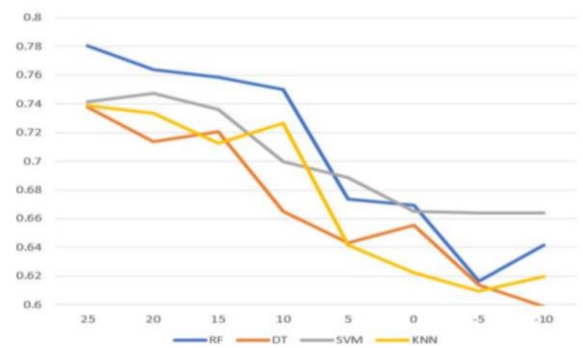

Fig. 4: The flow diagram of accuracy of classification methods by their SNR by converting the complex number to radio frequency format

Fig. 5: The flow diagram for sensitivity of RF by SNR

Fig. 6: The flow diagram for sensitivity of DT by SNR

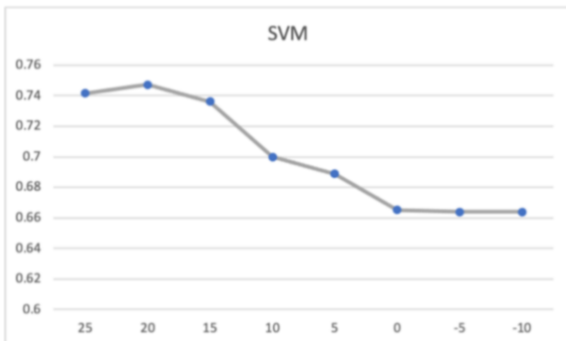

Fig. 7: The flow diagram for sensitivity of SVM by SNR

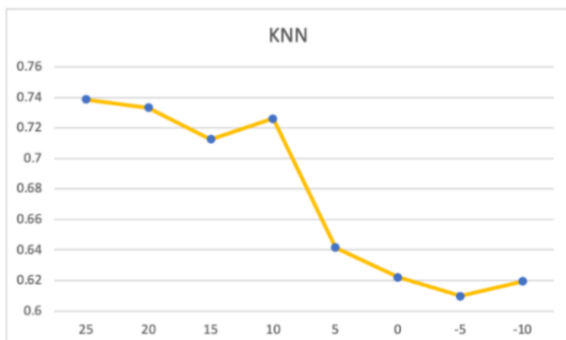

Fig. 8: The flow diagram for sensitivity of KNN by SNR

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 -10 dB to +25 dB and uses PCA to reduce the number of features and the data complexity. Furthermore, it classifies the modulation type using four machine learning algorithms: Decision Tree, Random Forest, Support Vectors Machine and k-nearest neighbors. The results show that the random forest algorithm has higher accuracy (88%) for low and medium noise rate affected signals. The Support Vector Machine algorithm shows better results for high noise rate affected signals (71%). The mean accuracy for all applied data is 73% for Decision Tree, 73% for Random Forest, 78% for support vectors machine and 74% for k-nearest neighbors. This study 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.

Authors Contributions

Mudhafar Haji Mala Abd: Participated in all experiments, coordinated the data-analysis and contributed to the writing of the manuscript.

Sadegh Aminifar: Designed the research plan, coordinated the data-analysis and organized the study.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and no ethical issues involved.

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