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Improvement of signal detection based on using machine learning

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HIGHLIGHTS

- This study performed signal detection for various types of modulated signals
- Simulations used pre-processing steps like fading noise, Gaussian noise, low-pass filtering for real-world scenarios
- Features like energy, power, skewness, kurtosis, zero-crossing rates, phase differences were statistically extracted
- Applying features to an SVM classifier achieved 98.72% detection accuracy across various noisy signal types

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ABSTRACT

During the communication system development over the years, detecting and identifying the signal from the affected noise had the major role and the most attention from the researchers. The deep learning algorithm has become a very attractive tool for distinguishing between signal and noise. Learning and training are the two important steps in designing any deep learning system. The proposed system depends on the support vector machine (SVM). The SVM is one of the most popular learning algorithms in different fields, such as signal processing, image processing, communication, and pattern recognition. The SVM classifier is a supervised learning algorithm that uses the closest data points as "support vectors" to build a hyperplane that divides classes. SVM is used to identify the large RADIOML 2018.01A dataset with various signal schemes. The paper strongly emphasized extracting the dataset's most essential features, which improved Support Vector Machines' capacity to detect signals in noisy and complicated situations. The measured accuracy for the SVM classier for QPSK, 8PSK, and 16 QAM equals 99.7%, 99%, and 99.6%, respectively. The final measured results show the proposed detection system's correctness, robustness, and flexibility based on utilizing the Support Vector Machines (SVM) classifier; this classifier approves its efficacy in signal detection.

1. Introduction

Radio signal processing is essential in engineering and all generations of wireless networks. The proliferation of advanced wireless technologies and ubiquitous connectivity has increasingly emphasized the need for an efficient and intelligent approach to processing radio signals [1]. In practical wireless communication systems, signals encounter various challenges stemming from the transmitter, radio frequency chain, and receiver, featuring components such as flexible coherent receivers. Also, the environment is pretty complex, and it is vulnerable to various interferences that change the nature of the transmitted signals. When signals travel, channel conditions can cause attenuation and distortion. Things like multipath propagation and Doppler shifts can even delay how quickly signals get through. To make matters worse, interference from other wireless devices and environmental noise can hurt how we detect those signals. Plus, essential factors such as signal bandwidth, sampling rate, and symbol rate really determine how accurate everything is.

It's interesting to note that our chosen modulation scheme affects how tough it is to detect these signals [2,3]. This paper mentions different machine-learning algorithms for signal detection and classification. However, the Support Vector Machine (SVM) classifier is considered one of the most common supervised classification algorithms used in signal classification and detection under the effect of noise [4]. This paper is divided into four sections: the first describes some of the previous work performed in modulated signal detection, and the second determines the methodology or way of designing the proposed system. The third discusses the result of the designed system and compares it with previous implementations. The final part of this paper is related to determining the conclusion of this work, in which the essential points are determined.

Various studies have been conducted in the field of communication systems, particularly in detecting modulated signals. Mingyang Du et al. [5], proposed an efficient classification and denoising system, known as DNCNet, for radar data. DNCNet consists of subnetworks for both denoising and categorization. The denoising subnetwork generates paired clean and noisy data

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using a unique radar signal classification and synthesis method. A two-stage training strategy is suggested to learn the network's denoising subnetwork efficiently. The denoising subnetwork is initially trained, and subsequently, its denoising outcomes and visual representation are strengthened to enhance the network's overall performance. The DNCNet stands out because it can control how radar signals are restored. It uses a unique 2D picture whitening method that fits with a 1D laser beam. The authors used a neat two-phase training method to ensure accurate classification. This technique helps improve the denoising process and also boosts how well the denoised results match what the classifier perceives. They used benchmark and synthetic datasets, showing evidence that DNCNet works excellently. In addition, they looked at all kinds of noise to make the research thorough. This included stochastic colored random noise, impulsive noise, and the usual additive white Gaussian noise [5].

Yang et al. [6], introduced an innovative technique for Automatic Modulation Classification (AMC) inspired by deep learning. Their work addresses a significant challenge in the field: the availability of sufficient labeled examples. Unlike traditional deep learning methods that rely heavily on large amounts of labeled data, this approach employs few-shot learning, providing a practical solution for scenarios where labeled data is scarce, a common issue in real-life applications. The authors' clever solution mixes signal modification tricks, and meta-learning strategies. This combo helps tackle the challenges of limited sample sizes and boosts class separation. The authors showed the utility of the proposed few-shot AMC technique using simulated experiments with the RadioML 2018.01A dataset. Notably, even with just a single sample per class, the technique achieves an excellent 74.21% classification accuracy. The accuracy jumped to 82.27%, slightly boosting to five examples per class. These findings highlight the approach's usefulness and show that it outperforms classic deep learning techniques, especially in cases where labeled data is few. Zhang et al. [7], proposed a modified recognition technique based on bidirectional feature fusion to enhance recognition performance across various channels. The suggested method begins with gathering different time- and frequency-domain features, which are subsequently sent into the computer network for conditioning signals.

Deep convolutional NNs based on the innovative residue contraction builder unit plus channel-wise thresholds (RSBU-CW) extract spatial properties. When spatial features interact with time information retrieved using LSTM, they produce diverse feature pairs [8,9]. The Mostly Shared Neural Network, the Probabilistic Neural Network (PNN) model, is adjusted to cross-fuse the network's extracted features, strengthening their redundancy and increasing the feature set further. The simulation results reveal that the recommended approach outperforms existing feature fusion approaches. Even in challenging multipath fading channels, the approach works effectively for recognition. Analyses using the publicly accessible dataset RadioML 2018.01A demonstrate exceptional accuracy, exceeding 95%, particularly when SNR is near 8 dB [10]. Automatic Modulation Classification (AMC) is an essential technology used in CRNs to use the available bandwidth best. Classical likelihood-based approaches, on the other hand, suffer from a high computational cost. To solve the problem, Kim et al. [11], proposed a novel convolutional neural network design for AMC applications. A bottleneck and asymmetric convolution structure reduce computational complexity in this approach. This approach's fundamental features are jumps to solve vanishing gradients and improve classification accuracy. The model classifies well across SNRs (-4 dB to 20 dB) using the 24 modulation classes from the RadioML 2018.01A dataset [10].

Cognitive radio (CR) challenges include automatic modulation categorization (AMC), which might boost spectrum efficiency. Kim et al. [11], introduced a hybrid deep learning model for AMC in CR settings using image- and signal-based approaches. Two CNNs are integrated into the suggested technique. The first, signal-based CNN (SBCNN), has the optimal filter size for prediction accuracy. A deep learning network is pre-trained by SBCNN to extract 24×1 characteristics from input signals. The image-based CNN is trained and evaluated after converting these characteristics into RGB heat map pictures with a scale range of -30 to +30. DeepSig: RADIOML 2018.01A yields encouraging results for IBCNN in experimental assessment [12]. Deep learning (DL) has transformed communication, computer vision, and signal processing research. Convolutional neural networks (CNNs) can automatically learn features without domain expertise, unlike typical machine learning (ML) methods. On the strength of DL's image classification success [13], presents a CNN-based solution for automated modulation categorization, a key problem in current communication systems. Parallel blocks of asymmetric convolutional layers and depth-concatenation of reusable features to aggregate deep features at many scales and skip-connections to counteract vanishing gradients are used in the CNN design. On the DeepSig: RadioML dataset, this approach classifies 24-modulation at +10 dB SNR with 85.10% accuracy.

2. Methodology

Signal detection is crucial in several domains, including medical imaging, sonar, and radar. Machine learning algorithms have become essential tools in this context. The application of Support Vector Machines (SVMs), a supervised learning algorithm intended to categorize data into distinct classes, is a popular technique for signal detection. Support vector machines (SVMs) accomplish this by finding a hyperplane in the data that successfully divides these classes; the data points closest to this hyperplane are called support vectors. The SVM-based approach for signal detection is depicted in Figure 1.

The first step in using SVMs for signal detection is to create a labeled dataset with various modulation schemes, such as QPSK, 8PSK, and QAM (16, 32, 64, 128, and 256). The study incorporates noise and develops models consistent with the classification goal to simulate real-world settings.

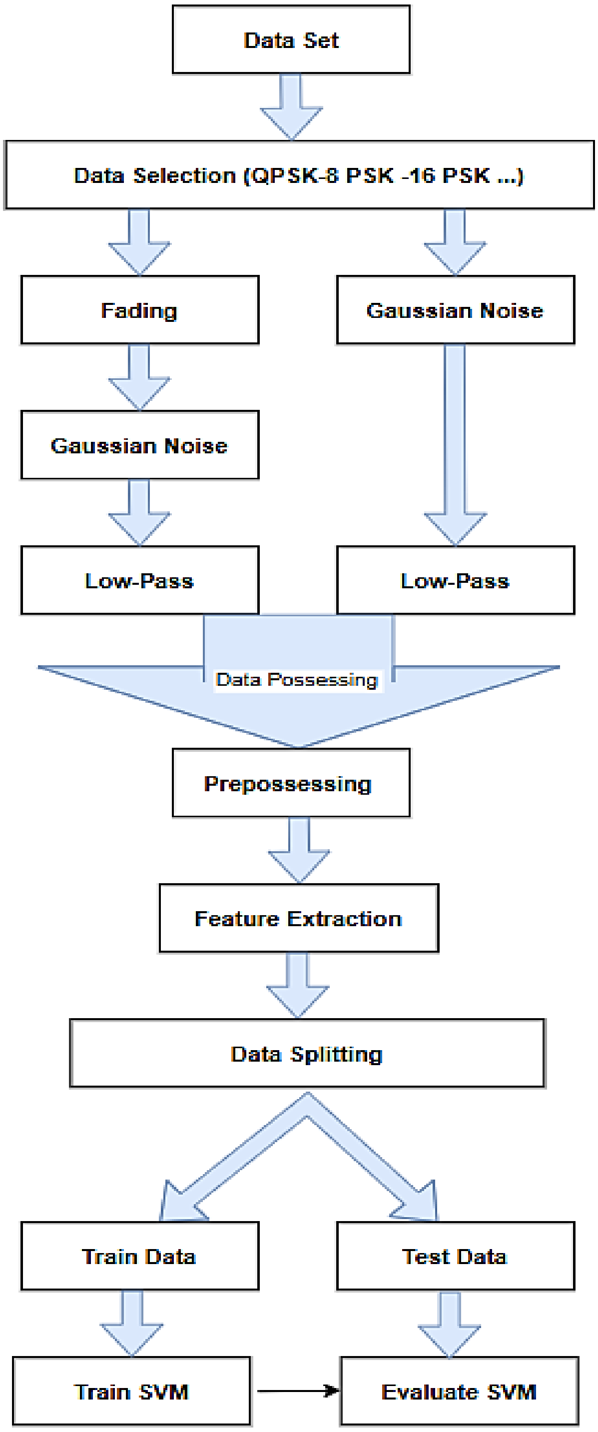

Figure 1: The proposed methodology

Then, relevant features are removed from the data to help the SVM differentiate signals better. By carefully training the SVM on this enhanced dataset, the algorithm can efficiently identify and categorize signals in fresh data by determining how close they are to the learned hyperplane. Thus, SVMs demonstrate their worth as reliable instruments for signal detection in various noisy signal situations.

2.1 Dataset description and selection

O'Shea et al. [13], generated RadioML 2018.01A datasets. The 24 different modulators covered a wide range of single-carrier modulation schemes. The study investigated multiple propagation situations, such as Over-The-Air (OTA) transmission channels of clean signals free of artificial weakness and simulated wireless channels created from a particular model. A root-raised cosine pulse shaping filter with different roll-off values (α) was used to shape digital signals [14]. For each instance in the synthetic datasets, random values were chosen for several variables, resulting in an uncorrelated and distinct channel initialization for each occurrence. The investigation focused on characterizing the channel impulse response envelope (H) for various delays (τ = [0 to 2.0 step 0.5]), which represent differing degrees of multipath fading under progressively difficult Rayleigh fading situations. In addition, two different dataset compositions were investigated.

With eleven classes representing signals with a low information density, similar to canonical Modified National Institute of Standards and Technology (MNIST) digits, the "Normal" dataset made for an easy-to-understand classification task at a high signal-to-noise ratio. On the other hand, all 24 modulations, including high-order modulations, were included in the "Difficult" dataset. Impairments above conventional expectations were imposed, and the classification was carried out within relatively brief observation windows comprising 210 samples despite being employed in high SNR, low-fading channel settings [14]. The difficulties related to this classification reflected real-world scenarios where decision-making mechanisms can't afford to wait for additional information, including quick receiver scanning or brief environmental signal bursts. The study acknowledged the inherent difficulties in getting nearly 100% classification rates on the entire dataset and investigated these impacts under low SNR settings ranging from -20 to 30 dB. This difficult situation provided a valuable baseline for comparison and further research projects. The dataset is stored in "hdf5" format as values of type complex floating-point with more than 2*106 samples, each with 210 complex floating-point values. The dataset contains 24 modulations (OOK, ASK (4, 8), PSK (1, 2, 3, 4, 5) 128APSK, 16QAM (4, 5, 6, 7, 8), AM_SSB_WC, SC, AM_DSB_SC, FM, GMSK, and OQPS), 26 SNRs (-20 dB to +30 dB in steps of 2 dB), 4096 signals in each modulation-SNR combination.

Each signal has 1024 complex time-series values. The values are complex floating-point In-phase and Quadrature (I/Q) components. The dataset has 24 modulations: OOK, ASK4, ASK8, BPSK, QPSK, PSK8, PSK16, PSK32, APSK16, APSK32, APSK64, APSK128, QAM16, QAM32, QAM64, QAM128, QAM256, AM_SSB_WC, AM_SSB_SC, AM_DSB_WC, AM_DSB_SC, FM, GMSK and OQPS. For each modulation, there are 26 SNR levels (-20 dB to +30 dB in steps of 2dB). In addition, there are 4096 frames per modulation and 1024 complex time-series samples per frame. Samples as floating point in-phase and quadrature (I/Q) components result in a (1024,2) frame shape, so the total number of "2555904" signals is The RadioML 2018.01A dataset helps research the effects of noise and channel impairments on the operation of digital communication systems, and for creating and testing signal-processing algorithms for these systems. The dataset has aided in creating novel signal-processing methods for digital communication systems and has been employed in numerous academic projects. The dataset structure is displayed in Figure 2.

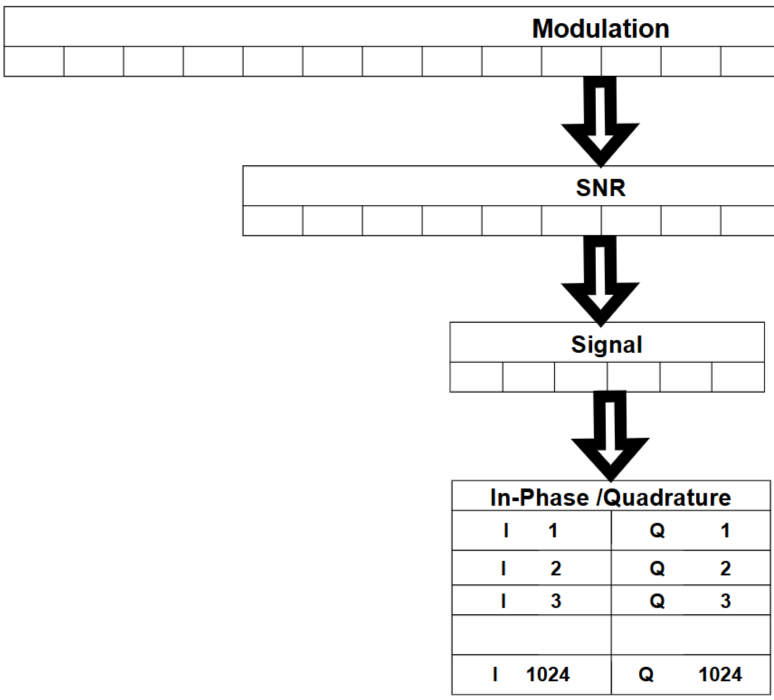

Figure 2: Dataset structure

Figure 3 shows how plotting in-phase (I) and quadrature-phase (Q) samples separately helps differentiate real and imaginary signal portions. This approach works well in communication systems, where exact phase and amplitude information is needed for signal processing. I/Q samples are plotted individually to assist in analyzing and modifying complicated signals and improve understanding. Examining the signal's in-phase and quadrature-phase components independently might reveal signal processing chain issues. This shows key signal characteristics. Figure 4 displays the I/Q diagram of the in-phase (I) and quadrature-phase (Q) components.

This represents the signal's real and imaginary components as in-phase and quadrature-phase. The scatter plot shows I and Q values from a signal sample at each position. Digital communication systems require constellation diagrams, which this I/Q diagram creates. Different modulation scheme symbols or signal points are shown on an I/Q plot in a constellation diagram. Every symbol's I and Q values determine its diagram placement, revealing modulation system-specific patterns. An algorithm selects a subset of the RADIOML dataset based on modulation schemes and SNR values. MPSK and MQAM modulation methods were carefully selected for study. The SNR values, -10 to -2 dB, were chosen for their relevance in communication system evaluation.

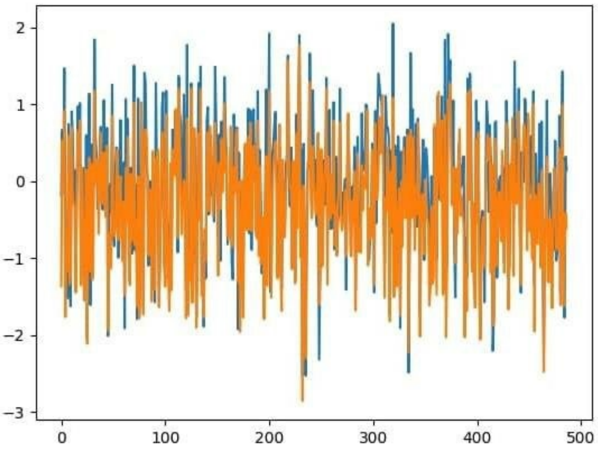

Figure 3: Plotting of I/Q sample

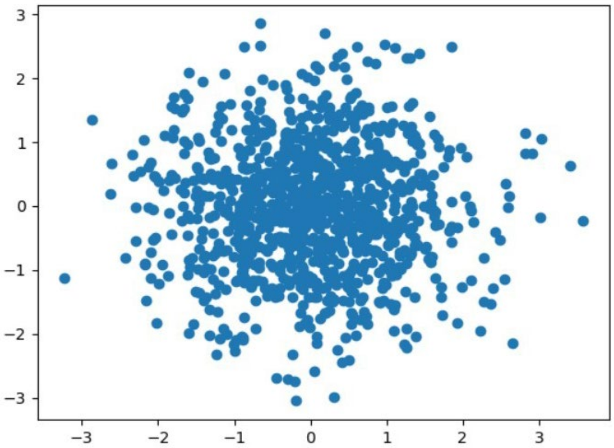

Figure 4: The Diagram of I/Q

2.2 Fading noise

When a received signal' nature and strength change due to changes made to the transmission medium, it's referred to as fading in wireless communications. These discrepancies can be attributed to multipath travel, which occurs when a signal travels via multiple channels before arriving at the receiving device [15]. This causes the signal components to arrive at the receiver at different times. Due to either advantageous (signal raising) or negative (signal reducing), disturbance at the receiver may result in varying signal intensity over time. In wireless communication, random and unwanted disturbances that could contaminate the original transmission are called noise. Possible explanations include atmospheric conditions, electronic interference, and other variables. When noise is present, the signal quality is reduced, and it may be more challenging to recognize and decode the intended data. "Fading noise" is the term used to describe how noise and fading signals interact to affect a wireless communication signal that is delivered. In other words, fading brought on by events like multipath propagation causes the signal's intensity to change over time. Random noise also affects the signal, further reducing its quality. In particular, even though the signal-to-noise ratio is low, the combined effect of these two factors may make it more difficult to distinguish and interpret the intended information. Based on this difficulty and to increase the study challenge, the study provided each selected signal from the data set with a fading noise.

2.3 Gaussian noise

A type of random noise known as Gaussian noise is commonly observed in many different systems, such as electrical equipment and communication channels. AWGN is another name for it [16]. The Gaussian distribution, often known as the normal distribution, describes its statistical properties. In mathematical terms, the Gaussian distribution describes a bell-shaped curve. The mean (average) value in this distribution is represented by the middle of the curve. The standard deviation determines the degree of data dispersion. When fewer values are found, most values tend to cluster closer to the mean. Gaussian noise introduces random fluctuations in the amplitude of the acquired signal, leading to potential errors in signal recognition and classification systems. The study was conducted for every signal provided with fading noise and Gaussian noise. This procedure demonstrates the difficulty of detecting the signal.

2.4 Feature extraction

Feature extraction includes extracting the main features for signals/noise. These features include "Skewness, Kurtosis, Imaginary Part, Real Part (Zero Crossing Rate), Mean Phase Difference, Energy, and Power." They are a versatile toolbox drawn from Amplitude Statistics, Time-Domain Features, and Phase Features.

2.4.1 Energy of signal

The energy provides crucial details regarding the characteristics of a signal over a specific period or series. The squares of a signal's magnitudes are summed over a predefined range to get its energy. Because larger magnitude signal components are given more weight in this mathematical process, stronger signal components have a greater impact on the predicted total energy [17]. Energy may be used to classify signals by energy level. Understanding signal energy helps in real-world situations. Communication systems may convey various messages using signals with varied energies. Studying their energy content can help distinguish these signals. Identifying signals by energy may significantly improve signal processing. Signal energy is crucial to noise detection. Noise doesn't overpower high-energy signals, and this greater possibility of popping out from background noise simplifies identification and processing. Thus, energy-based analysis improves signal quality and reliability in wireless communication when signal-to-noise separation is crucial.

2.4.2 Signal power

By measuring the average energy output per second, signal power shows the energy distribution of a signal across time. It measures all the energy a signal sends or contains over time to determine its power. Squaring the total number of samples, summing up all magnitude squares, and computing signal power yields signal power. Through this mathematical approach, one may determine the signal's average energy transmission rate and energy distribution over time. Signal power must be understood when comparing energy content or power. It can distinguish signal strengths, which is helpful in telecommunications and signal processing. Signals must overcome noise and interference to build a reliable communication system. Signal power is essential for noise analysis. It distinguishes extra noise power from signal power. Noise in communication networks reduces signal quality, making it harder to retrieve information. Signal power is a fundamental notion that describes signal energy distribution across time. It helps distinguish signal power from noise and compares signal intensity or energy levels. Communication systems and signal processing applications require understanding signal power for quality and dependability.

2.4.3 Signal skewness

Skewness is a statistical indicator that highlights signal or dataset probability distribution imbalance. It accurately estimates the range of values from a symmetrical distribution around the mean. Symmetric signals have approximately zero skewness. The signal's right tail is longer and has more skewness. A few bigger numbers stretch to the right, while most are clustered to the left. However, positive skewness suggests a longer left tail, concentrating most values on the right and distributing some smaller values to the left. Since it varies by signal type, skewness is a discriminative metric for signal categorization. Skewness also helps discover signal outliers and asymmetrical disturbances. Analyzing signal skewness reveals oddities. This helps with quality control and anomaly detection.

2.4.4 Zero crossing rate: real and imaginary part

The frequency range at which a signal crosses the zero axis or changes polarity is called the "zero crossing rate" (ZCR). It illuminates the signal's quick amplitude variations. Higher zero-crossing rates mean more orientational shifts or zero-axis crossings. This suggests signal oscillations or sudden variations. However, a signal with a lower zero crossing rate is steadier and has fewer sudden polarity shifts. ZCR measures signal variability and change. Machine learning techniques for signal detection can use ZCR. Zero crossing rates assist in categorizing signals and identifying features since they may vary by kind.

2.4.5 Mean discrete difference of phase

The discrete phase difference is the phase variation between two successive samples. This measurement measures the degree to which the phase of a complex-valued signal with both phase and magnitude components changes from sample to sample. The n-th discrete phase difference appears between samples spaced n intervals apart. Showing how the signal's phase changes over time helps explain its behavior. A positive phase difference implies a signal phase shift from the previous sample to the present one, whereas a negative phase difference indicates a phase shift. Complex signals benefit from it since it shows how a signal's phase varies with time or place. Signal recognition tasks use the n-th discrete phase difference to recognize signals with distinct parameters. The signal's phase shift over time may also be evaluated using the mean of the n-th discrete phase discrepancies. This statistic measures signal phase change over time. The mean of the n-th discrete phase shifts may be used to analyze the signal's average phase variation over time to find trends and patterns.

2.4.6 Normalizing and splitting

Normalizing characteristics aids data-driven analysis and machine learning. Its many benefits make it essential to training. Normalization converts a dataset's properties into a uniform scale so learning algorithms may use them. Normalizing feature scaling removes the accidental influence of larger features. This allows the model to converge fast and optimally. This accelerates convergence, improving model generalization. Data separation is an essential stage in machine learning that improves model training. The dataset is separated into training and testing halves during data splitting. This gives the model a range of data to prevent overfitting and test its generalization. Testing data sets an objective performance standard, whereas training data instructs the model. This tight separation improves the model's capacity to predict and extrapolate to unobserved data.

3. Results and discussion

This study measured and interpreted the model's performance using four primary metrics, each with its equation, and provided various perspectives on its success. The most comprehensible statistic is the accuracy statistic, which shows the proportion of accurately identified samples in the dataset. It is expressed as follows and offers a general evaluation of the accuracy of the model in Equation (1) [18]:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

where: TP refers to correctly classifying samples, so this is called a true positive, TN: refer to the correct classification of wrong samples, FP and FN refer to the false positive and false negative, respectively. This means the input samples were classified incorrectly. A model's precision is determined by minimizing false positives while accurately identifying positive samples. It is calculated in Equation (2) [18] :

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

A model's recall quantifies its ability to reduce false negatives while capturing all relevant positive samples. It is computed as follows in Equation (3) [18]:

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

The F1-score, a suitable trade-off between precision and recall, provides a single statistic representing the model's precision-recall trade-off. It is ascertained to be [19]:

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{4}$$

Comprehensive SVM model assessment yields good results. The model can categorize data despite noise with 98.8% accuracy, classifying positive samples while reducing false positives. The model's 99.5% recall rate lowers false negatives and captures all relevant positive samples. A 99% F1-Score indicates that the model balances the sensitive precision-recall trade-off. A detailed category representation in the Confusion Matrix gives further insights into the model's performance. True positives and negatives (27882 and 28730) show that this model can successfully distinguish positive and negative samples. The accuracy of the model and recall are equal to 589 for false positives and 143 for false negatives.

Therefore, this work proves that the SVM model can recognize signals across various noise levels, making it a viable real-world tool. A complete evaluation of the SVM model for 16QAM modulation examined noise and signal predictions across SNR levels. The results were significant, revealing a total of 212 signals. SVM found 4,066 signals in 30 noise predictions at -10 dB SNR, confirming its capacity to detect signals under challenging situations. At -8 dB, the SVM model produces 4,069 signal predictions and 27 noise predictions, performing well even with increasing noise. The SVM successfully detected 4,085 signals at -6 dB SNR with eleven noise predictions. The model's adaptability was even more apparent at -4 dB, with only 8 noise predictions and 4,088 signal predictions. Model predictive power was shown at -2 dB SNR. It correctly identified 4,094 signals and predicted two noises. This meticulous investigation corroborated a significant finding: when SNR lowers, signal strength reduces compared to noise, making it harder for the model to discriminate the signal from noise. As SNR levels change, the model changes its predictions, which matches signal-detecting practice. These results demonstrate the model's versatility and provide light on the intricate interaction between SNR levels, signal intensity, and noise, which is crucial in real-world signal identification.

3.1 Graphical analysis

An important part of the endeavor to evaluate the SVM model's performance at different SNR levels is a graphical examination. The curve, depicted in Figure 5, offers valuable insights into the model's resilience in signal detection. It was generated using an extensive dataset with SNR levels of -10:-2 dB and corresponding SVM accuracies. The curve both validates the model's performance and highlights how applicable the signal detection approach is. This demonstrates that SVM is an effective technique that can accurately predict signals even when noise is causing disruptions and in scenarios where noise presents significant obstacles. The model is a helpful tool for real-world applications where accuracy is critical, as demonstrated by this graphical analysis that encapsulates its capacity to detect signals at different SNR levels.

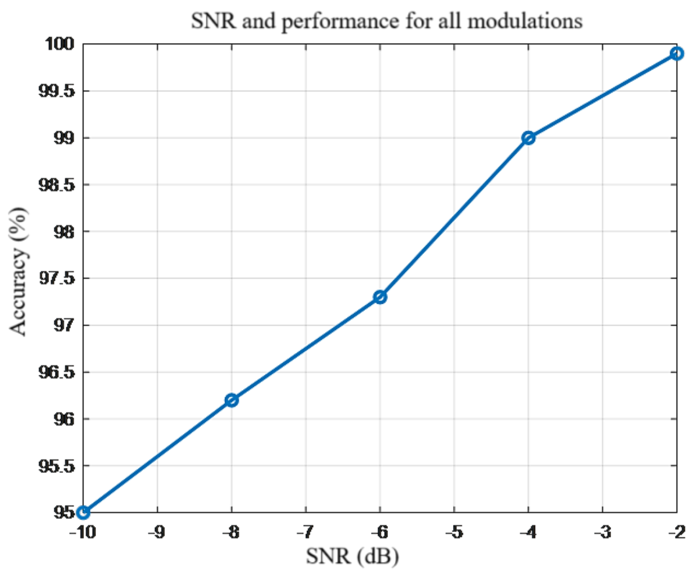

Figure 5: SNR and performance for all modulations

A graphical analysis illustrating the dynamic relationship between SVM accuracy and SNR levels concludes the study's thorough examination of 16QAM modulation. The curve in Figure 6 offers comprehensive information on the model's functionality. It was made with a meticulous dataset with the associated SVM accuracies and SNR of -10:-2 dB for 16QAM. The curve clearly shows how flexible the SVM is in response to varying SNR levels. Interestingly, SVM accuracy is increasing.

A graphical analysis of 8PSK modulation completes the study's exhaustive assessment. Figure 7 illustrates a curve covering a wide range of SNR values -10:-2 dB from the dataset. This curve visually represents how well the SVM performs about 8PSK modulation. The graphical analysis shows that the accuracy of the SVM model starts to trend noticeably higher as SNR levels decrease. This pattern makes perfect sense regarding how signal detection dynamics are understood. As SNR drops, noise has a more disruptive effect, which causes a small drop in model accuracy. Figure 8, show the relationship between SNR levels and SVM accuracy when signal modulated using QPSK modulation schame.

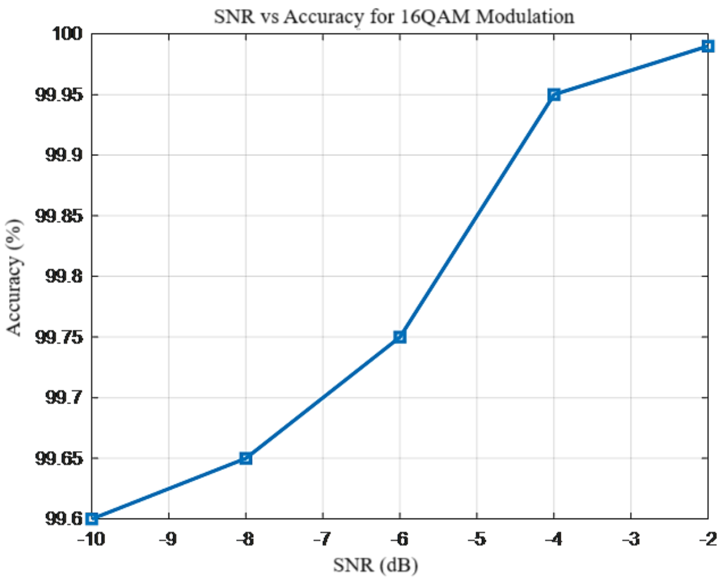

Figure 6: SNR and accuracy for modulation 16QAM

Review of the SVM model's performance in relation to QPSK modulation. The carefully constructed graph illustrates the dynamics of the SVM model's accuracy in QPSK modulation. Data from SNR values of -10, -8, -6, -4, and -2 dB were generated. The accuracy starts at a high level, showing how well the model performs under noise signals.

3.2 Comparison

Clerico et al. [20], present a unified approach for classifying telecom and radar data that uses Long-Short-Term Memory (LSTM) neural networks. The proposed approach aligns with a trend in the classification of radar signals, where long-short-term memory (LSTM) models were included in more complex designs. This combined approach shows the promise of similar technologies in several sectors by utilizing LSTM neural networks to improve radar and communication data classification accuracy. To analyze the findings [20], achieved an accuracy of 90% for QPSK with an SNR of 0. With SNR equal to -10, our proposed QPSK achieved 99.7% accuracy. Table 1 shows that our proposal's accuracy is higher than [16], and that its detection accuracy is indicated by a low signal-to-noise ratio (SNR). Table 1 displays the accuracy for 8PSK and 16QAM for both in [20] and our proposal. Our approach yielded an accuracy of 99% and 99.6% for 8PSK and 16QAM, respectively, with an SNR equal to -10, surpassing the accuracy in [20], which obtained 90% and 90% for 8PSK and 16 QAM, respectively, with an SNR equal to 4. Figure 7 shows the accuracy value for different SNR ratios for the signals modulated using the 8PSK modulation technique. Figure 8 shows the accuracy value for different SNR ratios for the signals modulated using the QPSK modulation technique.

The previous sections clearly show that most previous studies have several drawbacks. First, the researchers used a few numbers of samples for training and testing the designed system. Second, the detection accuracy must have been high when they used a limited number of samples. Still, they had a low detection accuracy because of the wrong classification of the used samples. Third, they test their system based on a limited SNR ratio. Therefore, it has become important to consider these drawbacks and design a robust and efficient system that tests on a sufficient number of samples (large dataset) and different SNR ratios. Table 1 compares the proposed and designed work of [20]. The comparison is made by considering different modulation schemes, SNR, and the final detection accuracy. Clearly, the proposed system achieves better detection accuracy than others.

Table 1: Accuracy comparison of QPSK, 8 PSK, and 16 QAM

Paper	Modulation	SNR	Accuracy%	Ref.
….	QPSK	0	90	[20]
Proposed work	QPSK	-10	99.7	….
….	8PSK	4	90	[20]
Proposed work	8PSK	-10	99	….
….	16QAM	4	90	[20]
Proposed work	16QAM	-10	99.6	….

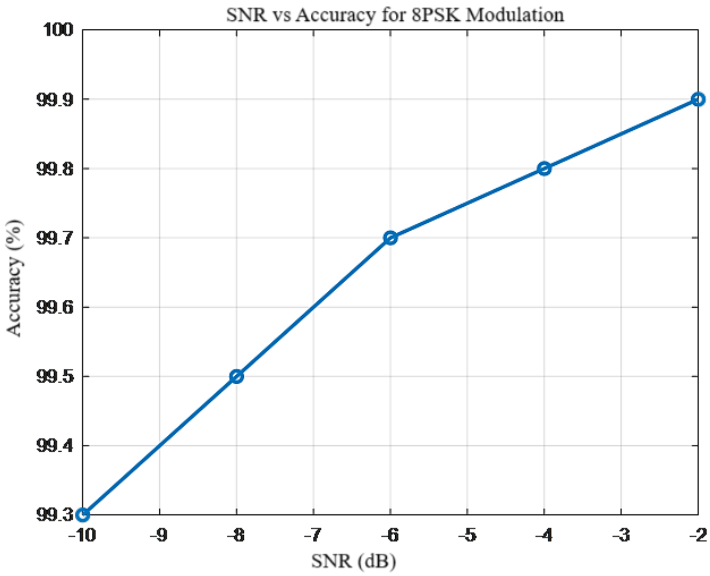

Figure 7: Curve between SNR and accuracy for modulation 8PSK

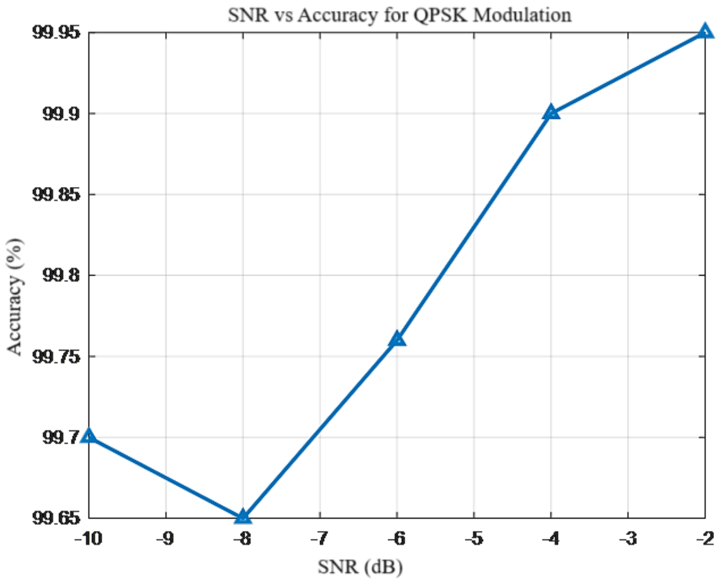

Figure 8: The Curve between SNR and accuracy for modulation QPSK

4. Conclusion

The designed system consists of three steps. The first is related to pre-processing the input signals. The pre-processing step is also called systematic pre-processing techniques such as fading noise, Gaussian noise, and low-pass filtering to simulate real-world communication scenarios. The input signal to this step is available in the form of the RADIOML 2018.01A dataset. This dataset has a total of "2555904" signals related to different modulation scams. The second step is the feature extraction. The pre-processed signal applies to the feature extraction to extract statistical and spectral features like energy, power, skewness, kurtosis, zero-crossing rates, and phase differences; these features effectively capture the characteristics of signals. After features are extracted for each signal, it becomes necessary to apply them to the last stage, which represents the classification stage. Evaluation metrics such as accuracy, precision, recall, F1-score, and confusion matrix were employed, showcasing the model's exceptional performance in classifying signals and noise. The study's systematic approach, encompassing pre-processing, feature extraction, and SVM-based classification, highlights the potential of machine learning in solving complex communication issues. The results indicate the method's effectiveness in increasing signal detection accuracy, offering promising prospects for developing reliable wireless communication systems. The final range of detection accuracy for the different modulation schemes is between 90 and 99.7. Finally, the main conclusion from this work is the ability to detect various kinds of signals with high detection accuracy. In comparison, the previous works used a limited sample and got a low detection accuracy. Thus, from the determined result, the proposed system approves its correctness, robustness, and reliability even when applied to signals modulated with a different modulation scheme and SNR levels.

For future work, this field deals with measuring different signal features or using different classification techniques trained and tested using another dataset.

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Data availability statement

The data supporting this study's findings are publicly available online. The link to the RADIOML 2018.01A dataset is: https://www.kaggle.com/datasets/pinxau1000/radioml2018

Conflicts of interest

The authors declare that there is no conflict of interest.

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