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Ensemble-Based Approach for Classification of Digitally Modulated Signals

Introduction

Digitally modulated signals are a critical component of modern communication systems, playing a vital role in transmitting data efficiently and reliably. These signals transmit data by altering the amplitude, frequency, or phase of a carrier signal, facilitating effective communication over various channels. With the rapid advancement in communication technologies, the diversity of modulation schemes has significantly increased, necessitating robust methods for their classification. This project focuses on employing machine learning techniques to classify these signals, as accurate classification is essential for various applications like mobile communication, Wi-Fi, satellite transmissions, and digital broadcasting. Moreover, effective classification aids in spectrum management, interference mitigation, and the optimization of communication protocols. By utilizing machine learning, the project aims to contribute to the development of more resilient communication systems capable of handling the complexities of modern data transmission.

Objective

The goal of this project is to develop a machine learning (ML) model that classifies different types of digitally modulated signals. By leveraging advanced feature extraction techniques and optimizing ML models, the project aims to enhance classification accuracy, even in the presence of noise and interference. Additionally, the project seeks to explore the interpretability of the models, ensuring that the decision-making process is transparent and can be understood in the context of signal characteristics. This could lead to practical insights into the performance of various modulation schemes in real-world scenarios.

Literature Review

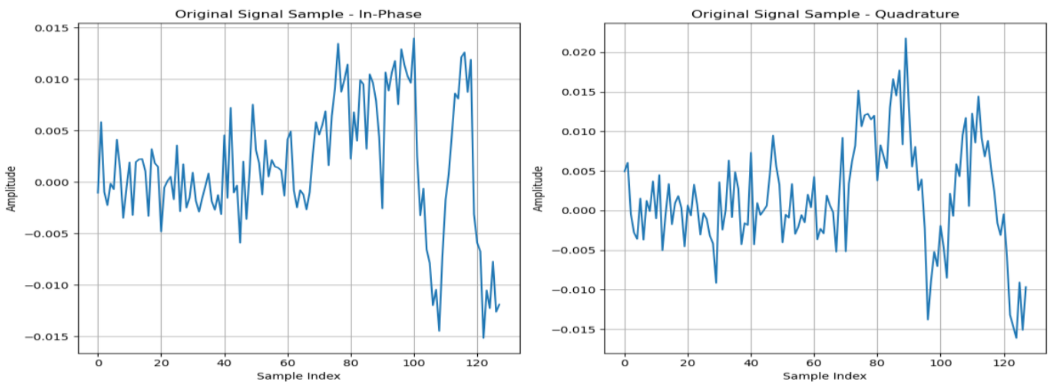
Recent research emphasizes the effectiveness of Sevcik Fractal Dimension (SFD) for feature extraction, enabling improved signal classification by capturing complex signal characteristics. This technique has been shown to provide a comprehensive representation of signal features, which enhances model performance. Furthermore, Deep Extreme Learning Machines (DELM) and optimization algorithms, such as Artificial Bee Colony (ABC), have proven effective for model training and performance improvement, offering robust solutions to complex classification challenges. Studies indicate that integrating advanced techniques like ensemble methods and hybrid models can significantly enhance the robustness of classification models. Additionally, recent works highlight the role of deep learning architectures in capturing intricate patterns within digitally modulated signals, showcasing their potential in surpassing traditional machine learning methods. Research also points to the importance of data augmentation techniques in improving model generalization by increasing the diversity of training datasets, particularly in scenarios with limited labelled data. Overall, the literature suggests that a combination of innovative feature extraction methods and advanced machine learning techniques can lead to substantial improvements in the accuracy and reliability of signal classification tasks.

Methodology

1. **Data Collection**

The dataset utilized in this project is the RML2016.10a dataset, which consists of 220,000 samples encompassing various modulation schemes and signal-to-noise ratios (SNR). The unique modulation schemes present in the dataset include 8PSK, AM-DSB, AM-SSB, BPSK, CPFSK, GFSK, PAM4, QAM16, QAM64, QPSK, and WBFM. Each sample is structured with two channels, in-phase and quadrature, and has a shape of (1000, 2, 128). This comprehensive dataset allows for a robust analysis of different signal classifications under various conditions.

To enhance efficiency in the experimentation process, we have opted to reduce the dataset by selecting a limited number of modulation schemes and specific SNR values. This reduction facilitates faster evaluations of different algorithms, as working with a smaller dataset minimizes computational demands and training times. By narrowing the focus, we enable quick iterations and streamline the analysis process, making it easier to interpret results and draw meaningful conclusions regarding the performance of various algorithms in classifying digitally modulated signals. This approach ultimately contributes to a more effective exploration of machine learning techniques for signal classification tasks.



DATA VISUALIZATION

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2. Feature Extraction

In this project, several key features were extracted to aid in the classification of digitally modulated signals.

- The Sevcik Fractal Dimension (SFD) quantifies the complexity of a signal by measuring its fractal nature, indicating how detail in the signal changes with scale. A higher SFD suggests a more complex signal structure, which can enhance classification accuracy. The SFD can be calculated using the formula:

  $$SFD = \log(N) / \log(e)$$

  where N is the number of data points in the signal.

- The Zero-Crossing Rate (ZCR) measures the frequency at which the signal changes from positive to negative, indicating signal variability. It helps differentiate between modulation schemes exhibiting different fluctuation levels and can be calculated using the formula:

  $$ZCR = (1 / (N - 1)) * \Sigma\ |sgn(x[n]) - sgn(x[n-1])|$$

  where sgn(x) is the sign function.

- Energy Measures assess the total energy of the signal in both in-phase and quadrature components, calculated as:

  $$Energy = \Sigma\ x[n]^2$$

  for each component x[n].

- The Peak-to-Average Power Ratio (PAPR) indicates the relationship between the peak power and the average power of the signal, calculated using:

  $$PAPR = \max(|x[n]|^2) / E[|x[n]|^2]$$

where E denotes the expected value. Finally, Statistical Measures such as mean, variance, skewness, and kurtosis are computed to capture the distributional properties of the signal. The formulas are as follows:

- Mean: $Mean = (1 / N) * \Sigma\ x[n]$
- Variance: $Variance = (1 / N) * \Sigma\ (x[n] - Mean)^2$
- Skewness: $Skewness = (1 / N) * \Sigma\ ((x[n] - Mean) / \sigma)^3$
- Kurtosis: $Kurtosis = (1 / N) * \Sigma\ ((x[n] - Mean) / \sigma)^4$

where σ is the standard deviation. These features collectively contribute to a robust classification framework for digitally modulated signals.

3. Data Normalization

Z-score normalization was applied to standardize the dataset, ensuring that each feature has a mean of 0 and a standard deviation of 1. This process transforms the data into a standardized format, which is particularly useful when dealing with features that are measured on different scales or have varying units. The Z-score for each data point is calculated using the formula:

$Z = (X - \mu) / \sigma$

where:

- X represents the original value,
- μ is the mean of the feature, and
- σ is the standard deviation.

By applying this normalization technique, we eliminate biases introduced by differing scales, allowing machine learning algorithms to converge faster and perform more effectively.

Furthermore, it enhances the stability of the models by reducing the risk of overfitting to features with larger ranges. This standardized dataset thus provides a solid foundation for training and evaluating the machine learning models used in the project.

4. Data Preparation

Missing values were removed, and categorical variables were encoded using LabelEncoder. The dataset was split into training (80%) and testing (20%) sets, with balanced class distribution across the sets.

5. Model Selection and Training

I trained various machine learning models to evaluate their performance on the classification task. The models included Naive Bayes, which offers a simple yet effective probabilistic approach; K-Nearest Neighbors (KNN), known for its intuitive distance-based classification; and Logistic Regression, which provides a solid foundation for binary classification tasks.

Additionally, we explored Support Vector Machine (SVM) for its ability to find optimal hyperplanes, Decision Trees for their interpretability, and Random Forest for its ensemble capabilities that enhance accuracy.

We also utilized Gradient Boosting, CatBoost, XGBoost, and LightGBM, all of which are powerful gradient boosting techniques that excel in handling complex datasets and improving predictive performance. Each model's performance was carefully assessed to determine the best approach for our specific use case.

6. Hyperparameter Tuning

Models were fine-tuned using hyperparameter optimization techniques, specifically employing Grid Search to enhance their performance and accuracy. Grid Search systematically explores a specified set of hyperparameter values for each model to identify the optimal combination that maximizes performance on the validation dataset.

For instance, the Random Forest model achieved an impressive accuracy of 99.22% after using Grid Search to fine-tune parameters such as maximum depth and minimum samples for splitting nodes.

This approach allowed for an exhaustive search over the defined parameter grid, balancing model complexity and generalization effectively. By leveraging Grid Search, the project aimed to maximize the effectiveness of each machine learning algorithm, ensuring robust and reliable classification of digitally modulated signals.

7. Stacking

Ensemble learning enhances model performance by combining predictions from multiple algorithms, leading to more robust classifications. In this project, I employed stacking to integrate various classifiers, including Naive Bayes and XGBoost.

By experimenting with different combinations of all the models, I achieved an impressive accuracy of 99.64% with the Naive Bayes and XGBoost combination. Stacking involves training multiple base models on the same dataset and using their predictions as input for a meta-learner, which improves final predictions.

This approach captures diverse patterns in the data, reduces the risk of overfitting, and ultimately enhances the classification accuracy of digitally modulated signals.

8. Cross Validation

At the end of the model evaluation process, cross-validation was performed to assess the robustness of the classifiers. The mean cross-validated accuracy achieved was 99.31%, indicating that the models consistently performed well across different subsets of the data.

Additionally, the standard deviation of 0.13% suggests minimal variability in the model's performance, reinforcing its reliability. This rigorous validation process ensures that the results are not merely artifacts of a specific train-test split, but rather indicative of the model's generalization capability

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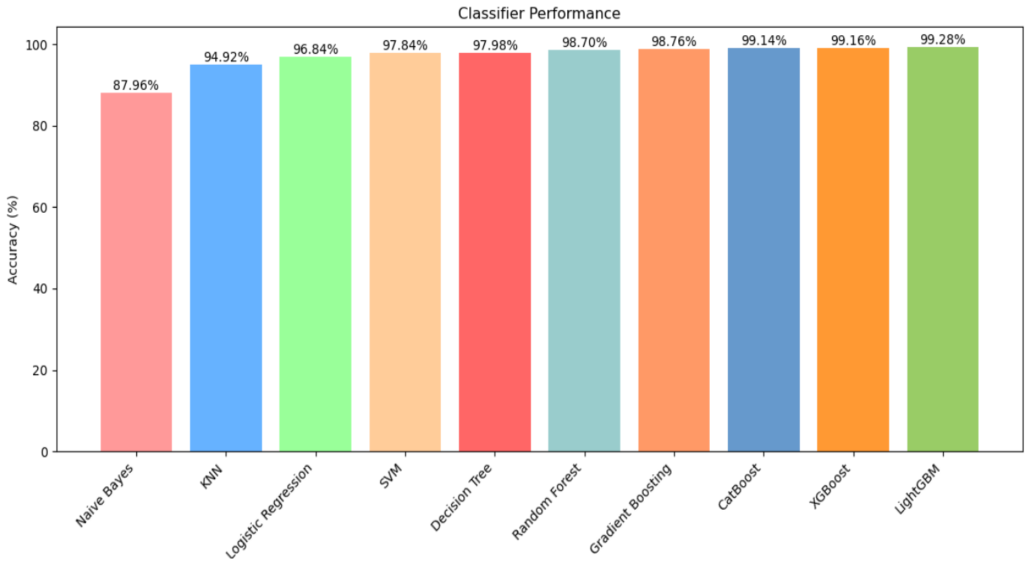
Results

Individual Classifier Performance



Stacking Results

	Naive Bayes	Decision Tree	Random Forest	Gradient Boosting	KNN	SVM	XGBoost	LightGBM	CatBoost
Naive Bayes	-	98.7	99.28	99.06	97.24	98.86	99.64	99.62	99.46
Decision Tree	98.7	-	99.24	99.22	98.88	99	99.62	99.52	99.48
Random Forest	99.28	99.24	-	99.26	99.24	99.38	99.58	99.54	99.44
Gradient Boosting	99.06	99.22	99.26	-	99.06	99.26	99.6	99.52	99.46
KNN	97.24	98.88	99.24	99.06	-	99.06	99.6	99.6	99.46
SVM	98.86	99	99.38	99.26	99.06	-	99.62	99.6	99.54
XGBoost	99.64	99.62	99.58	99.6	99.6	99.62	-	99.62	99.58
LightGBM	99.62	99.52	99.54	99.52	99.6	99.6	99.62	-	99.58
CatBoost	99.46	99.48	99.44	99.46	99.46	99.54	99.58	99.58	-

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Stacked Model Accuracy (Naive Bayes + XGBoost): 99.64%
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1000
           1       0.99      0.99      0.99      1000
           2       1.00      1.00      1.00      1000
           3       1.00      1.00      1.00      1000
           4       1.00      1.00      1.00      1000

    accuracy                           1.00      5000
   macro avg       1.00      1.00      1.00      5000
weighted avg       1.00      1.00      1.00      5000
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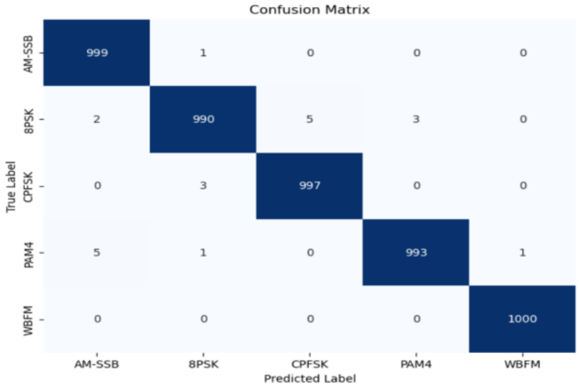
Classification Report



Confusion Matrix

Modulation/Class	DNN	CNN	NB+XG
AM-SSB	98.33	98.23	99.5
8PSK	98.29	100.0	99.3
CPFSK	97.49	99.4	99.6
PAM4	99.7	99.3	99.8
WBFM	98.5	99.9	100.0
Macro Avg	98.46	99.37	99.64
Weighted Avg	98.46	99.37	99.64

Precision

Modulation/Class	DNN	CNN	NB+XG
AM-SSB	100.0	100.0	99.9
8PSK	97.9	98.7	98.9
CPFSK	97.0	99.3	99.6
PAM4	99.0	99.8	99.8
WBFM	98.4	99.0	100.0
Macro Avg	98.46	99.36	99.64
Weighted Avg	98.46	99.36	99.64

Recall

Modulation/Class	DNN	CNN	NB+XG
AM-SSB	99.16	99.11	99.7
8PSK	98.1	99.35	99.1
CPFSK	97.24	99.35	99.6
PAM4	99.35	99.55	99.8
WBFM	98.45	99.45	100.0
Macro Avg	98.46	99.36	99.64
Weighted Avg	98.46	99.36	99.64

f-1 score

Metric	DNN	CNN	Naive Bayes + XGBoost
Training Time (s)	11.12	20.52	3.54
Prediction Time (s)	0.26	0.56	0.02
Initial Memory Usage (MB)	729.53	794.3	374.45
Peak Memory Usage (MB)	750.77	821.99	388.36
Test Accuracy (%)	98.46	99.26	99.64

Efficiency Comparision

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Inference

Stacking models demonstrated outstanding results, with Naive Bayes and XGBoost achieving 99.64% accuracy. This approach not only surpassed the performance of CNN and DNN models but also provided superior precision, recall, and F1 scores, highlighting its effectiveness in classifying digitally modulated signals.

The ensemble method exhibited lower time and space complexity compared to CNN and DNN models. This efficiency makes stacking a more practical choice for applications requiring quick and resource-friendly computations, especially in real-time signal classification scenarios.

By combining various algorithms, the stacking approach captures a diverse range of patterns in the data, resulting in a more robust classification model. This flexibility enables the model to adapt better to different modulation schemes and signal-to-noise ratios, enhancing its reliability across varied conditions.

Conclusion

The ensemble techniques, particularly stacking, significantly outperformed traditional classifiers. By combining models like Naive Bayes and XGBoost, the project achieved the highest classification accuracy, illustrating the value of leveraging multiple learning approaches. This method improves generalization and robustness, making it highly effective for classifying digitally modulated signals, even in noisy environments.

References

[1] K. N, M. A. A. Walid, S. Das, N. R, S. S and B. I. S, "Automated Digitally Modulated Signal Recognition and Classification using Machine Learning with Multimodal Information," *2023 Second International Conference on Augmented Intelligence and Sustainable Systems (ICAISS)*, Trichy, India, 2023, pp. 497-502, doi: 10.1109/ICAISS58487.2023.10250687.