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Multi-Class Electronic Waveform Recognition: Comparative Analysis of Classification Performances of Machine Learning Methods

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ABSTRACT

Electronic waveform classification is a critical area of research for separating and identifying signals from different sources. This study aims to classify visual representations of electronic waveform signals using classical machine learning methods. Using a dataset consisting of 7,000 images of 7 different electronic waveforms, the classification performance of 10 different machine learning algorithms was compared. In the study, the dataset was divided into training and test sets and all models were trained using the same feature set and evaluated according to classification metrics. The results revealed that Extra Trees and Random Forest algorithms were the most successful classifiers with 98.57% and 98.50% accuracy respectively. On the other hand, Naive Bayes and AdaBoost algorithms have been found to be inadequate for this type of data due to their low accuracy values. The findings show that bagging-based ensemble learning approaches achieve high accuracy in electronic waveform classification tasks and support the effectiveness of classical machine learning methods in the field of signal analysis. In this context, the study makes a significant contribution to the literature on the classification of electronic waveform datasets based on time-frequency images.

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Çok Sınıflı Elektronik Dalga Şekilleri Tanıma: Makine Öğrenmesi Yöntemlerinin Sınıflandırma Performanslarının Karşılaştırmalı Analizi

ÖZ

Elektronik dalga şekilleri sınıflandırması, farklı kaynaklardan gelen sinyalleri ayırma ve tanımlama açısından kritik bir araştırma alanıdır. Bu çalışmada elektronik dalga şekilleri sinyallerinin görsel temsillerinin klasik makine öğrenmesi yöntemleri kullanılarak sınıflandırılması amaçlanmıştır. 7 farklı elektronik dalga şekillerine ait 7.000 görüntüden oluşan bir veri seti kullanılarak, 10 farklı makine öğrenmesi algoritmasının sınıflandırma performansı karşılaştırılmıştır. Çalışmada, veri seti eğitim ve test setlerine ayrılmış ve tüm modeller aynı özellik seti kullanılarak eğitilmiş ve sınıflandırma metriklerine göre değerlendirilmiştir. Sonuçlar, Ekstra Ağaçlar ve Rastgele Orman algoritmalarının sırasıyla %98,57 ve %98,50 doğrulukla en başarılı sınıflandırıcılar olduğunu ortaya koymuştur. Öte yandan, Naive Bayes ve AdaBoost algoritmalarının düşük doğruluk değerleri nedeniyle bu tür veriler için yetersiz olduğu görülmüştür. Bulgular, torbalama tabanlı topluluk öğrenme yaklaşımlarının elektronik dalga şekilleri sınıflandırma görevlerinde yüksek doğruluk elde ettiğini ve sinyal analizi alanında klasik makine öğrenmesi yöntemlerinin etkinliğini desteklediğini göstermektedir. Bu bağlamda, çalışma elektronik dalga şekilleri veri kümelerinin zaman-frekans görüntülerine dayalı sınıflandırılması konusunda literatüre anlamlı bir katkı sağlamaktadır.

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1. Introduction

Today, the detection, classification and interpretation of electronic waveform signals have strategic importance in a wide variety of fields such as defense industry, remote sensing, communication systems, medical devices and industrial automation [1-4]. In particular, accurate separation of electronic waveforms plays a critical role in improving system performance and correctly interpreting environmental variables. The fact that these signals often come from different physical sources further complicates the classification problem. Analyzing these complex, multi-dimensional and noisy data using classical methods is both time-consuming and often fails to provide the desired accuracy. In this context, machine learning (ML) methods offer alternative and effective solutions in the field of signal processing with their ability to learn, classify and predict patterns in large datasets. In particular, presenting the features extracted from time-frequency images to ML algorithms gives promising results in terms of accuracy and processing efficiency [5-7]. As a matter of fact, various studies have shown that classical machine learning algorithms such as SVM, Random Forest, Extra Trees, AdaBoost give very successful results in signal classification tasks.

In studies specifically on the classification of electronic waveforms, visual representations of signals obtained in the time-frequency domain provide a valuable resource in terms of feature extraction and classification performance. The statistical and texture-based features obtained from these images constitute suitable input data for classical machine learning algorithms. This enables more effective and faster analysis of data that is difficult to analyze with traditional signal processing methods. This study aims to classify 7 different electronic waveforms based on their visual representations using classical machine learning algorithms. A total of 7,000 electronic waveform images were used, with 1,000 examples for each class. By resizing the images, converting from RGB to flat vector, digitizing the class labels and standardizing the data, the raw visual data was classified with various machine learning algorithms and the success rates were compared. The machine learning methods used are: Extra Trees, Random Forest, Decision Tree, SVM, Gradient Boosting, Logistic Regression, KNN, LDA, Naive Bayes and AdaBoost. As a result of the applied method, the highest success was achieved with Extra Trees (98.57% accuracy, ROC-AUC ≈ 0.9998) and Random Forest (98.50% accuracy, ROC-AUC ≈ 0.9996) algorithms. In addition, while the Decision Tree algorithm showed moderate performance with 92.93% accuracy, models such as Gradient Boosting (88.92%) and Logistic Regression (87.79%) showed lower performance. Naive Bayes and AdaBoost algorithms, on the other hand, failed to show sufficient success in the classification task with 68.64% and 39.35% accuracy rates, respectively. These findings show that ensemble learning methods are more effective than classical algorithms and stand out in the classification of electronic waveforms.

The method of our study is structured with an experimental modeling design based on the classification of visual electronic waveforms. The entire dataset was divided into training and testing, models were trained with the same parameter configurations and evaluated on success metrics (Accuracy, Recall, Precision, F1-score, Specificity and ROC-AUC). In this respect, the study provides both applied and comparative data on how classical machine learning algorithms can be used in the field of analysis of electronic waveforms. Therefore, this study reveals that electronic waveform data consisting of time-frequency images can be classified with high accuracy by classical machine learning methods; and provides important contributions to the processing of similar data types in the literature. The rest of the study is structured as follows: The second section comprehensively discusses the signal classification and machine learning based approaches in the relevant literature. The third section provides detailed information about the dataset, methods and algorithms used in the study. In the fourth section, the experimental results are presented with tables and graphs; performance comparisons are made. In the fifth and last section, the results are evaluated in general, the study limitations and future suggestions are discussed.

2. Related Works

Studies in the literature show that after the raw signals are passed through pre-processing steps and represented in time, frequency or combined domains, the features derived from these representations are analyzed with machine learning algorithms. These methods are widely used to increase the discrimination power between classes, discover complex data patterns and increase classification accuracy. Machine learning-based approaches are trained with different feature sets depending on the structure of the signal and the application area, and ultimately offer high accuracy, generalization success and interpretability. In this respect, machine learning models stand out as methods that provide reliable, flexible and effective solutions in the signal classification literature.

In a study performed on the PTB-ECG dataset, electrocardiogram (ECG) signals were converted into time-frequency images using the smoothed pseudo Wigner-Ville distribution (SPWVD) method and these images were classified using a Convolutional Neural Network (CNN). The obtained achievements such as 98.96% accuracy, 97% F1 score and 98% specificity reveal the high performance of the method. In addition, the study was compared with one of the traditional methods, Support Vector Machine (SVM); it was reported that SVM provided lower success with 85.1% accuracy. This shows that the SPWVD-CNN approach is more effective in classifying ECG signals [8]. In another study, researchers obtained time-frequency images (TFI) using the Choi–Williams distribution to classify LPI radar waves, automatically cropped the high-energy regions in these images, and performed dimension reduction with PCA (Principal Component Analysis). Both binary and multi-class SVM models were used on these reduced TFIs. By applying SVM parameter optimization, significant improvements were reported compared to other methods in the literature under low-SNR conditions. The cross-validation results obtained in the study showed superiority over classical methods in classification performance, especially in low-SNR environments [9].

In a different study, a hybrid method based on Wavelet-ICA and support vector machines (SVM) was proposed to automatically detect and remove biological artifacts such as eye blinks in EEG signals. SVM, trained with statistical features such as variance, skewness, entropy and amplitude range, distinguishes artifact components with high accuracy and preserves the meaningful part of the EEG signal. In tests conducted with EEGLAB data, the method showed superior performance compared to traditional thresholding methods with 99.1% accuracy and 97.1% sensitivity [10]. In another study, the classification of positive and negative emotions was aimed using EEG signals and channel selection was applied as a preprocessing step. In the study conducted on the DEAP dataset, theta band features extracted with the DWT method were classified with MLPNN and kNN algorithms; the five EEG channels that gave the best performance were selected. 77.14% accuracy was obtained with MLPNN and 72.92% with kNN. The results show that the channel and feature selection significantly increase the classification performance in EEG-based emotion recognition [11].

In another study, automatic machine learning based AUTO-SKLEARN system is developed for the identification of radar broadcast source signals. The system automates algorithm selection and hyperparameter tuning using Bayesian optimization and meta-learning methods, thus reducing the need for domain experts. In the experiments, the AUTO-SKLEARN algorithm was compared with the traditional k-means algorithm; AUTO-SKLEARN showed superior performance in terms of both accuracy rate (up to 96%) and stability. The high success rate in radar signal recognition task under different modulation and operating scenarios demonstrates the reliability and applicability of the method. In conclusion, this study shows that automatic machine learning approaches provide effective solutions in the field of radar signal processing [12].

In a study based on time-frequency analysis in the classification of electrocardiogram (ECG) signals, ECG signals were converted into time-frequency images using the smoothed pseudo Wigner-Ville distribution (SPWVD) method and the resulting images were classified using the Convolutional Neural Network (CNN) model. In experiments conducted on the PTB dataset, the model demonstrated high success by achieving 98.96% accuracy, 97% F1 score and 98% specificity. In addition, the study was compared with one of the traditional methods, Support Vector Machine (SVM); it was stated that SVM provided 85.1% accuracy. The obtained results show that SPWVD representations provide a powerful feature extraction in distinguishing normal and abnormal beats in ECG signals and are promising for clinical applications together with deep learning based models [13].

In another study, individual and combined finger movements were classified using surface EMG signals with SVM and ANN algorithms. After feature extraction, dimensionality reduction was applied with PCA and LDA, and the classification accuracy was evaluated with different combinations. The highest success rate was obtained with 96.67% accuracy in the PCA + ANN combination. The results show that this method can be effective especially in biomedical applications such as prosthetic hand control [14].

In another study, a method based on S-transform and Convolutional Neural Network (CNN) was proposed for the classification of power quality degradation (PQD) signals. By obtaining the time-frequency matrices of the signal with the S-transform, these matrices were presented as input to the CNN and classification was performed with the SoftMax layer. Compared to traditional methods, the proposed method stands out with its high classification accuracy (close to 99%) and strong noise immunity. In particular, consistent performance even at different signal-to-noise ratios has demonstrated the robustness of the method. In addition, the proposed model operates with lower processing time compared to methods such as PCA-SVM and PNN, indicating that it offers a practical and effective solution for real-time power system monitoring applications [15].

3. Materials and Methods

In this study, a multi-class machine learning approach is adopted to classify electronic waveforms based on their visual representations. First, a new dataset of 496×369 pixels in size consisting of a total of 7,000 images belonging to 7 different signal classes is prepared [16]. All signals were rescaled to 64×64 pixels. The images were converted from RGB format to one-dimensional vector structure to make them suitable for numerical analysis, labels were digitized and features were standardized. Following these preprocessing steps, the dataset was split into training (80%) and testing (20%). Modeling was performed using various machine learning algorithms (Extra Trees, Random Forest, Decision Tree, SVM, Gradient Boosting, Logistic Regression, KNN, LDA, Naive Bayes, AdaBoost) that can create both linear and non-linear decision boundaries for classification operations. Thus, the classification performances of different algorithms on the dataset were evaluated comparatively. The scheme of the method architecture used in the study is shown in Figure-1.

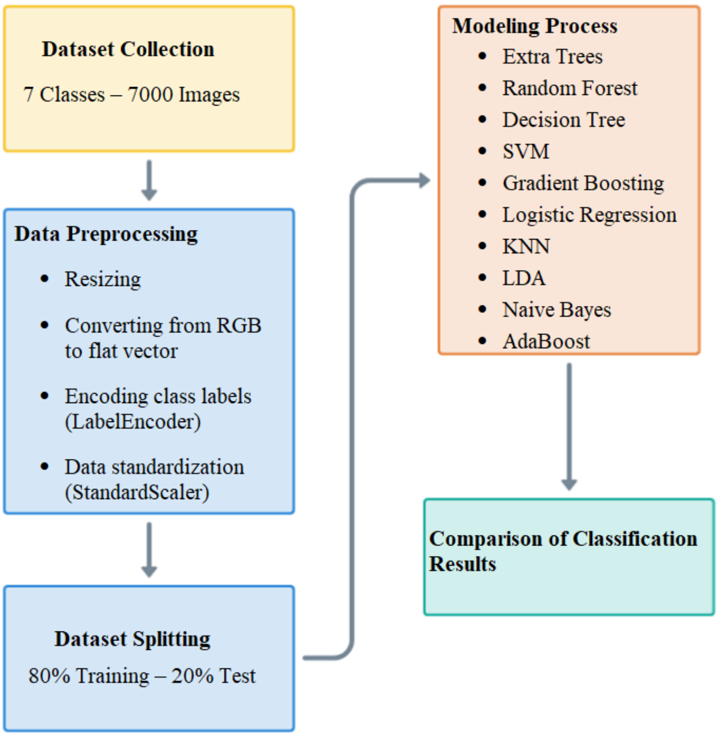
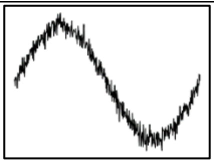
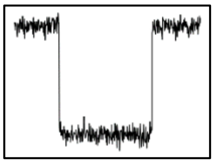
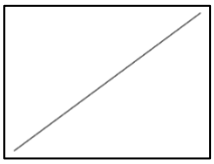
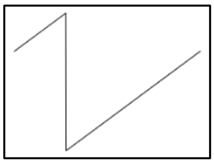
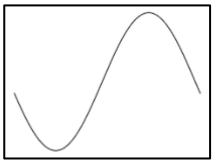
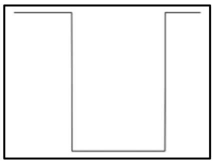
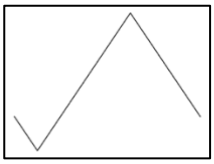


Figure 1. The method architecture used

3.1. Dataset

The dataset used in this study is a signal image set consisting of 7 classes. The dataset is divided into 7 classes, each representing a different signal type: noisy_sinus, noisy_square, ramp, sawtooth, sinus, square and triangle. The dataset consists of 7,000 samples in total, with 1,000 signal images belonging to each class. The signals in question were created to solve a multi-class classification problem and each signal type was classified by labeling. The diversity of the dataset is important in terms of representing different signal patterns, testing the discriminatory power of machine learning algorithms and increasing comparability between methods. The contents and images of the dataset used are shown in Table 1.

Table 1. Information on the dataset of electronic waveforms used in the study.

Class Name	Explanation	Number of Data	Sample Image
Noisy sinus	The mathematical model consists of social hierarchy, prey pursuit, encirclement and attack. It represents a sinusoidal waveform with added noise.	1000	
Noisy square	It consists of noisy square wave signals.	1000	
Ramp	They are signals with amplitude that increases or decreases linearly with time.	1000	
Sawtooth	They are sawtooth shaped signals that include linear increases and sudden decreases.	1000	
Sinus	It contains pure and regular sinusoidal waveform.	1000	
Square	It is a square waveform that transitions suddenly between high and low levels.	1000	
Triangle	It represents a triangular waveform that rises and falls symmetrically.	1000	
	Total	**7000**	

3.2. Data Preprocessing

The images of electronic waveforms used in the study were rescaled to 64×64 pixels to ensure that all samples were represented in a fixed size. The images in RGB format were flattened and converted to one-dimensional vectors and made compatible with machine learning algorithms. Class labels were digitized with LabelEncoder, and the attributes were standardized with the StandardScaler method. These steps were implemented to improve the learning process of the algorithms and to reduce the effect of data at different scales. Finally, the dataset was divided into 80% training and 20% testing.

3.3. Methods

In this study, classical machine learning algorithms were used to classify different electronic waveforms based on their visual representations. The applied methods were selected from models that can draw both linear and nonlinear decision boundaries; also, both single learners and ensemble approaches were included. In this way, it was aimed to evaluate the performance differences of the models used against various data patterns in a more holistic way. Below, the basic working principles of the 10 different machine learning methods used in the study, their place in the literature, and their known strengths and weaknesses in such classification problems are summarized.

3.3.1. Extra Trees (Extremely Randomized Trees)

Extra Trees algorithm is an ensemble learning method that works by creating multiple decision trees, similar to Random Forest. However, Extra Trees provides higher diversity by randomly selecting the data used in each tree and completely randomly determining the threshold values at the branching points. This structure can increase the classification accuracy while preventing overfitting, especially in high-dimensional and complex datasets [1].

3.3.2. Random Forest

The Random Forest algorithm is an ensemble model that creates many decision trees based on the bagging (bootstrap aggregating) method and makes predictions by combining the outputs of these trees with a majority vote. Since each of the decision trees is trained with different random subsamples and features, the model has a high generalization ability. It stands out by providing stable results in noisy and complex datasets [2].

3.3.3. Decision Trees

Decision trees are an intuitive and interpretable method that classifies data by dividing them into branches according to a specific target variable. The data is split into two using an attribute at each node of the tree and decisions are made at the leaf nodes. However, if the data is too complex or the tree depth is too large, the model may tend to overfit [3].

3.3.4. Support Vector Machine (SVM)

Support Vector Machines (SVM) is a powerful classification method based on supervised learning. Its main purpose is to find a hyperplane (decision boundary) that best separates data belonging to different classes. In linearly separable data, classes are separated from each other by creating a hyperplane with maximum margin. In nonlinear cases, the data is made separable by transforming it into a higher dimensional feature space via kernel functions. In this way, SVM can work effectively on both linear and nonlinear classification problems. Commonly used kernel functions include linear, polynomial, RBF (radial basis function) and sigmoid kernels. Due to its robust structure against noise and high generalization performance even on small sample sets, it is preferred in many areas such as biomedical signal processing, text mining, and image recognition [10].

3.3.5. Gradient Boosting

Gradient Boosting is a boosting method that creates a stronger model by repeatedly adding weak classifiers (usually short decision trees). Each new tree is trained by focusing on examples that the previous model classified incorrectly. Although this method is known for providing high accuracy, it is more sensitive than other methods in terms of hyperparameter tuning and training time [4].

3.3.6. Logistic Regression

Logistic regression is one of the basic methods that perform classification by creating a linear decision boundary. Although it was developed especially for binary classification, it can also be applied to multiple classes. It models the relationship between input variables and the class via the logit function. It is preferred as a basic starting model due to its easy interpretability [5].

3.3.7. K-Nearest Neighbors (KNN)

KNN is an example-based method where the decision is made based on the class labels of the K nearest neighbors in the training set of a new example to be classified. Despite its assumption-free and simple structure, this algorithm can be slow on large and high-dimensional datasets. In order to obtain accurate results, the selection of the appropriate distance metric and K value is critical [6].

3.3.8. Linear Discriminant Analysis (LDA)

LDA is a linear method used for both classification and dimensionality reduction. Its aim is to find a projection direction that minimizes the intra-class variance while maximizing the inter-class variance. It gives very successful results, especially when the classes have a normal distribution [7].

3.3.9. Naive Bayes

Naive Bayes classifier is based on Bayes theorem and assumes conditional independence among features. Despite this strong assumption, it can provide effective and fast results in many practical cases. It is frequently used in areas such as text mining, email filtering and sentiment analysis [8].

3.3.10. AdaBoost (Adaptive Boosting)

AdaBoost trains weak learners (e.g., single-layer decision trees) sequentially, giving more weight to misclassified examples at each step. The result is a strong classifier based on the weighted votes of all models. It may perform poorly on noisy data, but it provides high accuracy when well structured [9].

3.4. Performance Metrics

Experimental results were evaluated according to 6 different metrics. TP, TN, FP, FN structures were used in the calculation of these metrics.

TP (True Positive): An example belonging to the true positive class is correctly classified as positive by the model.

TN (True Negative): An example belonging to the true negative class is correctly classified as negative by the model.

FP (False Positive): A true negative example is incorrectly assigned to the positive class by the model.

FN (False Negative): A true positive example is incorrectly assigned to the negative class by the model.

3.4.1. Accuracy

It is the ratio of the examples that the model correctly classified to the total number of examples. It is the most common metric that shows the general performance level.

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

3.4.2. Recall (Sensitivity / True Positive Rate)

It is the rate at which n true positive classes are correctly identified by the model. It is used especially in cases where it is important not to miss examples.

$$Recall = \frac{TP}{(\mathrm{TP} + \mathrm{FN})} \tag{2}$$

3.4.3. Precision

It shows how many of the model's positive predictions are correct. It is important in situations where false alarms need to be reduced.

$$Precision = \frac{TP}{(\mathrm{TP} + \mathrm{FP})} \quad (3)$$

3.4.4. F1 Score

It is the harmonic mean of Precision and Recall values. It is used for evaluation in unbalanced class distributions.

$$F1\ Score = \frac{2\times(\mathrm{Precision} \times \mathrm{Recall})}{(\mathrm{Precision} + \mathrm{Recall})} \quad (4)$$

3.4.5. Specificity (True Negative Rate)

It is the rate at which negative classes are correctly identified. It is important to evaluate the impact of false positives.

$$Specificity = \frac{TN}{(\mathrm{TN} + \mathrm{FP})} \quad (5)$$

3.4.6. ROC-AUC (Receiver Operating Characteristic - Area Under Curve)

This metric measures the ability of a classification model to distinguish between positive and negative classes. It is the area that summarizes the classification performance of the model at different threshold values, measuring the balance between accuracy and error. Values close to 1 indicate high success.

$$AUC = \int_{O}^{1} TPR(FPR)d(FPR) \quad (6)$$

$$TPR(True\ Positive\ Rate) = \frac{TP}{(\mathrm{TP} + \mathrm{FN})} \quad (7)$$

$$FPR(False\ Positive\ Rate) = \frac{TP}{(\mathrm{TP} + \mathrm{FN})} \quad (8)$$

4. Results and Discussion

In this study, 10 different machine learning algorithms were evaluated for the classification of different signal types based on image representations. Comprehensive metrics such as accuracy, recall, precision, F1 score, specificity and ROC-AUC (Receiver Operating Characteristic - Area Under Curve) were used for performance analysis. The numerical results obtained are shown in Table 2, and the complexity matrices of each model are shown in Figure 2.

Table 2. Classification results using machine learning methods.

Model	Accuracy	Recall	Precision	F1 Score	Specificity	ROC-AUC
Extra Trees	0.98571	0.98604	0.98582	0.98575	1.00000	0.99980
Random Forest	0.98500	0.98525	0.98523	0.98503	1.00000	0.99959
Decision Tree	0.92929	0.92995	0.92906	0.92907	0.98333	0.95910
Support Vector Machine	0.92429	0.92449	0.92476	0.92344	1.00000	0.99497
Gradient Boosting	0.88929	0.88737	0.89700	0.88718	1.00000	0.97852

Logistic Regression	0.87786	0.87584	0.88781	0.87859	1.00000	0.95170
KNN	0.84714	0.85409	0.90180	0.86065	1.00000	0.98191
LDA	0.81857	0.81640	0.82922	0.80969	0.83465	0.90580
Naive Bayes	0.68643	0.68726	0.69002	0.67966	1.00000	0.84863
AdaBoost	0.39357	0.40458	0.39807	0.36664	1.00000	0.79010

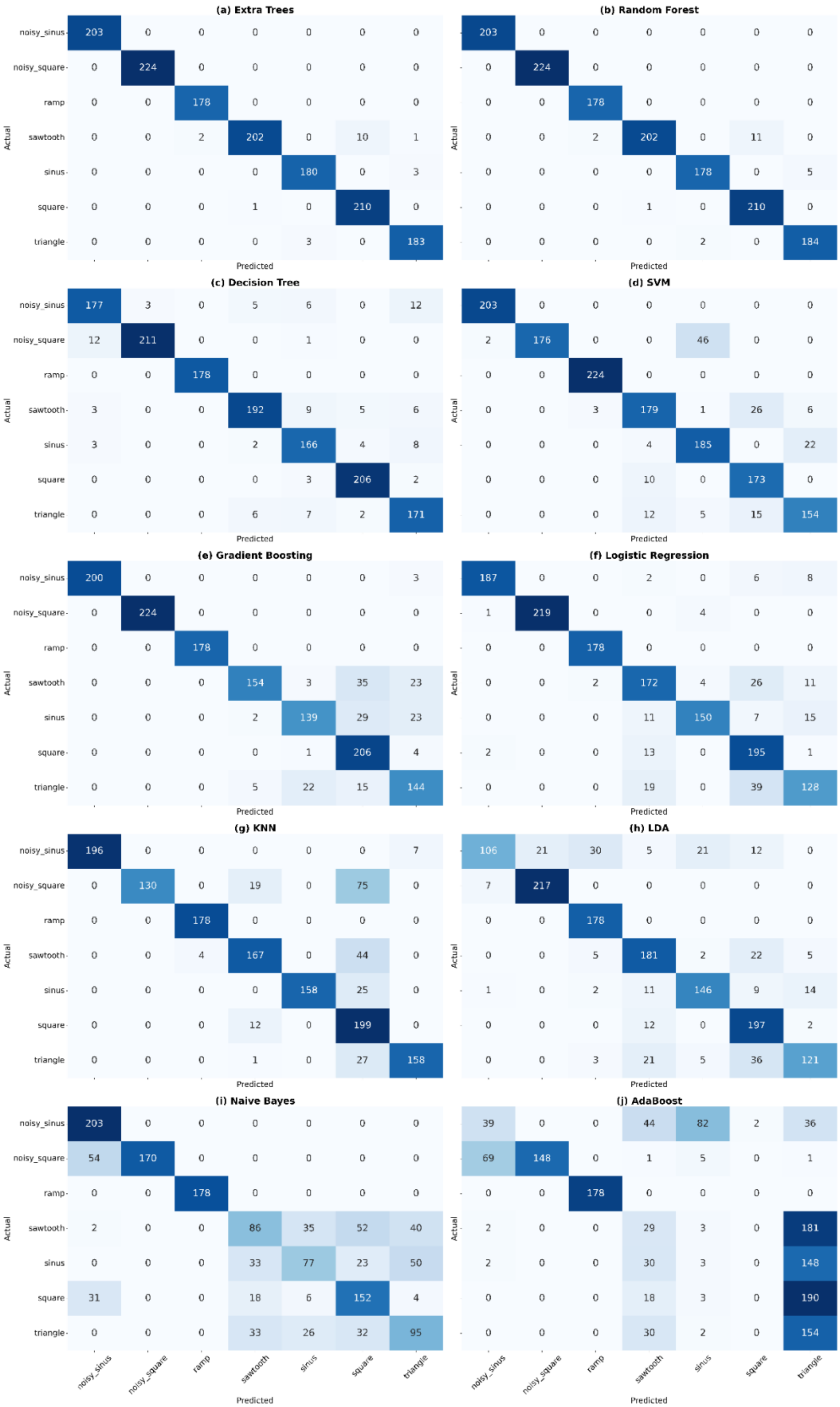


Figure 2. Complexity matrices of machine learning algorithms. a) Extra Trees, b) Random Forest, c) Decision Tree, d) SVM, e) Gradient Boosting, f) Logistic Regression, g) KNN, h) LDA, i) Naive Bayes, j) AdaBoost.

When Table 2 and Figure 2 are examined, the model with the highest success was the Extra Trees method. This method provided the highest overall performance in the study with 98.57% accuracy, 98.60% sensitivity and 99.98% ROC-AUC value. When Figure 2 is examined, it is seen that the model distinguishes all classes with very high accuracy. Similarly, the Random Forest algorithm produced successful results with 98.50% accuracy and 99.96% ROC-AUC values. These two ensemble methods optimized the classification performance by using the collective power of decision trees. The Decision Tree model, with an accuracy rate of 92.92%, provided a good starting level among the algorithms based on the basic tree structure. It was observed that the discriminative performance between classes was moderately balanced. The Support Vector Machine (SVM) model has an accuracy rate of 92.42% and a ROC-AUC score of 99.49%. It is understood that there was confusion, especially between some classes, but overall success was high. Gradient Boosting (88.93% accuracy) and Logistic Regression (87.78% accuracy) showed moderate performance as nonlinear and linear models. K-Nearest Neighbors (KNN) algorithm remained below the average in the study with 84.71% accuracy rate; especially the confusion rate increased between some classes. The Linear Discriminant Analysis (LDA) model achieved 81.85% accuracy and 90.58% ROC-AUC score. However, its performance was limited due to the class distributions not meeting the hypothetical requirements. Naive Bayes showed that its structure based on statistical assumptions was not suitable for this data structure with 68.64% accuracy. The AdaBoost algorithm showed the lowest success with 39.36% accuracy. It was determined that there was serious confusion between the classes.

This study demonstrates that ensemble learning algorithms (Extra Trees, Random Forest) in particular provide high success in signal-based multi-class image classification problems. It has been understood that ensemble approaches are more stable and error-tolerant compared to single learners (Decision Tree, Logistic Regression). As a result, model selection is of great importance in the classification of signal patterns; the evaluation of different metrics together plays a critical role in understanding class imbalances and overall performance.

5. Conclusion

This study aims to classify electronic waveforms based on their visual representations in the time-frequency domain using machine learning algorithms. In the experiments conducted on a dataset consisting of 7,000 images of 7 different signal types, 10 different classical machine learning algorithms were compared and each was evaluated with the same set of features. The results revealed that especially ensemble-based methods (Extra Trees and Random Forest) provide high classification performance.

Performance analyses were performed with various metrics such as accuracy, precision, sensitivity, specificity, F1 score and ROC-AUC. Extra Trees algorithm showed the highest success with 98.57% accuracy rate and 0.9998% ROC-AUC value. Similarly, the Random Forest algorithm has also produced quite successful results. However, Naive Bayes models based on statistical assumptions and AdaBoost models based on weak learners were inadequate for this type of signal data due to their low accuracy values. The study comprehensively compares the performance differences of different algorithms on signal data to reveal which types of models are more effective in such classification tasks. In particular, bagging-based ensemble methods have been found to offer high generalization capacity on datasets containing noisy and complex time-frequency images.

As a result, this study shows that classical machine learning methods can provide an effective solution for the classification of electronic waveforms based on time-frequency analysis. The findings obtained can contribute not only to the field of signal processing, but also to application areas such as image-based classification and industrial automation. In future studies, more detailed analysis of such visual signal representations with deep learning architectures is among the potential development areas that can further increase model performance.

Author Contribution

The authors' contribution rates in the study are equal.

Conflict of Interest Statement

The authors declare that there is no conflict of interest.

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