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Research Article

A Comparative Analysis of Various Classifier Algorithms alongside the Random Forest Method for the Classification of Satellite Images within the Realm of Artificial Intelligence

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Abstract
This work aims to assess many supervised learning algorithms, illustrate diverse supervised machine learning classification methodologies, and determine the optimal classification algorithm based on characteristics and the dataset. Often, intelligent systems execute supervised classification by using externally provided instances to formulate broad predictions regarding future situations. In this work, ten distinct machine learning methods were evaluated: Logistic Regression, Support Vector Machine (SVM), K-Neighbors, Naive Bayes (NB), Decision Tree, AdaBoost, Extra Trees, CatBoost, Gradient Boosting, and LightGBM. To execute the algorithms, Sentinel-2 satellite imagery and vector data were utilized and transformed into a CSV format for categorization. The dataset comprised 1,296 instances, with 17 independent variable features and one dependent variable for analysis. The findings indicate that CatBoost had the highest precision and accuracy among the algorithms evaluated. LightGBM, Extra Trees, and Random Forest classification algorithms were identified as the subsequent most accurate following SVM. This research indicates that priority should be considered while selecting a classifier to develop an effective classification model since precision (accuracy) and time consumption are key aspects in this selection process. Consequently, machine learning methods necessitate precision, accuracy, and minimal mistakes for supervised predictive modelling, so the choice of the classifier is subject to the specific objectives and circumstances required.
Keywords: Artificial Intelligence (AI), Machine Learning (ML), Data Mining Techniques, Supervised Machine Learning, F1-Score, Support Vector Machine (SVM).

1. Introduction

Artificial intelligence (AI) has been recognized as a vital contemporary application that has demonstrated its effectiveness and success across several domains. These domains including the implementation of satellite image classification [1]. “AI” is an exciting and rapidly evolving field within computer science that is dedicated to developing and creating machines and systems that can perform tasks that usually necessitate human intelligence [2]. For instance, problem-solving, learning, and decision-making [3]. Researchers are making strides in developing technologies that can simulate the human mind. While computers excel in many areas, human brains still outperform them in common sense, inspiration, and imagination [4, 5]. In recent years, machine learning has experienced rapid growth and has found numerous applications. It revolves around the automatic identification of meaningful data patterns and seeks to improve the adaptability and learning capacity of software applications [6]. "Artificial Intelligence" encompasses the fusion of computer science, physiology, and philosophy. Replicating the intricate behavior of the human brain, composed of billions of neurons, poses one of the most complex challenges in artificial intelligence. AI logic is based on concepts from philosophers and mathematicians, later utilized by AI systems [1, 7].

1.1. Previous Study

1.1.1. Supervised Classification Algorithms in Machine Learning: A Survey and Review

Machine learning enables machines to learn from data and make predictions without human involvement. Supervised learning, a key branch of machine learning, allows models to predict future outcomes based on past data. This paper compares widely used classification algorithms, acknowledging that it's impossible to cover all algorithms comprehensively in a single paper due to the rapid growth of the field [8].

1.1.2. Comparative Study of Four Supervised Machine Learning Techniques for Classification

In this study, four well-known supervised machine learning techniques: Decision Tree, K-Nearest Neighbor, Artificial Neural Network, and Support Vector Machine were used. The study aimed to gain insights into the key concepts of each technique, identify their strengths and weaknesses, and evaluate their performance through the practical application using measures like sensitivity and specificity. The study emphasized the importance of understanding the complexity of evaluating classifier performance and the need to find a classifier that best fulfils all criteria [9].

1.1.3. Comparison of Machine Learning Algorithms in Data Classification

Data mining involves extracting valuable information from raw data to reveal hidden patterns that can guide future decisions. Machine learning classifiers are employed to analyze the data, particularly in the context of predicting diseases and facilitating timely treatment. This study aims to compare the performance of various machine learning classifiers, such as Logistic Regression, Decision Tree, Naive Bayes, K-Nearest Neighbors, Support Vector Machine, and Random Forests, using two datasets and evaluating their accuracy, precision, and F-measure. The experimental findings indicate that Random Forests outperformed other classifiers, achieving 83% accuracy in heart disease prediction and 85% accuracy in predicting hepatitis [10].

1.2. Comparison of Supervised Machine Learning Classification Algorithms

Data mining is a crucial step in uncovering knowledge, using algorithms to identify patterns within data. In this study, evaluation of the performance of ten supervised learning Logistic Regression, Support Vector Machine (SVM), K-Neighbors, Naive Bayes (NB), Decision Tree, AdaBoost, Extra Trees, CatBoost, Gradient Boosting, and LightGBM-using various parameters to gauge their impact on the dataset [6]. A classification algorithm is employed to identify the category of data, such as faulty, fault-type, or healthy. Utilizing classifiers is an effective method for extracting valuable information, which is why they are presented in a dedicated section below [11].

Supervised learning is a crucial subset of machine learning algorithms that effectively predicts the output of new data by utilizing a labelled dataset. The model is trained using human-supplied labels, and its accuracy is then assessed using new data. There is a diverse range of popular supervised learning algorithms, and here are some of the most widely used ones:

1.2.1. The Ensemble Classifier

An ensemble classifier is a powerful machine-learning algorithm that harnesses the predictive abilities of multiple classifiers to build a robust model. This approach involves aggregating weak classifiers to effectively reduce the misclassification rate [12]. Ensemble learning combines individually trained classifiers, such as neural networks and decision trees, to improve model performance, including boosting, bagging, and random forest, particularly relevant to remote sensing. Random Forest is a widely used ensemble classifier, with a strong emphasis on its applications in satellite image processing [13].

1.2.2. CatBoost

CatBoost is a supervised machine learning method that is used by the Train Using AutoML tool and uses decision trees for classification and regression.

1.2.3. LightGBM

LightGBM is a high-performance gradient-boosting framework developed by Microsoft. It excels at constructing strong learners by gradually integrating weak learners through gradient descent. It cleverly utilizes techniques like Gradient-based One-Side Sampling (GOSS) to optimize memory usage and training time [14].

1.2.4. ExtraTrees

The Extra Trees Classifier is an ensemble learning technique that uses multiple uncorrelated decision trees to deliver precise classification results. Each decision tree in the Extra Trees Forest is constructed using the original training data, and at each test node, every tree receives a random sample of k features from the feature set. This process of random feature sampling gives rise to numerous uncorrelated decision trees, and the Gini Importance of the feature is computed for effective feature selection. Each feature is then ranked based on its Gini Importance, allowing the user to select the top k features as per their preference [14].

1.2.5. Random Forest
Breiman's random forest algorithm, developed in 2001, is an effective method for classification and regression. It combines randomized decision trees, shows strong performance with many variables, and provides valuable variable importance metrics [15].

1.2.6. Gradient Boosting
Gradient Boosting is a powerful boosting approach that combines numerous weak learners into strong learners. Each new model is trained to minimize the preceding model's loss function, such as mean squared error or cross-entropy, using gradient descent. In each iteration, the technique computes the gradient of the loss function about the current ensemble's predictions and then trains a new weak model to minimize this gradient. The predictions of the new model are then added to the ensemble, and the procedure is repeated until a stopping condition is reached [16].

1.2.7. Decision Tree
Decision trees (DT) are a valuable tool for classification as they organize instances based on their feature values. Each node represents a feature in an instance that requires classification, and its branches signify the potential values that the node can take on. This method allows for effective sorting and classification of instances based on their feature values, starting from the root node [17].

A decision tree is a predictive model used in data mining and machine learning. It links item observations to conclusions about the item's target value and can be referred to as regression trees or classification trees [18]. Decision tree classifiers often use post-pruning techniques, evaluating tree performance as they are pruned using a validation set. Nodes containing the most common class of training instances can be eliminated and reassigned [17].

1.2.8. Support Vector Machine (SVM)
The latest supervised machine learning methods include Support Vector Machine (SVM) models and classical multilayer perceptron neural networks. Both SVMs and neural networks have many similarities. SVMs are based on the concept of a "margin" on either side of a data class separation hyperplane. Reducing the margin maximises the distance between instances on either side of the separating hyperplane and the hyperplane itself, thereby reducing an upper bound on the expected generalization error [17].

1.2.9. Naive Bayes
Basic Bayesian networks are structured as directed acyclic graphs with multiple children (observed nodes) and a single parent (unobserved node), assuming independence between child nodes within the context of their parent. [19]. Bayes classifiers are usually less accurate than other more sophisticated learning algorithms (such as ANNs) [20]. Bayes classifiers are generally considered less accurate than more advanced learning algorithms, such as ANNs. However, recent research has shown that the Naive Bayes classifier occasionally outperformed other learning schemes in large-scale comparisons with state-of-the-art algorithms for decision tree induction, instance-based learning, and rule induction on standard benchmark datasets. This suggests potential advantages of the Naive Bayes classifier in certain scenarios. Additionally, averaged one-dependence estimators have been effective in addressing the attribute independence problem of the Bayes classifier [21].

1.2.10. K-Neighbors
KNN, short for K-Nearest Neighbor, is a versatile machine learning algorithm used for clustering or classifying data based on similarity. It can be applied in both unsupervised and supervised machine learning to analyze datasets and uncover patterns for effective categorization or grouping of data [22].

1.2.11. Logistic Regression
In this function, a class is used to build a multinomial logistic regression model with a single estimator. Logistic regression calculates class probabilities based on the distance from the boundary and the position of the boundary between classes. These probabilities shift more rapidly towards the extremes when the dataset is larger. Logistic regression enables robust predictions and is commonly used in statistics and data analysis [23, 24].

1.2.12. AdaBoost
The AdaBoost method, created by Freund and Schapire in 1997, is commonly employed for binary classification problems. It converts weak learners into strong ones by iteratively improving prediction

accuracy. AdaBoost merges several weak learners to form strong learners. Furthermore, there is a similar approach known as gradient-boosted trees, which utilizes CART (Classification and Regression Trees) as its foundational learner [16, 25].

1.3. Study Problem

The objective of this research is to evaluate and compare the performance of various classifiers in terms of accuracy, classification time, and error rates.

2. Data and Method

2.1. Study Area

The study was conducted on a section of the Al-Gazira scheme, which spans 2,200,000 acres. The study area itself covered approximately 139871.87 acres and was situated in the Al Kamlin Locality (Figure 1). The geographical coordinates of the study area range from latitudes 15.248703° N to 15.141209° N and longitudes 32.981824° E to 33.094350° E, usually based either on the Sudan reference system or WGS84 [26].

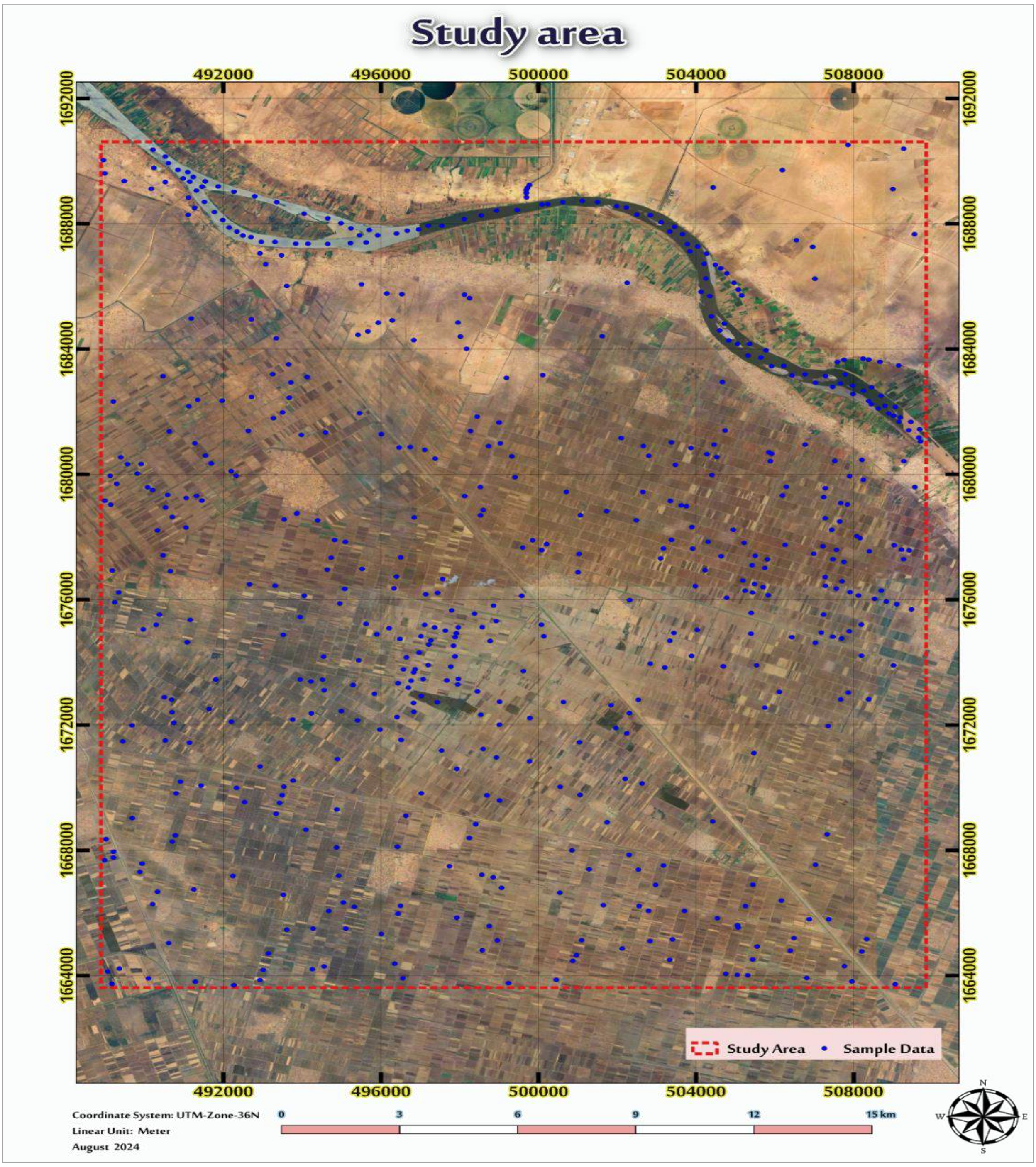

Figure 1. Study area.

2.2. Data

Several types of geospatial data have been used in this study; the data was a combination of satellite images Sentinel-2 for multitemporal data and ground truth data obtained from the field visit. All types of these data were converted to CSV (Table 1 and Table 2) shown the imagery data obtained from the USGS website and ground truth data. All data are in a metric unit's system's Universal Transverse Mercator (UTM) zone 36N projection [27].

Table 1. Raster data used in research.

Name	Date	Bands used
T36PVB-T115637	30-09-2019	13 bands
T36PVB-T080839	10-10-2019	13 bands
T36PVB-T080911	15-10-2019	13 bands
T36PVB-T102425	25-10-2019	13 bands

Table 2. Vector data of study area.

Name of layers	Date	Type of data
Ground truth data (field visit)	2019	Vector data

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	C	P	Q	R
1	Band_1	Band_2	Band_3	Band_4	Band_5	Band_6	Band_7	Band_8	Band_9	Band_10	Band_11	Band_12	Band_13	NDVI1	SAVI1	AVI1	Latitude	Longitude
2	959	1108	1512	2048	2344	2511	2673	2620	2738	2895	3114	3213	3027	0.122536	0.174966	-1E+09	15.29199504	32.8965632
3	970	1006	1422	1818	2436	2706	2899	2778	2897	2932	3185	3210	2908	0.208877	0.298249	-1.6E+09	15.29199508	32.89665634
4	970	976	1452	1932	2436	2706	2899	2822	2897	2932	3185	3210	2908	0.187211	0.267313	-1.6E+09	15.29199513	32.89674949
5	970	1042	1424	1808	2317	2662	2869	2728	3002	2932	3185	3188	2891	0.202822	0.289602	-1.5E+09	15.29199517	32.89684263
6	970	1154	1702	2078	2317	2662	2869	2996	3002	2932	3185	3188	2891	0.180922	0.258335	-1.9E+09	15.29199521	32.89693578
7	970	1210	1452	1784	2395	2805	3062	3232	3079	2932	3185	3276	3050	0.288676	0.412194	-2.8E+09	15.29199525	32.89702892
8	970	1166	1622	2060	2395	2805	3062	2756	3079	2932	3185	3276	3050	0.144518	0.206354	-1.3E+09	15.2919953	32.89712206
9	1034	1292	1734	2300	2593	2698	2908	2736	2953	3032	3331	3318	3186	0.086577	0.123621	-9.1E+08	15.29199534	32.89721521
10	1034	1208	1700	2286	2593	2698	2908	2648	2953	3032	3331	3318	3186	0.073368	0.104761	-7.3E+08	15.29199538	32.89730835
11	1034	1142	1634	2142	2428	2656	2873	2722	2962	3032	3331	3221	2991	0.119243	0.170265	-1.1E+09	15.29199543	32.8974015
12	1034	935	1426	1782	2428	2656	2873	2920	2962	3032	3331	3221	2991	0.242025	0.34558	-2E+09	15.29199547	32.89749464
13	1034	1116	1486	1894	2359	2657	2840	2618	2883	3032	3331	3142	2880	0.160461	0.229117	-1.2E+09	15.29199551	32.89758779
14	1034	1022	1444	1932	2359	2657	2840	2568	2883	3032	3331	3142	2880	0.141333	0.201805	-1.1E+09	15.29199555	32.89768093
15	968	1196	1604	2076	2200	2523	2704	2666	2729	2827	3294	3077	2924	0.12442	0.177656	-1.1E+09	15.2919956	32.89777407
16	968	935	1388	1858	2200	2523	2704	2580	2729	2827	3294	3077	2924	0.162686	0.232293	-1.2E+09	15.29199564	32.89786722

Figure 2. Converted data used in classification csv format.

The (Figure 2) showing the prepared data used in the classification and comparison of the classifier this data was prepared by using a combination of software Qgis and Excel.

2.3. Method

Comparative analysis was conducted in this paper as it can be considered a fundamental classification analysis tool. It sharpens our powers of description and plays a central role in concept formation by bringing suggestive similarities and contrasts among cases into focus. Comparative analysis is routinely used in testing hypotheses, it can also contribute to the inductive discovery of new hypotheses and theory-building. This paper examines various comparative classifiers between the classifiers and the random forest by using the Google Colab Platform.

The process begins with data collection from a variety of sources.

The initial source of data is satellite images with multi-temporal resolution obtained from the USGS website during the same season in 2019. Subsequently, a field visit is conducted to capture data that is utilized in the image classification process. The GIS software (Qgis) was used to preprocess the data by converting the merged images to point vector format and computing the indices to prepare features and instances of the study area image into points. The data was then divided into training and testing subsets and converted to CSV format for use in ML (Google Colab Platform) after the necessary libraries were added. Finally, all study area data was used to make predictions after the model was trained and tested. Then perform classification against random forests using a variety of classifiers.

3. Results and Discussion

Accuracy is defined as the proportion of true positives and true negatives among all accurate forecasts, and when all classes are balanced, the costs of false positives and false negatives are similar. The F1-score is the harmonic mean of precision and recall, which balances the trade-off between false positives and false negatives when dealing with imbalanced datasets or when the costs of false positives and false negatives are different [28].

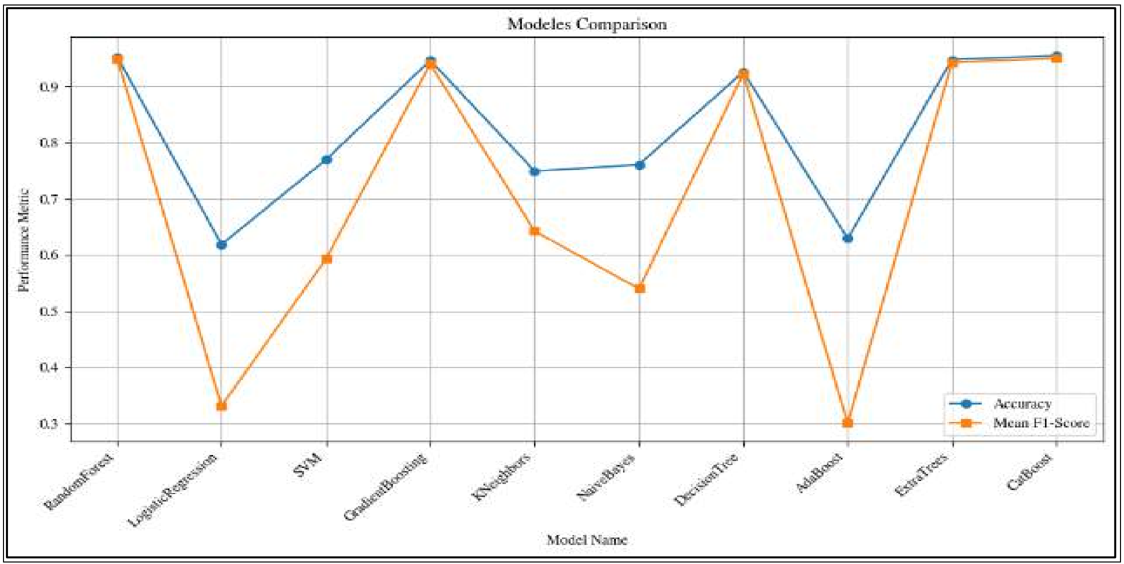

Figure 3. Classifiers comparisons.

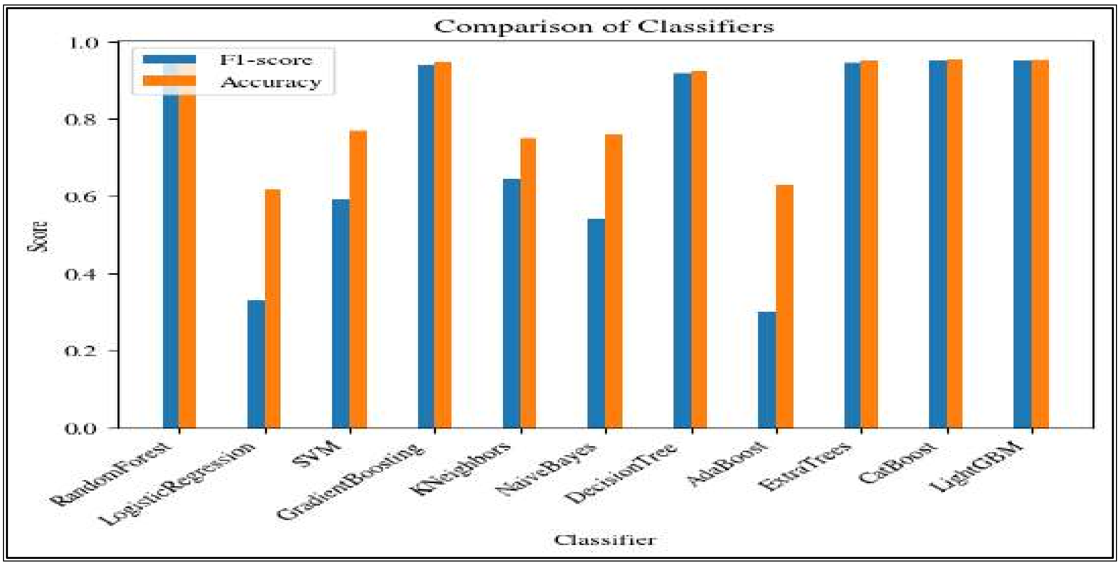

Figure 4. Accuracy and F1-score.

The results of the classifiers are shown in (Figure 3 and Figure 4), which shows the model comparisons for the various classifiers that were used in the comparison. When the accuracy and F1-score are close to one another, it indicates that the classification is good, and vice versa. According to the degree of similarity between accuracy and F1-score, the results indicate that certain classifiers were less accurate than others. The accuracy and F1-score can be used as metrics to assess model performance in classification, as shown in (Figure 3, and Figure 4). A close relationship between the two metrics typically indicates that the classification model is effective.

Table 3. Accuracy and F1-score.

No	Classifier (algorithm)	Accuracy	F1-score
1	CatBoost	0.9551	0.9499
2	LightGBM	0.9536	0.9493
4	Extra Trees	0.9507	0.9457
3	Random Forest	0.9493	0.9468
5	Gradient Boosting	0.9464	0.9398
6	Decision Tree	0.9232	0.9187
7	SVM	0.7696	0.5926
8	Naive Bayes	0.7609	0.5399
9	KNeighbors	0.7493	0.6424
10	AdaBoost	0.6290	0.3004
11	Logistic Regression	0.6188	0.3312

As shown in Table 3, the values of the accuracy of the F1-score of CatBoost, LightGBM, Extra Trees, Random Forest, and Gradient Boosting show how they are closest to each other, which indicates those classifiers are effective more than the other classifiers.

3.1. Feature Importance

Visualizing feature importance is essential for understanding the factors influencing model predictions, ranking features helps identify influential variables, reveal patterns, and assess model reliability. Common visualization techniques like bar charts, heatmaps, and decision trees offer insights into feature relationships and aid model enhancement. Understanding this helps analysts' priorities feature engineering or selection efforts (Figure 5), which features are important in classification.

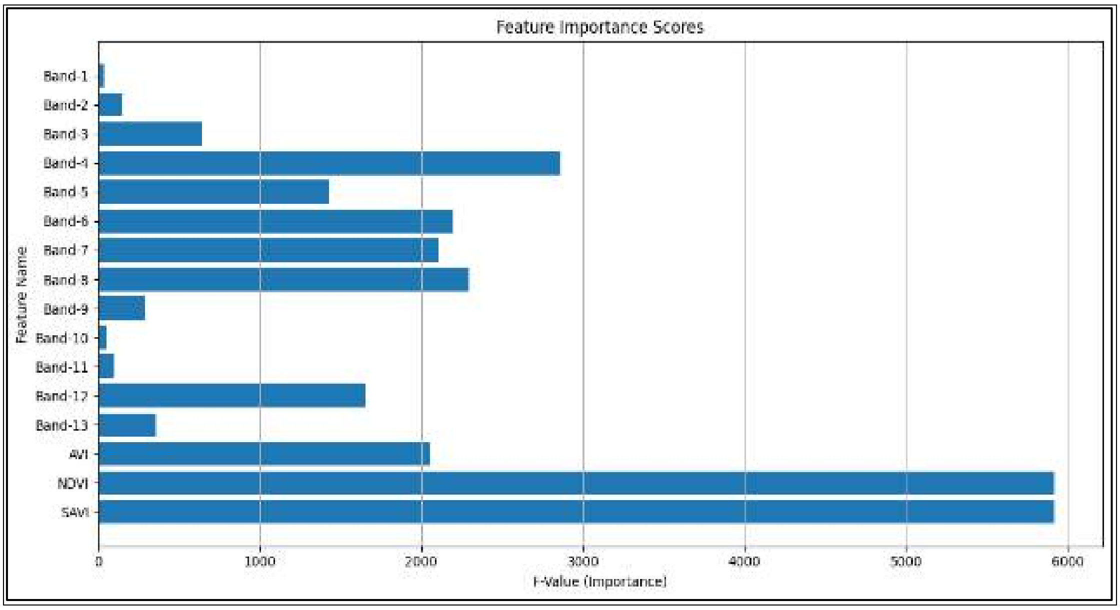

Figure 5. Feature importance and scores for visualization training and validation data.

The (Figure 5) shows the importance of features and effectiveness in the process of classification, and results and features like NDVI and SAVI have importance in the process.

3.2. The Classifier's Time Consumption

In assessing a classifier's performance, time consumption is important. It impacts how realistically a model can be implemented in real-world applications, especially those that require low latency.

3.3. Factors Affecting Time Consumption

3.3.1. Dataset Size: For training and prediction, larger datasets typically take longer to process.

3.3.2. Model Complexity: Training and prediction times are typically longer for more complicated models, such as deep neural networks with several layers and parameters.

3.3.3. Algorithm: Different algorithms have varying computational costs. For instance, decision trees are often faster to train than support vector machines.

3.3.4. Hardware: The processing power of the hardware (CPU, GPU) used for training and inference significantly affects the time taken.

3.3.5. Implementation: Efficient coding practices and optimization techniques can reduce computational overhead results are sorted by total time.

3.4. Measuring Time Consumption

To quantify the time consumption of a classifier, measure:

3.4.1. Training Time: The time it takes to fit the model to the training data.

3.4.2. Prediction Time: The average time required to predict a single data point.

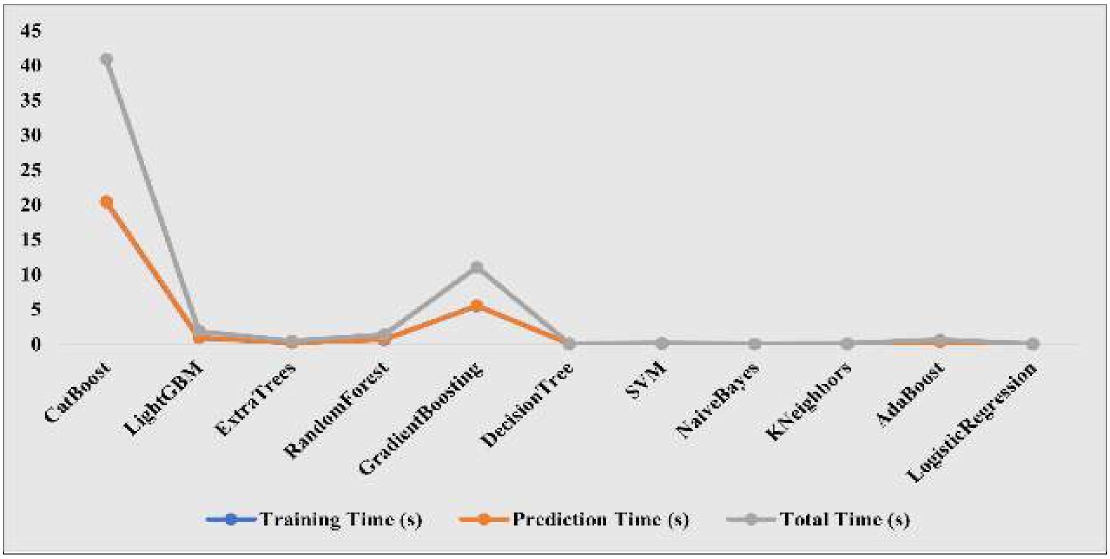

Figure 6. Training time and prediction time.

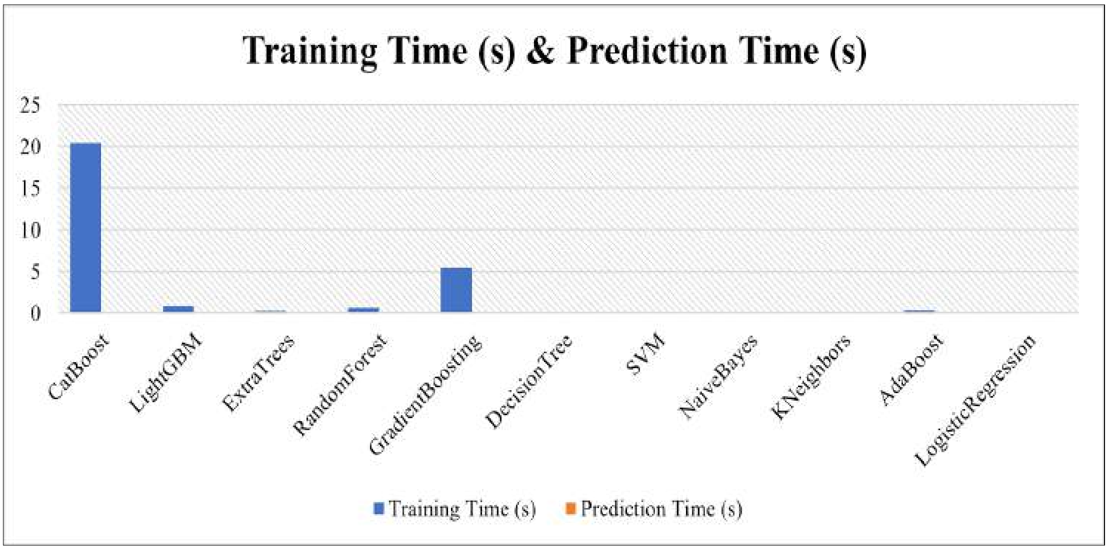

Figure 7. Time comparison for training and prediction for each classifier.

The (Figure 6, and Figure 7) shows the comparison of training time and prediction time; there is variation between them. CatBoost and Gradient Boosting consume the most resources for training and prediction, while the other classifiers have less variation between training and prediction.

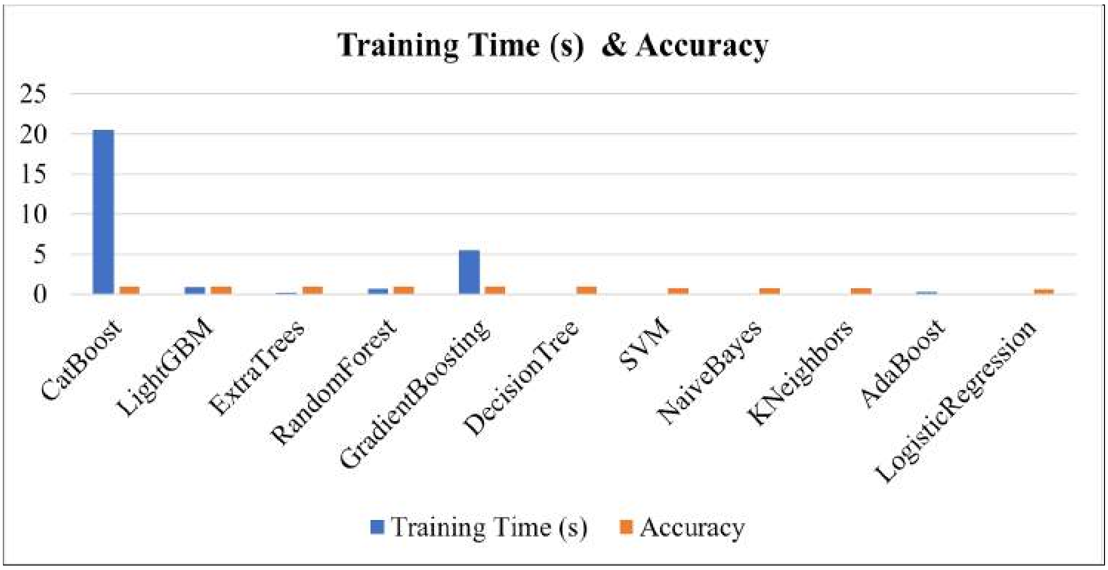

Figure 8. Training time and accuracy.

Table 4. Classifiers time consumption.

Classifier	Training time (s)	Prediction time (s)	Total time (s)
CatBoost	20.439838	0.017072	20.45691
LightGBM	0.898224	0.031677	0.929901
ExtraTrees	0.218582	0.018231	0.236813
Random Forest	0.651840	0.022670	0.674509
Gradient Boosting	5.508634	0.009395	5.518029
Decision Tree	0.025368	0.001694	0.027062
SVM	0.041954	0.033255	0.075208
Naive Bayes	0.004709	0.002585	0.007294
KNeighbors	0.003220	0.038719	0.041939
AdaBoost	0.313081	0.016746	0.329827
Logistic Regression	0.020513	0.001581	0.022094

Table 4, this represents that the CatBoost classifier consumes a total time of 20.45691s and LightGBM consumes a total time of 0.929901s, and they are the highest time consumption.

3.5. Assessment of Classifiers

A classifier comparison is an evaluation and comparison of the performance of multiple machine learning algorithms on a specific dataset this process becomes particularly important to ensure that the classifier is producing accurate and reliable results of the classifiers shown in Table 5.

Table 5. Assessment of classifiers.

No	Classifier	Training time (s)	Accuracy	Mean F1-score	Correctly classified	Incorrectly classified
1	KNeighbors	0.005300	0.749275	0.642376	517	173
2	Naive Bayes	0.003822	0.760870	0.539868	525	165
3	Decision Tree	0.026629	0.931884	0.927242	643	47
4	Logistic Regression	0.127501	0.618841	0.331243	427	263
5	SVM	0.195395	0.769565	0.592632	531	159
6	ExtraTrees	0.209152	0.950725	0.949128	656	34
7	AdaBoost	0.324337	0.628986	0.300399	434	256
8	LightGBM	1.108149	0.953623	0.949278	658	32
9	Random Forest	2.108149	0.950725	0.948906	656	34
10	Gradient Boosting	8.904269	0.946377	0.939794	653	37
11	CatBoost	19.379582	0.955072	0.949906	659	31

4. Conclusion and Recommendation

The process of selecting classifiers entails determining which algorithm performs better for the cases under consideration in this study. According to Table 5, CatBoost was the algorithm that performed the best in terms of accuracy and precision in the comparison process; however, it also required more time than other classifiers. To find the best classification probability, their optimization was also examined.

To perform the ML classification, the parameters must be fine-tuned extensively, and, at the same time, a large number of instances must be present in the data set. Developing the model for the algorithm is more than just about time. It is also about accuracy and precision. Thus, even the best algorithm for a specific set of data cannot guarantee accuracy.

In applying machine learning to data sets with logically different attributes, the key question is not whether one algorithm is superior to another, but under what conditions a particular method can significantly outperform others.

Declarations

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