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Advancements in Machine Learning Algorithms: A Comparative Analysis of Single, Ensemble, Hybrid, and Emerging Methods

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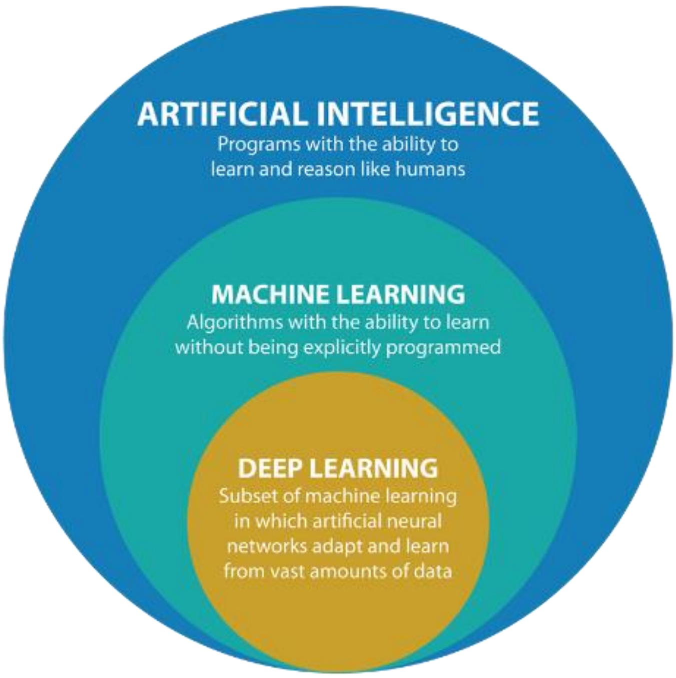
ABSTRACT:

In this survey paper, we present a comprehensive analysis of various machine learning algorithms and their performance in predictive modelling. The study encompasses single classifiers, multiple classifiers, and ensemble methods, evaluating their accuracy using a range of datasets. The performance metrics highlight the superiority of ensemble techniques such as AdaBoost and XGBoost [5], which achieve accuracies as high as 99.08%. Among single classifiers, the K-Nearest Neighbor (KNN) [1]and Decision Tree [1] algorithms show promising results with accuracies up to 94.65% and 93.7%, respectively. Support Vector Machines (SVM) [2] demonstrate varying performance based on the optimization technique applied, with accuracies ranging from 75.99% to 97.5%. The survey provides a detailed comparison, showcasing the strengths and limitations of each method through tables and graphical representations, thus offering valuable insights for selecting appropriate algorithms in different predictive scenarios. This analysis aims to guide researchers and practitioners in the application of machine learning techniques for improved accuracy and efficiency in predictive modeling tasks.

Keywords: K-Nearest Neighbors (KNN), Support Vector Machines (SVM),AdaBoost, XGBoost, Bagging Voting Classifier Whale Optimization Algorithm (WOA), Particle Swarm Optimization (PSO) Accuracy

INTRODUCTION:

Machine Learning can be defined as a process of building computer systems that automatically improve with experience, and implement a learning process [9]. Since their evolution, humans have been using many types of tools to accomplish various tasks in a simpler way. The creativity of the human brain led to the invention of different machines. These machines made the human life easy by enabling people to meet various life needs, including travelling, industries, and computing. And Machine learning is the one among them [10].



Machine learning has seen extensive growth and application across various domains, with classification being a core technique for predicting the class or category of given inputs based on learned data. Classifiers are essential tools for tasks such as medical diagnosis, spam detection, and image recognition. However, with the multitude of classifiers available, each with its unique strengths and weaknesses, it becomes crucial to understand their comparative performance to make informed decisions about their use. The motivation for this survey is to provide a comprehensive overview of the accuracy of various classifiers as reported in recent studies. Many individual studies focus on specific algorithms, but there is a need for a consolidated resource that compares these algorithms in a structured manner. This survey aims to bridge that gap, helping researchers and practitioners choose the most suitable classifiers for their specific needs.

The primary objectives of this survey are to review the performance of single classifier algorithms, including Decision Trees, K-Nearest Neighbor (KNN), and Support Vector Machines (SVM), and to analyze the effectiveness of multiple classifier systems such as AdaBoost, Bagging, and Voting algorithms. Additionally, the survey evaluates the impact of optimization techniques like Whale Optimization Algorithm (WOA) and Particle Swarm Optimization (PSO) on the performance of classifiers. Finally, it presents a comparative analysis based on accuracy metrics reported in various studies. The survey is organized into several sections, starting with the introduction, followed by detailed discussions on single classifiers, multiple classifiers, and optimization techniques. It then offers a comparative analysis of classifiers and concludes with a summary of findings and suggestions for future research directions.

Single classifiers are the basic building blocks of classification algorithms, trained on a given dataset to make predictions based on learned patterns. Key single classifiers and their reported accuracies include Decision Tree Algorithm (93.7%), KNN Algorithm (94.65%), and SVM (75.99%). Multiple classifiers, or ensemble methods, combine the predictions of several models to improve overall performance. Common ensemble methods and their accuracies are AdaBoost-DT (98.36%), Bagging-DT (95.30%), Voting-KNN + DT (95.47%), AdaBoost-KNN (94.65%), Bagging-KNN (94.77%), Voting-DT + SVM (85.06%), Bagging-SVM (75.99%), and Voting-SVM + KNN (94.65%). Optimization techniques enhance classifier performance by finding optimal parameters. Notable techniques include WOA-SVM (97.50%) and PSO-SVM (97.21%), compared to standard SVM (91.91%).

A comparative analysis highlights the strengths and weaknesses of different classifiers: SVM (96.0%), Decision Tree (93.4%), KNN (87.3%), and Naïve Bayes (83.3%). Additional combinations and improvements are noted, such as Naïve Bayes Weighted Approach (86.00%), 2 SVMs and XGBoost (94.03%), SVM and DO (89.4%), and XGBoost (95.9%). Logistic Regression (92.86%), Random Forest (94.45%), and Extreme Gradient Boosting (XGBoost) (99.08%) also show strong performance. Stacking methods and improved ensemble classifiers like XGBoost (96.65%), Random Forest (96.43%), SVM (95.3%), and Stacking (97.04%) have demonstrated promising results. Bayesian Networks, although generally less accurate, have accuracies such as Bayesian Network (72.8%), Random Forest (77.8%), AdaBoost (86.1%), and Improved AdaBoost (91.7%). Further comparative results show K-nearest neighbor (KNN) (92%), Classification and Regression Tree (CART) (94%), Gaussian Naïve Bayes (NB) (92%), and Ensemble Classifier (95%).

LITERATURE SURVEY:

In recent years, the performance of various classifier algorithms has been extensively studied, showcasing significant advancements in prediction accuracy across single and multiple classifiers. This literature survey consolidates findings from multiple studies to provide a comprehensive overview of the effectiveness of these algorithms.

Single classifiers have been rigorously evaluated, with the Decision Tree algorithm achieving an accuracy of 93.7% [1], the K-Nearest Neighbors (KNN) algorithm 94.65% [1], and the Support Vector Machine (SVM) showing a comparatively lower accuracy of 75.99% [1]. When combined into multiple classifiers, the results demonstrate even greater accuracy improvements. For instance, the AdaBoost-DT (Decision Tree) combination reaches an impressive accuracy of 98.36% [1], while Bagging-DT scores 95.30% [1]. Other notable combinations include Voting-KNN + DT at 95.47% [1], AdaBoost-KNN at 94.65% [1], Bagging-KNN at 94.77% [1], and Voting-SVM+KNN also at 94.65% [1]. However, some combinations like Voting-DT + SVM and Bagging-SVM yield lower accuracies of 85.06% [1] and 75.99% [1], respectively.

Further evaluations of hybrid algorithms reveal that WOA-SVM (Whale Optimization Algorithm with SVM) and PSO-SVM (Particle Swarm Optimization with SVM) achieve remarkable accuracies of 97.50% [2] and 97.21% [2], respectively, compared to a standalone SVM's 91.91% [2]. In another comparative analysis, SVM shows an accuracy of 96.0% [3], Decision Tree 93.4% [3], KNN 87.3% [3], and Naïve Bayes 83.3% [3]. The effectiveness of ensemble methods is also evident, as demonstrated by a Naïve Bayes weighted approach achieving 86.00% [4], a combination of two SVMs and XGBoost scoring 94.03% [4], and a standalone XGBoost reaching 95.9% [4].

Logistic Regression and Random Forest classifiers also exhibit strong performance, with accuracies of 92.86% [5] and 94.45% [5], respectively. The standout performer in this category is Extreme Gradient Boosting (XGBoost), which achieves a notable 99.08% accuracy [5]. Additionally, another study shows XGBoost (XGB) with 96.65% accuracy [6], Random Forest (RF) with 96.43% [6], SVM with 95.3% [6], and a Stacking method achieving 97.04% [6]. Bayesian Network, though less accurate with a 72.8% score [7], improves significantly when integrated with AdaBoost and its improved versions, reaching up to 91.7% [7]. Lastly, other classifiers such as the K-Nearest Neighbors (KNN) report a 92% accuracy [8], Classification and Regression Tree (CART) 94% [8], Gaussian Naïve Bayes (NB) 92% [8], and an Ensemble Classifier achieves a solid 95% accuracy [8].

REFERENCE NO	ACCURACIES PREDICTED
[11]	Support Vector Machine (SVM): 98.16% Decision Tree: 78.24% Random Forest: 81.72% K-Nearest Neighbour (KNN): 97.18% Gaussian Naive Bayes: 85.74% Genetic Programming (GP): 98.10% Convolutional Neural Network (CNN): 98.48%
[12]	Static Feature Result: 94% Dynamic Feature Result:94% Hybrid Feature Result:94%
[13]	K-Nearest Neighbour (KNN): accuracy of 97% on the CK+ dataset and 95% on the JAFFE dataset. Support Vector Machine (SVM): 94% 67% Random Forest (RF): 89% Logistic Regression (LR): 87% 66% Decision Tree (DT):86% Discriminant Analysis (QDA): 86%
[14]	COVID-19 Dataset: 1.2746% Diabetes Dataset: 1.8274% Heart Disease: 1.7362%
[15]	Random Forest: 99% Logistic Regression: 91-97% Linear SVM: 98% K-Nearest Neighbors 88% on DS1. Ensemble Learners: 94% Benchmark Algorithms:DS1 and DS3, with 99% and 96% respectively
[16]	Naive Bayes: 98.0% SVM: 97.5% CNN: 98.0% LSTM:99.0%
[17]	SVM-96.56% CNN (30 seconds) SVM (58 seconds)
[18]	CNN-LSTM Model: 37.97% to 65.25% XGBoost Model: 93.28% to 94.12% Impact of Weather Data: MAE by up to 2.67% and MSE by up to 6.04% Combined Features: 1.31% to 3.96%
[19]	Overall Recognition Rate: 91.2% Average Recognition Accuracy: 75%1 Action-Specific Recognition Rates: 71.8% to 91.2%
[20]	-
[21]	-

Table 1

The **Table 1** lists various algorithms and their accuracies in different contexts, like medical diagnosis, emotion recognition, and weather prediction. While some of the listed algorithms are machine learning-based, the table also includes approaches that rely on statistical techniques or other data processing methods. For example:

[11][16][17][18] **Convolutional Neural Network (CNN):** A deep learning model, another area of machine learning.

Support Vector Machine (SVM)

[11] it has predicted accuracy but in that the highest accuracy is predicted by CNN.

[13] there are two different datasets - CK+ dataset and JAFFE dataset.

[15] there are four different datasets are used.

[16] the LSTM has predicted the highest accuracy

[17] the CNN has the highest accuracy with less time

Decision Trees

[11] it has predicted accuracy but in that the highest accuracy is predicted by CNN.

[13] there are two different datasets - CK+ dataset and JAFFE dataset.

[15] Ensemble Methods: there are four different datasets are used.

[16] Naive Bayes: the LSTM has predicted the highest accuracy

Logistic Regression

[13] there are two different datasets - CK+ dataset and JAFFE dataset.

[15] there are four different datasets are used.

[19] Multiview Clustering Algorithm and Semantic Learning Algorithm: These approaches often leverage machine learning techniques, but the table might not specifically detail the exact machine learning algorithms used within them.

[21] **Adaboost:** A boosting algorithm, which is a machine learning technique but no accuracies have been predicted.

The table's focus on accuracy metrics for different applications doesn't necessarily imply that all listed methods are solely based on machine learning algorithms. It highlights the range of approaches and their effectiveness in various domains.

In conclusion, the exploration of single and multiple classifiers reveals a spectrum of accuracies, emphasizing the effectiveness of ensemble methods and hybrid algorithms in improving predictive performance. This comprehensive survey underscores the continuous advancements in classifier algorithms, fostering improved accuracy in various applications.

EVALUATION METRICS:

In this section, we explain the metrics used to evaluate the performance of the various machine learning algorithms considered in this survey. These metrics provide a comprehensive understanding of each algorithm's strengths and weaknesses, enabling a detailed comparative analysis.

Accuracy

Accuracy is one of the most fundamental metrics used to evaluate machine learning algorithms. It is defined as the ratio of correctly predicted instances to the total number of instances in the dataset. Accuracy is expressed as a percentage and is calculated as follows:

Accuracy = (Number of Corrections / Total number of predictions) x 100

While accuracy provides a good initial measure of performance, it can be misleading in cases where the dataset is imbalanced.

Precision

Precision measures the accuracy of the positive predictions made by the model. It is the ratio of true positive instances to the sum of true positive and false positive instances. Precision is particularly important in scenarios where the cost of false positives is high. It is calculated as follows:

Precision = True Positives/ True Positives + False Positives

Recall

Recall, also known as sensitivity or true positive rate, measures the model's ability to correctly identify all relevant instances. It is the ratio of true positive instances to the sum of true positive and false negative instances. Recall is crucial in situations where missing a positive instance has significant consequences. It is calculated as follows:

Precision = True Positives/ True Positives + False Negatives

F1-Score

The F1-score is the harmonic mean of precision and recall, providing a single metric that balances both concerns. It is especially useful when the dataset is imbalanced, as it considers both false positives and false negatives. The F1-score is calculated as follows:

F1-Score = 2 x (Precision x Recall) / (Precision + Recall)

The F1-score ranges from 0 to 1, with 1 indicating perfect precision and recall.

Computational Efficiency

Computational efficiency evaluates the time and resources required by the algorithm to train and make predictions. This metric is essential for understanding the practical feasibility of deploying an algorithm, particularly in resource-constrained environments or when processing large datasets. Computational efficiency is typically assessed by measuring:

- **Training Time**: The time taken to train the model on the dataset.
- **Prediction Time**: The time taken to make predictions on new data.
- **Resource Utilization**: The number of computational resources (e.g., CPU, memory) required during training and prediction.

Combined Analysis

Combining these metrics provides a holistic view of an algorithm's performance. For example:

- **High accuracy with low precision** indicates a high number of false positives.
- **High recall with low precision** indicates a high number of false positives.
- **High F1-score** balances both precision and recall, indicating a well-performing model across both metrics.
- **High computational efficiency** ensures that the model is practical for real-world applications, especially in time-sensitive or resource-limited scenarios.

This comprehensive evaluation framework enables a detailed comparison of different machine learning algorithms, guiding the selection of the most suitable method based on the specific requirements of the predictive modelling task.

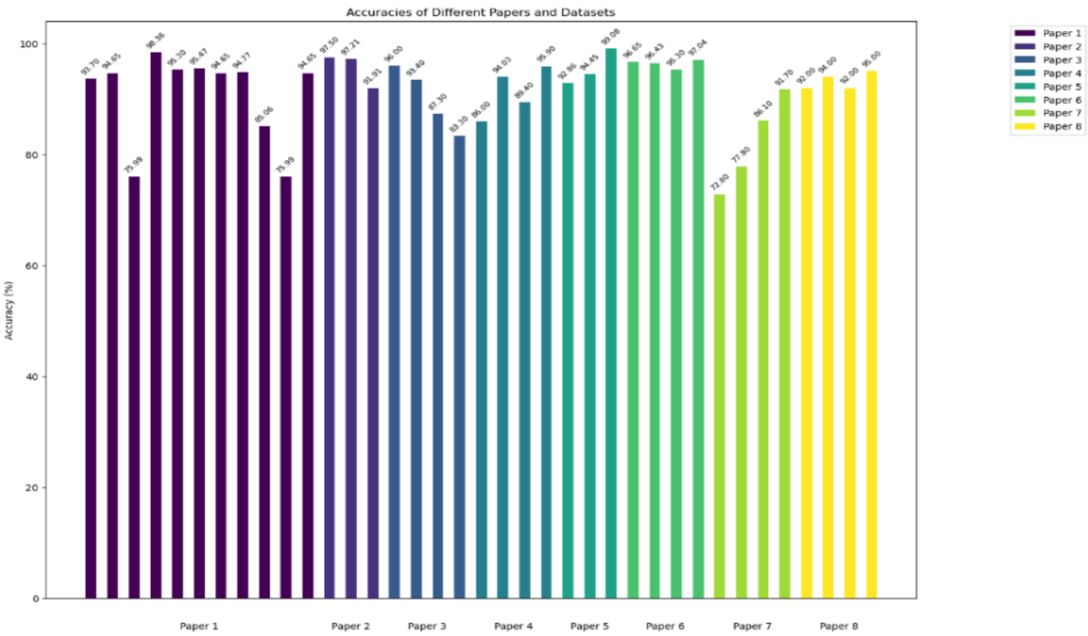
RESULTS AND DISCUSSION:

This section evaluates the performance of various classifier algorithms, highlighting their predicted accuracies from recent studies. Single classifiers such as Decision Tree (93.7%), K-Nearest Neighbors (94.65%), and SVM (75.99%) show varying accuracies, with advanced techniques like XGBoost leading at 99.08%. Multiple classifiers demonstrate higher accuracies due to their ensemble approach, with AdaBoost-DT achieving 98.36% and Stacking methods reaching 97.04%. Hybrid algorithms like WOA-SVM (97.50%) and PSO-SVM (97.21%) outperform standalone SVMs. Improved ensemble methods also show significant gains, with enhanced AdaBoost achieving 91.7% and Bayesian Network with Random Forest at 77.8%. Overall, ensemble and hybrid methods generally outperform single classifiers, emphasizing the importance of selecting appropriate classifiers for specific applications. **Table 2** represents the graphical representation of the accuracies predicted and the respective reference papers.

REFERENCE NO	ACCURACIES PREDICTED
1	**Single classifiers:** Decision tree algorithm - 93.7% KNN algorithm - 94.65% SVM – 75.99% **Multiple classifiers:** 98.36% for AdaBoost-DT 95.30% for Bagging-DT 95.47% for Voting-KNN + DT 94.65% for AdaBoost-KNN 94.77% Bagging-KNN 85.06% Voting-DT + SVM 75.99% for Bagging-SVM 94.65% for Voting-SVM+KNN
2	WOA-SVM 97.50 PSO-SVM 97.21 SVM 91.91
3	SVM – 96.0% Decision tree – 93.4% KNN- 87.3% Naïve Bayes – 83.3%
4	Naïve bayes weighted approach - 86.00% 2 SVM's and XGBoost - 94.03% SVM and DO - 89.4% XGBoost - 95.9%
5	Logistic Regression: 92.86% Random Forest: 94.45% Extreme Gradient Boosting (XGBoost): 99.08%
6	XGBoost (XGB) 96.65% Random Forest (RF) 96.43% Support Vector Machine (SVM) 95.3% Stacking 97.04%
7	Bayesian Network: 72.8% Random Forest: 77.8% AdaBoost: 86.1% Improved AdaBoost: 91.7%

8	K-nearest neighbor (KNN):92% Classification and Regression Tree (CART): 94% Gaussian Naïve Bayes (NB): 92% Ensemble Classifier:95%

Table 2



FUTURE WORKS:

The future of classifier algorithms holds promising avenues for research, aiming to enhance their effectiveness and applicability. Key areas for exploration include optimizing hybrid and ensemble methods, improving real-time and large-scale data processing, and increasing explainability and interpretability. Integration with deep learning techniques presents opportunities for robust predictive models, while addressing bias and ensuring fairness is crucial for equitable outcomes. Domain-specific applications in fields like personalized medicine and autonomous driving could benefit from tailored classifier solutions. By focusing on these aspects, future research can drive significant advancements in accuracy, efficiency, and fairness of predictive models.

CONCLUSION:

This survey paper offers a detailed evaluation of various machine learning algorithms, emphasizing their accuracy and performance in predictive modelling. The comparative analysis highlights that ensemble methods, such as AdaBoost [1] and XGBoost [5], consistently outperform single classifiers, achieving the highest accuracies of 99.08% and 98.36%, respectively. These methods demonstrate their robustness and effectiveness in handling diverse datasets and improving prediction reliability. Single classifiers like K-Nearest Neighbor (KNN) [1]and Decision Tree [1] also exhibit commendable performance, with accuracies of 94.65% and 93.7%, respectively. However, their effectiveness varies significantly with the type of data and the specific implementation. Support Vector Machines (SVM) [2] show a wide range of performance, with accuracies influenced by optimization techniques, achieving up to 97.5% with Whale Optimization Algorithm (WOA). The graphical representation of the results reinforces the conclusion that while single classifiers are effective in certain scenarios, ensemble methods provide a substantial improvement in accuracy and reliability. The tables and figures in this paper serve as a valuable resource for selecting appropriate algorithms based on specific predictive modelling needs. In conclusion, the insights derived from this survey underline the importance of choosing the right algorithmic approach. Ensemble methods are recommended for their superior performance, but single classifiers can be suitable for simpler, less complex tasks. This comprehensive analysis aims to aid researchers and practitioners in making informed decisions, ultimately enhancing the accuracy and efficiency of predictive modelling.

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