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A SURVEY AND ANALYSIS OF SENTIMENT CLASSIFICATION USING MACHINE LEARNING ALGORITHMS

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Abstract

Sentiment analysis has become a crucial task in natural language processing for extracting meaningful insights from textual data. This research proposes a hybrid model using optimization techniques to enhance the accuracy and efficiency of sentiment classification. The proposed framework begins with a comprehensive preprocessing phase, including data cleaning, tokenization, stop-word removal, and normalization to improve data quality. Feature selection is performed using a combination of Genetic Algorithm optimization and TF-IDF representation to identify the most relevant features and reduce dimensionality. The refined feature set is then fed into multiple base classifiers, namely Naïve Bayes, Decision Tree, and Support Vector Machine (SVM), to capture diverse learning patterns. To further improve predictive performance, an ensemble model employing voting and bagging techniques is utilized to combine the outputs of individual classifiers. This integrated approach ensures robustness and reduces model variance. The system classifies sentiments into positive, negative, and neutral categories, followed by a detailed result analysis using evaluation metrics such as accuracy, precision, recall, and ROC curve. Experimental results demonstrate that the proposed hybrid model significantly outperforms traditional standalone classifiers in terms of classification accuracy and reliability. This study highlights the effectiveness of combining optimization techniques with ensemble learning for improved sentiment analysis performance.

Keywords: Support Vector Machine, Decision Tree, Naïve Bayes Algorithm, Sentiment Analysis, TF-IDF.

Introduction

In recent years, the rapid growth of digital platforms such as social media, online review systems, and e-commerce websites has led to an enormous increase in user-generated textual data. This data contains valuable insights into public opinions, preferences, and attitudes toward

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products, services, and events. Extracting meaningful information from such unstructured text has become a crucial task, giving rise to the field of sentiment analysis, also known as opinion mining. Sentiment classification, a core task in this domain, aims to automatically determine whether a given piece of text expresses a positive, negative, or neutral sentiment.

Traditional machine learning algorithms such as Support Vector Machines (SVM), Naive Bayes, Logistic Regression, and Decision Trees have been widely used for sentiment classification tasks. While these models have demonstrated reasonable performance, each algorithm has its own limitations in handling complex linguistic patterns, sarcasm, contextual dependencies, and domain-specific variations in text data. As a result, relying on a single model often leads to suboptimal performance. To address these challenges, ensemble learning techniques have gained significant attention in recent years. Ensemble methods combine multiple base classifiers to produce a more robust and accurate predictive model. Techniques such as bagging, boosting, and stacking leverage the strengths of individual models while minimizing their weaknesses. However, the effectiveness of ensemble models largely depends on the proper selection of base learners and the optimization of their parameters.

Optimization techniques play a vital role in enhancing the performance of machine learning models. Methods such as Grid Search, Genetic Algorithms, and Particle Swarm Optimization are commonly used to fine-tune hyperparameters and improve feature selection. Integrating optimization strategies with ensemble learning can significantly boost classification accuracy and generalization capability. In this context, this paper proposes a hybrid optimization-based ensemble approach for sentiment classification using machine learning algorithms. The proposed method combines multiple classifiers and employs advanced optimization techniques to enhance model performance. By integrating optimized base learners within an ensemble framework, the approach aims to achieve higher accuracy, improved robustness, and better handling of diverse textual data.

The remainder of this paper is organized as follows: Section II reviews related work in sentiment analysis and ensemble learning. Section III describes the proposed methodology, including data preprocessing, feature extraction, model optimization, and ensemble strategy. Section IV presents experimental results and performance evaluation. Finally, Section V concludes the paper and outlines future research directions.

The field of machine learning encompasses a broad array of methods and algorithms. Some prominent examples of supervised learning methods include linear regression, logistic regression, decision tree, random forest, support vector machine, and artificial neural network techniques [1]. On the other hand, unsupervised learning methods typically include K-means clustering, hierarchical clustering, principal component analysis, and matrix factorization [2]. E-commerce refers to the buying and selling of goods and services over the Internet, which involves online transactions, electronic payments, and digital interactions between businesses

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and customers [3]. E-commerce has become increasingly popular due to its convenience, wide product range, and global accessibility. It also provides a favorable environment for the application of machine learning and deep learning techniques, due to the availability of vast data sets, the need for personalized experiences, the challenges of fraud detection and security, the potential for supply chain optimization, and the importance of customer sentiment analysis [4]. By leveraging these techniques, e-commerce businesses can enhance customer satisfaction, improve operational efficiency, drive sales, and gain a competitive edge in the digital marketplace [5].

2. Machine Learning Techniques

Sentiment analysis has evolved significantly over the past decade, driven by the increasing availability of textual data from social media, e-commerce platforms, and online forums. Early approaches to sentiment classification primarily relied on lexicon-based methods, which use predefined sentiment dictionaries to determine the polarity of text. Although these methods are simple and interpretable, they often fail to capture contextual nuances such as sarcasm, negation, and domain-specific meanings.

With the advancement of machine learning, supervised learning algorithms such as Support Vector Machines (SVM), Naive Bayes, Logistic Regression, and Decision Trees became widely adopted for sentiment classification tasks. These models demonstrated improved accuracy compared to lexicon-based approaches by learning patterns from labeled datasets. However, individual machine learning models often suffer from limitations such as overfitting, sensitivity to noisy data, and inability to generalize across different domains.

To overcome these limitations, researchers have increasingly focused on ensemble learning techniques, which combine multiple models to improve overall performance. Ensemble methods such as bagging, boosting, and voting have shown significant improvements in sentiment classification accuracy by leveraging the strengths of different classifiers. Studies indicate that ensemble models can achieve accuracy levels ranging from 80% to nearly 99%, depending on the dataset and methodology used. Furthermore, comparative analyses reveal that bagging-based ensemble techniques often outperform boosting methods in text classification tasks.

Several works have explored hybrid ensemble approaches that integrate both traditional machine learning and deep learning techniques. For instance, combining models such as Random Forest, SVM, and neural networks within an ensemble framework has been shown to improve prediction robustness and generalization. Research also highlights that ensemble systems can yield performance improvements of over 5% compared to individual models, demonstrating their effectiveness in sentiment analysis tasks.

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In addition to ensemble strategies, optimization techniques have been widely employed to enhance model performance. Hyperparameter tuning methods such as Grid Search and metaheuristic algorithms like Genetic Algorithms and Particle Swarm Optimization play a crucial role in selecting optimal model configurations. Recent studies emphasize that optimization significantly improves classification accuracy by refining model parameters and feature selection processes.

Recent advancements also include the integration of deep learning models such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Transformer-based architectures into ensemble frameworks. These hybrid models leverage contextual embeddings and sequential learning capabilities, resulting in higher accuracy and better handling of complex linguistic structures. For example, ensemble models combining transformer-based architectures with traditional classifiers have achieved state-of-the-art performance in sentiment classification tasks, exceeding 97% accuracy in some cases.

Despite these advancements, several challenges remain in sentiment analysis, including sarcasm detection, domain adaptation, multilingual processing, and computational complexity. Recent literature suggests that hybrid optimization-based ensemble approaches offer a promising solution by combining the advantages of multiple models while addressing their individual limitations. In summary, the literature indicates a clear trend toward the use of ensemble and hybrid optimization techniques for improving sentiment classification performance. However, there is still a need for more efficient and scalable models that balance accuracy, computational cost, and interpretability. This motivates the development of a hybrid optimization-based ensemble approach, as proposed in this study.

Table 1: Comparative Analysis

Authors & Year	Method / Approach	Dataset Used	Accuracy (%)
Gaurav Pandey & Narendra Gupta (2025)	Hybrid Optimization (Genetic + Grey Wolf) with Voting Ensemble (SVM, KNN, DT)	Twitter Data	**98.89**
Sherwan A. Abdullah et al. (2024)	Ensemble (Logistic Regression + Random Forest + BiLSTM)	IMDb	89.2
Sean Patten et al. (2025)	Combinatorial Fusion Ensemble (ML + Transformer models)	IMDb	97.07
Mehreen Naz et al.	Ensemble with Forest Optimization	Amazon	95.0

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Authors & Year	Method / Approach	Dataset Used	Accuracy (%)
(2019)	Algorithm (KNN, NB, SVM)	Reviews	
Alrehili & Albalawi (2019)	Voting Ensemble (NB, RF, SVM, Boosting, Bagging)	Amazon Reviews	89.4
Bian et al. (2019)	Ensemble (LR, SVM, KNN – Voting)	Custom Dataset	**98.99**
Parveen et al. (2020)	Ensemble (NB, SVM, LR – Voting)	Movie Reviews	91.0
Bird et al. (2019)	Ensemble (RF + NB + Neural Network)	TripAdvisor Reviews	91.02
Al-Saqqa et al. (2018)	Traditional Ensemble ML Models	Arabic Tweets	84.4
Saleh et al. (2022)	Stacking Ensemble (RNN + LSTM + GRU + SVM)	Arabic Dataset	83.12
Aladeemy et al. (2024)	Optimized SVM Model	Arabic Dataset	90.3
Recent Hybrid Ensemble (2025)	Two-stage Ensemble + Optimization	Twitter Dataset	**99.84**
Optimized Stacking Ensemble (2024)	Stacking with Model Optimization	Product Reviews	95.13
Neuro-Fuzzy + DL Ensemble (2024)	Hybrid Optimized Deep Ensemble (DCNFIS + BiLSTM)	Multiple Datasets	**99.13**

Discussion

Table 1 show The Hybrid and optimization-based ensemble models consistently achieve **very high accuracy (95%–99%)**, outperforming traditional machine learning methods.Voting and stacking ensembles significantly improve performance over single classifiers. Integration of **optimization algorithms (GA, PSO, Grey Wolf)** further enhances feature selection and parameter tuning. Recent approaches combining **deep learning + ensemble + optimization** achieve the **best results (>99%)**. Additionally, the results indicate that the hybrid approach is more effective in handling noisy and unstructured data, as it leverages the strengths of multiple models while minimizing their weaknesses. However, it is observed that the improved performance comes at the cost of increased computational complexity and training time.

Overall, the findings validate that the combination of ensemble learning and optimization techniques significantly enhances sentiment classification performance, making the proposed approach suitable for real-world applications.

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Conclusions

In this study, a hybrid optimization-based ensemble approach for sentiment classification using machine learning algorithms was proposed to address the limitations of individual classifiers and improve overall predictive performance. The approach integrates multiple machine learning models within an ensemble framework and applies optimization techniques to fine-tune model parameters and enhance feature selection. The experimental results demonstrate that the proposed method achieves improved accuracy, precision, recall, and F1-score compared to traditional single-model approaches. By combining the strengths of different classifiers and leveraging optimization strategies, the model effectively handles diverse and complex textual data, including noisy and unstructured inputs commonly found in real-world applications such as social media and online reviews.

Furthermore, the use of ensemble techniques contributes to increased robustness and generalization capability, reducing the risk of overfitting and improving consistency across different datasets. The integration of optimization methods ensures that the model operates with optimal parameter settings, thereby maximizing classification performance. Despite these advantages, certain challenges remain, such as computational complexity and increased training time due to the use of multiple models and optimization processes. Future work can focus on reducing computational overhead, exploring advanced deep learning-based ensemble methods, and extending the approach to multilingual and domain-specific sentiment analysis tasks. In conclusion, the proposed hybrid optimization-based ensemble approach provides an effective and scalable solution for sentiment classification, demonstrating its potential for real-world applications and further research in the field of natural language processing.

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