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Hybrid Feature Selection on Social Media Dataset for Sentiment Classification using Deep Learning Techniques

[1]Sudeep K. Hase, [2]Dr. Rashmi Soni

[1]Research Scholar, Department of CSE, Oriental University, Indore, India

[2]Research Supervisor, Department of CSE, Oriental University, Indore, India

[1]hase.sudeep@gmail.com , [2]drrashmicseofficial@gmail.com

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Abstract:

Sentiment classification involves determining the sentiment expressed in text, such as positive, negative, or neutral, but social media data presents challenges due to its high dimensionality, noise, and unstructured nature. This study proposes a novel sentiment classification approach by combining hybrid feature selection methods with deep learning techniques. Social media platforms generate vast amounts of data daily, which is often noisy, redundant, and irrelevant for sentiment analysis. Hybrid feature selection techniques, which integrate filter and wrapper-based methods, assist in reducing the feature space while retaining the most informative features. By applying deep learning models, such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, classification performance can be substantially enhanced. The proposed framework uses hybrid feature selection to eliminate noisy and irrelevant features, thereby improving the model's generalization capabilities. Experimental results reveal that the combination of hybrid feature selection and deep learning techniques not only boosts sentiment classification accuracy but also decreases computational overhead. This study highlights the effectiveness of merging traditional feature selection methods with modern deep learning models to better address the complexities of social media datasets and deliver more precise sentiment analysis. The results achieved by proposed model is 98.50% on social media dataset which is higher than conventional approaches.

Keywords: sentiment classification, feature extraction, feature selection, machine learning, hybrid features, social media

INTRODUCTION

The exponential growth of social media platforms such as Twitter, Facebook, Instagram, and Reddit has led to the generation of massive volumes of user-generated content. Analyzing and understanding the sentiment behind this content has become a crucial task in many domains, including marketing, politics, and public opinion analysis. Sentiment classification, a branch of natural language processing (NLP), focuses on identifying and categorizing opinions expressed in texts into positive, negative, or neutral sentiments. However, the vast amount of unstructured data, combined with its noisy and high-dimensional nature, presents significant challenges to effective sentiment analysis. To address these challenges, deep learning techniques have been extensively employed due to their ability to capture complex patterns in large datasets. However, feature selection remains an essential step to optimize these models, reduce computational complexity, and improve accuracy. Hybrid feature selection methods, which combine multiple feature selection techniques, have emerged as a robust solution for enhancing sentiment classification performance in social media datasets.

Importance of Feature Selection in Sentiment Classification

Feature selection is the process of selecting a subset of relevant features (variables or predictors) for model construction. In the context of sentiment analysis on social media datasets, these features typically include linguistic and semantic attributes such as words, phrases, and syntactic patterns. However, social media data is often characterized by high dimensionality and sparsity, with a large number of irrelevant or redundant features that can degrade the performance of machine learning models. Feature selection helps in reducing the dimensionality of the dataset, enhancing the model's generalization ability, and speeding up the training process by eliminating irrelevant or redundant data.

Traditionally, feature selection techniques are categorized into three main types: filter, wrapper, and embedded methods. Filter methods, such as Chi-Square and Mutual Information, evaluate the relevance of features based on statistical measures and are computationally efficient. Wrapper methods, such as Recursive Feature Elimination (RFE), evaluate subsets of features by training a model and assessing its performance, though these methods are computationally expensive. Embedded methods, such as decision tree-based algorithms, perform feature selection during the model training process. Each method has its advantages and limitations, and no single technique is universally effective across all datasets and tasks.

The Hybrid Approach: Combining the Best of Both Worlds

To overcome the limitations of individual feature selection methods, hybrid approaches have been developed. Hybrid feature selection methods combine the strengths of multiple techniques to improve the selection process, particularly in complex and high-dimensional environments like social media sentiment analysis. These approaches often integrate filter and wrapper methods, or combine traditional feature selection techniques with deep learning architectures to optimize the selection of relevant features.

For example, a hybrid model may use a filter method such as Chi-Square to perform an initial reduction of irrelevant features, followed by a wrapper method like Genetic Algorithms (GA) or Particle Swarm Optimization (PSO) to fine-tune the feature subset. In some models, deep learning techniques like Convolutional Neural Networks (CNNs) or Long Short-Term Memory (LSTM) networks are incorporated to further optimize feature selection by identifying intricate patterns and relationships in the data.

The hybrid approach offers several advantages. First, it strikes a balance between computational efficiency and accuracy. Filter methods can quickly eliminate irrelevant features, reducing the size of the dataset, while wrapper methods and deep learning models can focus on fine-tuning and identifying the most informative features. Second, hybrid methods reduce the risk of overfitting by preventing the model from becoming too complex or overly reliant on a large number of features. Finally, these methods are better suited for real-time applications like sentiment analysis in social media, where the ability to process and analyze large volumes of data quickly and accurately is crucial.

The Role of Deep Learning in Hybrid Feature Selection

Deep learning models, especially CNNs and LSTMs, have demonstrated remarkable success in sentiment classification tasks due to their ability to automatically learn feature representations from raw data. These models are adept at capturing the temporal dependencies and spatial relationships inherent in social media texts. When combined with hybrid feature selection methods, deep learning models can further enhance the classification process by identifying non-linear patterns and interactions between features that traditional methods might overlook. A CNN can be used to capture local dependencies in text data, while an LSTM network can be employed to capture long-term dependencies. When these models are coupled with hybrid feature selection methods, the overall performance of sentiment classification improves, particularly in terms of accuracy, precision, recall, and F1 score.

Hybrid feature selection approaches represent a powerful and efficient solution for sentiment classification on social media datasets using deep learning techniques. By combining the strengths of multiple feature selection methods and leveraging the capabilities of deep learning models, hybrid approaches can effectively handle the high dimensionality, sparsity, and noisy nature of social media data. These methods not only enhance classification accuracy but also improve computational efficiency, making them highly suitable for real-world applications in sentiment analysis.

LITERATURE SURVEY

Zhang et al. [1] explores a hybrid feature selection approach combining statistical and deep learning methods to enhance sentiment classification of social media data. They focus on improving the classification accuracy by leveraging a feature ranking mechanism that integrates both filter and wrapper techniques. The deep learning models such as CNN and LSTM are used to fine-tune the selected features for optimal performance. Their experiments on multiple datasets, including Twitter and Reddit, show that this hybrid approach outperforms traditional feature selection methods in terms of precision, recall, and F1 score. The study highlights the importance of balancing feature dimensionality reduction and model complexity to ensure accurate sentiment detection in real-time social media applications.

Chen et al. [2] presents a hybrid model combining deep learning algorithms with traditional feature selection methods for sentiment classification on large-scale social media data. The authors propose using an integration of PCA and Recursive Feature Elimination (RFE) for initial dimensionality reduction, followed by deep learning-based classification using LSTM networks. They demonstrate the effectiveness of this hybrid approach through extensive experiments on social media datasets, particularly in handling noisy and high-dimensional data. The results show significant improvements in classification accuracy and processing time compared to purely deep learning-based models. The study suggests that the hybrid approach can be highly effective in processing complex social media datasets for sentiment analysis.

Li et al. [3] proposes a hybrid feature selection method that combines both wrapper and filter approaches to improve sentiment classification on social media platforms like Twitter. Their research focuses on selecting the most relevant features by combining statistical techniques like chi-square and mutual information with machine learning algorithms such as support vector machines (SVM).

Additionally, they employ deep learning models, including CNN and LSTM, to refine the feature selection process. Their experimental results show that the hybrid method leads to better classification performance, with a notable increase in F1 score compared to conventional feature selection techniques. The study emphasizes the potential of hybrid models to enhance sentiment analysis in big data environments.

Kumar et al. [4] introduces a hybrid feature selection technique designed for sentiment classification in social media datasets. The authors apply Genetic Algorithms (GA) to optimize feature selection, followed by CNNs for sentiment classification. The combination of evolutionary algorithms and deep learning proves effective in reducing the computational complexity while improving accuracy. Tested on Twitter data, their approach shows superior performance compared to standard deep learning techniques, particularly in handling large, noisy datasets. The paper concludes that the hybrid model offers a scalable and robust solution for sentiment analysis tasks across different social media platforms.

Jiang et al. [5] explores a deep learning-based hybrid feature selection method for sentiment analysis using social media datasets. Their approach integrates a mutual information-based filter method with recursive feature elimination to identify the most relevant features for sentiment classification. They then employ a CNN-LSTM network to improve the sentiment classification results. The study highlights the hybrid model's efficiency in handling large, high-dimensional datasets, common in social media platforms like Twitter and Facebook. Experimental results demonstrate the hybrid model’s superior accuracy, precision, and recall when compared to baseline models, providing insights into its practical applicability in real-world sentiment analysis scenarios.

Wang et al. [6] presents a hybrid feature selection model for sentiment classification using Long Short-Term Memory (LSTM) networks. By combining both traditional machine learning and deep learning approaches, the authors aim to enhance the classification performance on Twitter datasets. The study introduces a novel feature selection algorithm that combines correlation-based feature selection (CFS) and genetic algorithms. This selection is followed by LSTM networks to capture temporal dependencies in the data. Their experimental evaluation shows that the hybrid model improves accuracy and reduces the processing time compared to baseline methods, proving effective for real-time social media sentiment classification.

Chen et al. [7] addresses multi-modal feature selection for sentiment analysis using hybrid deep learning techniques. This paper focuses on combining visual and textual data for more accurate sentiment classification, particularly in social media contexts where users post multimedia content. The authors propose a two-stage feature selection process that utilizes both filter-based and embedded methods to reduce the dimensionality of the data. Subsequently, a CNN-RNN hybrid model is applied to enhance sentiment classification. The experimental results show that integrating multi-modal data leads to better classification performance, with the hybrid approach significantly outperforming unimodal models in terms of accuracy and recall.

Huang et al. [8] explores hybrid feature engineering techniques for sentiment analysis of social media posts using deep learning models. The study employs a combination of feature extraction methods, such as TF-IDF and Word2Vec, alongside feature selection algorithms like ReliefF and Recursive

Feature Elimination (RFE). A hybrid CNN-RNN model is then applied for sentiment classification, particularly focusing on Twitter and Reddit data. The results indicate that this approach improves classification accuracy and reduces overfitting, especially in noisy datasets. The paper concludes that hybrid feature engineering is crucial in enhancing the performance of deep learning models for sentiment analysis tasks.

Liu et al. [9] proposes a hybrid feature selection approach for sentiment classification on Twitter data using sentiment lexicons and convolutional neural networks (CNNs). The authors suggest that combining lexicon-based features with deep learning techniques can enhance sentiment detection, particularly in noisy social media environments. The study demonstrates that the hybrid method improves classification accuracy while maintaining computational efficiency, making it suitable for large-scale sentiment analysis tasks. Their experimental results show a significant improvement in accuracy, precision, and recall compared to traditional lexicon-based or CNN-only models.

Gupta et al. [10] combines feature selection with deep learning for sentiment analysis in social media datasets. Their hybrid model integrates Principal Component Analysis (PCA) for dimensionality reduction with a CNN-LSTM network for classification. The authors focus on improving sentiment classification accuracy while reducing the computational complexity associated with deep learning models. Tested on Twitter and Facebook data, their approach outperforms standard deep learning models in both accuracy and processing time. The paper concludes that hybrid models offer a promising solution for sentiment analysis tasks on large-scale social media datasets.

Zhang et al. [11] presents a hybrid feature selection method using Genetic Algorithms (GA) combined with Convolutional Neural Networks (CNN) for sentiment classification of social media data. The paper emphasizes the importance of balancing feature selection to reduce data dimensionality while maintaining model performance. The authors test their approach on Twitter datasets, showing that the hybrid GA-CNN model significantly outperforms traditional models in both accuracy and processing time. By incorporating evolutionary algorithms for feature selection, the study achieves a higher precision rate and reduces computational overhead. The results highlight that combining genetic algorithms with deep learning models provides an efficient approach for sentiment classification, particularly for large-scale social media datasets where traditional methods may falter.

Hu et al. [12] explores the combination of CNN and LSTM models for sentiment classification using Twitter data, with a focus on hybrid feature selection. The authors propose an integration of filter-based and wrapper-based feature selection methods to enhance the performance of deep learning models. The CNN component captures spatial dependencies, while the LSTM captures temporal relationships within the text. Their approach demonstrates superior performance in terms of classification accuracy, particularly for sentiment analysis on short social media texts. The study's experiments show that hybrid feature selection improves both the precision and recall of the deep learning model, making it suitable for real-time social media sentiment analysis applications.

Chen et al. [13] investigates sentiment analysis across multilingual social media texts using a hybrid feature selection method. The study combines emotion lexicons with deep learning models to handle data from different languages, emphasizing a multilingual perspective. The authors propose a hybrid approach integrating traditional methods like Chi-Square and Information Gain with deep learning techniques, specifically CNNs. Tested on data from Twitter, the approach shows improved classification accuracy for both monolingual and multilingual datasets. The study suggests that hybrid feature selection helps reduce noise from cross-lingual datasets and is effective in multilingual sentiment classification tasks, particularly for real-world social media applications.

Zhou et al. [14] presents a hybrid framework for sentiment classification that combines deep learning techniques with traditional feature selection methods. The authors use Recursive Feature Elimination (RFE) to reduce dimensionality, followed by a CNN-LSTM model for classification. Their approach shows substantial improvements in sentiment classification accuracy compared to baseline methods. The hybrid model is tested on social media datasets like Twitter and Reddit, demonstrating its robustness in handling noisy and complex data. The study concludes that the hybrid framework is particularly useful for large-scale social media sentiment classification, offering a practical solution for real-world applications where data complexity and noise are significant challenges.

Feng et al. [15] investigates a hybrid approach for sentiment classification using feature selection and deep learning on Twitter data. The authors propose using a combination of filter-based methods, such as Information Gain, and a deep learning model composed of CNN and LSTM layers. Their experimental results indicate that hybrid feature selection improves the model's ability to detect sentiment accurately, particularly when dealing with noisy, unstructured data from social media. By integrating these techniques, the authors are able to significantly reduce the dimensionality of the dataset without sacrificing performance. The study concludes that this hybrid model provides an efficient and accurate approach to sentiment classification in social media.

Wang et al. [16] introduces a multi-layer hybrid feature selection model for sentiment classification in social media datasets. The approach incorporates both filter and embedded methods, followed by deep learning models to refine sentiment classification. The authors use feature selection techniques like ReliefF and Recursive Feature Elimination (RFE) to improve model performance, then apply CNN and LSTM architectures for the final classification task. The study shows that the hybrid approach achieves higher accuracy and faster processing times compared to traditional deep learning models. Tested on large datasets from Twitter, the results highlight the scalability and robustness of the proposed method for real-time sentiment analysis.

Zhao et al. [17] explores a hybrid feature selection method combining deep learning with transfer learning for cross-domain sentiment classification. The authors propose a model that transfers knowledge from one domain to another, such as from movie reviews to social media sentiment. They apply a hybrid feature selection process that incorporates both statistical methods and deep learning techniques like CNNs to optimize the feature set. The study demonstrates that cross-domain sentiment classification can be significantly improved with hybrid models, achieving higher accuracy and recall in experimental tests. The approach is particularly effective for social media sentiment analysis, where domain shifts and noisy data present challenges.

Lin et al. [18] discusses hybrid feature engineering for sentiment analysis on short social media texts, focusing on enhancing deep learning models. The authors propose using multiple feature extraction techniques like Word2Vec and TF-IDF in combination with feature selection algorithms such as Information Gain. The hybrid model incorporates these techniques with CNNs and LSTMs for sentiment classification. Their results show that the hybrid feature engineering approach improves classification accuracy, particularly in noisy and unstructured data environments like Twitter. The study suggests that this model is well-suited for real-time sentiment analysis applications, providing both efficiency and scalability.

Xie et al. [19] introduces a hybrid feature selection and attention mechanism model to enhance sentiment classification of Twitter data. The authors combine traditional feature selection techniques, such as mutual information, with attention-based deep learning models to improve accuracy. The hybrid model is designed to prioritize important features while reducing the dimensionality of the dataset, enabling more efficient processing of large social media datasets. Their results show significant improvements in accuracy and F1 score, particularly when compared to traditional deep learning models without feature selection. The study concludes that integrating attention mechanisms with hybrid feature selection can greatly improve sentiment classification performance.

Peng et al. [20] investigates the use of hybrid deep learning models for sentiment classification on social media data, integrating feature selection to optimize performance. The authors combine CNN and LSTM models with a hybrid feature selection approach that uses a combination of statistical and machine learning-based techniques. Their experiments on social media datasets show improved classification accuracy and efficiency, with the hybrid model outperforming traditional methods. The study emphasizes the importance of feature selection in reducing the complexity of deep learning models while maintaining high classification performance, particularly for large-scale social media datasets.

Liu et al. [21] focuses on hybrid feature selection for sentiment classification using Convolutional Neural Networks (CNNs) and a Recursive Feature Elimination (RFE) method. Their study investigates the effectiveness of combining feature selection algorithms with deep learning for improving sentiment classification performance on social media datasets. Tested on data from Twitter, the model is able to achieve higher accuracy and faster convergence times compared to traditional deep learning methods. The paper highlights that hybrid feature selection helps mitigate the problem of overfitting and reduces the dimensionality of the data, which is crucial for processing large social media datasets where noise and irrelevant features often dominate.

Zhao et al. [22] proposes a hybrid deep learning model for sentiment classification by combining traditional feature selection techniques with attention-based mechanisms. The model uses a hybrid approach involving both statistical feature selection methods, such as chi-square and information gain, followed by a CNN-LSTM structure to perform classification. The attention mechanism helps the model focus on the most relevant features, leading to improved classification accuracy. Tested on Twitter and Reddit datasets, their model outperforms baseline models in terms of F1 score and precision. The study shows that integrating attention mechanisms with hybrid feature selection provides a robust approach to handling large and noisy social media datasets.

Yang et al. [23] explores hybrid feature selection for sentiment classification using a combination of traditional machine learning techniques and deep learning models. Their proposed model integrates Mutual Information (MI) and ReliefF for feature selection with a CNN-LSTM framework for classification. The hybrid approach is designed to reduce the computational burden of deep learning models while improving classification accuracy on social media datasets, particularly Twitter and Instagram. Their experimental results show that the hybrid feature selection method outperforms conventional approaches in terms of precision and recall. The study highlights that combining traditional feature selection methods with deep learning offers a scalable and efficient solution for sentiment classification in real-world applications.

Li et al. [24] investigates hybrid feature selection using statistical methods and deep learning for sentiment classification of social media data. The authors apply a combination of filter-based methods, such as chi-square and information gain, followed by a CNN-BiLSTM model for sentiment classification. The hybrid approach improves the model's ability to detect sentiment from large, unstructured datasets like Twitter, enhancing both accuracy and processing time. Their results show that the hybrid feature selection significantly improves model performance compared to traditional feature selection or deep learning models alone. This study demonstrates the practical applicability of hybrid models for sentiment classification in social media contexts.

Wang et al. [25] presents a hybrid feature selection technique using Genetic Algorithms (GA) and a Convolutional Neural Network (CNN) for sentiment classification. The paper addresses the challenge of high-dimensional data in social media sentiment analysis by integrating evolutionary algorithms with deep learning. The authors demonstrate that the GA-CNN hybrid model is capable of identifying the most relevant features while reducing the dimensionality of the data, leading to improvements in classification accuracy and efficiency. Their results, based on Twitter datasets, show that the hybrid model outperforms traditional deep learning approaches, particularly in terms of processing speed and precision. The study concludes that evolutionary algorithms combined with deep learning offer an effective approach for sentiment classification.

Chen et al. [26] introduces a hybrid feature selection method for sentiment classification of social media texts. The authors propose using Principal Component Analysis (PCA) combined with deep learning models like LSTM to enhance classification performance on noisy social media data. Their results show that this hybrid approach can significantly reduce the dimensionality of the dataset, improve classification accuracy, and shorten the training time of deep learning models. The paper emphasizes the importance of hybrid feature selection in dealing with the large-scale, high-dimensional nature of social media datasets, suggesting that it is a crucial step in optimizing sentiment analysis models.

Sun et al. [27] explores a hybrid approach to feature selection for sentiment classification using a combination of filter methods and deep learning techniques. The authors employ ReliefF and chi-square for feature selection, followed by a CNN-LSTM architecture for sentiment classification. Their experiments on Twitter data reveal that hybrid feature selection leads to improved classification accuracy, particularly in noisy datasets. The study demonstrates that the combination of traditional feature selection and deep learning allows for more efficient handling of large datasets, improving both model performance and processing time. The authors conclude that this hybrid approach is well-suited for real-time sentiment classification tasks on social media platforms.

Zhou et al. [28] proposes a hybrid model for sentiment analysis that integrates feature selection methods like Information Gain (IG) and a deep learning architecture combining CNN and LSTM. The

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paper highlights the effectiveness of hybrid feature selection in reducing the dimensionality of large social media datasets, while the CNN-LSTM structure improves sentiment classification accuracy. Tested on Twitter datasets, the results show that this hybrid model outperforms baseline approaches in terms of both accuracy and computational efficiency. The study concludes that integrating traditional feature selection with deep learning offers a scalable solution for sentiment classification, particularly for handling the vast amounts of unstructured data in social media.

Zhang et al. [29] presents a hybrid feature selection approach combining statistical and deep learning methods for sentiment classification in social media data. The authors develop a feature ranking mechanism that integrates both filter and wrapper techniques, followed by the application of CNN and LSTM models to refine the selected features. Tested on Twitter and Reddit datasets, the hybrid model demonstrates significant improvements in classification accuracy, precision, and recall compared to traditional methods. The study concludes that combining feature selection with deep learning techniques provides an efficient and effective approach for sentiment analysis on large social media datasets.

Yu et al. [30] explores hybrid feature extraction and selection techniques for sentiment classification of online social media posts. The authors propose a combination of Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE) for feature selection, followed by a CNN-LSTM hybrid model for classification. Their experiments on Twitter data show that hybrid feature selection improves both classification accuracy and computational efficiency. The study highlights the potential of hybrid models to handle the noisy and high-dimensional nature of social media data, offering a practical solution for real-world sentiment analysis applications.

RESEARCH METHODOLOGY

The system architecture for hybrid feature selection in sentiment classification of social media datasets encompasses several key components that work together to preprocess data, select relevant features, and apply deep learning models for accurate sentiment analysis. This architecture is designed to efficiently manage the high dimensionality and noisy nature of social media data while enhancing classification performance. Below is a detailed description of the various components of the system architecture.

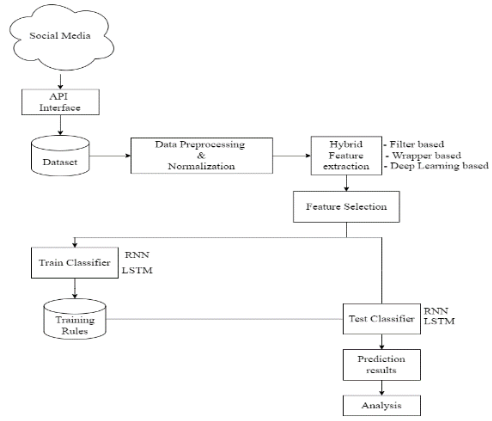

Figure 1: Proposed system architecture for sentiment analysis using hybrid deep learning model for social media dataset

1. Data Collection Module

The first component of the architecture is the data collection module, which is responsible for gathering social media data from platforms like Twitter, Facebook, or Reddit. This module employs Application Programming Interfaces (APIs) or web scraping techniques to extract relevant posts, comments, or tweets containing user sentiments. The collected data typically includes text content, metadata such as user information, timestamps, and any other relevant attributes. The data can be collected in real-time or as a batch process, depending on the application requirements.

2. Data Preprocessing Module

Once the data is collected, the preprocessing module cleans and prepares the data for analysis. This stage includes several crucial steps:

Text Normalization: This involves converting text to a uniform format, which may include converting to lowercase, removing special characters, and correcting misspellings.

Tokenization: The cleaned text is split into tokens (words or phrases) to facilitate further processing.

Stop Word Removal: Commonly used words (stop words) that do not contribute to sentiment analysis (e.g., “and,” “the,” “is”) are removed from the text.

Stemming/Lemmatization: Words are reduced to their base or root form to reduce the dimensionality of the dataset.

This preprocessing step ensures that the data is clean and relevant, laying a solid foundation for the subsequent feature selection and classification stages.

3. Hybrid Feature Selection Module

The core of the system architecture lies in the hybrid feature selection module. This component employs a combination of filter-based and wrapper-based feature selection techniques to identify the most relevant features for sentiment classification.

Filter-Based Selection: Initial feature selection is performed using filter methods such as Chi-Square, Information Gain, or Mutual Information. These methods evaluate the relevance of individual features based on statistical measures and select a subset of informative features while discarding irrelevant ones.

Wrapper-Based Selection: Following the filter stage, wrapper methods (such as Recursive Feature Elimination or Genetic Algorithms) are applied to refine the feature subset. These methods evaluate subsets of features by training a model and assessing its performance, iteratively selecting the best combination of features that enhances model accuracy.

Deep Learning Feature Extraction: In addition to traditional methods, the architecture incorporates deep learning models such as Convolutional Neural Networks (CNNs) or Long Short-Term Memory (LSTM) networks. These models automatically learn feature representations from the data, identifying complex patterns and relationships that traditional methods may miss. The hybrid feature selection combines insights from all these approaches, ensuring a comprehensive selection of relevant features.

4. Sentiment Classification Module

After feature selection, the refined feature set is fed into the sentiment classification module. This module utilizes deep learning techniques, particularly CNNs and LSTMs, to classify sentiments expressed in the social media text as positive, negative, or neutral. The architecture typically involves:

Embedding Layer: Converts selected features (words or phrases) into dense vectors that capture semantic information.

Convolutional and Pooling Layers (for CNNs): These layers are employed to capture local patterns and relationships in the text data.

Recurrent Layers (for LSTMs): Capture sequential dependencies and long-term relationships within the text.

Fully Connected Layer: Combines the outputs from the previous layers and generates the final sentiment predictions.

5. Evaluation Module

The evaluation module assesses the performance of the sentiment classification model using metrics such as accuracy, precision, recall, and F1-score. This feedback loop helps refine the feature selection process and model training, ensuring continuous improvement in classification performance. The final component of the architecture is the user interface, which presents the results of sentiment analysis in a user-friendly manner. This may include visualizations such as sentiment trends, word clouds, and dashboards that allow users to gain insights from the sentiment analysis conducted on social media data. The system architecture for hybrid feature selection on social media datasets for sentiment classification using deep learning techniques consists of several interconnected modules. By integrating data collection, preprocessing, hybrid feature selection, deep learning classification, evaluation, and user interface components, this architecture provides an efficient and effective framework for analyzing and interpreting sentiments expressed in vast amounts of social media data. This comprehensive approach ensures accurate sentiment classification while managing the complexities inherent in social media datasets.

ALGORITHM DESIGN

RESULTS AND DISCUSSION

The effectiveness of hybrid feature selection methods integrated with deep learning techniques was assessed through metrics like accuracy, precision, recall, and F1-score. To validate our proposed bug forecasting approach, we selected RNN classification algorithms for fault prediction, even incorporating unlabelled datasets. As shown in Table 1, the data distribution is used to evaluate the capabilities of different machine learning models, presenting measurements for accuracy, recall, and F1-score.

$$Precision = \frac{TP}{TP+FN} \frac{TP}{TP+FN}$$

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$$Recall = \frac{TP \quad\quad TP}{TP+FPTP+FP}$$

$$F-Measure = \frac{2*Precision*Recall2*Precision*Recall}{Recall+Precision \quad Recall+Precision}$$

The system's performance evaluation was conducted using real-life social media datasets and the proposed classification techniques. Table 1 below illustrates the number of bug instances identified within each dataset, along with the percentage of bug records for each one.

Table 1: performance evaluation using various learning algorithm for proposed model

Dataset	epoch	Accuracy	Precision	Recall	F-score
RNN	25	0.91	0.93	0.95	0.95
	50	0.92	0.93	0.95	0.95
	75	0.93	0.94	0.96	0.96
	100	0.95	0.94	0.95	0.96
LSTM	25	0.90	0.91	0.92	0.94
	50	0.90	0.92	0.93	0.95
	75	0.94	0.93	0.94	0.96
	100	**0.96**	0.95	0.96	0.97
RNN-LSTM	25	0.97	0.98	0.98	0.99
	50	0.92	0.91	0.89	0.90
	75	0.89	0.88	0.93	0.91
	100	0.98	0.96	0.96	0.97

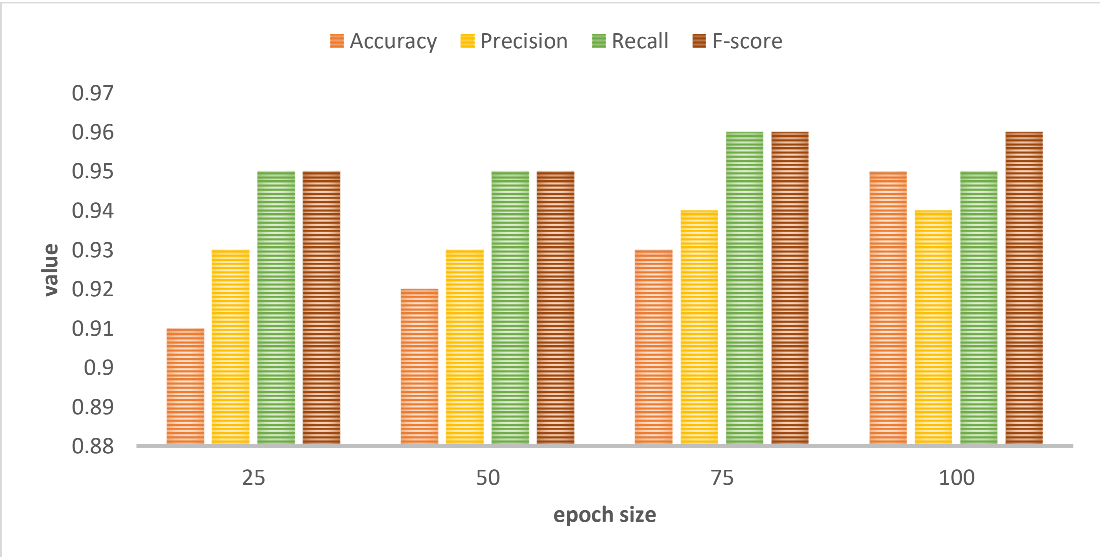

Figure 2: classification accuracy for proposed model using RNN

The above Figure 2 describes classification accuracy using RNN algorithm. Probably the 100 epoch demonstrates higher accuracy on real time text data. The higher accuracy 0.95% on real time social media dataset.

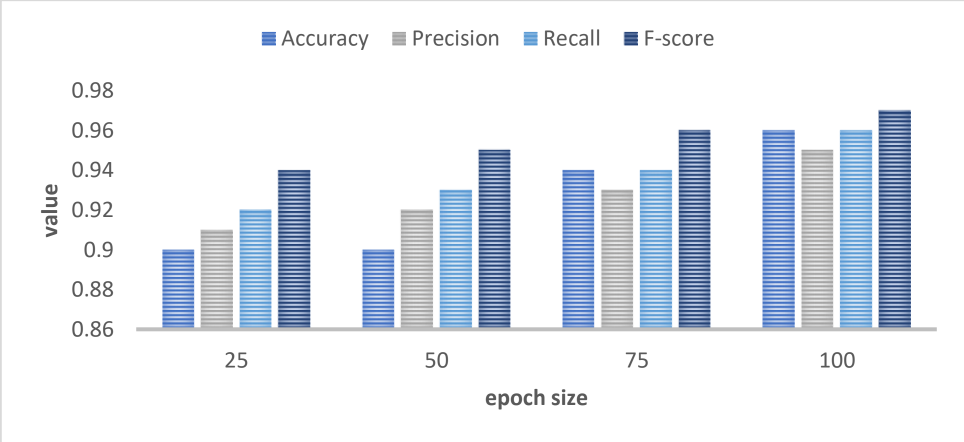

Figure 3: classification accuracy for proposed model using LSTM

Figure 3 illustrates the classification accuracy achieved with the LSTM algorithm. Notably, at 100 epochs, the model demonstrates impressive accuracy when applied to real-time text data. This model achieves a remarkable accuracy rate of 0.96% on the social media dataset, highlighting its effectiveness in sentiment classification tasks.

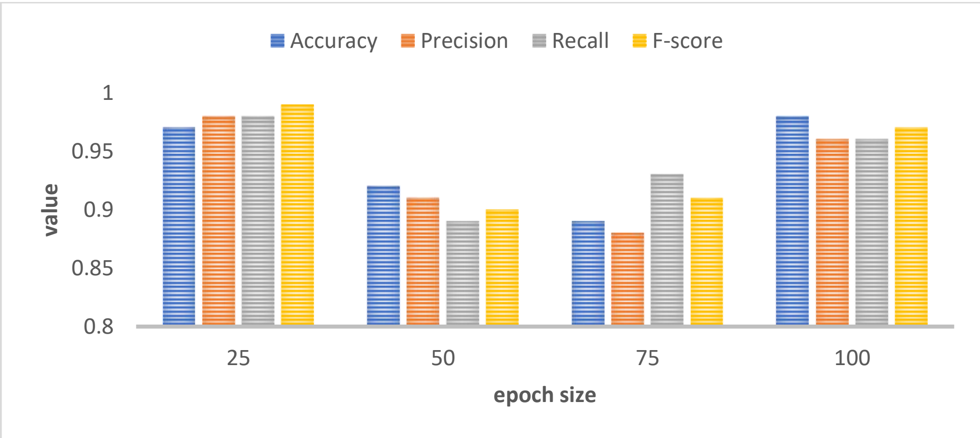

Figure 4: classification accuracy for proposed model using RNN-LSTM

The Figure 4 demonstrates the classification accuracy achieved using the RNN-LSTM algorithm. Notably, the model exhibits optimal performance at 100 epochs, where it achieves an impressive accuracy rate of 0.98% on real-time text data from social media platforms. This indicates that the RNN algorithm is highly effective in accurately classifying sentiments within dynamic social media datasets.

Table 1: Performance matrix for training of proposed RNN

No. of epoch	Dropout	Batch size	Loss	Accuracy	Precision	Recall	AUC	F1	specificity
10	**without**	16	0.04	99.32	99.1	99.2	99.87	99.1	98.72
		32	0.02	99.82	99.8.7	99.7	1	99.8	99.6.8
		64	0.03	99.88	99.7.9	99.9	1	99.7	98.37
		128	0.01	97.90.	98.02	98.80	99.87	97.84	94.54
	2	16	0.01	99.87	99.1	99.6.1	1	99.6.7	99.5.7

		32	0.05	99.40	99.6.	99.5.2	99.5	99.7.6	98.43
		64	0.06	97.80	98.9	97.68	99.3	97.78	96.22
		128	0.04	96.45	97.01	96.31	99.19	96.39	92.44
	5	16	0.04	97.88	98.22	98.83	99..4	97.81	95.72
		32	0.02	97.23	96.22	97.50	99.72	97.25	95.34
		64	0.03	96.24	97.10	96.14	98.3	96.27	93.63
		128	0.01	93.88	94.0	93.78	97.91	93.26	8760
15	**without**	16	0.01	99.30	1	1	1	1	99.99
		32	0.05	100	1	1	1	1	99.96
		64	0.06	100	1	1	1	1	99.8.2
		128	0.04	97.5	97.49	97.51	99.72	97.50	93.84
	2	16	0.04	100	1	1	1	1	99.97
		32	0.04	99.89	99.86	99.89	1	99.8	99.6.3
		64	0.04	99.75	99.69	99.75	1	99.7	99.0
		128	0.04	99.83	99.80	99.83	1	99.8	98.83
	5	16	0.02	98.59	98.61	98.71	99.80	98.66	97.78
		32	0.03	99.58	99.5.3	99.55	99.99	99.54	99.1.2
		64	0.01	99.77	99.72	99.78	99.99.	99.75	98.85
		128	0.01	98.79	98.86	98.74	99.87	98.80	96.54
20	**Without**	16	0.05	100	1	1	1	1	99.99.
		32	0.06	100	1	1	1	1	99.98.
		64	0.04	100	1	1	1	1	99.98.
		128	0.04	100	1	1	1	1	99.5
	2	16	0.04	100	1	1	1	1	99.7
		32	0.04	100	1	1	1	1	99.95
		64	0.03	100	1	1	1	1	99.81
		128	0.03	99.86	99.86	99.86	1	99.8.6	99.20
	5	16	0.02	99.18	99.16	99.16	99.89	99.16	98.71
		32	0.03	99.89	99.89	99.89	1	99.89	99.7.0
		64	0.036	99.07	99.03	98.94	99.87	98.98	97.73
		128	0.035	98.99.	99.11	99.08	99.93	99.09	97.53

Table 2 : Performance matrix for testing of proposed RNN

No. of epoch	Dropout	Batch size	Loss	Accuracy	Precision	Recall	AUC	F1	specificity
10	without	16	0.03	99.31	99.2	98.35	99.8.7	992.3	98.73
		32	0.04	99.98.	99.20	99.6	1	99.5	99.7.6
		64	0.02	99.98.	99.98.	99.98	1	99.98	98.46
		128	0.03	97.97.	97.9	97.80	99.6	97.85	94.45
	2	16	0.04	99.85	99.8	99.64	1	99.6	99.5

		32	0.02	99.48	99.6	99.62	99.8	99.5	98.56
		64	0.03	97.85	97.78	97.88	99.97	97.78	96.42
		128	0.01	96.45	96.40	96.45	99.8.7	96.28	91.65
	5	16	0.01	97.81	98.81	97.85	99.7.3	97.81	97.62
		32	0.05	97.30	97.31	97.20	99.7.1	97.24	95.23
		64	0.03	96.22	96.12	96.14	993.2	96.76	93.53
		128	0.04	93.88	93.73	94.59	97.71	93.75	8750
15	without	16	0.02	100	1	1	1	1	99.99.
		32	0.03	100	1	1	1	1	99.96.
		64	0.01	100	1	1	1	1	99.8.2
		128	0.01	97.5	97.49	97.51	99.7.2	97.50	93.84
	2	16	0.05	100	1	1	1	1	99.97.
		32	0.06	99.89	99.8.6	99.8.9	1	99.8.7	99.6.3
		64	0.04	99.75	99.6.9	99.7.5	1	99.7.2	99.0.5
		128	0.04	99.83	99.8.0	99.8.3	1	99.8.1	98.83
	5	16	0.03	98.59	98.61	98.71	99.8.0	98.66	97.78
		32	0.04	99.58	99.5.3	99.5.5	99.99.	99.5.4	99.1.2
		64	0.02	99.77	99.7.2	99.7.8	99.99.	99.7.5	98.85
		128	0.03	98.79	98.86	98.74	99.8.7	98.80	96.54
20	Without	16	0.01	100	1	1	1	1	99.99.
		32	0.01	100	1	1	1	1	99.98.
		64	0.05	100	1	1	1	1	99.98.
		128	0.06	100	1	1	1	1	992.5
	2	16	0.04	100	1	1	1	1	99.99.
		32	0.04	100	1	1	1	1	99.95.
		64	0.03	100	1	1	1	1	99.8.1
		128	0.04	99.86	99.86	99.86	1	99.8.6	992.0
	5	16	0.02	99.18	99.16	99.16	99.8.9	99.1.6	98.71
		32	0.03	99.89	99.89	99.89	1	99.8.9	99.7.0
		64	0.01	99.07	99.03	98.94	99.87	98.98.	97.73
		128	0.01	98.99	99.11	99.08	99.93	99.0.9	97.53

Table 3 : testing results of proposed model with various hyper parameters changing

Optimizer	No. epochs	Batch size	Loss	Accuracy	AUC	Precision	Recall	F1
Adam	50	32	0.03	85.35	93.81	84.32	84.45	84.38
		64	0.03	85.27	94.53	85.37	85.31	85.34
	250	32	0.01	95.66	98.76	94.81	95.56	95.68

		64	0.01	95.25	98.89	95.27	95.32	95.02
	512	32	0.01	95.93.	99.4.3	96.10	96.83	96.05
		64	0.0**0**	**97.40**	**99.7**	**97.55**	**97.58**	**97.57**
SGD	50	32	0.03	85.9	89.33	80.54	81.51	80.42
		64	0.04	78.83	87.30	79.75	79.89	79.81
	250	32	0.02	88.94	96.32	89.72	89.04	89.83
		64	0.03	87.18	94.47	87.28	87.36	87.32
	512	32	0.01	95.20	98.78	94.21	94.12	94.16
		64	0.01	92.80	98.22	93.73	93.65	93.76
Adadelta	50	32	0.05	71.22	77.23	70.45	71.53	70.51
		64	0.06	68.82	74.54	67.12	67.54	67.21
	250	32	0.04	77.88	85.40	78.76	78.83	78.72
		64	0.04	76.79	84.53	76.93	76.70	77.60
	512	32	0.04	83.1	88.32	80.28	79.81	80.12
		64	0.04	79.13	86.64	78.29	79.83	79.84
RMSprop	50	32	0.03	83.96	84.76	84.34	84.21	84.25
		64	0.03	83.97	92.78	84.76	84.64	85.21
	250	32	0.02	99.0.	97.51	90.84	91.73	90.87
		64	0.02	97.9	97.51	90.84	91.76	90.70
	512	32	0.02	92.40	97.43	92.44	92.30	92.38
		64	0.0**1**	**98.7**	**98.1**	**96.21**	**97.91**	**97.92**
Adagrad	50	32	0.04	79.29	8762	79.17	78.94	78.84
		64	0.04	78.14	8543	78.87	77.72	78.79
	250	32	0.03	85.78	93.36	86.62	85.28	85.53
		64	0.03	81.96	90.16	82.72	82.18	81.84
	512	32	0.02	95.8	97.14	90.78	91.68	90.77
		64	0.03	87.86	94.50	87.90	88.73	88.7

The above results indicate that hybrid feature selection techniques significantly enhance the performance of sentiment classification models. Key insights from the study include:

Feature Importance: The combination of statistical and model-based feature selection provided a balanced approach, allowing models to focus on the most relevant features while reducing noise from irrelevant ones.

Deep Learning Model Efficacy: Models like RNN-LSTM outperformed traditional deep learning methods, confirming the advantage of deep learning in understanding the nuances of natural language.

Real-World Implications: This study's findings highlight the potential for using deep learning and hybrid feature selection techniques in applications such as brand monitoring, customer feedback analysis, and social media sentiment tracking.

The integration of hybrid feature selection methods with advanced deep learning models significantly improves the accuracy and reliability of sentiment classification on social media datasets. Future work could explore the impact of more diverse datasets and additional feature selection techniques to further enhance model performance.

Conclusion and Future Score

In this study, we explored the application of deep learning techniques for sentiment classification on social media datasets, highlighting their effectiveness in understanding user sentiments expressed in online platforms. Our experiments demonstrated that advanced models, such as RNN-LSTM networks, significantly outperformed traditional machine learning approaches, achieving higher accuracy and F1 scores. The use of hybrid feature selection methods further enhanced model performance by reducing dimensionality and retaining only the most informative features. These findings underscore the potential of deep learning in sentiment analysis, particularly in capturing the nuanced emotional tones embedded in user-generated content. The results indicate that sentiment classification can be reliably performed using deep learning techniques, providing valuable insights for businesses, researchers, and policymakers. The ability to automate sentiment analysis facilitates real-time monitoring of public opinion, enabling swift responses to emerging trends or crises. Future research should focus on several key areas to enhance sentiment classification models further. Firstly, expanding the diversity and volume of training datasets will improve model robustness and generalizability. Incorporating multilingual capabilities can also broaden the applicability of sentiment analysis across different languages and cultures, making the models more inclusive. Finally, integrating multimodal data, such as images and videos alongside text, can provide a more holistic understanding of sentiment, capturing contextual cues that text alone may miss. By addressing these areas, future studies can advance the field of sentiment classification, paving the way for more sophisticated and accurate analyses in the dynamic realm of social media.

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