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Research Article

An Intelligent Opinion Mining System with the Assistance of Bi-Directional Deep Recurrent Neural Network for Sentiment Analysis

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ABSTRACT

Opinion mining, also referred to as sentiment analysis, has been an important research topic for identifying and analyzing opinions in natural language text. Computational linguistics and information retrieval are combined to extract and assess subjective information from textual data in this interdisciplinary field. In this work, I present a Bidirectional Deep Recurrent Neural Network (BDRNN) based framework for sentiment polarity detection. In this work, we propose the Sentiment Analysis using BDRNN (SA-BDRNN) system, which aims to overcome the challenges in extracting unbiased opinions from text corpora. A dataset of labeled sentiments is used for training and evaluation to assure good model performance. Then the framework aims to mine sentiments effectively from source documents and improve the understanding of important contextual information. Finally, the SA-BDRNN system is benchmarked against state of the art methods, including Convolutional Neural Networks (CNN), Support Vector Machines (SVM), and an optimized SVM using Particle Swarm Optimization (SVM-PSO). Experimental results show that the proposed SA-BDRNN framework outperforms the best previous solutions in terms of sentiment classification accuracy and robustness, and hence can be a promising solution to advanced opinion mining applications.

Keywords: Opinion mining, neural network, tweet, optimization, text mining, deep learning, and sentiments.

1. INTRODUCTION

Opinion Mining research is the objective of creating an automated system for determining personal opinion/views from a text written in natural language. It is not based on the proposal of the mining keywords available on the web, but mining the context of the available keyword. In recent years, Ontology has emerged as an effective tool in the field of information science and it effectively solves complex problems such as storage and sorting [1]. Also, to design Ontology, there is no predefined thumb rule. Like any approach, there are some obstacles in it, the problem with this approach is that there is a limited limit of pre-declared words; Either we can say that there is no specific way of knowing the orientation of any word. We have much research in opinion mining in past. In the previous approach firstly, we extract the Opinion and then secondly we describe the document classification approaches which determine the semantic orientation of the documents (or their sentences) with the advent of E-Commerce in last decade, a huge number of products were purchased and sold on the web by the Internet users [2]. As more and more users are being familiar with the Internet, they are writing more on the Internet about themselves and their experiences about the products that they have purchased [3, 4].

The user now posts much detailed information about the product while mentioning its specific features and related experience. This online word-of-mouth text is now well-accepted and becoming a new measurable source of marketing intelligence [5, 6].This large amount of reviews could be explored by intelligent NLP-based algorithms to have an in-depth analysis of opinions about the product. This automaton is also required due to the size and locations of reviews, which are ever-increasing. To keep track of their product reputation and brand value in the market, companies take great interest in users' feedbacks and reviews. Based on these data, companies take the necessary actions for promotions and advertisement of the product. For the organizations, it is important to be informed about what their consumers think about their product. This information may be used for target-marketing and to deal with the competition [7].

The foremost challenge in Opinion Mining process is to locate the correct sources of quality opinions in the web. Most of the existing technologies used the web crawlers to find-out the opinionated text on a specific topic from the web. No specific web search mechanism is reported till now for opinionated text. Another challenge of opinion mining lies at the nature of domain-dependent text to be processed. As various users express their feeling, experiences or suggestions by using different types of words and using different sentence structure, it is hard to find out a general rule-set to process such text. Also, noise and incorrectness of text from the Internet make it difficult to process the extracted web documents into a meaningful form [8, 9].

Opinion mining is a mining tool to automate the process of extraction of relevant text from the source, generating product attributes (features) and classification of related opinions into good, poor or mixed. Opinion Mining is the process of identifying and removing subjective information using natural language processing, computational linguistics, and text analysis. It has two main phases, in the first phase opinion words are to be extracted from the text (Extraction) and in second phase their polarities are to be calculated (Classification). Motivated by this background, in the presented thesis, we attempt to define approaches for automatic acquisition and understanding of opinions from web documents [10].

Sentiment analysis is a study which analyzes people's opinion, feelings, evaluation, attitude and emotions towards any type of Entities like Products. Sentiment Analysis is a relevant text of the text that concludes and recognizes subjective information in the source material and helps the business to understand the social emotion of its brand, product or service while monitoring online conversations. More often than not, analysis of social media streams utilizes basic emotional analysis and count based metrics, but lacks deeper understanding [11]. The task of sentiment classification is to extract opinions from text and classify content as positive, negative or neutral [12].

Traditional approaches focus on three levels: document, sentence, and feature aspect. Where document level analysis assumes sentiment is uniform, sentence level analysis considers each sentence, which represents one sentiment. But in real world scenarios, these assumptions tend to fail. This limitation is addressed by feature level sentiment classification, which analyzes clauses or phrases, identify the specific object features commentated by opinion holders and their sentiment polarity (positive, negative or neutral) [13]. In software reviews, for example, where nuanced opinions are the norm, this approach is particularly effective.

Sentiment analysis at document level classifies the overall sentiment of a text, and at sentence level it detects sentiment in individual sentences. Lack of opinion is neutral sentiment. Analysis at feature level helps address the limitations of higher level approaches [14]. The whole idea behind aspect-based Sentiment analysis is to provide a way for our users to remove specific aspects from a piece of text and to set the emotion aside for each aspect. Our customers use it to analyze not only the sense of overall review but also to analyze website reviews, comments, Facebook, tweets and customer feedback forms, but in particular, the author likes or dislikes it from that text [15].

Opinion is a personal statement of a person about something. These statements are greatly influenced by the information, observations, and experiences of a person who is making an opinion. Such opinions about the product may be very useful for the potential buyers to have an idea about the product, before the actual purchase. Online reviews are readily available on the Internet and frequently used by all. Manufactures and Service Providers also take advantages of product review information to know their comparative brand reputation in the market [16, 17].

The SA-BDRNN, proposed here, is a reliable machine learning based sentiment analysis framework for mining opinions on social media. The scheme leverages a dynamic approach for semantic analysis, analyzing real time user behaviors and emotions in topics of interest. The main operation of this is to classify user sentiments by way of a Bidirectional Recurrent Neural Network (BDRNN) to classify opinion as positive or negative sentiment. In addition, the model includes both forward and backward context in the data, improving sentiment classification accuracy. The SA-BDRNN combines real time user feedback and behavior analysis for a better understanding of user emotions and opinions on social media platforms.

2. RELATED WORKS

In table 1 we give a complete analysis of the different studies in the field of opinion mining, and highlight some of the key advancements and methodologies. The studies presented here range over different domains such as fuzzy logic applications, sentiment analysis on social media platforms, opinion mining in software engineering, and educational feedback analysis. Deep learning, language models, and statistical methods have been used in different datasets to demonstrate their applicability in feature processing, classification, and polarity detection of sentiment. The results highlight the importance of tailored approaches for domain specific challenges in artificial intelligence and natural language processing.

Table 1. Comprehensive Analysis of Opinion Mining

Study Focus	Techniques/Approaches	Dataset Details	Key Findings	Reference
Applications of fuzzy logic in opinion mining	Fuzzy logic for feature processing, classification, and emotion detection	Over 120 articles reviewed from the past decade	Highlights fuzzy logic applications for sentiment analysis and identifies challenges and opportunities in the domain	[18]
Social Opinion Mining	Opinion dimensions: sentiment, emotion, sarcasm, irony; NLP, AI techniques	485 studies spanning 2007-2018	Insights into multiple platforms and applications across industries such as marketing, healthcare, and governance	[19]
Opinion mining in software engineering	Opinion mining in software development activities	185 studies on approaches, datasets, tools	Categorizes software development applications, evaluates performance, and highlights SE-specific challenges	[20]
Sentiment analysis of student feedback	Statistical and Opinion Mining techniques	Synthetic toy dataset for demonstration	Proposes a sentiment polarity computation strategy; highlights applications in academic analytics	[21]
Sentiment analysis for low-resource languages	Language models, deep learning, domain-specific corpora	Greek social media dataset	Achieved >80% accuracy; developed Greek-specific models outperforming generic models by 2%	[22]

Public sentiment on solar energy	RoBERTa for sentiment classification	266,686 tweets (Jan-Dec 2020), 6,300 annotated tweets	Sentiment varies across regions; positive sentiment linked to net metering policies and Democratic-leaning states	[23]
Health information behavior on social platforms	Opinion mining model for COVID-19 vaccine dispute	Douban platform group posts	Linear relationship between attitudes; subjective language dominates, and opinions remain stable over time	[24]

Opinion mining has seen significant advancement, however, several gaps remain. As current approaches struggle with domain specific challenges like low resource languages, ambiguity of subjective expressions and contextual nuances of sentiment analysis, there is a need to either enhance or develop new techniques for dealing with these challenges. Some of the traditional models are not able to capture the complex linguistic patterns especially for multimodal datasets and underrepresented languages. Additionally, many existing methods consider only a limited set of opinion dimensions, and ignore the interaction between factors such as sarcasm, emotion, and polarity of sentiment. Real time dynamic data streams are mostly inadequately handled by most of the frameworks or these do not incorporate comprehensive techniques such as fuzzy logic or advanced deep learning models to handle the uncertainty and variability in opinion mining tasks.

To address the limitations identified, the proposed work uses a Bi-Directional Deep Recurrent Neural Network (BDRNN) framework as a robust solution. The model also incorporates bidirectional processing to learn context from past as well as future sequences, making it better suited to understand more complex linguistic patterns. The additional enrichment of the approach with fuzzy logic is achieved by dealing with uncertainty and imprecision in sentiment analysis. The proposed system is also benchmarked on a variety of datasets to show its effectiveness across several domains and tasks. With this comprehensive approach, multimodal data, domain specific nuances and real time opinion dynamics are better handled, and the state of the art in opinion mining is advanced.

3. PROPOSED METHODOLOGY

The proposed SA-BDRNN Scheme includes 4 stages shown in Figure 1,

- Construction of words representing sentiments
- Categorizing sentimental words using BDRNN
- Process of Balancing words
- Prediction of positive and negative polarity tweets

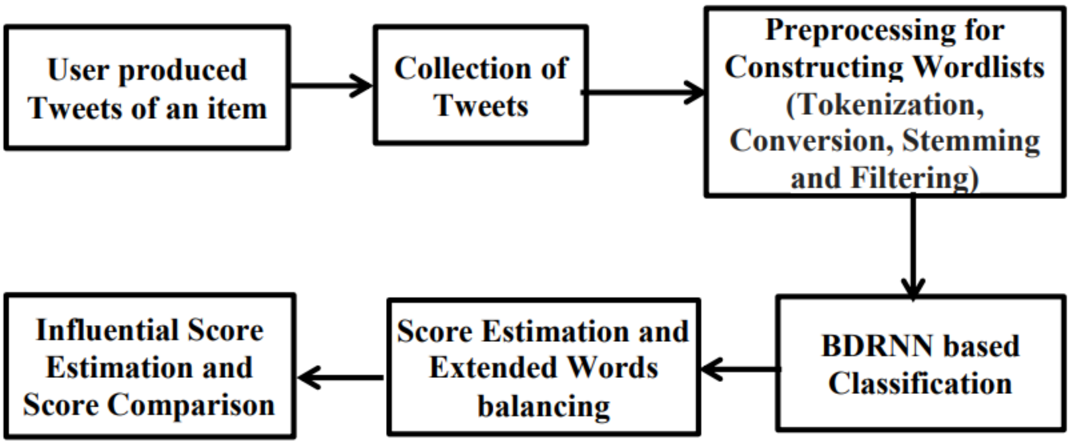

Figure 1. System Model of SA-BDRNN Scheme

X_i (i=1... n) - Group of items, people or services considered for comparison

T = {X1 , X2 .... Xn } - Focused context

Construction of words representing sentiments

The proposed SA-BDRNN Scheme proposes an efficient method of constructing sentiment word repositories from a small subset of hashtags to improve sentiment classification accuracy. Unlike existing methods that require large manually tagged hashtag sets, this approach is able to select a minimal set (2–3 per group) of semantically related hashtags in positive and negative sentiment groups. The benefit of this is a significant reduction in processing time with no loss in classification precision. First, we collect the posts, which focus on some topic (**Xi**) and identify the hashtags with high contextual relevance. To avoid categorizing sentiments with neutral hashtags, they are excluded. Comprehensive data preprocessing is included in the repository building process. Elements such as hashtags, HTML tags, URLs, symbols, emoticons are tokenized. Conversion converts letters to lower case and standardizes repeated characters. The morphological stemming removes conjugations and plural forms; filtering adds related adjectives and verbs to enhance sentiment representation. Then, transitional sentiment words (positive, negative and neutral) are refined for accuracy.

The first of these steps is to apply a neutral bias, and we test thresholds between 0.4 and 0.8 to find a value (which we set to 0.7) that minimizes classification errors. For negative, neutral, and positive words sentiments are classified as -1, 0, and +1 respectively. This approach is empirical, thus ensuring robust categorization of sentiment words. The SA-BDRNN Scheme focuses on a smaller set of highly relevant hashtags, uses systematic preprocessing and threshold tuning to construct an annotated sentiment word repository with high accuracy and low error rates. Moreover, the method not only improves classification efficiency but also addresses the problem of effective handling of diverse, noisy, and ambiguous textual data. As a result, it is a reliable approach for scalable sentiment analysis of diverse domains.

Categorizing sentimental words using BDRNN

Bidirectional Recurrent Neural Networks (BDRNNs) are proposed to be used in the SA-BDRNN scheme for the efficient sequential learning of Natural Language Processing (NLP). It employs Deep Recurrent Neural Networks (DRNN), which consist of two RNNs: There two RNNs, the first one identifies F_{hs}^1 and the second one F_{hs}^2. As Equation (1) shows, the output sequence (Y_O) of the DRNN is based on the input sequence (X_i).

$$Y_o = A(W_{m(hs)}^1 * F_{hs}^1 + W_{m(hs)}^2 * F_{hs}^2 + O_{BIAS} \text{---------}(1)$$

Where, A(*) - Activation function, O_{BIAS} Output bias, and $w_{m(hs)}^2$ Weight of the hidden sequences.

Forward and backward activations are shown in the following Equations.

$$F_{hs}^1 = f(W_m^{n-1} * F_{hs(n-1)}^t + W_m^n * F_{hs(n)}^{t-1} + B_{hs(n)}^1) \text{---------}(2)$$

$$F_{hs}^2 = f(W_m^{n-1} * F_{hs(n-1)}^t + W_m^n * F_{hs(n)}^{t+1} + B_{hs(n)}^1) \text{---------}(3)$$

In the proposed scheme, the performance is improved by using a DRNN with three hidden layers to effectively learn the transitional sentiment words. It tackles the problems of non conventional language found in social media like uppercase text and words with repeated letters, often neglected in sentiment analysis. To balance and manage such extended words, the scheme incorporates steps to improve the accuracy of sentiment representation.

Process of balancing words

The polarity degrees (P_t) related to opinions are found by incorporating the scores of the associated words at a particular point of time. Messages with specific length are considered as shown in Equation 4

$$P_t = \sum_{i=1}^{n} Wordscore_i \text{---------}(4)$$

Given an empirical threshold, tweets are categorized into sentiment classes (Positive, Neutral, and Negative). The positive sentiment is further divided into weak ($0 < p(t) \leq 3$), moderate ($4 \leq p(t) \leq 6$) and strong ($p(t) \geq 7$). Negative sentiment follows a similar division: p(t) is weak ($-3 \leq p(t) < 0$), moderate ($-6 \leq p(t) \leq -4$), and strong ($p(t) \leq -7$). If the sentiment score = 0, then its classified as neutral.

Prediction of positive and negative tweets

The Proposed SA-BDRNN puts forward an improved way of sentiment analysis, which is tackling the shortcomings of current literature on sentiment analysis methods, which categorizes sentiments as positive, negative, or neutral depending on derived emotions and words. Building on this, researcher further extended this to categorize polarity into high, moderate, negative, and weakly positive sentiments and found their use of strongly positive and strongly negative indicators to be impractical in many real-world scenarios. To overcome this, SA-BDRNN scheme uses class impact differences to better determine dominant public opinion in a particular field or subject.

For the SA-BDRNN scheme, sentiment prediction is performed by assigning weights of -3 through +3 depending on the intensity of sentiment. These weights are defined to provide a nuanced classification of opinions: Weights are assigned strongly positive sentiments at +3, moderately positive sentiments at +2, and weakly positive sentiments at +1. A weight of 0 is assigned for neutral sentiments, and -1, -2, and -3 for weakly negative, moderately negative, and strongly negative sentiments, respectively. With this structured weighting system, public opinion is able to be analyzed at a granular level of sentiment intensity and polarity.

Metrics that take into account balancing of weight are then used to calculate the Degree of Impact (DoI) for each opinion in order to further improve sentiment analysis accuracy. This guarantees that sentiment classes are equally represented and that atypical sentiment indicators do not affect the result. As the SA-BDRNN scheme depends on the balanced weighting approach, it is more robust to identify dominant sentiments based on different datasets. The SA-BDRNN scheme integrates these innovations to provide a more textured, accurate sentiment analysis. It effectively solves the problems in the traditional methods and offers a powerful tool for the applications which need the context sensitive sentiment evaluation. It is especially valuable for domains where we need to understand the intensity and impact of sentiment.

$$DoI_t = W_t + N_t^L + N_t^{RT} \text{---------}(5)$$

Where, W_t Weights related to every class, N_t^L Number of liked opinions, and N_t^{RT} Number of Retweeted opinions.

Finally, the total rating (Rate X_i) associated with the opinions is found based on the collective sum of DoI and the amount of tweets exchanged between the consumers about the Item of Interest (IoI) as shown in Equation 6.

$$Rate(X_i) = \frac{\sum_{i=1}^{n} DoI_t}{N_{PL}} \text{---------}(6)$$

Where, NPL- Number of positive likes.

The opinion, that is highly rated, is taken as the maximum likelihood of likes given by consumers over the internet for the item.

4. RESULT AND DISCUSSION

Simulation experiments are performed to evaluate the performance of the proposed SA-BDRNN scheme for various parameters such as the number of vectors and vocabulary, number of hidden layers, count and size of filters, dropout rates, regularizers and activation functions. The robustness and efficiency of the scheme in sentiment analysis is analyzed systematically to these parameters. The details of the dataset used for evaluation, which consists of training, validation, and testing data from real time Twitter messages are given in Table 1. The dataset consists of 52,630 training samples, 7,000 validation samples and 7,000 testing samples with same number of positive and negative sentiments.

Table 1. Tweet Data set and Sample taken for Analysis

	Dataset	Positive	Negative	Total
Language of real time dataset twitter messages	Training	26410	26210	52630
	Validation	3500	3500	7000
	Testing	3500	3500	7000

The accuracy and loss curves (Figures 2 and 3) are used as the main performance metrics of the SA-BDRNN scheme. A key metric is classification accuracy or the percentage of correct predictions out of total predictions. We also evaluate sensitivity and specificity to measure how much the model predicts true positives and true negatives. The results of these metrics give us a detailed understanding of how the model classifies documents into different sentiment categories.

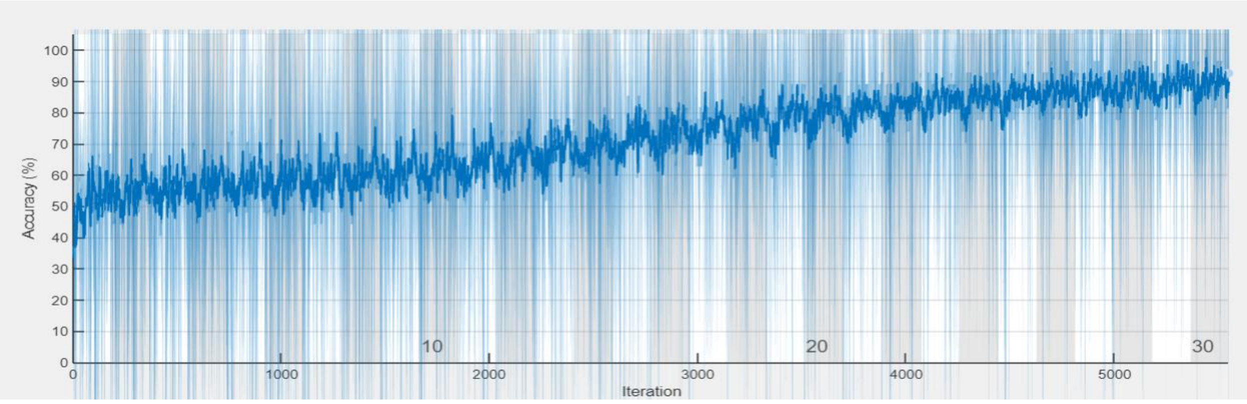

Figure 2. Comparison of Accuracy

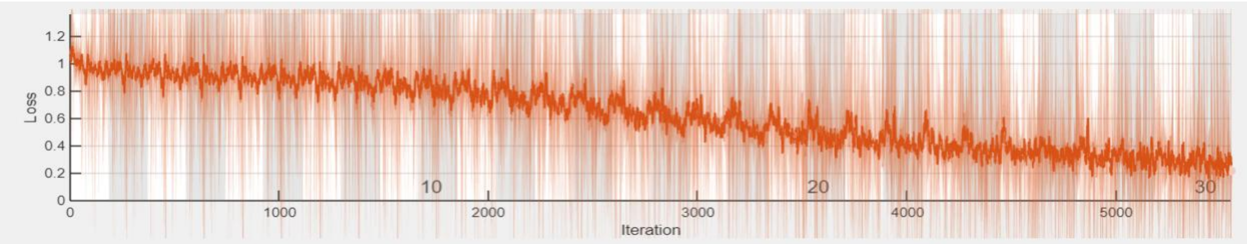

Figure 3. Comparison of Loss

The accuracy of classifications is calculated by dividing the number of accurate classifications by the total number of classifications, and multiplying by 100. Sensitivity is how well a model can predict true positives for each category and specificity is how well a model can predict true negatives. All category models can use these metrics. Table 2 and Figures 4-6 show the illustration of the performance measures.

Table 2. Comparison of Performance

Algorithm	Sensitivity	Specificity	Accuracy	Error Rate
SVM	80	84	83.56	1.189
SVM+PSO	81.22	85	86	1.012
CNN	81.56	91.67	87.78	0.99a
SA-BDRNN	83.66	97.52	90.15	0.985

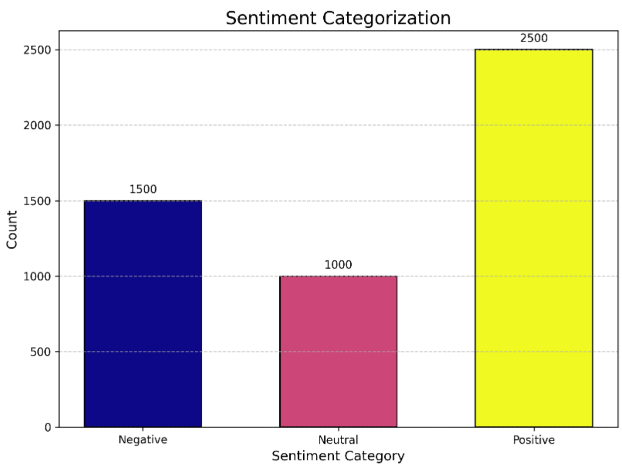

Figure 4. Comparison of Class Distribution

SA-BDRNN is compared with other algorithms such as SVM, SVM+PSO and CNN in Table 2. As a case study, the proposed SA-BDRNN scheme exhibits an accuracy of 90.15%, sensitivity of 83.66%, and specificity of 97.52%. Furthermore, the error rate of SA-BDRNN is the lowest at 0.985, better than the other models.

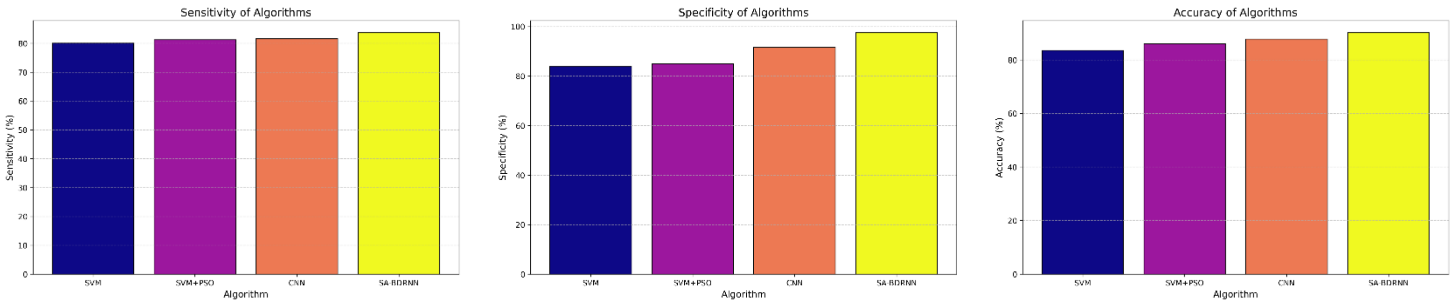

Figure 5. Comparison of Performance

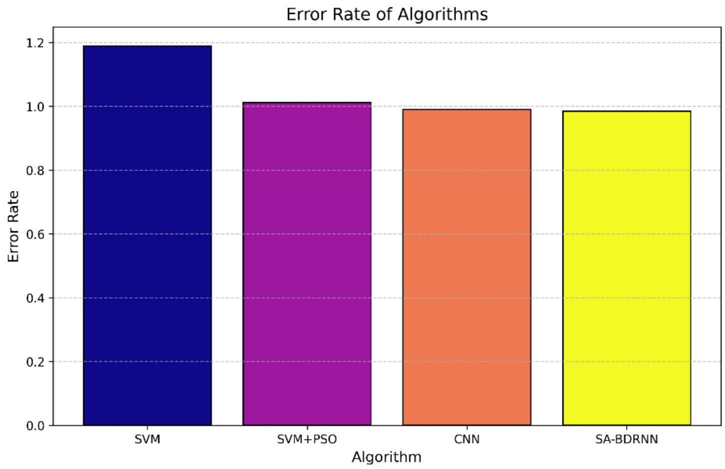

Figure 6. Comparison of Error Rate

The class distribution, performance measures and error rates are shown in Figures 4-6. The results suggest that the SA-BDRNN scheme can significantly improve the classification performance. Not only does the approach improve accuracy and specificity, but it also reduces error rate in sentiment analysis tasks. The scheme's superior performance validates its potential for real time applications in opinion mining and sentiment analysis.

Table 1 presents a dataset that gives a complete overview of the sentiment classification tasks carried out using SA-BDRNN scheme. The dataset is real time Twitter messages of positive, negative and neutral sentiments. The training data is 52,630 samples, validation and testing data 7,000 samples, which ensures balanced evaluation and model robustness. The performance of the proposed SA-BDRNN scheme is analyzed using this dataset.

Figure 7. Sentiment Word Cloud

Figures 2 and 3 show the scheme's learning capability during training and validation with accuracy and loss curves. A key performance metric of classification accuracy is defined as the proportion of correct predictions to the total predictions. In addition, sensitivity indicates how well the model classifies true positives, and specificity indicates how well the model classifies true negatives correctly. However, it became clear that the SA-BDRNN scheme is able to achieve a remarkable classification accuracy of 90.15%, better than others like SVM, SVM+PSO, CNN.

Comparative performance of the model is shown in Table 2, and corresponding visual comparisons (Figures 4–6). SA-BDRNN scheme shows highest sensitivity (83.66%) and specificity (97.52%) amongst all the evaluated models, indicating better discrimination of sentiment. Also, the model error rate of 0.985 is the lowest, which proves that the model is accurate in sentiment analysis tasks.

Figures 4 and 7 confirm the model's robustness to imbalanced datasets, and the sentiment word cloud (Figure 7) visually displays the importance of sentiment indicative words. The proposed scheme offers error rates reduction, increases classification accuracy, and shows improved specificity, thus making it suitable for real time opinion mining applications. The results from SA-BDRNN show that it outperforms past models, and that it has the potential to improve sentiment analysis, overcoming the limitations of previous models and precisely classifying sentiments in real world datasets.

5. CONCLUSION

Using Deep Recurrent Neural Network (DRNN)-based learning for user behavior prediction, the proposed SA-BDRNN scheme effectively analyzes social media data. The scheme shows significant improvement in performance metrics by building a polarity driven word list and balancing extended words for efficient sentiment classification. Results show 90% accuracy improvement and 13% true positive rate improvement over varying training iterations, reflecting the robustness of the method. These findings validate the scheme for real world sentiment analysis tasks. The result of this could be further work where we integrate Convolutional Neural Networks (CNN) with Long Short Term Memory (LSTM) models to amalgamate a unified framework to handle diverse linguistic structures. This advancement might improve the scheme's ability to deal with complex datasets in general, and increase the ability of sentiment classification across different social media platforms. The proposed approach provides a solid starting point for applying deeper deep learning techniques to opinion mining and user behavior analytics.

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