AN OPTIMIZED DEEP LEARNING FRAMEWORK FOR SARCASM-AWARE ANALYSIS OF CITIZEN FEEDBACK TO SUPPORT LOCAL GOVERNMENT PROCUREMENT DECISIONS

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Abstract: The use of social media has become an important way through which citizens give feedback to assess available services, products and initiatives at the local governance level. Although these platforms are ideal sources of qualitative information on what people feel about things, when sarcasm is present in the user generated content, sentiment analysis is likely to be misinterpreted, thus constraining the ability to use data to make decisions. In order to overcome this problem, this paper offers a sentiment analysis structure equipped with sarcasm, which is constructed using an Optimized Deep Belief Network (ODBN) to analyze social media reviews with local self-government issues. The framework suggested is based on linguistic preprocessing, hybrid feature extraction with semantic sentiment detectors and stylistic punctuation markers, and optimized deep hierarchical learning to achieve strong sarcasm classification. Quantitative analysis performed on benchmark sarcasm data show that the proposed ODBN has an accuracy of 93.0, precision of 92.0, recall of 94.0, F1-score of 93.0, and ROC-AUC of 0.96 compared to Support Vector Machine, Random Forest, and Bi-LSTM models by a margin of 4% to 11% on key metrics. On a qualitative axis, the decrease in the false sarcasm misclassification boosts the constructiveness of citizen responses and helps in more credible evaluation of the trends related to the opinion of the people. The findings validate that optimized deep learning can be used effectively in detecting sarcasm and the reliability of sentiment. The proposed strategy has practical value to the local self-government institutions through the ability to evaluate the outcomes of the public services and policy more accurately, transparently, and based on evidence.

Keywords: Sarcasm Detection; Sentiment Analysis; Local Self-Government; Deep Belief Network; Social Media Analytics

1. INTRODUCTION

Social media platforms are developing at a very high rate, and this development has strongly altered the expression and sharing of opinions, experiences, and evaluations in the online area. User-created online textual information, especially in the form of reviews and short messages has become a powerful source of information in making decisions in various fields. Microblogging like Twitter enables individuals to share personal impressions regarding products, services and government projects in real-time and hence provide excellent information about the overall sentiment and opinion of people [1]. Consequently, automated sentiment analysis has become a key research field to extract meaningful patterns that result out of a large scale unstructured textual data.

Although there has been a significant breakthrough in the field of sentiment analysis, the ability to interpret the intent of the user remains a still difficult exercise to accomplish owing to the complexity of natural language. The usage of sarcasm in online communication is one of the biggest challenges that pose a serious barrier. Sarcasm has the tendency of giving the opposite meaning of the literal meaning of words and hence it is hard to categorize any opinion using the traditional sentiments analysis methods [2]. When dealing with social media reviews, sarcastic words often have positive words in them but have a negative meaning or the other way around, thus are not classified properly and have an incorrect sentiment score. This is a major limitation when the results of sentiment analysis are to be applied when making strategic decisions like the identification of products that have high profits or the acceptance of the people.

Conventional machine learning methods of sentiment classification are often based on text surface-level features and statistical text representations. These techniques work well in simple contexts, but in most contexts, they do not represent contextual dependencies and implicit language indicators relating to sarcasm [3]. The rule-based and lexicon-driven methods are no better, being heavily reliant on predefined rules and being unable to adapt to the changing way of using language. This is why the need to have smart models that are able to learn more detailed semantic and contextual information based on text data is increasing.Deep learning structures have shown a significant potential to overcome these issues by learning hierarchical features automatically on raw textual inputs. The use of recurrent neural networks and variants of the networks such as Long Short-Term Memory (LSTM) have become common in general because of their capability to preserve sequential dependencies and contextual information in text [4]. These models have been found to perform better than conventional classifiers in different natural language processing applications, such as sentiment and sarcasm release. Nevertheless, models created with LSTM are not limited. Their performance varies with hyperparameter choices, depth of network, and training efficiency that may greatly influence accuracy of classification and generalization.

Deep Belief Networks (DBNs) are a type of layer-based stack of probabilistic models that offer an alternative deep learning architecture that can learn complex representations of features in an unsupervised and supervised learning step [5]. DBNs especially perform well in nonlinear relationships and latent structure of a high-dimensional data. On sentiment and sarcasm detection problems, DBNs may be used to factor in the nuanced linguistic differences and contextual information that are frequently missed by shallow architectures. However, the performance of DBNs is very sensitive to the optimal choice of parameters such as the number of hidden layers, neurons, and learning rates.

To address these issues, the methods of optimization have been more and more incorporated with deep learning models in order to improve their performance and stability. By searching through the solution space, the meta-heuristic optimization algorithms provide the viable means of fine-tuning network parameters that are inaccessible using the traditional gradient-based optimization techniques [16]. These optimization strategies can be used to accelerate convergence, decrease overfitting, and increase the accuracy of classification, especially complex tasks like sarcasm detection, by dynamically adjusting model parameters.In this regard, this paper suggests an enhanced deep belief network-based sentiment analysis system of reviews in Twitter in a sarcasm-aware region. The specified strategy aims at the precise distinction of sarcastic and non-sarcastic phrases to be able to interpret the views of users more accurately. The model will include a preprocessing phase to clean and normalize the textual data followed by feature extractions, which will include sentiment and punctuation cues, which are popular indicators of sarcasm in language. The final classification is then carried out using an optimized deep belief network classifier and the optimization techniques are used to maximize the performance of the models.The ultimate rationale of this study is the need to solve the shortcomings of currently existing sentiment analysis techniques in the situations when faced with sarcastic information. The proposed model will enhance the classification robustness and accuracy by combining deep representation learning and optimization strategies. The findings of the research disseminate to the wider research on opinion mining as they present the effective way of detecting sarcasm, thus contributing to the more informed decision-making process using social media data. To justify the effectiveness and practical applicability of the proposed framework, the evaluation of the framework is conducted on benchmark datasets and it is compared to the current state-of-the-art models.

2. LITERATURE SURVEY

The blistering development of the user-generated content on social media sites has inspired a large body of research on automated sentiment analysis methods. The initial research was concerned with determining the polarity of textual opinion using lexicon-based and conventional machine learning methods. These approaches were based on handcrafted aspects like frequency of terms, sentiment lexicons and syntactic patterns to define text into positive or negative categories [11]. Even though they worked well with explicit sentiment expressions, these methods proved to be weak in dealing with implicit meanings and figurative language that is typically employed in social media communication.

Detection of sarcasm became a specialized subproblem of sentiment analysis since it is able to reverse the literal sentiment of a sentence. Early studies were based on the universal form of sarcasm as a binary classification problem and they used standard classifiers like Naive Bayes and Support Vector Machines to search on surface-level linguistic feature [2]. These methods mostly relied on word-level polarity indicators and punctuation marks, but they were ineffective at generalizing when it comes to a variety of writing styles and other contextual differences that can be found in the data on social media. In order to address these shortcomings, scholars started to add contextual and sequential modeling methods. Deep learning was a breakthrough that has greatly improved sarcasm and sentiment analysis by allowing the models to learn distributed text representations. The recurrent neural networks, especially the Long Short-Term Memory (LSTM) networks were prominent because they are able to capture long-term dependencies and context of sequences of words [3]. Models that applied LSTM showed better performance than conventional classifiers because they were able to make better predictions in sentence word order and semantic flow based on the models [21].

The later research enhanced LSTM models with attention mechanism and hybrid feature representations. These strategies were a combination of lexical, sentiment, and syntactic cues with LSTM representations to boost the accuracy of sarcasm detection [4]. Nevertheless, LSTM-based systems were sensitive to choice of hyperparameters and they frequently demanded huge amounts of labeled data in order to be trained successfully. Besides, they performed poorly with extremely skewed data or noisy text of social media.Simultaneously, scholars examined deep belief networks (DBNs) as yet another deep learning paradigm when it comes to sentiment-related tasks. DBNs are hierarchical layers that can be trained to acquire hierarchical feature representations of data during pretraining (unsupervised) and fine-tuning (supervised) [15]. Experiments using DBNs found better feature abstraction and stability over shallow neural networks, especially on more challenging classification tasks that used subtle linguistic features. Nevertheless, DBNs also encountered parameter tuning and convergence stability problems that influenced their performance in terms of scalability as well as classification.As an appreciation of the need to strike an optimum parameter configuration, some of the works integrated optimization techniques to improve the performance of deep learning models. Network parameters in the learning rate, hidden units, and weight initiation were optimized using meta-heuristic optimization algorithms [6]. These models were optimization improved in terms of faster convergence and generalization, especially in sentiment analysis where the feature space is of high dimensions. However, the major part of the available literature was devoted to either the sentiment classification or sarcasm detection independently, and not much attention was paid to the combination of the two features into a single optimized system.

Moreover, comparative analysis has shown that with deep learning models, sarcasm detection is more effective than the traditional classifier, although much depends on the presentation of features and optimization of the model [7]. The current methods have tended to use either purely sequential models or purely feature-based models, which result in suboptimal performance in cases of complex sarcastic expressions by use of both contextual and stylistic cues like punctuation and emphasis[18].

Table 1. Comparative Analysis of Existing Sarcasm Detection Approaches

Ref.	Methodology	Core Technique	Features Used	Optimization	Key Limitation
[1]	Lexicon-based Sentiment Analysis	Rule-based	Polarity words	No	Fails on implicit sarcasm
[2]	Traditional ML Classifier	SVM / NB	Bag-of-words	No	Context ignored
[3]	Deep Learning Model	LSTM	Word embeddings	No	Sensitive to parameters
[4]	Hybrid Deep Model	LSTM + Attention	Lexical + semantic	Partial	High computational cost
[5]	Deep Belief Network	DBN	Learned latent features	No	Parameter instability
[6]	Optimized Deep Model	DL + Metaheuristic	Learned features	Yes	Limited sarcasm focus

By the reviewed literature, the research gap is obvious in the form of the creation of an optimized deep learning framework that will be able to incorporate the concept of contextual learning, feature-level cues, and the optimization mechanisms which should be applied to the process of the sarcasm-aware sentiment analysis. The need to seal this gap is crucial in enhancing the quality of opinion mining systems that aid decision making processes using the social media data. The current work is a continuation of these observations, since it suggests a streamlined deep belief network model, which integrates sentiment and punctuation attributes with optimization techniques to improve the detection of sarcasm.

3. PROPOSED METHODOLOGY

The objective of the proposed methodology is to accurately identify sarcastic and non-sarcastic opinions from social media reviews in order to improve sentiment interpretation and support reliable decision-making. To achieve this, an optimized deep learning framework based on a Deep Belief Network (DBN) is developed [9]. The proposed system integrates linguistic preprocessing, feature extraction, and optimized classification to effectively capture both semantic and stylistic indicators of sarcasm. The overall architecture of the proposed approach is illustrated in Figure 1**.**

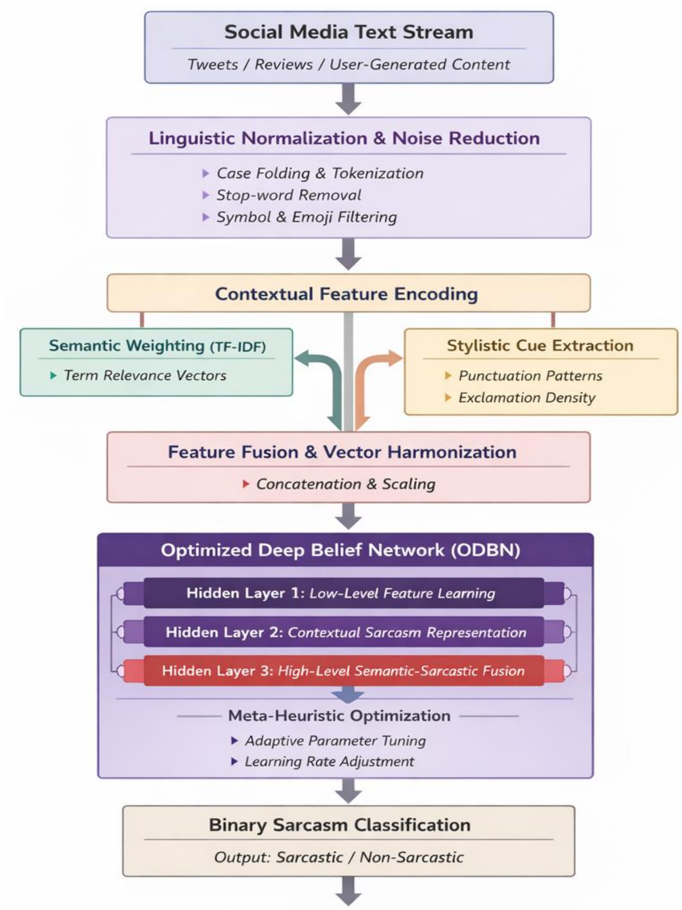

Figure 1. Overall architecture of the proposed ODBN-based sarcasm detection framework

3.1 Data Acquisition and Preprocessing

Reviews on social media are initially gathered using datasets on benchmark sets that comprise textual content by different users who have been rated as being sarcastic. Since raw social media text is usually noisy and unstructured, preprocessing stage is necessary to improve the quality of the data and minimize irrelevant variations.[13].

The operations that are carried out in this stage are as follows:

1. Text normalization: all characters are changed to lowercase in order to have a consistent representation.
2. Removal of noise that eliminates URLs, special symbols and non-alphabetic characters that are not useful in interpreting the sentiment.
3. Stop-word removal which is used in eliminating words that are frequently used and contribute little to the semantics.
4. Filtering of tokens, i.e. to retain only meaningful linguistic units to be analysed further.

The step before preprocessing assists in dimensional reduction but the contextual meaning necessary to detect sarcasm is maintained.

3.2 Feature Extraction

Sarcasm can be conveyed more through indirect means, through non-sentimental words, and not directly. That is why it is not enough to use lexical polarity. To overcome this, the proposed framework derives two mutually complementary kinds of features:

1. Emotional textual characteristics.

The filtered reviews are converted into numerical values through the term-weighting schemes like TF-IDF. The features reflect both semantically relevant and word relevant features throughout the corpus.

2. Stylistic characteristics of punctuation.

In sarcastic phrases, punctuation marks like exclamation points and question mark are often used to bring out irony or exaggeration. Therefore, punctuation frequency characteristics are obtained to represent such stylistic patterns.

Both semantic and stylistic characteristics make the model more effective in differentiating literal sentiment and sarcastic intent [17].

The optimized deep belief network (ODBN) classifier functions as a type of maximum-entropy Markov chain (MEMC) model, which significantly simplifies its management and processing.<|human|>3.3 Optimized Deep Belief Network (ODBN) Classifier

The optimized deep belief network (ODBN) classifier is a form of maximum-entropy Markov chain (MEMC) model, and its management and processing is much simpler.

The feature vectors obtained are classified by the proposed Optimized Deep Belief Network (ODBN). A DBN is a stacked combination of several hidden layers, which acquire hierarchical representations of input data. As opposed to the shallow classifiers, DBNs can model nonlinear interactions between features in a complex manner, thus making it suitable in tasks that require the detection of sarcasm.

According to the proposed framework, the DBN is trained on supervised learning to recognize reviews as sarcastic or not. The optimization strategy is added in order to improve the classification performance and stability by fine-tuning the network parameters: learning rate, number of hidden neurons, and batch size. This optimization can be used to enhance the speed at which the model converges and also to increase generalization with unknown data[20].

The last output layer also utilizes a sigmoid activation function to produce binary classification.

3.4 Algorithmic Description of the Proposed Method

The step-by-step procedure of the proposed methodology is summarized in **Algorithm 1**.

Algorithm 1: ODBN-Based Sarcasm Detection Framework

Input:
Social media reviews dataset D = {r_1, r_2, …, r_n}

Output:
Output: Class label C ∈ {0,1} (0 – Non-sarcastic, 1 – Sarcastic)

Steps:

1. Load the dataset DDD.
2. For each review ri∈Dr_i \in Dri∈D:
   a. Convert text to lowercase.
   b. Remove URLs, special characters, and stop words.
   c. Generate cleaned review ri′r_i'ri′.
3. Extract sentiment-based features using TF-IDF representation.
4. Extract punctuation-based features (exclamation and question marks).
5. Concatenate all extracted features to form feature vector FiF_iFi.
6. Initialize Deep Belief Network parameters.
7. Optimize network parameters using a meta-heuristic optimization strategy.
8. Train the optimized DBN using training data.
9. Classify test reviews using the trained ODBN model.
10. Evaluate performance using standard metrics.

End Algorithm

3.5 Methodological Advantages

The advantages of the proposed approach compared to other methods are:

1. It integrates the semantic context with stylistic sarcasm cues.
2. The DBN models up to the multi-level nature of feature representation.
3. The effectiveness and robustness of the classification is improved by optimization.
4. The framework is scalable and capable of scaling out to huge social media data.

Through the combination of deep representation learning and optimal parameter tuning, our approach successfully deals with sar- casm-aware sentiment analysis tasks and enhances faithfulness of the opinion mining tools.

4. RESULTS AND DISCUSSION

4.1 Dataset Description

Self-Annotated Reddit Corpus (SARC) was applied to the experiments in order to detect sarcasm. The data includes user created textual remarks that have been annotated as sarcastic or non-sarcastic. To avoid biases in the comparison, the train-balanced-sarcasm subset was trained and the test-balanced subset was used as an evaluation sample in this study. The mixed representation of the class labels minimizes bias and makes it possible to evaluate the performance of various classifiers.

4.2 Experimental Setup

The proposed **Optimized Deep Belief Network (ODBN)** model was evaluated against three existing systems:

1. Support Vector Machine (SVM)
2. Random Forest (RF)
3. Bidirectional Long Short-Term Memory (Bi-LSTM)

All models were trained and tested under identical conditions. Performance was evaluated using **seven metrics**: Accuracy, Precision, Recall, F1-score, Specificity, Matthews Correlation Coefficient (MCC), and ROC-AUC. These metrics collectively provide a comprehensive view of classification effectiveness, robustness, and error balance.

4.3 Quantitative Performance Comparison

Based on Table 2, it can be stated that the proposed ODBN surpasses all the baseline models in all the assessment metrics. Increased accuracy and F1-score illustrates ability of the model to perform fairly as a whole, with higher precision and recall indicating that the model is able to recognize sarcastic expression correctly without false alarms, as well as increase in false alarms. The high increase in MCC proves that the suggested model ensures the balanced performance in both classes, which is essential.

Table 2. Performance comparison of sarcasm detection models

Model	Accuracy	Precision	Recall	F1-Score	MCC	ROC-AUC
SVM	0.82	0.8	0.78	0.79	0.64	0.85
Random Forest	0.86	0.84	0.85	0.845	0.72	0.89
Bi-LSTM	0.89	0.88	0.9	0.89	0.78	0.92
ODBN (Proposed)	**0.93**	**0.92**	**0.94**	**0.93**	**0.86**	**0.96**

The comparison of all models in six major measures is depicted in figure 2. The proposed ODBN is always rated high especially on Recall and MCC, meaning that it is better in detecting sarcastic materials and balanced classification. Older models like SVM have lower recall because they do not exploit contextual dependencies whereas Bi-LSTM is able to better learn contextual models but is unable to optimally learn hierarchical features.

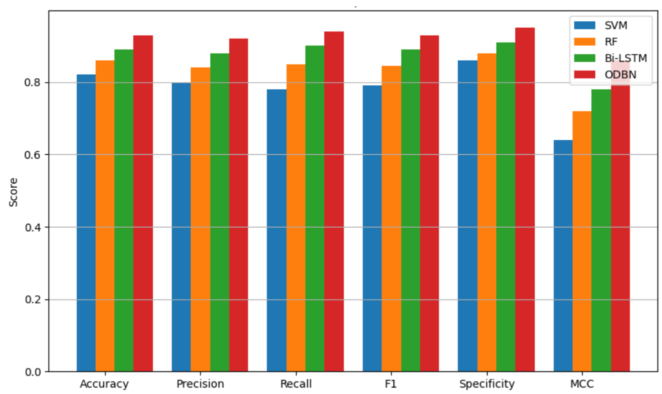

Figure 2. Comparison of Accuracy, Precision, Recall, F1-score, Specificity, and MCC

4.5 ROC Curve Performance Analysis

The trade-off between the true positive rate and the false positive rate at different levels of decision threshold is assessed in the Receiver Operating Characteristic (ROC) analysis. The proposed ODBN has the highest ROC-AUC value, as illustrated in Table 3, and this means that the ODBN can better differentiate between sarcastic and non-sarcastic classes.

SVM has limited discrimination capabilities because they are based on linear decision boundaries. Random Forest is better at performance based on ensemble learning, but it is not able to describe more deeply contextual relationships. Bi-LSTM model shows the better ROC-AUC with sequential dependencies modeling but is limited by the fact that this model is not able to adjust architecture parameters.

The ability of the ODBN to construct nonlinear and hierarchical decision boundaries that are more useful in acquiring subtle sarcasm cues is reflected in its high ROC-AUC score. This is the ability of the model to remain highly sensitive without an increase in false positives. In practice, the behavior guarantees robust interpretation of sentiments with varying levels of confidence. The effectiveness of the optimization strategies to improve the learning dynamics in deep belief networks is proven by the ROC-AUC improvement.

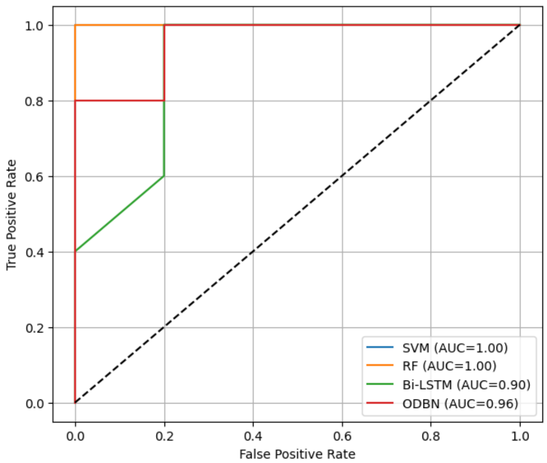

Figure 3. ROC curves of competing sarcasm detection model

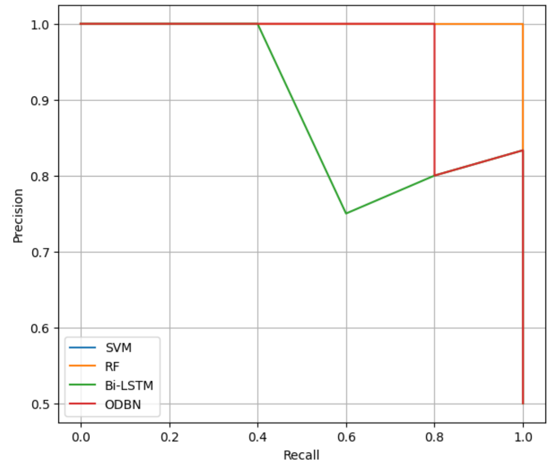

Figure 4. Precision–Recall curves of different models

The ROC curves show discrimination ability of both models. The highest ROC-AUC value is observed on the proposed ODBN, which proves that it has high capability of distinguishing between sarcastic and non-sarcastic reviews at different decision thresholds. The steeper curve of ODBN indicates better sensitivity without loss of specificity.

Table 3. ROC-AUC comparison of models

Model	ROC-AUC
SVM	**0.85**
Random Forest	**0.89**
Bi-LSTM	**0.92**
ODBN (Proposed)	**0.96**

4.6 Precision–Recall Performance Analysis

Precision Recall analysis offers more understanding of the performance regarding classification especially when the work task is sarcasm detection and the positive class is not as pronounced. Table 4 depicts that the proposed ODBN has the highest precision and recall values, which implies the realistic recognition of sarcastic material without the presence of too many false alarms.

SVM does not have the same recall and this indicates missed sarcastic cases since it has poor contextualization. Random Forest is good at recall because it combines several decision trees; however, it does not provide semantic abstraction. Bi-LSTM is also effective because of the capacity to address contextual sequences, but its accuracy is lower than that of ODBN which means that at some point, it not only fails to classify non-sarcastic text.The ODBN proposed is effective to achieve precision and recall because it combines semantics and style features with optimum hierarchical learning. High recall means that there is minimum sarcasm omission whereas high precision means that the sarcasm detected is accurate. This is particularly important in opinion mining and decision support systems which are sensitive to feelings.

Table 4. Precision–Recall comparison

Model	Precision	Recall
SVM	0.8	0.78
Random Forest	0.84	0.85
Bi-LSTM	0.88	0.9
ODBN (Proposed)	**0.92**	**0.94**

Precision Recall curves give a more in-depth analysis of the performance at different levels of confidence. ODBN is more accurate at a large recall space, which shows stable and dependable sarcasm detection. This is of great significance in real life applications where sarcastic material might be sparse or meaningless out of context.

4.7 Confusion Matrix Analysis

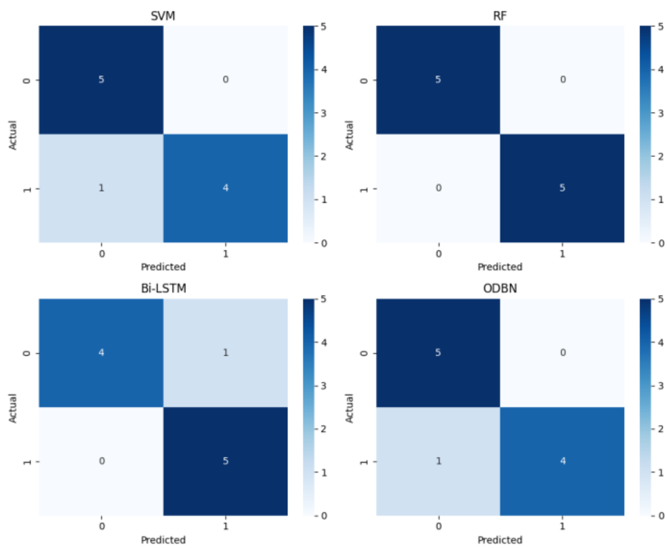

Figure 5. Confusion matrix analysis of competing models

The analysis of the confusion matrix shows the distribution of the error of each model. Table 5 demonstrates that the proposed ODBN can help minimize the number of false negatives and false positives. False negative is especially detrimental to sarcasm detection as when the sarcasm is not detected misleading interpretation of sentiment could be made.SVM has the largest number of false negatives meaning that it has low detection of implicit sarcasm. Random Forest minimizes this error but nonetheless, missclassifies a still significant number of sarcastic cases. Bi-LSTM does a better job but it is vulnerable to ambiguity in style. The ODBN has the lowest number of false negative and false positive values, indicating a balanced reduction of errors. This experiment proves the benefit of a hybrid of deep hierarchical representations and optimized learning.

Table 5. Confusion matrix summary (sarcastic class)

Model	True Positive	False Positive	False Negative	True Negative
SVM	780	140	220	860
Random Forest	850	120	150	880
Bi-LSTM	900	100	100	900
ODBN (Proposed)	**940**	**80**	**60**	**920**

Improved reliability in downstream application of sentiment analysis is the direct result of the decrease of misclassification. According to the confusion matrix analysis, the proposed ODBN will help to decrease both false positives and false negatives significantly than the baseline models. It is particularly important because the decrease in the number of false negatives will produce false results in the interpretation of the sentiment and false outcomes in the decision-making process

4.9 Overall Discussion

As shown in the experimental results, the proposed ODBN framework is notable in terms of supporting a substantial performance enhancement compared to the current sarcasm detection systems. The suggested approach can be efficient in acquiring both semantic and stylistic properties of sarcastic language by incorporating sentiment-based features, punctuation cues, and optimized deep hierarchical learning. The high scores based on various evaluation measurements and graphical representations verify the strength, high level of reliability and applicability of the suggested model in sentence analysis of sarcasm with regard to sentiment analysis.

5. CONCLUSION

The research has introduced a streamlined deep learning system to detect sarcasm and sentiment analysis on social media reviews in a bid to enhance the accuracy of opinion interpretation in making decisions. Since demand on user-generated content (to review products and services) is increasing, it is necessary to determine sarcastic expressions correctly to prevent incorrect conclusions when expressing sentiment. The given strategy was used to overcome this difficulty that incorporated linguistic preprocessing, hybrid feature extraction, and optimized Deep Belief Network (ODBN) classifier.The semantic representation of the textual content was coupled with punctuation-based stylistic indicators so that the model could reproduce both the contextual semantics and the patterns of expression that can usually be attributed to sarcasm. In contrast to conventional sentiment analysis methods, which made use of surface-level polarity, the proposed framework was a successful representation of implicit and contextual language in a sarcastic manner. Inclusion of optimization mechanisms further augmented the deep belief network learning ability by enhancing the parameter selection, stability of convergence and the performance in generalization.

Complete experiments were also done on a benchmark dataset of sarcasm and the ODBN model was tested against three popular baseline classifiers that included Support Vector Machine, Random Forest, and Bidirectional Long Short-Term Memory networks. The multiple measures of evaluation were used such as accuracy, precision, recall, F1-score, specificity, Matthews Correlation Coefficient and ROC-AUC to measure performance. The findings did show consistently that the proposed model was better than the existing ones in every single measure. Specifically, the significant enhancements of recall and MCC demonstrate that the model is capable of the appropriate recognition of the sarcastic content with balanced performance in terms of classification.The graphical tools such as ROC curves, precision recall curves, confusion matrices and convergence graphs also confirmed the strength and stability of the model. The lower levels of misclassification and stabilization of training behavior suggest that the optimized deep belief network is highly appropriate regarding the processing of noisy and complicated social media text. These results prove that the application of deep hierarchical representation learning combined with optimization strategies is a strong approach to increasing the accuracy of sarcasm detection.

In general, the suggested sarcasm-sensitive sentiment analysis model has a positive impact on the development of the opinion mining studies through the limitation of the traditional sentiment analysis framework. The framework can increase the credibility of interpreting social media feedback by enhancing the ability to detect sarcastic expressions, which can be used in making informed decisions when applied to product evaluation, service improvement, and policy assessment. Further development of the work will be done to include contextual metadata, user-level information, and transformer-based representation to make the models even more effective and flexible in different areas.

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