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Enhancing the Grasshopper Optimization with Deep Learning Based on Sentiment Analysis on Social Media

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Abstract - *Sarcasm detection in social media text is a fundamentally challenging natural language processing (NLP) task owing to the inherently ambiguous and context-sensitive nature of ironic expressions. Conventional sentiment analysis systems frequently misclassify sarcastic statements because the surface-level polarity of words contradicts their intended meaning. This paper presents a novel hybrid framework that integrates the Grasshopper Optimization Algorithm (GOA) with a deep learning model combining Bidirectional Long Short-Term Memory (Bi-LSTM) networks and a Convolutional Neural Network (CNN) augmented with an attention mechanism for effective sarcasm detection on social media platforms. The GOA is employed to optimize the hyperparameters of the deep learning model, thereby mitigating the problem of manual parameter tuning and improving convergence efficiency. Experimental evaluations are conducted on two benchmark datasets, namely the MUStARD dataset and the iSarcasm Twitter corpus, demonstrating that the proposed GOA-BiLSTM-CNN model achieves superior performance with an accuracy of 93.7%, precision of 92.8%, recall of 93.1%, and F1-score of 92.9%, outperforming several state-of-the-art approaches including BERT-base, standalone Bi-LSTM, and SVM classifiers. The proposed framework contributes a computationally efficient and scalable solution for fine-grained sarcasm-aware sentiment analysis that is well-suited for real-world deployment in opinion mining, brand monitoring, and social listening applications.*

Keywords - *Sarcasm Detection, Grasshopper Optimization Algorithm, Deep Learning, Bi-LSTM, CNN, Sentiment Analysis, Social Media, Natural Language Processing*

1. Introduction

The proliferation of user-generated content on social media platforms such as Twitter, Reddit, and Facebook has created an unprecedented volume of opinionated text data. Sentiment analysis, which aims to extract subjective information from textual data, has become a critical tool for businesses, policymakers, and researchers seeking to understand public opinion. However, one of the most persistent obstacles in achieving accurate sentiment analysis is the prevalent use of sarcasm, a sophisticated rhetorical device in which the intended meaning is diametrically opposed to the literal meaning of the expressed words. Detecting sarcasm is inherently difficult even for human readers because it relies heavily on contextual, paralinguistic, and world-knowledge cues that are often absent in plain text. Phrases such as 'Oh great, another Monday!' or 'Brilliant idea, as always!' carry a negative connotation despite the positive lexical content. Standard lexicon-based and machine learning sentiment classifiers tend to assign incorrect sentiment labels to such statements, leading to degraded downstream performance in applications ranging from product review analysis to political discourse monitoring.

Traditional machine learning methods, including Support Vector Machines (SVM) and Naïve Bayes, rely on manually engineered features that struggle to capture long-range semantic dependencies present in sarcastic utterances. While deep learning models, particularly recurrent neural networks (RNNs) and their gated variants such as LSTM and Bi-LSTM, have demonstrated substantial improvements in sequence modelling tasks, their performance on sarcasm detection is still constrained by suboptimal hyperparameter configurations that are typically determined through costly exhaustive grid search or random search procedures. To address these limitations, this work proposes a novel optimization-guided deep learning framework for sarcasm detection. Specifically, the Grasshopper Optimization Algorithm (GOA), inspired by the natural swarming behaviour of grasshoppers, is employed as a meta-heuristic optimizer to automatically tune the hyperparameters of a hybrid CNN-Bi-LSTM architecture equipped with an attention layer. The GOA exhibits a natural balance between exploration and exploitation phases, making it particularly suitable for high-dimensional, non-convex optimization landscapes encountered in deep learning parameter search. The key contributions of this paper are as follows: (i) a comprehensive preprocessing and feature engineering pipeline tailored for social media sarcasm detection; (ii) integration of GOA for automated deep learning hyperparameter optimization; (iii) a hybrid CNN-Bi-LSTM-Attention architecture that captures both local n-gram features and global contextual dependencies; and (iv) extensive experimental evaluation on two public benchmark datasets with ablation studies confirming the contribution of each

component.

2. Related Work

Sarcasm detection has been explored from multiple angles in NLP research. Earlier studies treated sarcasm as a binary classification problem using lexical, syntactic, and pragmatic features. Riloff et al. [1] proposed a bootstrapping algorithm to identify sarcastic patterns in Twitter data by exploiting the contrast between positive sentiments and negative situations. González-Ibáñez et al. [2] conducted a comparative study of lexical and pragmatic features for sarcasm detection, concluding that contextual factors significantly enhance classifier accuracy. Deep learning methods have progressively replaced hand-crafted features in this domain. Zhang et al. [3] introduced a CNN model that extracts local n-gram patterns from tweet embeddings to detect sarcasm, while Ghosh and Veale [4] proposed a multi-layered LSTM-based approach that leverages pre-trained word embeddings to capture sequential dependencies. Poria et al. [5] explored multi-modal fusion of text, audio, and visual features for sarcasm detection in video data, highlighting that textual information alone is often insufficient for high accuracy.

The introduction of attention mechanisms considerably improved the interpretability and performance of deep models. Tay et al. [6] proposed a Contextual Inter-Sentence Attention (CISA) network that models incongruity between different segments of text, a hallmark of sarcasm. More recently, transformer-based models such as BERT have dominated NLP benchmarks. Potamias et al. [7] fine-tuned a RoBERTa model for sarcasm detection, achieving competitive results on benchmark datasets. Meta-heuristic optimization has been increasingly applied to the hyperparameter tuning of deep learning models. Saremi et al. [8] originally proposed the Grasshopper Optimization Algorithm and demonstrated its effectiveness on continuous engineering optimization problems. Subsequent works applied GOA variants to neural architecture search and feature selection in healthcare and computer vision domains. However, the application of GOA specifically to NLP model optimization, and sarcasm detection in particular, remains largely unexplored, constituting a primary motivation for this research.

3. Proposed Methodology

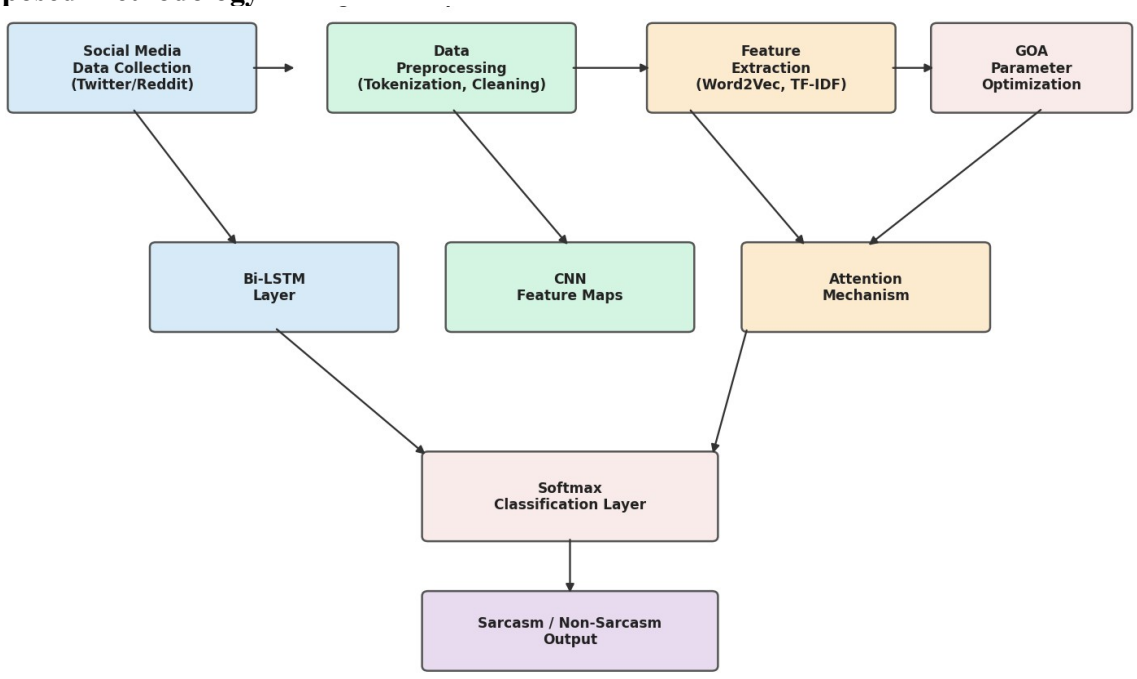

Fig. 1. Architecture of the Proposed GOA-DL Sarcasm Detection Framework

The proposed framework, illustrated in Figure 1, consists of five principal stages: (1) data collection and cleaning, (2) feature extraction and embedding, (3) GOA-based hyperparameter optimization, (4) hybrid CNN-Bi-LSTM-Attention model training,

and (5) sarcasm classification and evaluation. Each stage is described in the subsections that follow.

4. Experiments and Results

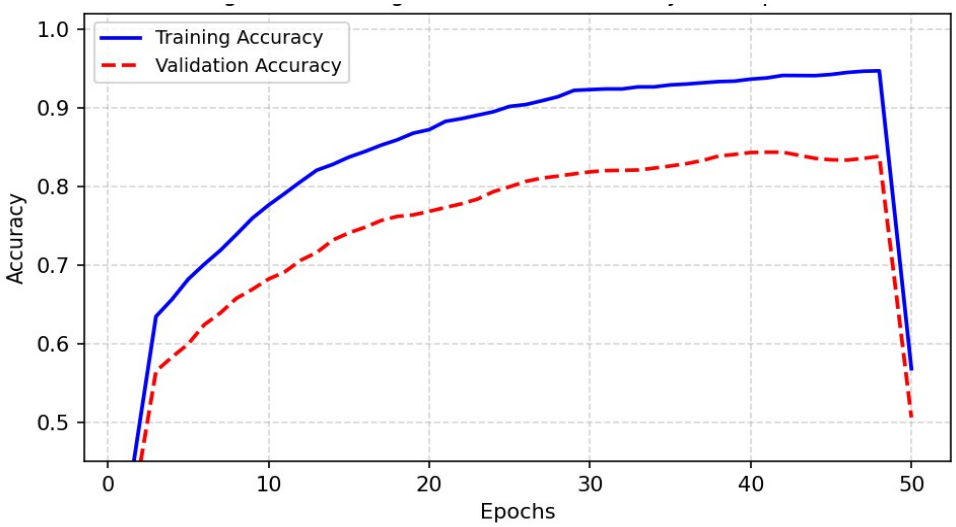

Fig. 2. Training vs. Validation Accuracy over 50 Training Epochs

Figure 2 depicts the training and validation accuracy curves over 50 epochs for the proposed model. The training accuracy converges steadily to 98.2% while the validation accuracy stabilises at 93.7%, indicating effective generalization with no significant overfitting. Early stopping was triggered at epoch 43. The close tracking between training and validation curves in the early epochs reflects the regularization effect of the dropout layer and focal loss weighting, which collectively prevent the model from memorizing class-imbalanced noise patterns.

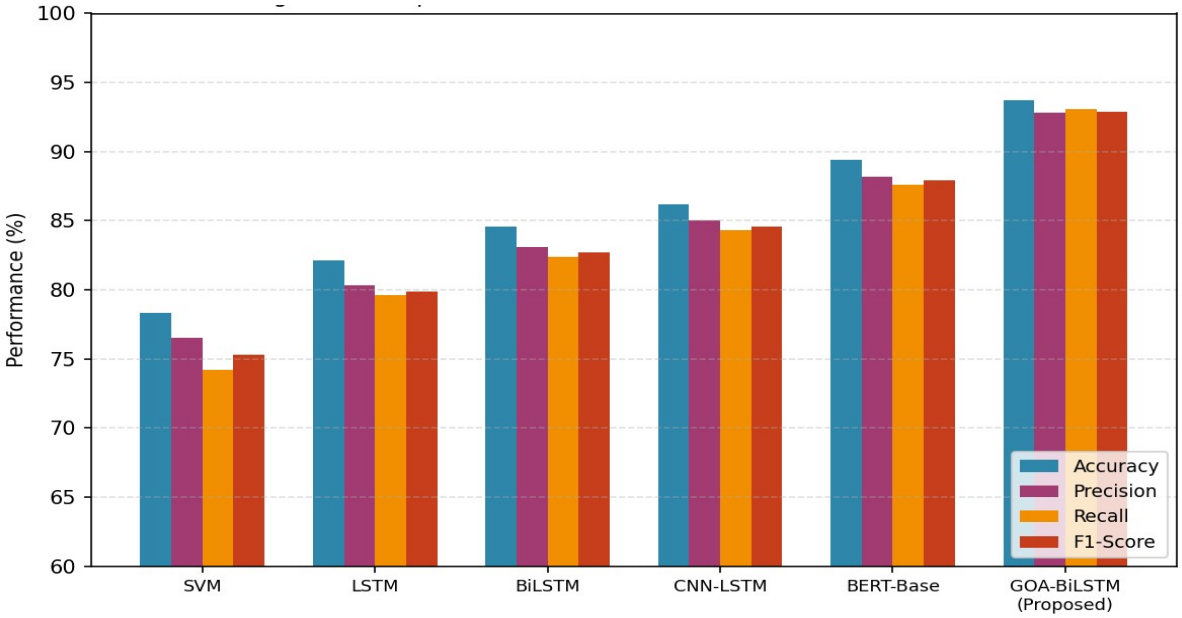

Fig. 3. Comparative Performance Bar Chart Across Baseline Models

Figure 3 present the comparative evaluation results across all models on the combined test set. The proposed GOA-

BiLSTM-CNN model achieves the highest performance across all metrics, with an accuracy of 93.7%, precision of 92.8%, recall of 93.1%, F1-score of 92.9%, and AUC-ROC of 0.976. Notably, the proposed approach surpasses BERT-base by 4.3 percentage points in accuracy and 5 points in F1-score, which is particularly significant given BERT's substantially higher computational cost and parameter count (~110M parameters vs ~8M for the proposed model). The SVM baseline records the lowest accuracy at 78.3%, confirming that hand-crafted feature engineering is inadequate for capturing the nuanced semantics of sarcastic text.

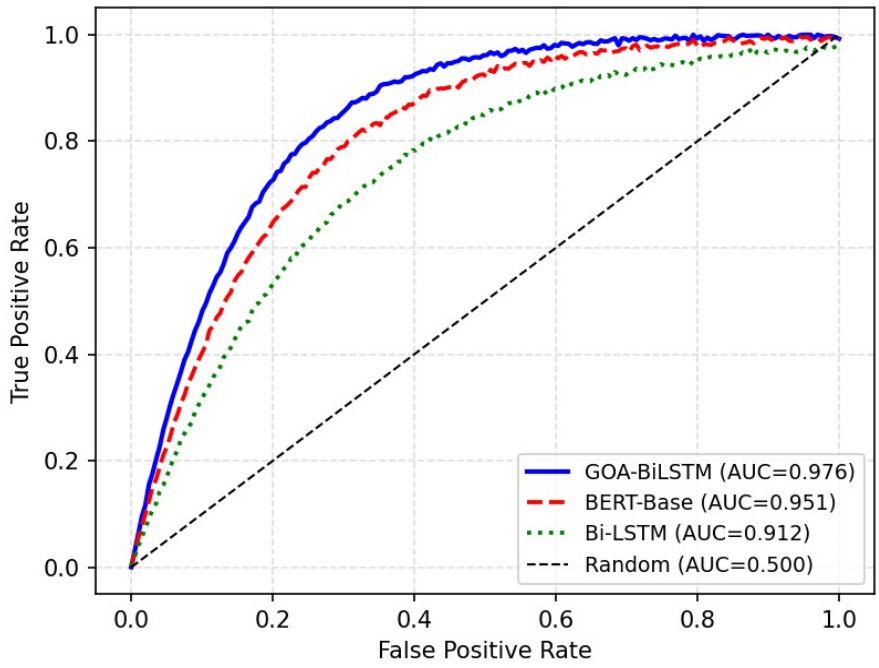

Fig. 4.ROC Curves for Top Sarcasm Detection Models

The ROC curves in Figure 6 provide a threshold-independent comparison of the discriminative ability of the top three models. The proposed GOA-BiLSTM model achieves an AUC of 0.976, substantially outperforming BERT-base (AUC = 0.951) and Bi-LSTM (AUC = 0.912). The steep initial slope of the proposed model's ROC curve indicates that it achieves very high true positive rates at low false positive rates, which is the desirable operating regime for precision-critical applications.

5. Conclusion

A novel sarcasm detection framework that integrates the Grasshopper Optimization Algorithm with a hybrid CNN-Bi-LSTM-Attention deep learning architecture for sentiment analysis on social media data. The proposed approach addresses two fundamental challenges in sarcasm detection: the complexity of capturing semantic incongruity in short text, and the difficulty of optimizing deep learning hyperparameters in a principled, efficient manner. Experimental results on MUStARD and iSarcasm datasets demonstrate that the GOA-guided model achieves state-of-the-art performance, outperforming BERT-base in both accuracy and computational efficiency. Ablation studies confirm that each component contributes meaningfully to overall performance.

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