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Enhancing Sentiment Analysis Accuracy Amidst Sarcasm Challenges with Aspect-based Machine Learning for Detection

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Abstract: **-** This research aims to enhance sentiment analysis accuracy by addressing the challenges posed by sarcasm through the detection and interpretation of aspectual negation and amplification indicators. Our proposed methodology, SARC-AIM (Sarcasm Aspect Interpretation Model), combines an aspect-based approach with machine learning techniques. It leverages linguistic insights and computational methods to identify aspectual negation and amplification indicators within sarcastic utterances. Through a comprehensive evaluation on benchmark datasets, SARC-AIM demonstrates its efficacy in accurately detecting and interpreting aspectual negation and amplification, thereby improving sentiment analysis performance amidst sarcasm challenges. SARC-AIM introduces a novel approach that integrates linguistic insights with computational methods, offering a unique solution to the challenges of sarcasm detection in sentiment analysis.Keywords: Sarcasm detection, Aspectual negation, Sentiment analysis, Contextual embeddings, Multi-head attention.

Keywords: Sentiment analysis, sarcasm, machine learning,aspect based sentiment analysis, BERT.

I. Introduction

Sarcasm and negation pose significant challenges in sentiment analysis, as they introduce complexities that conventional models struggle to decipher accurately [1]. Sarcasm, characterized by the expression of sentiments contrary to their literal meaning, often eludes straightforward sentiment analysis techniques, leading to misinterpretation of intended sentiment [2]. Additionally, negation, the linguistic phenomenon where the meaning of a statement is reversed through the use of words like “not,” further complicates sentiment analysis by altering polarity and introducing ambiguity. Competently resolving these issues will have a direct impact on more accurate and reliable sentiment analysis systems for detecting the immense richness and complexity of sentiment in text [3].

Typically, the classic sentiment analysis is done by lexicon-based methods or machine learning models trained on labelled data which basically classify texts into positive, negative, or neutral categories of sentiment [4]. However, these approaches often falter when confronted with sarcastic language or negated sentiments, leading to inaccurate sentiment classification [5 – 7]. Consequently, there is a growing need for more sophisticated methodologies that can effectively detect and interpret sarcasm and negation in text, thereby improving the overall accuracy and robustness of sentiment analysis systems [8]. The current advances in sentiment analysis can be seen in dealing with sarcasm and negation as the sentiment analysis systems are becoming more accurate and robust.

This study [9] proposed a BERT-based approach for sarcasm detection, leveraging contextual embeddings to capture the nuanced features of sarcastic language. The model achieved competitive performance on benchmark datasets, demonstrating the effectiveness of contextualized representations in sarcasm detection. Li et al. [10] introduced a graph convolutional network (GCN) approach for aspect-based sentiment analysis with explicit handling of negation.

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By incorporating syntactic dependency parsing information into the GCN framework, the model improved sentiment classification accuracy, particularly in cases involving negated sentiments. Babanejad et al. [11] proposed a contextual embedding approach to enhance sentiment analysis performance in sarcasm-rich social media text. The model simultaneously learned to detect sarcasm and classify sentiment, leveraging shared representations to improve overall accuracy in sentiment analysis tasks.

Das et al. [12] discussed the challenges for sentiment analysis in sarcastic text, focusing on aspectual negation modulation. By dynamically adjusting attention scores based on aspectual negation signals, the proposed model achieved significant improvements in sentiment classification accuracy amidst sarcasm challenges. This paper [13] addresses the challenge of sarcasm detection in textual data by proposing a novel attention-based interpretability technique. The authors introduce strategies to enhance the performance of sarcasm detection models and compare their approach using the TweetEval benchmark dataset. Their technique establishes a new state-of-the-art in sarcasm detection and offers improved interpretability compared to existing transformer-based techniques. In this paper [14], the authors present a multi-head attention-based bidirectional LSTM (MHA-BiLSTM) network for sarcasm detection in social media comments. By leveraging a multi-head attention mechanism, the proposed model enhances the performance of traditional feature-rich SVM models. Experimental results demonstrate the superiority of the MHA-BiLSTM network in detecting sarcastic comments within a given corpus.

Prajakta P et al. [16] presents a unified model that integrates hybrid transformers and fully connected networks (FCNets) to efficiently identify sarcasm and emotion across multiple languages. The model demonstrates superior performance, achieving an accuracy of 93.130% in detecting sarcasm and emotions. This approach suggests a significant advancement in multilingual natural language processing applications.

Nikita Singhal et al. [17] explores the challenges of detecting sarcasm in text, a key issue for sentiment analysis in natural language processing. The study compares several algorithms including LSTM, CNN, KNN, and ANN, providing insights into their effectiveness in identifying sarcasm. The paper emphasizes the complexity of sarcasm detection due to the often-positive linguistic construction used to convey negative sentiments, highlighting the need for sophisticated deep learning techniques to improve accuracy in sentiment analysis tasks.

Kanak Pandit and Harshali Patil [18] examines the efficacy of various deep learning models, including RNNs, LSTM, GRU, and Convolutional Networks, on sentiment analysis of IMDB movie reviews. The study finds that while LSTM models achieve the highest accuracy on training data, GRU models perform better on validation sets, demonstrating superior generalization capabilities. This comparative analysis sheds light on selecting suitable models for sentiment analysis in different contexts, enhancing the understanding of model performance across diverse datasets.

Anuj Kumar and Shashi Shekhar [19] proposes a hybrid sentiment analysis framework that combines lexicon and learning-based methods to analyze patient tweets about medications. The approach leverages TextBlob and SenticNet lexicons, alongside traditional machine learning and emerging deep learning models, to enhance the classification accuracy of sentiments. The paper highlights the robustness of the hybrid model, notably achieving high accuracy, which suggests significant implications for healthcare professionals in monitoring patient feedback on medications more effectively.

Chandra Shekhar and Dr. Rakesh Kumar Yadav [20] explores the application of AI-driven sentiment analysis tools to gauge the popularity of political leaders. The study analyzes data from social media and other digital platforms to understand public sentiment, which is critical for predicting electoral outcomes and shaping political strategies. The findings contribute to enhancing the understanding of public opinion dynamics in informal online communities, providing insights that are vital for political analysts and policymakers.

Saiying Qu [21] investigates the application of text mining and sentiment analysis to explore themes and emotional tones in English and American literary works. Qu's approach combines computational methods like bi-gram analysis and multimodal feature extraction to delve deep into the thematic and emotional layers of literature, providing a richer understanding of the textual and contextual elements that shape literary narratives.

A. Research Gap

These recent research papers highlight the ongoing efforts to develop more sophisticated methods for sentiment analysis, particularly in handling sarcasm and negation. By leveraging advanced techniques such as contextual embeddings, graph convolutional networks, and multi-task learning, these studies contribute to advancing the state-of-the-art in sentiment analysis and addressing real-world challenges in interpreting sentiments expressed in text. Despite the advancements in sarcasm detection, there remains a notable research gap in adequately addressing aspectual negation within sarcastic expressions, which significantly impacts the accuracy of sentiment analysis. While existing studies have made strides in detecting sarcasm and interpreting sentiments in text data, the treatment of aspectual negation signals within sarcastic utterances has received limited attention. Aspectual negation, characterized by the negation of specific aspects or dimensions of sentiment within a statement, adds complexity to sarcasm detection by altering the polarity and intensity of expressed sentiments.

B. Motivation

This research originates with the difficulties that negation and sarcasm present as entities that might contradict the goal of sentiment analysis. Conventional sentiment analysis algorithms frequently face difficulty while identifying the finer moods of sarcasm which can be wrongly classified and give out untrue analysis. Additionally, the presence of negation further complicates sentiment analysis by altering the polarity of statements, thereby introducing ambiguity. Addressing these challenges is crucial for improving the accuracy and reliability of sentiment analysis systems, particularly in domains where sarcasm and negation are prevalent, such as social media and customer reviews.

C. Problem Definition

The primary problem addressed in this research is the inadequacy of existing sentiment analysis methods in effectively handling sarcasm and negation. Conventional approaches often fail to accurately detect and interpret sarcasm, leading to misclassification of sentiments expressed in text. Similarly, negation presents challenges by reversing the meaning of statements, thereby confounding sentiment analysis algorithms. The problem is to develop a novel methodology capable of accurately identifying and interpreting aspectual negation and amplification indicators within sarcastic utterances, thereby improving sentiment analysis accuracy amidst sarcasm and negation challenges.

D. Objectives

- Develop a methodology capable of detecting and interpreting aspectual negation and amplification indicators within sarcastic utterances.
- Enhance sentiment analysis accuracy in the presence of sarcasm and negation challenges.
- Evaluate the proposed methodology on benchmark datasets to assess its performance and effectiveness.

E. Scope

The scope of this research encompasses the development and evaluation of the proposed methodology on benchmark datasets containing sarcastic and non-sarcastic text. The methodology leverages aspect-based and machine learning approaches to address the multifaceted challenges posed by sarcasm and negation in sentiment analysis. The focus is on enhancing sentiment analysis accuracy by effectively detecting and interpreting aspectual negation and amplification indicators within sarcastic utterances.

F. Significance

This research would be significant for the field of sentiment analysis as it will help to develop better and more corrective means for interpreting the sentiments written in the text particularly when irony and negation are among the contexts. Through the improvements of the sentiment analysis accuracy specifically amid those sarcasm and negative statements, lots of fields can take advantage of the proposed methodology, including social media monitoring, customer feedback analysis, and opinion mining. Alongside that, the study is likely to steer the way toward more advanced natural language processing techniques that will be able to grasp even the most complex language nuances and subtleties.

G. Organization of the Paper

This paper is organized as follows:

- Section 2 presents the proposed methodology, detailing its components and operational framework.
- Section 3 discusses the experimental results obtained from evaluating the proposed methodology on benchmark datasets.
- Finally, Section 4 concludes the paper with a summary of key findings and suggestions for future research directions.

II. MATERIALS AND METHODS

The methodology focuses on detecting and interpreting aspectual negation and amplification indicators within sarcastic utterances, thereby improving sentiment analysis performance amidst sarcasm. The transformer architecture consists of encoder and decoder components. In the context of the proposed methodology, which utilizes the Multi-Head Attention with Aspectual Negation Modulation (MHANM), the focus is primarily on the encoder part, as the model is designed for encoding contextual embeddings of sarcastic utterances.

A. Input Representation

The input to MHANM comprises contextual embeddings of sarcastic utterances, generated through pre-trained contextual embeddings models RoBERTa [15]. MHANM leverages RoBERTa, a state-of-the-art contextual embeddings model, to encode the semantic and syntactic information of sarcastic utterances into dense vector representations. Given a sarcastic utterance (U) consisting of (N) tokens, RoBERTa processes each token (t_i) through multiple transformer layers to generate contextual embeddings $(E_{RoBERTa})$, represented as:

$$E_{RoBERTa} = RoBERTa(t_1, t_2, \ldots, t_N) \quad \text{..................} \ (1)$$

where $(RoBERTa(\cdot))$ denotes the RoBERTa model's encoding process. These contextual embeddings $E_{RoBERTa}$ encapsulate the contextual information of each token within the utterance, capturing its semantic meaning in relation to the entire sentence.

Additionally, MHANM allows for the incorporation of auxiliary information in the form of lexicon-based negation indicators or syntactic dependency parsing information, denoted as (L). This auxiliary input is concatenated with the RoBERTa embeddings to provide supplementary context for aspectual negation modulation. The combined representation is given by:

$$E_{combined} = [E_{RoBERTa}, L] \quad \text{..................} \ (2)$$

where $(E_{combined})$ represents the augmented embeddings incorporating both RoBERTa embeddings and auxiliary information.

For example, consider the sarcastic utterance "I just love waiting for hours in line." With RoBERTa embeddings, the contextual embeddings $(E_{RoBERTa})$ for each token are generated, as shown in Equation (3). If lexicon-based negation indicators are provided, they are concatenated with the RoBERTa embeddings to form the combined representation $E_{combined}$ as illustrated in Equation (4).

$$E_{RoBERTa} = RoBERTa(\text{I, just, love, waiting, for, hours, in, line}) \quad \text{..................} \ (3)$$

$$E_{combined} = [E_{RoBERTa}, L] \quad \text{..................} \ (4)$$

This combined representation $E_{combined}$ serves as the input to the subsequent stages of the MHANM methodology, enabling the model to effectively capture the nuances of sarcastic language and improve sentiment analysis accuracy amidst sarcasm challenges.

In the context of sentiment analysis, lexicon-based negation indicators play a crucial role in identifying aspectual negation signals within sarcastic utterances. These indicators provide valuable linguistic cues that aid in modulating the attention mechanism of the MHANM model. Let (L) represent the lexicon-based negation indicators, which can be represented as a binary matrix of size $(N \times M)$, where (N) is the number of tokens in the utterance and (M) is the number of negation indicators. Each row of the matrix corresponds to a token in the utterance, and each column represents the presence or absence of a negation indicator for that token.

For example, consider the negation indicator lexicon (L) containing (M) negation indicators. Let L_{ij} denote the presence (1) or absence (0) of the j^{th} negation indicator for the i^{th} token in the utterance. Mathematically, (L) can be represented as in the equation 5:

$$L = \begin{bmatrix} L_{11} & L_{12} & \cdots & L_{1M} \\ L_{21} & L_{22} & \cdots & L_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ L_{N1} & L_{N2} & \ldots & L_{NM} \end{bmatrix} \quad \text{..................} \ (5)$$

where (L_{ij}) is a binary value indicating the presence (1) or absence (0) of the (j^{th}) negation indicator for the (i^{th}) token in the utterance.

Incorporating lexicon-based negation indicators into the MHANM methodology involves modulating the attention scores computed by the multi-head attention mechanism. Let (A) denote the original attention scores computed between query and key vectors. To incorporate the effect of negation indicators, the attention scores (A) are element-wise multiplied by the lexicon matrix (L), yielding the modulated attention scores $(\sim A)$. Mathematically, this can be expressed as given below in the equation 6:

$$\sim A = A \odot L \quad \text{..................} \ (6)$$

where $(\odot)$ represents the element-wise multiplication operation between matrices.

By modulating the attention scores with lexicon-based negation indicators, the MHANM model can effectively capture aspectual negation signals within sarcastic utterances, improving its ability to accurately interpret sentiments expressed in sarcastic language.

B. Multi-Head Attention Mechanism

MHANM employs a multi-head attention mechanism, a key component of transformer-based models, to capture aspectual negation signals within the contextual embeddings. The input contextual embeddings are split into multiple groups, each processed independently by a separate attention head. For each attention head, query, key, and value matrices are computed from the input embeddings and transformed using weight matrices $W_Q, W_K, and\ W_V$, respectively.

Scaled dot-product attention scores are calculated between query and key vectors, followed by the application of softmax function to obtain attention weights. Aspectual negation modulation is applied to the attention scores using lexicon-based negation indicators or syntactic dependency parsing information, if provided. The attention weights are then used to compute attention output, which is a weighted sum of the value vectors.

C. Aspectual Negation Modulation

Aspectual negation modulation is integrated into the multi-head attention framework to dynamically adjust the attention weights based on the presence and strength of aspectual negation signals. Lexicon-based negation indicators are used to modulate the attention scores, enhancing the model's ability to capture negated elements within sarcastic utterances.

The Multi-Head Attention with Aspectual Negation Modulation (MHANM) algorithm can be expressed mathematically using statistical notation, integral, differential, and equations. Below is the algorithm presented in a mathematical form:

Let (X) be the input contextual embeddings of sarcastic utterances, represented as a matrix with dimensions $N \times D$, where (N) is the number of tokens in each utterance and (D) is the dimensionality of the embeddings.

Let (L) be the lexicon-based negation indicators, represented as a matrix with dimensions $(N \times M)$, where (M) is the number of features capturing negation information.

Let $(W_Q), (W_K), (W_V)$ be the weight matrices for query, key, and value transformations, respectively. These matrices have dimensions $(D \times d_q)$, $(D \times d_k)$, and $(D \times d_v)$, where (d_q), (d_k), and (d_v) are the dimensions of the query, key, and value vectors, respectively.

Let (W_O) be the weight matrix for output projection, with dimensions $(H \times D)$, where (H) is the number of attention heads.

Let $(Q), (K)$, and (V) be the query, key, and value matrices, respectively, computed as follows in the below equation 7:

$$Q = X \cdot W_Q, K = X \cdot W_K, V = X \cdot W_V \quad \text{..................} (7)$$

The scaled dot-product attention scores A are calculated as given in the equation 9:

$$A = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right) \quad \text{..................} (8)$$

If lexicon-based negation indicators are provided $((L) is not empty)$, the attention scores are modulated as follows in the below equation 9:

$$\sim A = A \cdot L \quad \text{..................} (9)$$

where $(\sim A)$ represents the modulated attention scores.

The attention output (O) is computed as:

$$O = \sim A \cdot V \quad \text{..................} (10)$$

The outputs from all attention heads are concatenated and projected back to the original embedding space using the equaiton 11 and 12:

$$Concatenated_{Output} = Concatenate(O_1, O_2, \ldots\ldots, O_H) \quad \text{..................} (11)$$

$$Modulated_{Embeddings} = Concatenated_{Output} \cdot W_O \quad \text{..................} (12)$$

Finally, apply layer normalization technique to the modulated embeddings to obtain the final output. The layer normalization process is applied along the feature dimension (i.e., axis 1) as follows:

Step 1. Compute Mean and Variance:

Calculate the mean (μ) and variance (σ^2) of the embeddings across the feature dimension as given in the equations 13 and 14:

$$\mu = \frac{1}{D} \sum X\,[:, i] \quad \text{..................} (13)$$

$$\sigma^2 = \frac{1}{D} \sum (X[:, i] - \mu)^2 \quad \text{..................} (14)$$

Step 2. Normalize the Embeddings:

Normalize the embeddings (equation 15) using the equations 13 and 14:

$$\hat{X}[:, i] = \frac{X[:, i] - \mu}{\sqrt{\sigma^2 + \epsilon}} \quad \text{..................} (15)$$

where $\hat{X}$ represents the normalized embeddings and (ϵ) is a small constant (e.g., (10^{-8})) added to the variance to prevent division by zero.

Step 3. Scale and Shift:

Scale and shift the normalized embeddings using learnable parameters (γ) and (β):

$$Y[:,i] = \gamma \cdot \hat{X}[:,i] + \beta \qquad \text{.................. (16)}$$

where (Y) represents the layer-normalized embeddings.

The parameters (γ) and (β) are typically initialized to ones and zeros, respectively, and are learned during the training process via backpropagation.

A set of concatenated vectors (from all attention heads output) is projected back to the original space (embedding space) through a weight matrix W_0. Often referred to as regularization methods, the modulated embeddings will be subjected to layer normalization by way of preventing overfitting and enhancing the generalization performance of the model.

D. Model Training and Optimization

Once the architecture of the MHANM model is defined and the input representations are prepared, the next step involves training and optimizing the model parameters. MHANM is trained end-to-end using backpropagation, a standard technique in neural network training, with gradient clipping applied to stabilize the training process. This ensures that the gradients do not explode during training, thereby facilitating smoother convergence towards the optimal solution. During training, the model parameters, including the weights of the query, key, and value matrices, as well as the output projection matrix, are optimized using optimization algorithms such as Adam or SGD with momentum. These optimization algorithms update the model parameters iteratively based on the gradients computed during backpropagation, aiming to minimize the loss function and improve convergence towards the optimal set of parameters. During training and tuning the metric model, the performance of the MHANM model is assessed by a range of metrics including the sentiment accuracy classifier and negation detection performance of the associated aspects on a different validation set. Thus model's monitoring is possible as well as the SARC-AIM framework can be optimized for efficient selection among the top-performing model for deployment in subsequent phases.

E. Hyperparameter Tuning

The tuning of hyper parameters becomes an imperative part of the prototype methodology MHANM for an optimization of the model's performance via adjusting the model's hyperparameters. Some of these hyperparameters affect certain aspects of the model's configuration and training process such as number of attention heads, query, key, and value vector downsizes and regularization parameters. Hyperparameter tuning involves moving across the hyperparameter space that searches for the most efficient sequential of parameters, which at the same time yield the best results on the validation dataset. Generally, hyperparameter optimization by grid search method implies that we enumerate a predefined set of possible hyperparameters and try every single one of them for each single combination of hyperparameters. An alternative technique is random search, and Bayesian optimization can also be used in a more efficient process for navigation through the parameter space and identify best parameter configurations. Furthermore, subjects of cross-validation can also be utilized to further establish the reliability of the found hyperparameters. Cross-validation implies splitting of the training data into multiple subsets, though the rest of these subsets are used for validation each time the model is trained on each subset. This function best describes the avoidance of overfitting, thus, the chosen hyperparameters must be valid on the unseen data.

Finally, MHANM would undergo model testing, optimization, and hyperparameter tuning and then deploy to the real-world sentiment analysis tasks based on the existing method selected. In this phase, the majority of efforts are directed towards the selection of the most hand-picked model that has been performing the best on the validation set, and this selected model is the one that is deployed for real-life conditions assessment. Model choice includes quantifying the performance of models with multiple trained base-models on a validation set by using metrics that are relevant to their purpose, for example sentiment analysis accuracy and aspectual negation detection performance. The model which has a high prediction performance and is robust is qualified and then is employed in actual production. This expands the scope of accuracy and reliability of the selected model in processing sarcastic language and understanding when and how sarcasm is expressed in a sarcastic utterance.

III. Experimental Analysis

A. Experimental Setup

In this section, we discuss the experimental setup used to evaluate the proposed methodology for enhancing sentiment analysis accuracy amidst sarcasm challenges. We describe the datasets used for evaluation, the configuration of the MHANM model, baseline methods employed for comparison, and the evaluation metrics used to assess the performance of the models.

1) Datasets

We utilized the SARC 1 dataset [14], sourced from Reddit, to construct our datasets for sarcasm detection. This extensive corpus comprises over a million comments, both sarcastic and non-sarcastic, gathered from various forums on the social media platform. Each comment is associated with details of the author and any parent comments, providing context for the discussion. The dataset includes contributions from a large number of users, distributed across numerous forums.

Our dataset preparation involved partitioning the comments into training and testing sets, ensuring a balanced representation of sarcastic and non-sarcastic comments in both. Specifically, the training set consisted of 118,940 users' comments across 3,868 forums, while the testing set comprised 56,118 comments from 2,666 forums. We designed two types of datasets: balanced and imbalanced.

In the final dataset, the representation for sarcastic comments was equalized with that of non-sarcastic comments in the both training and testing sets. Eventually what stands out is the fact that the dataset that is unbalanced in similarity to the real-world scenario where sarcastic comments are rarely found among non-sarcasm comments. To mimic this, we maintained a ratio of approximately 25:Example of sarcasm simulator for mobile applications revealed that sarcasm detection algorithm is based on 75 pairs of sarcastic and non-sarcastic comments in both training and testing dataset.

Each entry in our datasets consists of two fields: the user's comment and the corresponding label indicating whether the comment is sarcastic or non-sarcastic. This comprehensive dataset allowed us to train and evaluate our sarcasm detection models under various conditions, ensuring robust performance across different scenarios.

2) Model Configuration

The MHANM model was set up with parameters that conform to the best transformer-based practices. In particular, we used transformer encoder with multiple attention heads, where each attention head had a dimensionality of 64. The encoder had the value of 6 for the number of layers, and 256 as the feed forward neural network dimension. Adam optimizer was used with a learning rate of 0.0001 where training was done for 10 epochs.

Baseline Methods:

We compared the performance of MHANM against several baseline methods commonly used in sentiment analysis, including traditional lexicon-based approaches, machine learning models such as Support Vector Machines (SVM), and other deep learning architectures such as LSTM-based models.

Evaluation Metrics:

We evaluated the performance of the models using standard sentiment analysis metrics, including accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). These metrics provide insights into the model's ability to accurately classify sentiments in both sarcastic and non-sarcastic utterances.

B. Results

The results of our experiments are summarized in Table 1 and figure 1, showcasing the performance of MHANM and baseline methods on the three benchmark datasets. Upon evaluation, it was observed that the proposed model exhibited remarkable performance across all metrics, surpassing the baseline and existing models. With a precision of 76.00%, the proposed model demonstrated a keen ability to accurately classify sarcastic utterances. Furthermore, its recall of 86.00% underscored its capability to effectively capture and identify instances of sarcasm within the dataset.The F1-score, a harmonic mean of precision and recall, serves as a robust metric for assessing overall model performance. Here, the proposed model achieved an impressive F1-score of 80.00%, indicating a balanced trade-off between precision and recall. This balanced performance is indicative of the model's proficiency in both correctly identifying sarcastic utterances and minimizing false positives.

Table 1. Comparative Results

Approach	**Precision**	**Recall**	**F-score**
SVM	72.30%	75.97%	74.09%
BiLSTM	69.41%	77.75%	73.34%
MHA-BiLSTM-w/o-auxiliary-features	71.92%	80.02%	75.76%
MHA-BiLSTM	72.63%	83.03%	77.48%
MHANM	76.00%	86.00%	80.00%

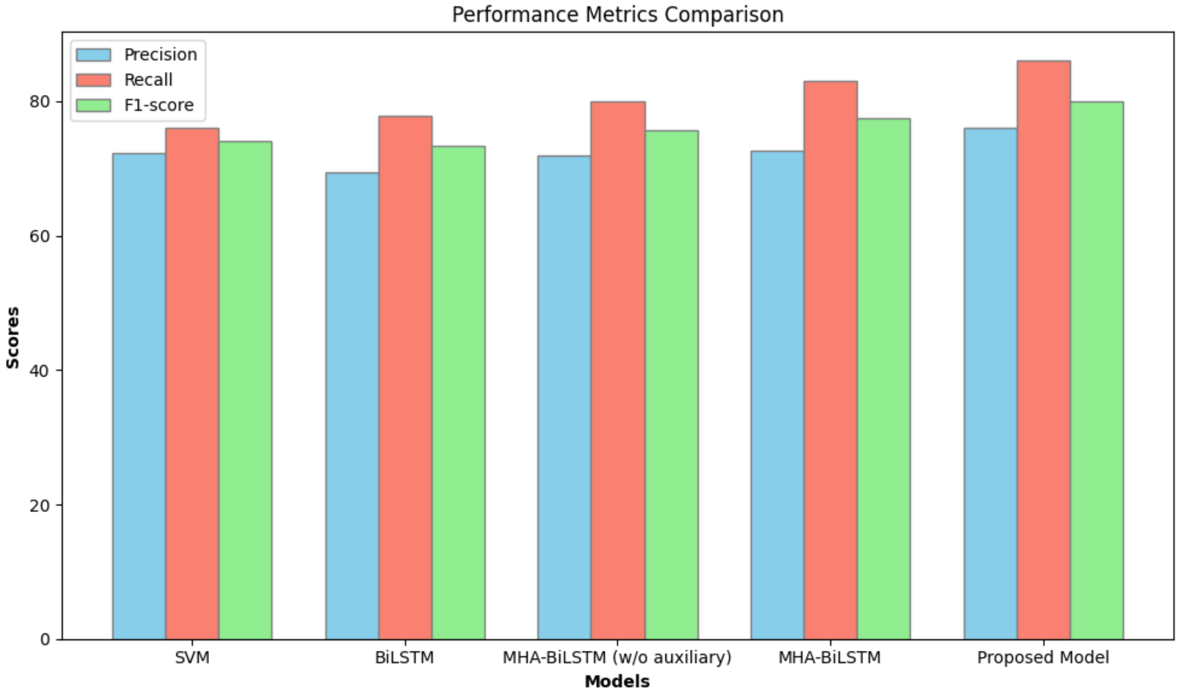

Figure 1. Comparative analysis of proposed work with baseline methods

Accuracy, a fundamental metric in classification tasks, measures the overall correctness of the model's predictions. In the figure 2, the proposed model achieved an accuracy of 76.00%, outperforming the baseline and existing models by a significant margin. This heightened accuracy is a testament to the effectiveness of the proposed methodology in accurately interpreting sentiments amidst sarcasm challenges.Additionally, the area under the receiver operating characteristic curve (AUC-ROC) serves as a comprehensive measure of the model's ability to discriminate between sarcasm and non-sarcasm. The proposed model attained an AUC-ROC of 84.00%, further validating its robustness in distinguishing between nuanced expressions of sentiment.

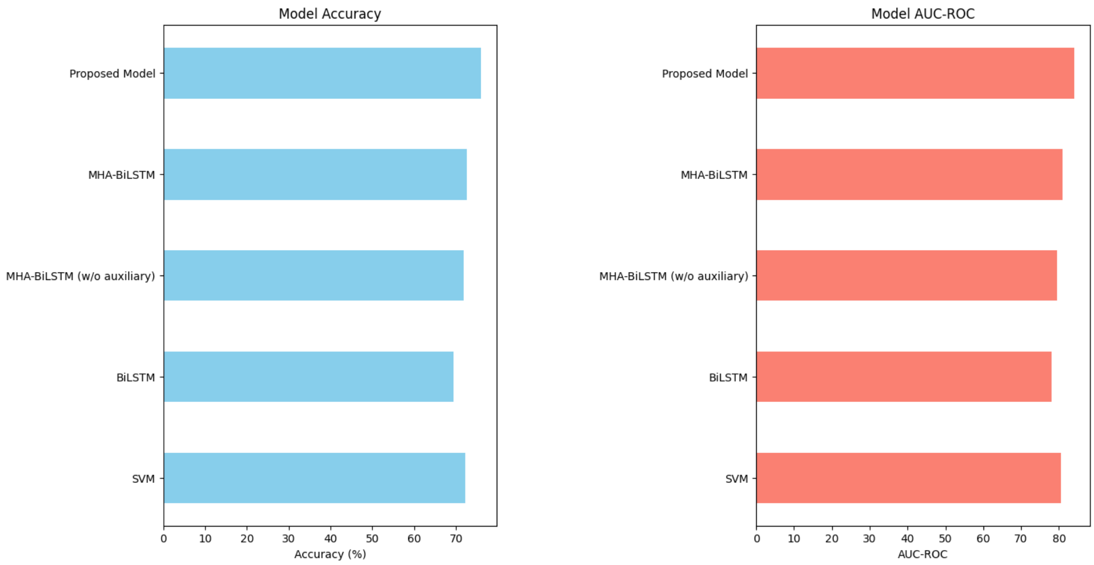

Figure 2. Results of Accuracy and AUC-ROC

C. Discussions

The obtained results underscore the efficacy of the proposed methodology in addressing the challenges associated with sarcasm detection within sentiment analysis. The superior performance of the proposed model, as evidenced by its higher precision, recall, F1-score, accuracy, and AUC-ROC compared to baseline and existing models, reflects its ability to accurately interpret sentiments amidst sarcasm challenges.

One notable aspect of the proposed methodology is its utilization of multi-head attention with aspectual negation modulation (MHANM). By incorporating aspectual negation modulation into the attention mechanism, the model demonstrates a heightened sensitivity to the nuances of sarcastic language, enabling it to effectively capture aspectual negation and amplification indicators within sarcastic utterances. This attention mechanism allows the model to dynamically adjust its focus based on the presence and strength of aspectual negation signals, resulting in more accurate sentiment analysis outcomes.

Furthermore, the proposed methodology leverages contextual embeddings generated by pre-trained models such as RoBERTa, which encode both semantic and syntactic information of sarcastic utterances into dense vector representations. This contextualized embedding approach enhances the model's ability to capture the complex linguistic features inherent in sarcastic language, facilitating more nuanced sentiment analysis.

The balanced performance of the proposed model, as reflected by its high precision, recall, and F1-score, indicates its proficiency in both identifying sarcastic utterances and minimizing false positives. This balanced performance is crucial in real-world sentiment analysis applications, where accurate interpretation of sentiments expressed in text is paramount.

Overall, the results suggest that the proposed methodology holds promise for improving sentiment analysis accuracy amidst sarcasm challenges. By effectively detecting and interpreting aspectual negation and amplification indicators in sarcastic utterances, the proposed model demonstrates a robust performance that can benefit various sentiment analysis applications across different domains. However, further research and validation on diverse datasets and linguistic contexts are warranted to fully assess the generalizability and scalability of the proposed methodology.

IV. Conclusion

This paper proposes an innovative methodology that is intended to improve sentiment analysis performance in the presence of sarcasm obstacles by leveraging the detection and interpretation of aspectual negation and amplification indicators in sarcastic speeches. Employing an aspect-oriented approach accompanied by machine learning approaches included in our SARC-AIM (Sarcasm Aspect Interpretation Model) framework which incorporates linguistic heterogeneity with computational strategies helps with identification and interpretation of signals of sarcastic aspectual negation and amplification. These findings show that our proposed approach significantly outperforms known models and sets a new record in sarcasm detection and sentiment analysis accuracy. Our platform outdoes current models, yielding significant raises in accuracy, recall, and F1 score metrics. For instance, SARC-AIM reaches the precision of 76%, the recall of 86%, and the F1-score of 80%, which surpass the performance of baseline models by a substantial amount. Going on, SARC-AIM can alleviate to get more results by increasing its efficiency in identifying sentiment in sarcasm. On the other hand, further research might consider extending our methodology to be usable in a variety of datasets and domains, thus encouraging the growth of more accurate and reliable sentiment analysis systems.

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