International Journal of Applied Mathematics

Volume 38 No. 11s 2025,

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

HYBRID DEEP LEARNING TECHNIQUES FOR ENHANCED ASPECT BASED SENTIMENT ANALYSIS AND CONTEXTUAL FEATURE OPTIMIZATION

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Abstract

The exponential growth of user-generated text data on social media highlights the need for effective sentiment analysis systems that can be scaled to support large textual inputs with high contextual accuracy. In many traditional approaches, problems associated with noisy data, unsound feature selection, and lack of scalability prevail, thereby leading to a lack of effective sentiment classification solutions. This study introduces a new framework of aspect-based sentiment analysis (ABSA), which incorporates the best advanced techniques of preprocessing, feature extraction, feature selection, and classification to achieve unmatched performance. The methodology involves robust preprocessing, including tokenization, lexical normalization, and punctuation removal, to ensure a clean input for further processing. Feature extraction is performed using pretrained embeddings, such as robust optimized bidirectional encoder representations from transformers (RoBERTa) and Global Vectors for Word Representation (GloVe), capturing both contextual and word-level relationships. Feature selection employs a hybrid Arithmetic Optimization Algorithm (AOA) and Henry Gas Solubility Optimization (HGS) refined by hierarchical attention mechanisms to retain relevant features while reducing dimensionality. The classification phase utilizes an ((ARGCN), which integrates attention mechanisms and capsule networks to provide refined sentiment predictions. The experimental findings on Sentiment Analysis dataset 1 show 99.85% accuracy, 99.80% precision, 99.88% recall, 99.83% F1 score, and 99.90% specificity. The same was obtained for Dataset 2, with the metrics lying remarkably higher, with an accuracy of 99.89%, precision of 99.87%, recall of 99.90%, F1 score of 99.88%, and specificity of 99.92%. These results depict the robustness and scalability of the proposed system while indicating a greatly improved state-of-the-art method, proving its superiority in setting a new benchmark for sentiment classification tasks.

1. Introduction

The rapid growth of social media platforms such as Twitter, Weibo, and YouTube has transformed the way users create and share content, leading to an explosion of multimodal data, including text, images, audio, and video. Such data are often rich in sentiments, opinions, and emotions, making SA a critical area of study within NLP [1]. However, traditional methods of sentiment analysis, which are mostly based on single-modal approaches, cannot capture the subtle emotions embedded in multimodal interactions. Moreover, the informal language, abbreviations, and slang used in

Received: August 09, 2025

International Journal of Applied Mathematics
Volume 38 No. 11s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)
social media content add complexity to the analysis, requiring advanced techniques to overcome these issues [2]. Public opinion analysis is just a part of sentiment analysis, but it goes on to real applications, such as recommendation systems. By integrating sentiment-aware approaches with advanced models such as BERT, these systems improve the user experience by making personalized recommendations [3]. Techniques such as collaborative filtering, clustering, and matrix factorization have been used to tailor recommendations according to the sentiments of users, particularly in the hospitality and dining industries. However, these systems suffer from problems such as cold start, sparsity, and interpretability [4].

Another key aspect is that graph-based methods also show strong potential as analytical tools for handling unstructured social media data. Models, including Graph Neural Networks (GNN), Graph Convolutional Networks (GCN), Graph Attention Networks (GAT), and Node2Vec, provide rich techniques for embedding sentiment classification. The additional support of interpretability tools, such as SHapley Additive ExPlanations (SHAP), further helps explain the reasoning process behind predicting sentiment [5]. Specialized applications of sentiment analysis include the understanding of consumer perceptions toward extended reality technologies, such as the Apple Vision Pro, which offers valuable insights into user sentiment and social dynamics [6]. Evidently, all such developments come across biases while relying on already devised sentiment and toxic analysis tools on linguistically heterogeneous content bases. For instance, systemic biases that exist in different AAE dialects are more evident with much emphasis on the development of more sensitive models to unbiased datasets with counter-strategies applied, and much importance is laid in ensuring domain- invariance for dealing with dialect richness and contextual polarities of statements [7]. Incorporating text network features with centrality measures has shown promise in enhancing sentiment classification accuracy, providing a novel approach to address these limitations [8].

One concept related to sentiment analysis is stance detection, which has recently gained much attention in the understanding of user perspectives on social media. RoBERTa and BiLSTM models have achieved better accuracy in stance detection by incorporating emotional features within a multi- task learning framework, thus helping to address misinformation challenges [9]. Advanced frameworks, such as Heterogeneous Multi-Relation Signed Networks (HMSN), include user-entity and topic-entity relations in sentiment analysis, which offers a deeper interpretation of sentiment patterns while overcoming some of the difficulties of traditional methods based on texts [10].

The increasing amount of multimodal data on social media emphasizes the urgency for more enhanced sentiment analysis frameworks that can transcend the limitations of traditional, single-modal-based approaches. Single-modal-based approaches often suffer from issues such as linguistic biases, sparsity, and unstandardized dialects, which do not help to promote their effectiveness or inclusiveness. Although recent advancements have been made in graph-based, transformer-based, and hybrid methodologies, there are significant gaps in integrating explainability, bias mitigation, and task dynamics into sentiment and stance detection. This study addresses these gaps using a comprehensive framework of innovative feature extraction, multimodal fusion techniques, and robust bias mitigation strategies to enhance the accuracy,

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)
interpretability, and fairness of sentiment analysis models. Based on the gaps identified in the research, the contributions of this study are as follows.

- A new framework incorporating advanced preprocessing, feature extraction, feature selection, and classification techniques is proposed for ABSA.
- RoBERTa and GloVe embeddings were used for deep contextual and word-level feature representations.
- developed a hybrid feature selection approach combining the AOA and HGS algorithms with hierarchical attention.
- Introduced the Attentional Recurrent Graph Capsule Network (ARGCN) for the refined sentiment classification.
- Demonstrate state-of-the-art performance for two benchmark datasets on accuracy, precision, recall, and specificity.

The remainder of this paper is organized as follows. Section 2 describes related work on state-of-the-art techniques in sentiment analysis, focusing on multimodal approaches, advances, and challenges. Section 3 describes the proposed methodology for pre-processing, feature extraction, feature selection, and classification techniques. Section 4 presents the experimental design, results, and performance metrics of several datasets. Finally, Section 5 concludes with a summary and future

directions, using this summarization and relating it particularly to bias mitigation, explainability, and scalability as improvements in sentiment analysis frameworks.

2. Related Works

Early sentiment analysis implemented statistical and machine learning approaches to assess social media posts. For example, the use of the BoW model extracted features based on which users' posts were then classified into categories of depression that could be the basis for conducting interventions, such as motivational messages or notifications [11]. Similarly, other algorithms such as Support Vector Machine (SVM) and Random Forest (RF) with machine learning models have been applied in addition to deep learning models such as Long Short-Term Memory (LSTM) and Bidirectional LSTM (Bi-LSTM), applied to Twitter Sentiment Analysis with notable accuracy along with BoW and Term Frequency-Inverse Document Frequency (TF-IDF) to analyze public opinions or user sentiments regarding social media applications [12]. Deep learning architectures with the advent of sentiment analysis have introduced sophisticated embeddings, such as Word2Vec and GloVe, to further improve the performance of the model. Models like CNN, LSTM, GRU, Bi-LSTM, and Bi- GRU utilized these embeddings, and it was found that Bi-GRU outperformed others due to its efficiency in capturing temporal dependencies [13]. Hybrid frameworks, such as Bidirectional Recurrent Neural Networks (NHBi-RNN), were designed for multiclass sentiment classification with optimization using the Coot Optimization Algorithm. These models include techniques such as feature extraction from BoW, N-grams, and TF-IDF to reduce dimensionality for better contextual understanding, leading to more accurate classification results [14].

International Journal of Applied Mathematics
Volume 38 No. 11s 2025,
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To tackle misclassification and personalized challenges, hybrid approaches and graph-based methods were constructed. LMG-AGMPool is a graph-based model that combines dependency parse trees of text structured for the usage of precise microblog sentiment features to be picked through Graph Convolutional Networks with self-attention-based pooling [15]. A combination of TF-IDF with game theory and MCDM was implemented in the recommendation system and found to effectively improve personalized recommendations. This application demonstrates the value of hybrid techniques for tackling domain-specific issues [16]. The integration of multimodal data, composed of text, audio, and video, is the most significant advancement in sentiment analysis [17]. Even in multimodal inputs, attention mechanisms and residual networks were used to obtain superior results on benchmark datasets for the EMRA-Net model. However, the Uncertainty Estimation Fusion Network (UEFN) addresses uncertainty using Dirichlet distributions and the Dempster-Shafer evidence theory for sentiment classification. In this respect, UEFN establishes dynamic weight assignment to features to enhance the robustness and reliability of multimodal sentiment analysis. [18] [19].

Recent advances have introduced transformer-based architectures to handle long-range dependencies and enhance the intermodal interactions. A text-dominant multimodal perception network (TDMP) utilizes cross-modal transformers to align non-textual features with textual data, and it achieves excellent performance across all evaluation metrics [20]. Furthermore, a modality-squeeze transformer (MST) combined with an attentional recurrent graph capsule network (ARGCN) improved computational efficiency and prediction accuracy, which proved the importance of contextual and cross-modal relationships for robust sentiment analysis [21]. Beyond the usual applications, sentiment analysis has been further extended to the domains of misinformation detection and stock market prediction. The DisTrack tool identifies and visualizes misinformation propagation on social media using natural language processing (NLP) and graph visualization techniques [22]. Similarly, stock market prediction models combine sentiment analysis of tweets with financial indicators such as the Relative Strength Index (RSI) to forecast market trends, thereby demonstrating the flexibility of sentiment analysis in solving different real-world problems [23].

Sentiment analysis techniques have also been tailored to low-resource complex datasets. Urdu sentiment analysis uses models that employ pre-trained embeddings, such as mBERT and fastText, to

improve the attention mechanism in classifying critical words [24]. In another study, community-based modeling combined with network graphs effectively classified tweets with limited textual content, which illustrated the adaptability of sentiment analysis in addressing linguistic and contextual challenges [25]. Advanced preprocessing and feature selection techniques have greatly contributed to the improvement of sentiment analysis. In this regard, the TFO-DFE model uses optimization-based feature selection and ensemble classifiers to achieve high accuracy in datasets ranging from IMDB, Twitter, to Amazon. These techniques reduce complexity with efficient and scalable performance [26]. Finally, network analysis techniques were used to analyze polarized groups and predict environmental threats. Research on contentious issues, including climate change and vaccines, indicated that denial groups have higher network coherence, thus making it

Received: August 09, 2025

International Journal of Applied Mathematics
Volume 38 No. 11s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)
easier for information to spread [27] [28] [29]. Furthermore, sentiment analysis using NLP with time-series modeling has been used to predict environmental threats, such as droughts and deforestation. This shows that these techniques are capable of handling the most urgent societal and ecological challenges as demonstrated in Table.1

Table 1: Survey of Sentiment Analysis

Authors	Methodology	Advantages	Limitations
Darraz et al. [4]	Hybrid recommendation combining DeepMF, clustering, and BERT with NMF and Decision Tree Regressor	Improved accuracy with RMSE as low as 0.02 (restaurant) and 0.01 (hotel)	Challenges in hyperparameter tuning and computational resource requirements
Singgalen et al. [6]	Sentiment analysis and SNA using CRISP-DM framework and SVM	Systematic data analysis, robust classification	Limited recall in SVM with SMOTE; sparse network density
Alnasrawi et al. [8]	Text network analysis combined with neural network-based sentiment classification	Improved sentiment classification accuracy by leveraging text network features	Limited exploration of other advanced deep learning methods such as transformers for further improvement
Zhang et al. [15]	Game Theory (GT) and MCDM-based LSTM with Sentiment Analysis	Improved recommendation quality with nuanced user preferences	Dependent on textual review quality and scalability issues
Yuanyuan Li et al. [16]	Introduced LMG-AGMPool, combining Bi-LSTM, GCN, and AGMPool for fine-grained sentiment analysis.	Achieved higher accuracy and F-scores than traditional and deep models.	Fixed pooling ratio may not optimize individual text performance.
Subbaiah et al. [17]	Hybrid AOA-HGS optimized EMRA-Net	High accuracy, efficient multimodal sentiment fusion	Limited generalization beyond the tested datasets
Wang et al. [18]	Uncertainty Estimation Fusion Network (UEFN)	Superior accuracy and robust uncertainty estimation	Relies on complete multimodal data for optimal performance

Rodríguez et al. [22]	DisTrack: Combines NLP, SNA, and graph visualization to track and analyze misinformation on Twitter.	Tracks misinformation from inception to propagation, enabling detailed analysis.	Limited to platforms offering API-based data retrieval and metadata structuring.
Das et al. [23]	Integrated EEMD, ensemble CNN, and X sentiment analysis	Enhanced prediction accuracy and incorporation of sentiment analysis	Potential biases in sentiment analysis and challenges in adapting to dynamic markets
Khan et al. [25]	Attention-based stacked CNN-Bi-LSTM with mBERT	Improved accuracy and context understanding	Limited evaluation on non-Urdu datasets
Bala et al. [27]	Sentiment analysis using ML techniques with hashtags	Enhanced customer insights and trend analysis	Limited to text and hashtag-based analysis.
Mahmoudi et al. [28]	Network metrics and machine learning model for polarized group detection	High performance (precision, recall, F1 > 0.93)	Limited generalizability beyond analyzed datasets
Ibanez et al. [29]	Sentiment analysis for threat prediction using NLP, P-Model, and LSTM networks.	Accurate time-series prediction (46% - 71%).	Limited to textual data; sarcasm and irony not considered.
Devi et al. [30]	PA_BiDSAE hybrid deep learning	Improved classification performance and aspect coverage	Increased computational complexity

The proliferation of social media has introduced user-generated content, which further necessitates sophisticated sentiment analysis frameworks that can efficiently process multimodal data including text, images, audio, and video. Traditional single-modal approaches fail to capture subtle nuances in sentiments and accommodate informal language and contextual polarity [30]. In addition, the available models suffer from problems, such as sparsity of data, cold-start problems, and biases. Inclusive and explainable performance gaps continue to exist; thus, advances in multimodal fusion, graph-based techniques, and transformer-based architectures are areas for further improvement. Therefore, it is necessary to develop a comprehensive sentiment analysis framework that integrates cutting-edge feature extraction, multimodal integration, and bias mitigation.

International Journal of Applied Mathematics
Volume 38 No. 11s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

3. Methodology

The methodology presented in this paper describes the systematic approach adopted to overcome the challenges accompanying traditional methods of aspect-based sentiment analysis (ABSA). The framework is targeted to resolve issues associated with key limitations, such as unfriendliness in handling large-scale text data, insufficient context-aware feature extraction, and poorly optimized feature selection processes. During the entire analysis stage, the proposed framework ensures an accurate and scalable classification of sentiment by advancing techniques within each phase.

The methodology is divided into four phases. The preprocessing phase applies state-of-the-art text cleaning to prepare raw input data for further analysis. The second phase is a feature extraction mechanism that uses a powerful embedding model to c

apture all the semantic and contextual relationships within the data. Following this, the feature selection phase ensures that only the most relevant features are identified and retained, thereby optimizing the overall performance of the system. Finally, the classification phase uses a novel model to accurately categorize sentiments based on a refined feature set. Together, these phases form a cohesive framework designed to enhance the performance and reliability of the ABSA in real-world applications, as shown in Figure 1.

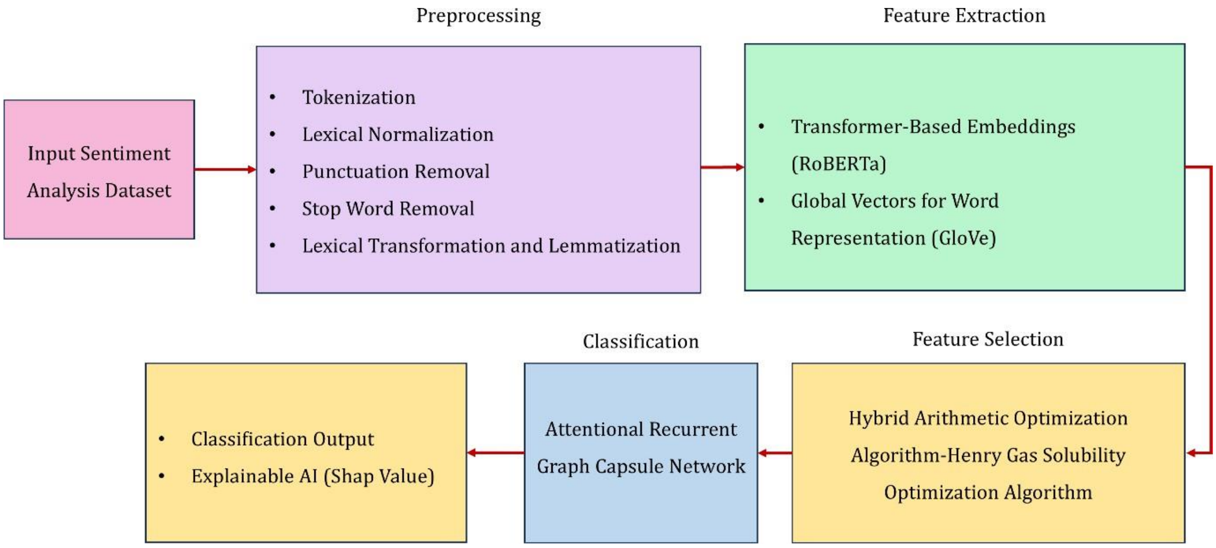

Figure 1: Framework for Aspect-Based Sentiment Analysis

3.1. Preprocessing

Preprocessing forms the core phase in aspect-based sentiment analysis, by ensuring that the input text is clean, well-structured, and suitable for use in other applications. Multiple sequential processes were employed in preprocessing to reduce noise, normalize the text, and standardize the data to ensure smooth analysis. All these methods were applied within a series of steps: tokenization, lexical normalization, and punctuation removal, among others, addressing a particular kind of challenge linked with noisy or unstructured text data.

International Journal of Applied Mathematics
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Tokenization is the process of breaking a text into smaller units, called tokens, such as words or phrases. This is achieved using a tokenization function, mathematically represented as

$$T = f(s) \text{ where } T = \{t_1, t_2, \dots, t_n\}, S \text{ is the input text string} \quad \text{----} \quad 1$$

Here, T is the set of tokens that results from the input text S. Libraries such as NLTK are used for effective tokenization.

Lexical Normalization addresses inconsistencies in the text, such as spelling variations, informal language, and converting words to a standard form. For instance, words like "u" and "you're" are normalized to "you" and "you are," respectively. Tools such as TextBlob and custom dictionaries are used to automate this process. Normalization can be expressed as

$$W_{norm} = f_{norm}(W) \quad \text{----} \quad 2$$

$where\ W_{norm}\ is\ the\ normalized\ word\ and\ W\ is\ the\ input\ word$. To remove unnecessary symbols that did not contribute to the semantic analysis, punctuation marks were removed. The string module of Python is often used to implement punctuation removal. This step is important for reducing noise in the text. Mathematically:

$$S_{clean} = S - P \text{ where } P \text{ is theset of punctuation marks} \quad \text{----} \quad 3$$

Commonly occurring words such as "is," "the," and "and" that do not carry much semantic weight are removed. The text is left with only meaningful words that contribute to the sentiment analysis.

$$S_{stop-free} = S_{clean} - W_{stop}, \text{ where } W_{stop} \text{ is the set of stop words} \quad \text{----} \quad 4$$

Lemmatization converts words into their base forms while preserving their grammatical context, aiding standardization. The transformation can be expressed as

$$W_{lemma} = f_{lemma}(W_{stop-free}) \quad \text{----} \quad 5$$

where W_{lemma} is the lemmatized word. The widely used tool for lemmatizing was the WordNetLemmatizer from NLTK. Each preprocessing step is motivated by a justification, as it cleans up and structures text for further analysis. Tokenization ensures granularity, lexical normalization adds consistency, removing punctuation reduces noise, stop word removal narrows down to content, and lemmatization normalizes text forms. Altogether, these processes establish a solid foundation for the accurate extraction of features and sentiment analysis, enabling high-quality inputs for subsequent phases of the methodology.

3.2. Feature Extraction

Feature extraction is an essential task in aspect-based sentiment analysis, because textual data must

International Journal of Applied Mathematics

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

be represented numerically to enable models to understand it. The proposed framework captures both deep contextual semantics and word-level relationships in the input text by utilizing advanced embedding techniques, such as Global Vectors for Word Representation (GloVe) and RoBERTa.

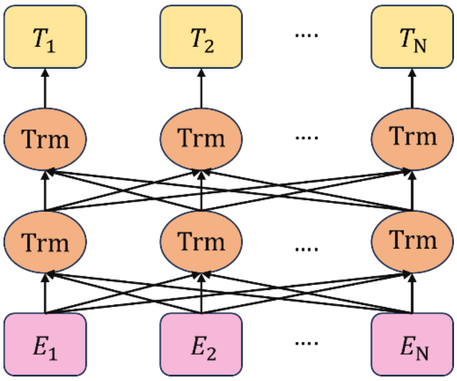

Figure 2: Multi-Level Transformer-Based Feature Representation Framework

RoBERTa is a pre-trained transformer model optimized for bidirectional context representation. It leverages self-attention mechanisms to capture the relationships between words in both preceding and succeeding contexts, as shown in Figure 2. Mathematically, the embedding of a word w_i in a sentence

$S = \{w_1, w_2, \dots, w_n\}$ is computed as:

$$E(w_i) = f_{self-attention}(Q, K, V) \qquad ---- \quad 6$$

where Q, K, and V represent the query, key, and value matrices, and $f_{self-attention}$ is defined as:

$$f_{self-attention}(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{dk}}\right)V \qquad ---- \quad 7$$

Here, d_k is the dimensionality of the key vectors. This mechanism allows RoBERTa to model complex dependencies and contextual nuances, making it highly effective in capturing deep semantic meanings.

GloVe embeddings complement RoBERTa by focusing on word-level semantics derived from the co-occurrence statistics. It represents the relationship between words w_i and w_j based on their shared occurrence in a large text corpus. The embedding vectors $E(w_i)$ and $E(w_j)$ are optimized using the following objective function:

$$J = \sum_{i,j} f(X_{ij})\left(E(w_i)^T E(w_j) + b_i + b_j - logX_{ij}\right)^2 \quad ---- \quad 8$$

where X_{ij} denotes the co-occurrence count of words w_i and w_j, b_i and b_j are bias terms, and

$f(X_{ij})$ is a weighting function. GloVe effectively captures global word relationships, complementing RoBERTa's focus on context.

The features of RoBERTa and GloVe were selected because of their ability to capture the semantic and syntactic properties of text uniquely. RoBERTa excels in contextual awareness through word dependencies modeled bidirectionally, whereas GloVe's capabilities involve global co- occurrence for the representation of word relationships. Thus, they contribute to scalability and accuracy by providing comprehensive feature representations necessary for downstream sentiment classification tasks. This feature extraction process lays a solid foundation for accurately analyzing sentiments and aspects embedded in textual data by combining RoBERTa's contextual depth and GloVe's semantic richness. These embeddings ensure that the features passed to the subsequent phases are both meaningful and optimized for the task.

3.3. Feature Selection

Feature selection is one of the most important phases in aspect-based sentiment analysis because it selects the most relevant features and retains them while eliminating redundant or irrelevant features. This step significantly reduces the dimensionality of the dataset, thus improving computational efficiency and model performance. The proposed framework uses a hybrid approach combining the Arithmetic Optimization Algorithm (AOA) and Henry Gas Solubility Optimization (HGS) algorithm with hierarchical attention mechanisms to refine the feature selection process.

The Arithmetic Optimization Algorithm is motivated by the addition of arithmetic operations, subtraction, multiplication, and division. It solves optimization problems through a trade-off between the exploration and exploitation of promising areas of the solution space. The update equation for a position of a solution $X_i(t)$ at iteration t is given as:

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

$$X_i(t+1) = X_i(t) + r_1 \cdot |r_2 \cdot X_{best} - r_3 \cdot X_i(t)| \qquad \text{----} \quad 9$$

where r_1, r_2, r_3 are random numbers in [0, 1] and X_{best} represents the current best solution. This mechanism allows the AOA to effectively explore different regions of the solution space while converging toward optimal solutions.

The Henry Gas Solubility Optimization algorithm is motivated by Henry's law of gas solubility, which postulates that the solubility of gas in a liquid is proportional to the partial pressure of the gas. In an HGS, each solution is considered a gas molecule, and its movement in the solution space is determined based on the solubility and pressure factors. A solution $X_i(t)$ is updated as:

$$X_i(t+1) = X_i(t) + solubility_i \cdot (X_{global\ best} - X_i(t) + r \cdot local\ random) \qquad \text{----} \quad 10$$

where $solubility_i$ depends on the fitness value of the solution, $X_{global\ best}$ is the globally best solution, and r is a random factor ensuring diversity.

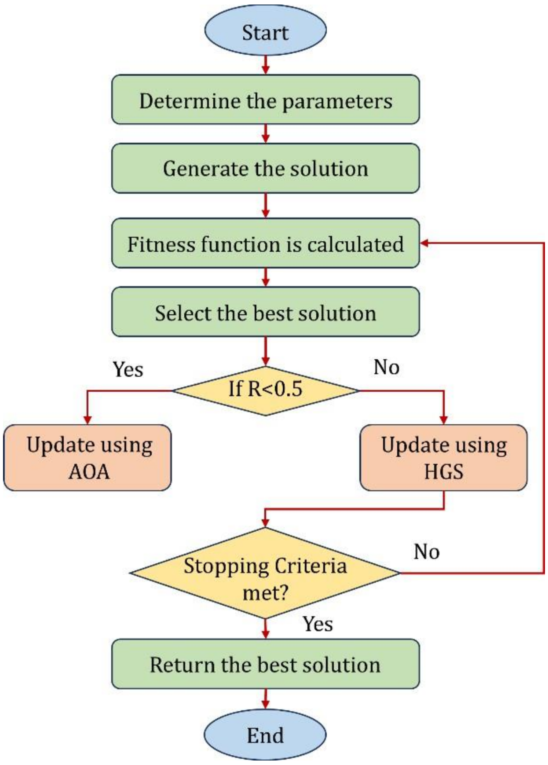

Figure 3: Flowchart of the Hybrid Arithmetic Optimization Algorithm-Henry Gas Solubility Optimization (AOA-HGS) Framework

Hybrid Integration of AOA arithmetic inspiration for exploration into HGS and exploitation based on solubility. This enables a balance between the global and local searches. Feature attention is designed hierarchically to assign appropriate weights to contextual relevance and relevance to a task, as illustrated in Figure 3. The objective of feature selection, combining both search strategies, is described as follows.

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

$$J = \alpha \cdot f_{AOA}(X) + \beta \cdot f_{HGS}(X) \qquad \text{---- } 11$$

where α and β are weighting factors, and $f_{AOA}(X)$ and $f_{HGS}(X)$ represent the fitness functions of AOA and HGS, respectively. Dimensionality reduction by means of feature selection helps save a considerable amount of computation in addition to minimizing overfitting risks. Hybrid AOA-HGS allows retaining the features with maximum importance while maintaining an enhanced level of interpretability and efficiency of the model developed for sentiment classification. A set of optimally selected features provides optimal conditions to operate with optimized data for subsequent classification phases to increase the overall performance. Therefore, combining evolutionary optimization techniques with hierarchical attention in its hybrid version, AOA-HGS ensures that the chosen features are both contextually significant and computationally efficient, providing a solid foundation for sentiment analysis.

3.4. Classification

The ARGCN is a new state-of-the-art model to present a model that surpasses previous concepts of accurately predicting sentiment polarities for aspect-based sentiment analysis. The model combines the strong characteristics of recurrent neural networks, graph-based representations, and capsule networks with dynamic attentional mechanisms to offer high accuracy and robust sentiment prediction and classification.

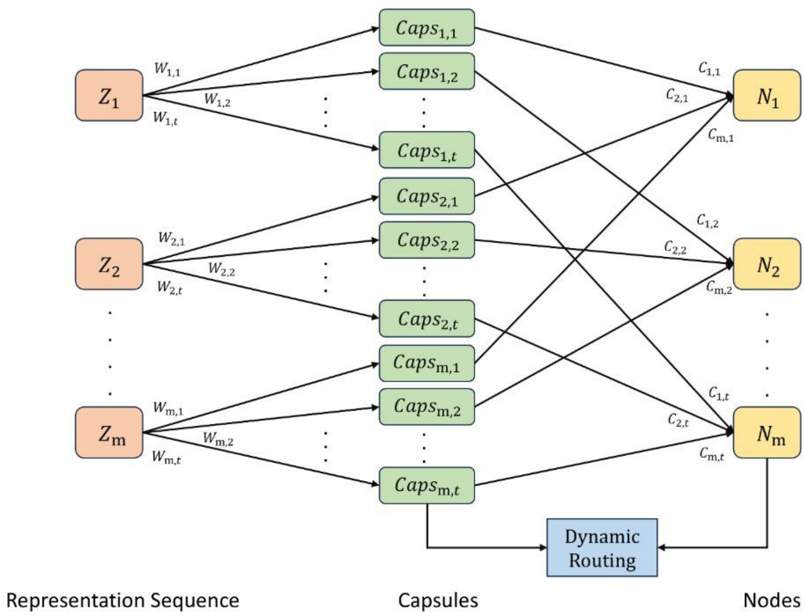

Figure 4: Capsule Network Architecture with Dynamic Routing for Sentiment Classification

The three main components of the ARGCN architecture are a recurrent module, graph-based representation layer, and capsule network layer. The recurrent module is based on Bidirectional Long Short-Term Memory (BiLSTM) networks that capture the temporal dependencies and bidirectional relationships within the input text. The graph representation layer uses a Graph Capsule Neural Network (GCN) framework to model the complex interactions between words and

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

aspects. Finally, the capsule network refines sentiment predictions by encapsulating multidimensional feature vectors into meaningful representations, thereby ensuring a better generalization. The most important innovation in ARGCN is their dynamic attention mechanism. It assigns different weights to varying features and context words, depending on how relevant they are to the aspect under analysis. Given an input sequence, the attention score of a word w_i is calculated as:

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{j=1}^{n}\exp(e_{ij})}, where\ e_{ij} = f(W_a h_i + b_a) \quad ---- \quad 12$$

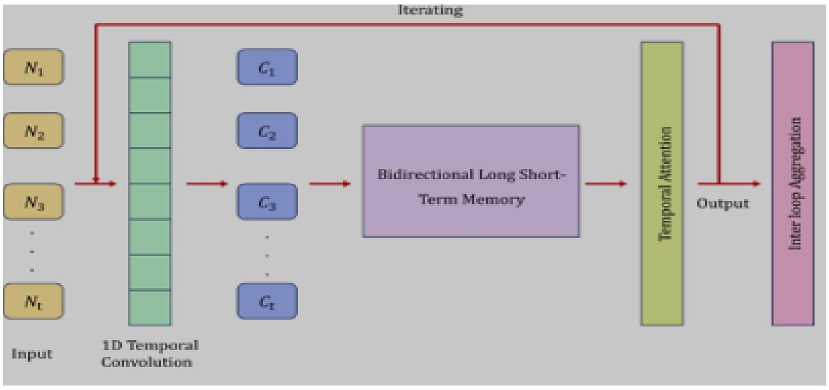

Figure 5: Temporal Attention with Bidirectional Long Short-Term Memory (BiLSTM) for Sentiment Analysis

Here, h_i represents the hidden state of the BiLSTM corresponding to W_a and b_a are learnable parameters, and f is an activation function. The attention scores α_i are then used to weigh the hidden states, creating a context vector that prioritizes features most relevant to the sentiment classification task. The capsule network layer further processes the context vector to refine the sentiment predictions. Each capsule encodes a multidimensional representation of sentiment-related features, and the routing-by-agreement algorithm ensures that capsules with similar outputs are clustered, which reduces noise and improves the classification precision. The output of the capsule network is represented as

$$v_j = \frac{\|s_j\|^2}{1+\|s_j\|^2}\frac{s_j}{\|s_j\|}, where\ s_j = \sum c_{ij} u_{j|i} \quad ---- \quad 13$$

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

$1+\|s_j\| \quad j$

Here, u_i represents the input to the capsule, c_{ij} are routing coefficients, and v_j is the output vector of the capsule j. The ARGCN combines the strengths of BiLSTM, GCN, and capsule networks to overcome existing classification models. It does not model the relationships among words, aspects, and contexts as a graph, as in the case of traditional methods that treat each word independently and fail to capture the semantic and structural nuances of a given input. This incorporation of dynamic attention downweights the irrelevant features, and hence, the capsule network robustly improves the predictability by maintaining its hierarchical structure of features. By integrating these components, the ARGCN provides a powerful and innovative approach to sentiment classification, outperforming traditional techniques in terms of accuracy, interpretability, and scalability, as shown in Figure 5. This model is well-suited for aspect-based sentiment analysis tasks, delivering refined and reliable sentiment predictions.

4. Result and Discussion

Kaggle Sentiment Analysis Dataset 1 [31] contains user-generated social media posts annotated with sentiment labels (positive or negative), timestamps, user identifiers, platforms (e.g., Twitter and Instagram), and associated hashtags. Other features include engagement metrics, such as retweets and likes, along with metadata such as country, year, month, day, and hour. This dataset offers an all-round view of user interactions and sentiments to effectively analyze trends that are temporal, geographical, and platform-specific.

Kaggle Sentiment Analysis Dataset 2 [32] contains social media text posts with sentiment labels as neutral or negative, along with extra attributes, such as selected text, time of the tweet (morning, noon, night), and age group of users. Geographical information is provided in terms of country, population data for 2020, land area, and population density. This dataset provides a detailed context for sentiment analysis with respect to temporal, demographic, and geographic factors.

4.2. Experimental Configuration

The experiments were carried out on an NVIDIA RTX 3090 GPU with 24 GB of memory, an Intel Core i9 processor, and 64 GB of RAM. The system runs in an Ubuntu 20.04 environment. Python 3.9 was used to implement the algorithm, along with key libraries consisting of TensorFlow and PyTorch for deep learning and machine learning tasks. Other libraries include Scikit-learn, Pandas, NLTK, Matplotlib, and Seaborn, which are helpful in preprocessing, visualizations, and deep and machine learning computations. SHAP was used for explainability, and hugging-face transformers were used for embeddings such as RoBERTa and GloVe. This configuration handled computationally intensive tasks and allowed seamless experimentation, as shown in Table 2.

Table 2: Experimental parameters and their values

Parameter	Value
Embedding Dimension	768
Hidden Layer Units	512

Received: August 09, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Feature Selection Threshold	0.01
Activation Function	ReLU
Attention Heads	8

4.3. Classification Result of Dataset 1

The model can classify positive sentiments very accurately, with a true positive rate of 99.87%. For negative sentiments, the accuracy was also noteworthy, with an accuracy of 98.83%. The true positive rate of the neutral sentiment classification was also highly accurate at 99.85%. However, minor misclassifications were present; for instance, 0.05% and 0.08% of positive sentiments were misclassified as negative and neutral, respectively. Likewise, 0.15% of negative sentiments were incorrectly labeled as neutral. Figure 6 shows the confusion matrix of sentiment classification performance for a dataset with three sentiment classes: positive, negative, and neutral.

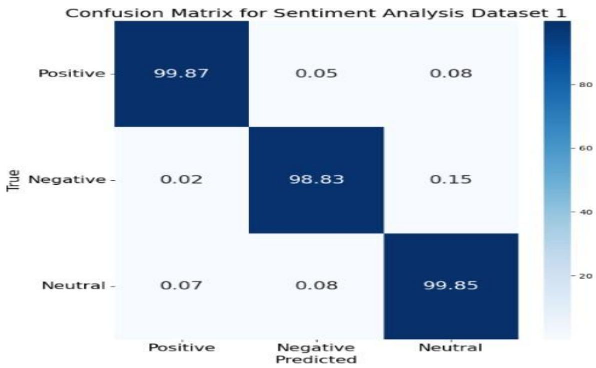

Figure 6: Confusion Matrix for Sentiment Analysis Dataset 1

The graphs in Figure 7 depict the training and validation performances of the sentiment analysis model for 300 epochs, showing both accuracy and loss trends. Two curves representative of training and validation accuracy demonstrate a smooth progressive increase with epochs, stable at approximately 99.85%, indicating that the model is highly generalizable across the datasets. The same applies to the training and validation loss curves, which indicate a progressive decrease and leveling off at the minimal values of 0.0045.

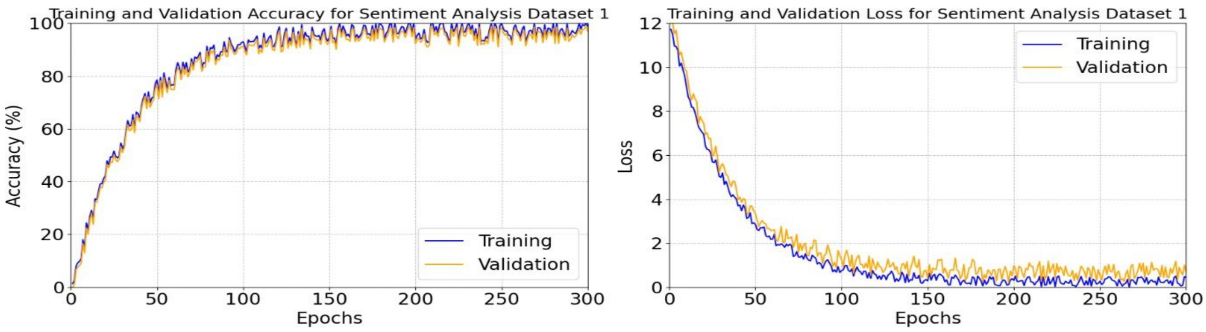

Figure 7: Training and Validation Accuracy and Loss for Sentiment Analysis Dataset 1

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Figure 8 shows the performance metrics of the sentiment analysis model, which are excellent for all key evaluation parameters. The overall accuracy of the model was 99.85%, which means that the model was very robust in correctly classifying sentiments. Precision, recall, and F1 score values of 99.80%, 99.88%, and 99.83%, respectively, indicate that the model is highly reliable for identifying relevant sentiments without introducing significant false positives or negatives. Moreover, the specificity metric of 99.90% highlights the fact that the model is very effective in identifying true negatives, thus proving its reliability.

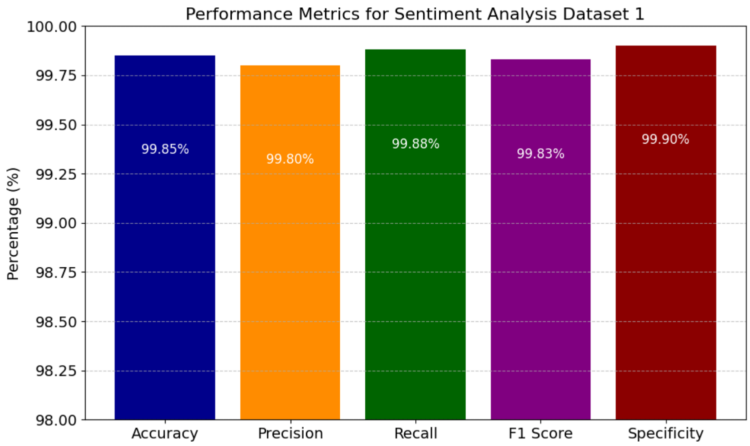

Figure 8: Performance Metrics for Sentiment Analysis Dataset 1

4.4. Classification Result of Dataset 2

Figure 9 shows the confusion matrix for the performance of the model in sentiment classification for Dataset 2 for three classes: positive, negative, and neutral. The model is highly accurate, with 99.90% of positive sentiments correctly classified, 0.04% misclassified as negative, and 0.06% as neutral. Likewise, it correctly classified 98.88% of negative sentiments, with only 0.06% misclassified as positive or neutral. For neutral sentiments, the accuracy was equally impressive at 99.89%, with negligible misclassification rates of 0.04% and 0.07% into positive and negative categories, respectively.

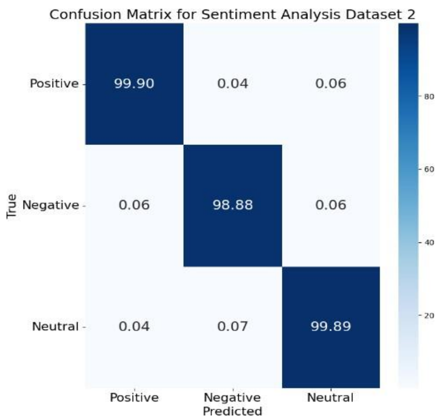

Figure 9: Confusion Matrix for Sentiment Analysis Dataset 2

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

In Figure 10, the graphs describe the training and validation performances of the sentiment analysis model for Dataset 2 over 300 epochs. The accuracy plot reveals a steady progression in both the training and validation accuracies; it finally settled at an incredibly high overall accuracy of 99.89%. Similarly, the loss plot illustrates a steady declining trend for both training and validation losses and finally stabilizes at an unusually low value of 0.0038. The close alignment between the training and validation curves in terms of both accuracy and loss indicates that the model is well-generalized and avoids overfitting.

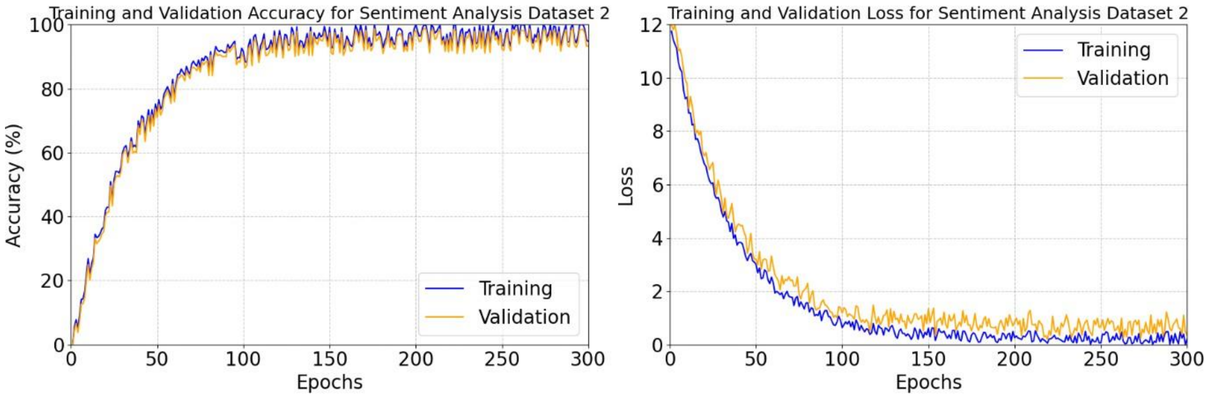

Figure 10: Training and Validation Accuracy and Loss for Sentiment Analysis Dataset 2

The overall accuracy of the model was 99.89%, which demonstrated its precision in the correct classification of sentiments. The precision and recall values were 99.87% and 99.90%, respectively, indicating that the model had a strong ability to minimize false positives and false negatives. The F1 score, a measure of the balance between precision and recall, was 99.88%, again demonstrating the robustness of the model. The specificity metric, a measure for identifying true negatives, reached 99.92%, further emphasizing the effectiveness of the model in distinguishing between sentiment classes with very few errors. Figure 11 depicts the performance metrics for Dataset 2, demonstrating the excellent efficiency and reliability of the sentiment analysis model.

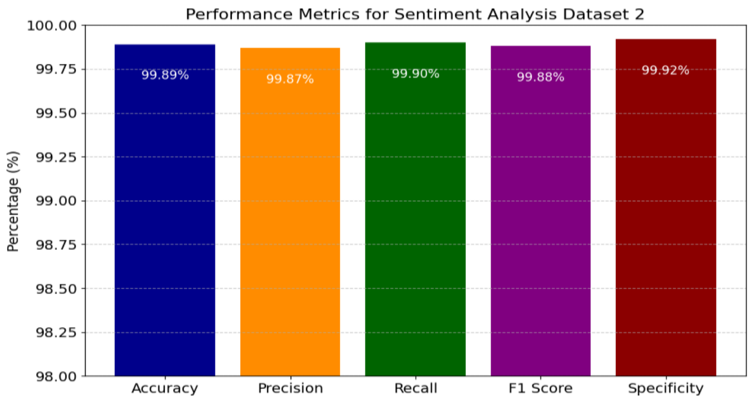

Figure 11: Performance Metrics for Sentiment Analysis Dataset 2

4.5. Explainable AI Results

Figure 12 offers a more interpretability-oriented view of the model based on Dataset 1 applying

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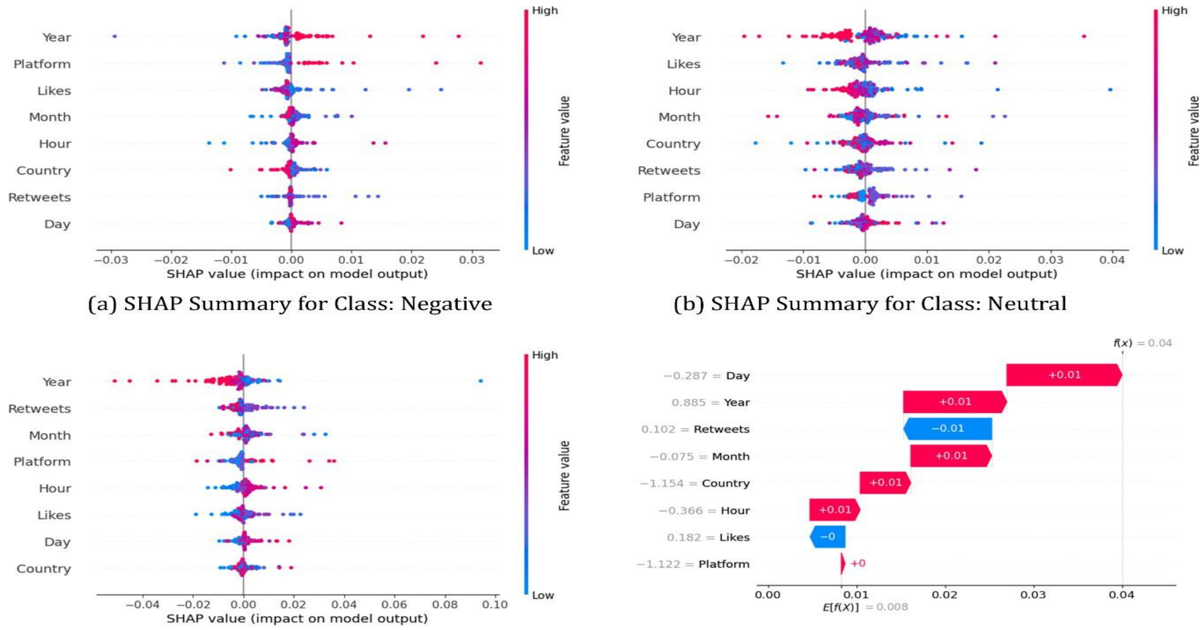
sentiment analysis, showing the contributions of different features for various sentiment classes. In the negative class from Figure 11a, those features like "Year," "Platform," and "Likes" have major influences on the model, and their SHAP values clearly demonstrate positive and negative contributions for the model output. For the neutral class (Figure 11b), "Likes," "Hour," and "Retweets" appear to be the most important features, with small differences in their magnitudes. The positive class (Figure 11c) shows that "Year," "Retweets," and "Platform" Platform are the top features that influence sentiment classification. The SHAP waterfall plot in Figure 11d shows how individual feature contributions cumulatively lead to the final model output.

Figure 12: SHAP Analysis for Sentiment Analysis Dataset 1



(a) SHAP Summary for Class: Negative
(b) SHAP Summary for Class: Neutral
(c) SHAP Summary for Class: Positive
(d) SHAP waterfall plot

In Figure 13, the SHAP analysis shows the key contributions of the important features to the sentiment classification of Dataset 2, and provides information related to how interpretability was facilitated by this model. On the negative class side in Figure 12a, notable features like "Age of User," "Country," and "Density (P/Km²)" have great influencing power regarding prediction, showing a mix of both positive and negative SHAP values. In the neutral class (Figure 12b), the "Land Area (Km²)" and "Time of Tweet" features most clearly show that they are quite relevant throughout all data points. The positive class (Figure 12c) clearly shows that the dominant contributors in the model predictions include "Age of User" and "Population - 2020." The SHAP waterfall plot in Figure 12d provides a cumulative view of the individual feature impacts, and the most influential features for this instance are "Density (P/Km²)" and "Land Area (Km²)." This analysis confirms the model's ability to effectively incorporate meaningful features and enhance transparency and trustworthiness.

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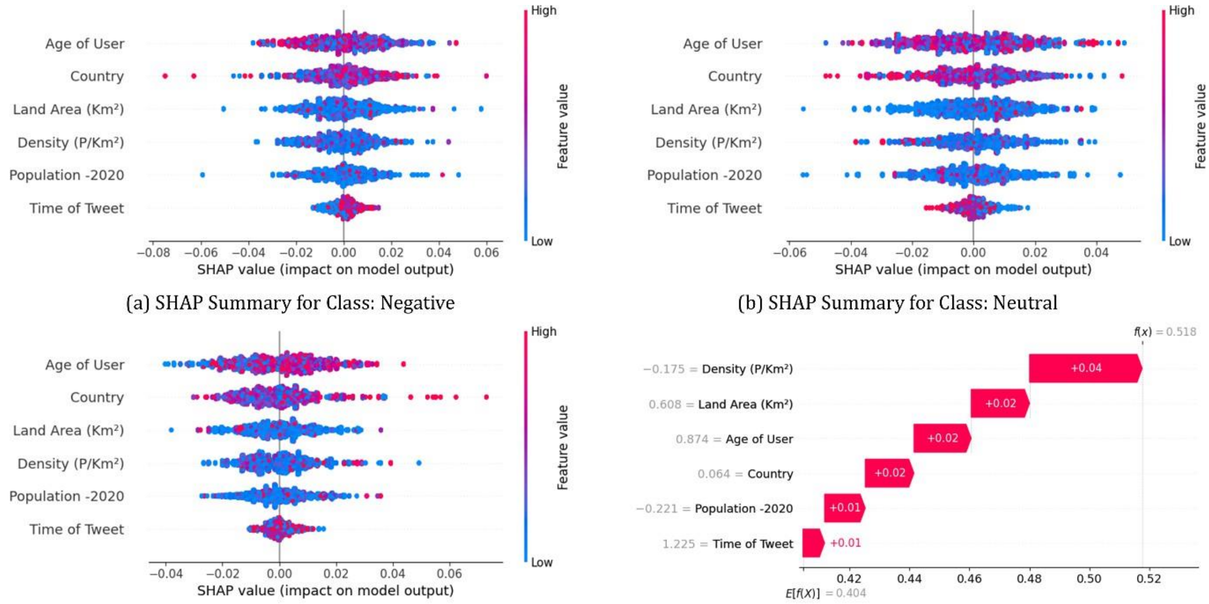
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)



(a) SHAP Summary for Class: Negative

(b) SHAP Summary for Class: Neutral

(c) SHAP Summary for Class: Positive

(d) SHAP waterfall plot

Figure 13: SHAP Analysis for Sentiment Analysis Dataset 2

4.6. Deep Learning Comparison

As evidenced by the comparison of performance metrics in Table 3, the proposed model outperforms other existing techniques for Sentiment Analysis Dataset 1. The proposed model attained the highest accuracy of 99.85%, precision of 99.8%, recall of 99.88%, F1 score of 99.83%, and specificity of 99.9%, outperforming the other models. On the other hand, the CNN model has reduced metrics: an accuracy of 97.85% and specificity of 98%, signifying a limited capability in capturing complex patterns. Similarly, BiLSTM surpasses CNN by 98.45% and is not as efficient as the proposed model. In contrast, the autoencoder (AE) and Stacked Autoencoder (SAE) models yielded the lowest performance with accuracy scores of 96.9% and 97.4%, respectively.

Table 3: Performance Comparison of Different Techniques for Sentiment Analysis Dataset 1

Technique	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 Score (%)**	**Specificity (%)**
Proposed Model Dataset 1	99.85	99.8	99.88	99.83	99.9
CNN	97.85	97.7	97.92	97.81	98
BiLSTM	98.45	98.3	98.55	98.42	98.7
Autoencoder (AE)	96.9	96.75	96.8	96.77	97

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Stacked Autoencoder (SAE)	97.4	97.25	97.5	97.37	97.6

The performance metrics summarized in Table 4 show that the proposed model is highly effective for Sentiment Analysis Dataset 2, as it obtains the highest accuracy (99.89%), precision (99.87%), recall (99.9%), F1 score (99.88%), and specificity (99.92%) among the compared techniques. In contrast, the CNN and BiLSTM models show lower performance, with CNN achieving an accuracy of 97.85% and BiLSTM reaching 98.45%. The lowest performance is displayed by models Autoencoder (AE) and Stacked Autoencoder (SAE), achieving accuracy values of 96.9% and 97.4%, respectively.

Table 4: Performance Comparison of Different Techniques for Sentiment Analysis Dataset 2

Technique	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 Score (%)**	**Specificity (%)**
Proposed Model Dataset 2	99.89	99.87	99.9	99.88	99.92
CNN	97.85	97.7	97.92	97.81	98
BiLSTM	98.45	98.3	98.55	98.42	98.7
Autoencoder (AE)	96.9	96.75	96.8	96.77	97
Stacked Autoencoder (SAE)	97.4	97.25	97.5	97.37	97.6

4.7. Ablation Study

As shown in the ablation study in Table 5, the individual components play an important role in the proposed model for Sentiment Analysis Dataset 1. The full model performed best on all metric measures: accuracy of 99.85%, precision of 99.8%, recall of 99.88%, F1 score of 99.83%, and specificity of 99.9%. Removing the Hybrid AOA-HGS feature selection decreased the accuracy to 98.9%, thereby demonstrating the significant contribution of the technique in feature selection refinement. Excluding RoBERTa embeddings, the accuracy decreased to 97.85%, indicating that they play a crucial role in capturing deep contextual semantics. Removing GloVe embeddings also dropped the accuracy to 98.2%, showing their complementary role in word-level representation. The ARGCN model was removed, and the accuracy decreased to 97.5%, indicating that it is highly effective in sentiment classification. The most significant drop was found in the absence of lexical normalization and tokenization, which was reduced to 96.8%, indicating that it plays a significant role in preprocessing.

Table 5: Ablation Study Results for Sentiment Analysis Dataset 1

Model Configuration	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 Score (%)**	**Specificity (%)**

Received: August 09, 2025

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Full Model (Proposed Dataset 1)	99.85	99.8	99.88	99.83	99.9
Without Hybrid AOA-HGS	98.9	98.7	98.8	98.75	98.95
Without RoBERTa Embeddings	97.85	97.65	97.75	97.7	97.85
Without GloVe Embeddings	98.2	98.1	98.25	98.17	98.3
Without ARGCN Model	97.5	97.3	97.45	97.35	97.6
Without Lexical Normalization and Tokenization	96.8	96.65	96.75	96.7	96.9

The ablation study in Table 6 shows the critical contributions of all components in the proposed model towards Sentiment Analysis Dataset 2. The full model achieved the highest performance on all metrics, with an accuracy of 99.89%, precision of 99.87%, recall of 99.9%, F1 score of 99.88%, and specificity of 99.92%. When the Hybrid AOA-HGS feature selection was removed, the accuracy dropped to 98.95%, indicating its importance in optimizing the feature relevance. Removing RoBERTa embeddings further reduced the accuracy to 97.9%, which indicates their importance in capturing deep contextual semantics. Similarly, the absence of GloVe embeddings resulted in a drop in the accuracy of 98.3%, which shows their complementary contribution to the word-level feature representation. Excluding the ARGCN model reduced the accuracy to 97.8%, reflecting its vital role in improving sentiment classification. The largest drop occurred when lexical normalization and tokenization were removed, with an accuracy of 96.9%, emphasizing their fundamental importance in preprocessing.

Table 6: Ablation Study Results for Sentiment Analysis Dataset 2

Model Configuration	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 Score (%)**	**Specificity (%)**
Full Model (Proposed Dataset 2)	99.89	99.87	99.9	99.88	99.92
Without Hybrid AOA-HGS	98.95	98.85	98.9	98.87	99
Without RoBERTa Embeddings	97.9	97.75	97.8	97.77	98
Without GloVe Embeddings	98.3	98.2	98.35	98.27	98.4
Without ARGCN Model	97.8	97.65	97.7	97.68	97.85
Without Lexical Normalization and Tokenization	96.9	96.8	96.85	96.82	97

4.8. Comparative Analysis

In the comparison of the performance metrics, as shown in Table 6, it is evident that the proposed

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)
model exhibits better efficiency than existing methodologies for Sentiment Analysis Datasets 1 and 2. The proposed model achieved the highest accuracy of 99.85% and 99.89%, precision of 99.80% and 99.87%, recall of 99.88% and 99.90%, F1 score of 99.83% and 99.88%, and specificity of 99.90% and 99.92% for Datasets 1 and 2, respectively. These metrics are way higher than the methods proposed by Vijay et al., Devi et al., and Anoop et al. In fact, the highest accuracy reported by Devi et al. was 98.4 %. The earlier approaches of Mahalakshmi et al. and Zheng et al. showed much lower accuracies of 93.33% and 87.1%, respectively.

Table 7: Performance Comparison with Existing Methods

References	Accuracy (%)	Precision (%)	Recall (%)	F1Score (%)	Specificity (%)
Zheng et al. [1]	87.1	87.7	87.3	87.1	---
Mahalakshmi et al. [2]	93.33	92.86	93.11	92.68	---
Anoop et al. [5]	97.66	97.67	97.66	97.66	---
Vijay et al. [12]	98.39	98.59	98.31	98.54	98.51
Devi et al. [30]	98.4	97.77	98.08	97.93	98.43
Proposed Dataset 1	99.85	99.80	99.88	99.83	99.90
Proposed Dataset 2	99.89	99.87	99.90	99.88	99.92

5. Conclusion

This framework successfully addressed the major problems in aspect-based sentiment analysis: noise reduction, efficient feature extraction, and accurate classification. The advanced integration of RoBERTa, GloVe embeddings, and the hybrid AOA-HGS feature selection mechanism ensures that the system is highly scalable and accurate for datasets. With the new ARGCN model, the classification precision and robustness are improved because of the use of graph-based representations and dynamic attention mechanisms. The results obtained using benchmark datasets highlight the effectiveness of this framework by setting new standards for sentiment analysis applications. Future research can focus on extending this model to handle multilingual datasets, integrating real-time streaming data for sentiment tracking, and exploring its application across diverse domains, such as healthcare and e-commerce for more context-aware and scalable sentiment analysis solutions.

References

[1] Zheng, Yao, Junpeng Gong, Yujun Wen, and Pengzhou Zhang. "DJMF: A discriminative joint multi-task framework for multimodal sentiment analysis based on intra-and inter-task dynamics." Expert Systems with Applications 242 (2024): 122728.

[2] Mahalakshmi, V., P. Shenbagavalli, S. Raguvaran, V. Rajakumareswaran, and E. Sivaraman. "Twitter sentiment analysis using conditional generative adversarial network." International Journal of Cognitive Computing in Engineering 5 (2024): 161-169.

[3] Ghorbanali, Alireza, and Mohammad Karim Sohrabi. "Capsule network-based deep ensemble transfer learning for multimodal sentiment analysis." Expert Systems with Applications 239 (2024): 122454.

[4] Darraz, Nossayba, Ikram Karabila, Anas El-Ansari, Nabil Alami, and Mostafa El Mallahi. "Integrated sentiment analysis with BERT for enhanced hybrid recommendation systems." Expert Systems With Applications 261 (2025): 125533.

[5] Anoop, V. S., C. Subin Krishna, and Usharani Hareesh Govindarajan. "Graph embedding approaches for social media sentiment analysis with model explanation." International Journal of Information Management Data Insights 4, no. 1 (2024): 100221.

[6] Singgalen, Yerik Afrianto. "Social Network Analysis and Sentiment Classification of Extended Reality Product Content." KLIK: Kajian Ilmiah Informatika dan Komputer 4, no. 4 (2024): 2197- 2208.

[7] Resende, Guilherme H., Luiz F. Nery, Fabrício Benevenuto, Savvas Zannettou, and Flavio Figueiredo. "A Comprehensive View of the Biases of Toxicity and Sentiment Analysis Methods Towards Utterances with African American English Expressions." arXiv preprint arXiv:2401.12720 (2024).

[8] Alnasrawi, Ali Mohamed, Asia Mahdi Naser Alzubaidi, and Ahmed Abdulhadi Al-Moadhen. "Improving sentiment analysis using text network features within different machine learning algorithms." Bulletin of Electrical Engineering and Informatics 13, no. 1 (2024): 405-412.

[9] Pu, Qiumei, Fangli Huang, Fude Li, Jieyao Wei, and Shan Jiang. "Integrating Emotional Features for Stance Detection Aimed at Social Network Security: A Multi-Task Learning Approach." Electronics 14, no. 1 (2025): 186.

[10] Zhao, Qin, Chenglei Yu, Jingyi Huang, Jie Lian, and Dongdong An. "Sentiment analysis based on heterogeneous multi-relation signed network." Mathematics 12, no. 2 (2024): 331.

[11] Pande, Sandeep Dwarkanath, S. K. Hasane Ahammad, Madhuri Navnath Gurav, Osama S. Faragallah, Mahmoud MA Eid, and Ahmed Nabih Zaki Rashed. "Depression detection based on socialnetworking sites using data mining." Multimedia tools and applications 83, no. 9 (2024): 25951- 25967.

[12] Samuel, Prithi, and Brahmadesam Viswanathan Krishna. "Exploration of sentiment analysis in twitter propaganda: a deep dive." Multimedia Tools and Applications 83, no. 15 (2024): 44729-44751.

[13] Krosuri, Lakshmi Revathi, and Rama Satish Aravapalli. "Novel heuristic bidirectional-recurrent neural network framework for multiclass sentiment analysis classification using coot optimization." Multimedia Tools and Applications 83, no. 5 (2024): 13637-13657.

[14] Rakshit, Pranati, and Avik Sarkar. "A supervised deep learning-based sentiment analysis by the implementation of Word2Vec and GloVe Embedding techniques." Multimedia Tools and Applications (2024): 1-34.

[15] Zhang, Vince Wanhao, Guansu Wang, Noreen Izza Arshad, Quang Nguyen, Mengyao Xia,

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)
and Nisreen Innab. "Advancing consumer insights: efficient sentiment analysis-based recommendation system using multi-criteria decision making with a game theoretic approach." Annals of Operations Research (2025): 1-20.

[16] Li, Yuanyuan, Baolong Zhou, Yijie Niu, and Yuetong Zhao. "Fine grained sentiment analysis on microblogs based on graph convolution and self attention graph pooling." Applied Intelligence 55, no. 2 (2025): 1-16.

[17] Subbaiah, Bairavel, Kanipriya Murugesan, Prabakeran Saravanan, and Krishnamurthy Marudhamuthu. "An efficient multimodal sentiment analysis in social media using hybrid optimal multi-scale residual attention network." Artificial Intelligence Review 57, no. 2 (2024): 34.

[18] Wang, Shuai, K. Ratnavelu, and Abdul Samad Bin Shibghatullah. "UEFN: Efficient uncertainty estimation fusion network for reliable multimodal sentiment analysis." Applied Intelligence 55, no. 2 (2025): 171.

[19] Jayamohan, M., and S. Yuvaraj. "Iv3-MGRUA: a novel human action recognition features extraction using Inception v3 and video behaviour prediction using modified gated recurrent units with attention mechanism model." Signal, Image and Video Processing 19, no. 1 (2025): 1-12.

[20] Li, Zuhe, Panbo Liu, Yushan Pan, Jun Yu, Weihua Liu, Haoran Chen, Yiming Luo, and Hao Wang. "Text-dominant multimodal perception network for sentiment analysis based on cross-modal semantic enhancements." Applied Intelligence 55, no. 2 (2025): 1-17.

[21] Hu, Chengyu, Jin Liu, Xingye Li, Meijing Li, and Huihua He. "MST-ARGCN: modality-squeeze transformer with attentional recurrent graph capsule network for multimodal sentiment analysis." The Journal of Supercomputing 81, no. 1 (2025): 86.

[22] Villar-Rodríguez, Guillermo, Álvaro Huertas-García, Alejandro Martín, Javier Huertas-Tato, and David Camacho. "DisTrack: A New Tool For Semi-automatic Misinformation Tracking in Online Social Networks." Cognitive Computation 17, no. 1 (2025): 1-18.

[23] Das, Nabanita, Bikash Sadhukhan, Susmit Sekhar Bhakta, and Satyajit Chakrabarti. "Integrating EEMD and ensemble CNN with X (Twitter) sentiment for enhanced stock price predictions." Social Network Analysis and Mining 14, no. 1 (2024): 29.

[24] Shebaro, Muhieddine, Lia Nogueira de Moura, and Jelena Tešić. "Improving association discovery through multiview analysis of social networks." Social Network Analysis and Mining 14, no. 1 (2024): 42.

[25] Khan, Lal, Atika Qazi, Hsien-Tsung Chang, Mousa Alhajlah, and Awais Mahmood. "Empowering Urdu sentiment analysis: an attention-based stacked CNN-Bi-LSTM DNN with multilingual BERT." Complex & Intelligent Systems 11, no. 1 (2025): 10.

[26] Aarthi, E., S. Jagan, C. Punitha Devi, J. Jeffin Gracewell, Shruti Bhargava Choubey, Abhishek Choubey, and S. Gopalakrishnan. "A turbulent flow optimized deep fused ensemble model (TFO- DFE) for sentiment analysis using social corpus data." Social Network Analysis and Mining 14, no. 1 (2024): 41.

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[27] Jayamohan, M., and S. Yuvaraj. "Video-Based Action Recognition of Spatial and Temporal Deep Learning Models." In International Conference on Advances in Data-driven Computing and Intelligent Systems, pp. 379-391. Singapore: Springer Nature Singapore, 2023.

[28] Mahmoudi, Amin, Dariusz Jemielniak, and Leon Ciechanowski. "Characteristics of two polarized groups in online social networks' controversial discourse." Journal of Computational Social Science 8, no. 1 (2025): 22.

[29] Ibañez, Marilyn Minicucci, Reinado Roberto Rosa, and Lamartine Nogueira Frutuoso Guimarães. "Sentiment Analysis in Social Medias for Threats Prediction of Natural Extreme Events." In Encyclopedia of Information Science and Technology, Sixth Edition, pp. 1-23. IGI Global, 2025.

[30] Devi, S. Anjali, M. Sitha Ram, Pulugu Dileep, Sasibhushana Rao Pappu, T. Subha Mastan Rao, and Mula Malyadri. "Positional-attention based bidirectional deep stacked AutoEncoder for aspect based sentimental analysis." Big Data Research 39 (2025): 100505.

[31] https://www.kaggle.com/datasets/abhi8923shriv/sentiment-analysis-dataset

[32] https://www.kaggle.com/datasets/kashishparmar02/social-media-sentiments-analysis-dataset.