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Optimized Sentiment Analysis Framework Using Swarm Intelligence and Ensemble Machine Learning

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Abstract* — Sentiment analysis has become crucial in understanding public opinion across diverse domains like social media, e-commerce, and customer feedback. This paper explores the integration of optimization techniques, particularly swarm intelligence, and ensemble machine learning algorithms to enhance sentiment analysis accuracy and scalability. We propose a framework that leverages the artificial butterfly algorithm for feature reduction and ensemble machine learning for sentiment polarity determination. The effectiveness of the framework is validated using datasets such as IMDB, Semeval, and SST, comparing results. Experimental results demonstrate significant improvements in sentiment analysis performance.

Keywords — Sentiment Analysis, Swarm Intelligence, Ensemble Machine Learning, Artificial Butterfly Algorithm, Feature Reduction, IMDB Dataset, Semeval Dataset, SST Dataset.

I. INTRODUCTION (SIZE 10 & BOLD)

(In recent years, sentiment analysis has emerged as a pivotal tool in understanding public opinion and consumer behavior across various domains such as social media, e-commerce, and customer feedback analysis. This burgeoning field leverages advanced computational techniques, primarily optimization and machine learning algorithms, to extract and interpret sentiment from textual data at scale.

Optimization techniques play a crucial role in refining sentiment analysis models, enhancing their accuracy, efficiency, and scalability. These techniques enable researchers and practitioners to fine-tune algorithms, parameters, and features, thereby optimizing the overall performance of sentiment analysis systems. Moreover, machine learning algorithms provide the foundational framework for sentiment analysis, enabling systems to learn from labelled data and make predictions on unseen text based on learned patterns and relationships.

This introduction sets the stage for exploring how optimization and machine learning intertwine to propel sentiment analysis forward, empowering businesses and organizations to derive actionable insights from vast amounts of textual data. By examining the intersection of these methodologies, we can uncover innovative approaches, challenges, and future directions in harnessing sentiment analysis to its fullest potential.

The process of analyzing digital text to determine if the emotional tone of the communication is neutral, positive, or negative is known as sentiment analysis. Nowadays, businesses deal with enormous volumes of text data, such as emails, customer service chat transcripts, comments and reviews on social media, and reviews. By scanning this content, sentiment analysis tools can automatically determine the author's position on a given issue. Companies use sentiment analysis data to improve customer service and build brand reputation.

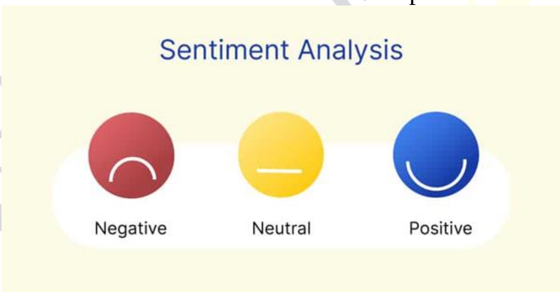

Figure 1 Sentiment Analysis

A. *Which methods are used in sentiment analysis'?*

Software for sentiment analysis uses three primary methods.

Rule-based Approach

Sentiment analysis using the rule-based approach entails locating and rating "specific keywords" according to pre-established lexicons. Lexicons are lists of words that indicate the intention, feeling, and tone of the writer. In order to assess the emotional impact of terms, marketers give sentiment scores to both positive and negative lexicons. To estimate overall sentiment, the software searches sentences for terms that are included in the lexicon, adds up the sentiment scores of those words, and then compares the total score to predefined sentiment bounds.

Example of 'Rule-based Analysis'

Imagine a system where terms like "poor," "highly expensive," and "difficult" are in the negative lexicon and terms like "happy," "affordable," and "fast" are in the positive lexicon. Scores for positive and negative words range from -1 to -10, respectively. To detect subtleties such as double negatives (e.g., not awful as positive sentiment), certain rules are applied. A sentiment score above 3 indicates a positive sentiment, while scores between -3 and 3 denote mixed sentiment.

Pros and Cons of Rule-based Approach

Setting up a rule-based sentiment analysis system is simple, but scaling it up can be difficult. Lexicons must constantly grow as new intent-related keywords appear in text inputs. Furthermore, this method might not be accurate when dealing with statements that are influenced by different cultural situations.

'Machine Learning' (ML) Approach

The machine learning method uses methods like deep learning and neural networks to train software to recognize emotional content in text. To reliably predict sentiment in unidentified data, a sentiment analysis model is developed and repeatedly trained on known datasets.

Training in ML Approach

During training, data scientists use sentiment analysis datasets containing numerous examples. The ML software learns from these datasets to draw conclusions autonomously. Training with diverse examples enables the software to understand how different word combinations influence sentiment scores.

Pros and Cons of ML Approach

ML sentiment analysis excels in processing a wide range of text data with high accuracy, provided it undergoes comprehensive training. However, ML models are specific to the datasets they are trained on, necessitating retraining when applied to different domains.

Hybrid Approach

Hybrid sentiment analysis integrates both ML and rule-based systems to optimize speed and accuracy in contextual intent extraction from text. By leveraging features from both methodologies, hybrid systems enhance overall performance.

Figure 2 Challenges in sentiment analysis

Despite advancements in natural language processing (NLP) technologies, machines still face significant challenges in accurately understanding human language nuances. One such challenge is sarcasm, where sentences like "Yeah, great. It took three weeks for my order to arrive" can confuse sentiment analysis systems due to the ironic nature of the statement. Similarly, negation poses difficulties as well; sentences like "I wouldn't say the subscription was expensive" or across sentences like "I thought the subscription was cheap. It wasn't." can lead to misinterpretations if not analyzed contextually. Moreover, multipolarity in sentences, such as "I'm happy with the sturdy build but not impressed with the color," further complicates sentiment analysis, requiring advanced techniques like aspect-based sentiment analysis to parse out conflicting sentiments towards different aspects of the same entity. These challenges underscore the ongoing complexity in achieving nuanced and accurate sentiment analysis in computational systems, necessitating continued research and development in the field of NLP.

B. Role of Machine Learning in Sentiment Analysis

Machine Learning has fundamentally transformed the landscape of sentiment analysis by providing powerful tools to decipher and classify the rich tapestry of human emotions expressed through text. Through techniques like supervised learning with Support Vector Machines and neural networks, Machine Learning models can discern sentiment with remarkable accuracy, facilitating tasks such as sentiment polarity classification and sentiment intensity analysis. Moreover, the advent of deep learning has enabled the development of sophisticated models like Recurrent Neural Networks and Transformer architectures, such as BERT and GPT, which excel in capturing intricate semantic relationships and contextual nuances inherent in language. These advancements not only enhance the ability to detect sentiment across various domains and languages but also enable the analysis of complex sentiment patterns such as sarcasm, irony, and mixed sentiments within texts. By harnessing Machine Learning, practitioners can unlock deeper insights from textual data, empowering applications ranging from customer feedback analysis and social media monitoring to market research and public opinion analysis. As Machine Learning continues to evolve, it promises further advancements in sentiment analysis, driving innovation and efficiency in understanding and leveraging human sentiment at scale.

Social media has become a ubiquitous platform where billions of individuals connect, interact, and share opinions, experiences, and commentary daily. Extensive research [1–3] underscores the profound impact of social media on modern communication. Sentiment analysis plays a crucial role in deriving insights and indirect inferences from vast datasets. Analyzing text in languages with intricate morphologies, like Arabic, poses significant challenges at multiple levels. Machine learning has emerged as a pivotal component in addressing these challenges. Today, machine learning permeates various aspects of our lives, from everyday tasks such as weather forecasting and document processing to more specialized domains like network management [4], transportation [5], text analytics [6,7], and bioinformatics [8]. The widespread adoption of machine learning across diverse scientific disciplines is driven by its impressive results and predictive capabilities in tackling complex classification problems.

Automated Sentiment Classification: Machine Learning techniques facilitate the automated detection and categorization of sentiment expressed in textual data. By training models on labeled datasets, Machine Learning algorithms learn to recognize patterns in text that correlate with positive, negative, or neutral sentiments. This automation allows for efficient processing of large volumes of text, enabling organizations to extract actionable insights and trends from customer reviews, social media posts, and other textual sources without manual annotation.

Figure 3 Automated Sentiment Classification

Supervised Learning Techniques: When you check the distribution, the process of tracking the distribution of the text is completed. How it works: train and test. We feed the recorded data to the machine learning algorithms for processing. The algorithm is trained with a list of data and provides the desired elements (predefined groups). During testing, the algorithm feeds untested data and classifies them according to the training level. Sent emails are categorized according to their content. Linguistic research, thinking, reflection, and emotional analysis all rely on observation. It can be used for certain applications, such as identifying emergencies by analyzing millions of online messages. This is a needle in a haystack problem. We want smart public transportation to take this situation under control. The class must be trained with high accuracy to detect emergencies in millions of online conversations. Private unemployment, for example, requires years of education, and the creation of a multi-class classification will improve the results of the previous classification to solve this problem.

Figure 4 Supervised Learning Techniques

Unsupervised learning?

Machine learning that derives knowledge from unlabeled data is called unsupervised learning. This means there are no prefixes or categories in the file. The goal of unsupervised learning is to find patterns and relationships in data without explicit instructions. The process of teaching the machine unlabeled or classified data and allowing the algorithm to make decisions based solely on the data without human attention is called unsupervised learning control. In this case, the machine's job is to classify non-uniform objects based on similarities, patterns, and differences, without prior training on the objects. According to the education audit, the absence of a teacher means that the machine does not learn. The machine's ability to detect hidden patterns in anonymous objects is therefore subject to its own limitations.

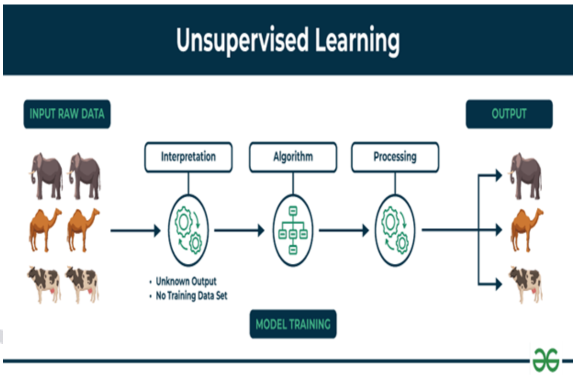

Figure 5 Unsupervised learning

Unsupervised learning to analyze collected animal data and differentiate between many groups based on the characteristics and behaviors of the animals. These clusters may represent different animal species, enabling you to classify the animals without relying on pre-existing labels.

Deep learning Techniques

Deep learning approaches have revolutionized sentiment analysis by leveraging advanced neural network architectures like Recurrent Neural Networks (RNNs), Long Short-Term Memory networks (LSTMs), and transformer models such as BERT and GPT. These models excel in capturing contextual dependencies and semantic nuances within textual data, enabling more accurate sentiment classification across diverse domains. By employing techniques like word embeddings and transfer learning, deep learning frameworks can extract meaningful representations of sentiment from large datasets, addressing challenges such as sarcasm and context-specific expressions. These advancements have broadened the scope of sentiment analysis applications, from social media monitoring and customer feedback analysis to market research and beyond, providing businesses and researchers with powerful tools to glean actionable insights from textual data with unprecedented accuracy and efficiency.

Figure 6 Deep learning Techniques

II. Literature Review

Medhat et al. (2014) [9]: Medhat et al. provide a comprehensive overview of sentiment analysis (SA), focusing on recent advancements in algorithms and applications. They categorize recent studies based on their contributions to SA techniques and discuss emerging areas like transfer learning and emotion detection. Their survey aims to offer insights into the evolving landscape of sentiment analysis, highlighting its growing importance in various domains.

Wankhade et al. (2022) [10]: Wankhade et al. emphasize the increasing significance of sentiment analysis in extracting and analyzing opinions from online platforms like social media. They explore methodologies and challenges within sentiment analysis, aiming to enhance its accuracy and applicability through natural language processing and text mining techniques.

Onan (2021) [11]: Onan discusses sentiment analysis as essential for extracting attitudes and opinions from textual data, particularly focusing on deep learning methods applied to product reviews on Twitter. The study evaluates various word embedding techniques and their impact on sentiment analysis accuracy, highlighting the effectiveness of deep learning models in this context.

Hew, K. F., et al. (2020) [12]: Hew et al. examine sentiment analysis within Massive Open Online Courses (MOOCs), aiming to understand factors influencing student satisfaction using machine learning and hierarchical modeling. Their research identifies key predictors of MOOC success, offering insights to optimize course design and delivery based on learner feedback.

Jain, P. K., et al. (2021) [13]: Jain et al. explore machine learning techniques in consumer sentiment analysis within the hospitality and tourism sector. Their systematic literature review identifies effective methodologies and research gaps, providing a foundation for future studies in leveraging sentiment analysis for business insights.

Hussein et al. (2018) [14]: Hussein et al. survey sentiment analysis challenges and techniques, focusing on analyzing user-generated content from internet platforms. They highlight the complexities of interpreting sentiments and discuss methods to address these challenges, emphasizing the application of sentiment analysis across diverse domains.

Cambria et al. (2017) [15]: Cambria et al. provide a historical perspective on sentiment analysis, discussing its evolution and ongoing challenges. They underscore the need for practical solutions to improve sentiment analysis systems, aiming to benefit both businesses and society through enhanced understanding of human sentiment.

Dang et al. (2020) [16]: Dang et al. review recent advancements in sentiment analysis using deep learning models, focusing on enhancing sentiment polarity accuracy across different datasets. They compare various deep learning techniques and input features to assess their effectiveness in improving sentiment analysis outcomes.

W. Zhang, et al. (2023) [17]: W. Zhang et al. concentrate on aspect-based sentiment analysis (ABSA), categorizing existing literature and highlighting advancements in handling complex sentiment elements. They discuss the role of pre-trained models and future directions for ABSA research, aiming to enhance sentiment analysis capabilities in diverse linguistic and domain-specific contexts.

Onan, A. (2021) [18]: Onan explores sentiment analysis in educational contexts, focusing on MOOC evaluations. The study utilizes deep learning approaches to analyze sentiment in educational feedback, demonstrating superior performance in classification tasks compared to traditional methods.

Chauhan et al. (2021) [19]: Chauhan et al. examine sentiment analysis methodologies for predicting significant decisions based on social media data, particularly focusing on election outcomes. They review existing techniques and propose future research directions to improve prediction accuracy using sentiment analysis.

Elfaik, Hanane and Nfaoui, El Habib. (2021) [20]: Elfaik and Nfaoui discuss challenges in Arabic sentiment analysis, emphasizing the complexities of dialectical variations and implicit expressions. They propose a Bidirectional LSTM Network approach to enhance sentiment analysis accuracy in Arabic, contributing to advancements in this specialized field.it.

III. Objectives

- To develop an optimized sentiment analysis framework for various review datasets (IMDB, Semeval, and SST) using swarm intelligence for feature reduction.
- To enhance sentiment polarity determination accuracy with an ensemble machine learning approach and the artificial butterfly algorithm.
- To compare and validate the proposed framework with Lin et al. (2020)

IV. Methodology

The mechanism for sentiment analysis of textual data is explained in this section. Figure 3.1 illustrates the overall suggested algorithm, which consists of four stages: feature selection, pre-processing, data extraction from datasets, and ‘classification’.

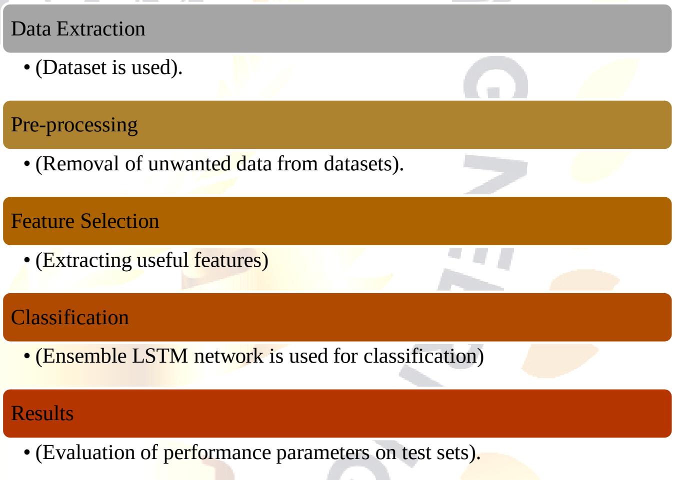

Figure 7 Proposed Flow Diagram

Dataset Extraction

In this section of the research methodology, a dataset is created. For data preparation, data is first collected datasets. In this work, ‘three datasets’ are used i.e., IMDB, Semeval, and SST.

Data Pre-processing

Cleaning the unprocessed data that has been gathered from various sources is essential. We call this stage "data pre-processing." During pre-processing, extraneous phrases like commas and special symbols are eliminated from the datasets because they don't add to the sentiment ratings of the sentences or documents. A clean dataset is created for additional processing after the gathered dataset is examined item by entity and superfluous entities like URLs, special symbols, commas, etc. are eliminated.

Feature Selection

The feature selection procedure for the suggested methodology, which is described below, is depicted in Figure 3.2:

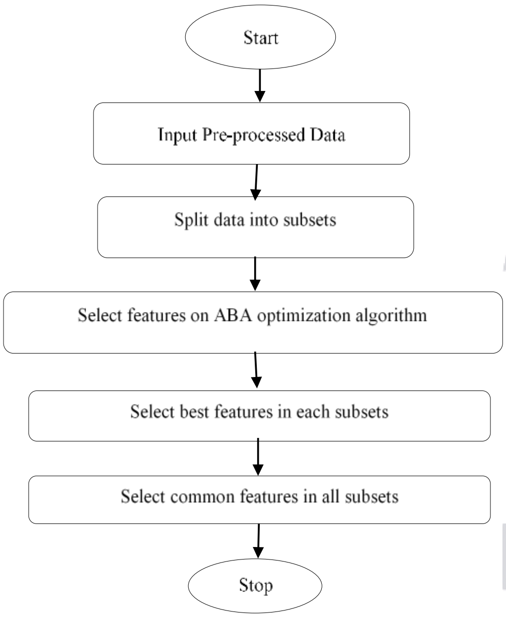

Figure 8 Flowchart of feature Selection

To generate a feature vector based on positive and negative scores from sentiment data dictionaries, each word's sentiment score in a sentence is summed up. This approach calculates the overall sentiment score for the entire sentence.

Inspired by the mate-finding behavior of speckled woods, the Artificial Butterfly Optimization (ABO) algorithm was devised. Speckled woods are butterflies that prefer living on woodland borders where sunlight creates sunspots on trees. In the ABO algorithm, butterflies are divided into two groups based on their fitness: sunspot butterflies, which have higher fitness, and canopy butterflies, which have lower fitness. Each group follows a distinct flight strategy:

Sunspot Mode: Butterflies with better fitness are categorized as sunspot butterflies. They utilize a flight strategy aimed at maximizing exposure to sunspots.

Canopy Mode: Butterflies with lower fitness are canopy butterflies. They employ a flight strategy focused on competing for access to sunspots occupied by sunspot butterflies.

Key rules governing butterflies in the ABO algorithm include:

Male Attraction: Male butterflies strive to fly towards sunspots to increase the chances of encountering female butterflies.

Sunspot Occupation: Sunspot butterflies aim to occupy and maintain positions in desirable sunspots within the habitat.

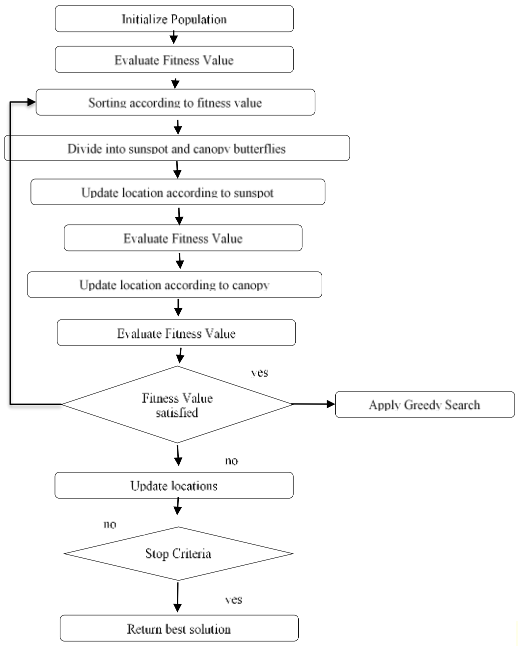

Figure 9 Algorithm for (Artificial Butterfly of Optimization)

Each butterfly flies toward a randomly selected sunspot butterfly as follows:

$$P_i^{n+1} = P_i^n + \frac{P_k^n - P_i^n}{x_k^n - P_i^n})(Ub - Lb)s\beta \qquad (3.2)$$

Where, 'Ub= upper bound'

Lb= 'Lowe bound'

The s 'parameter decreases' linearly from 1 to se , as follows:

$$s = 1 = (1 - S_e)\frac{n}{N} \qquad (3.3)$$

where 'N = Max' iteration

Classification

In this study, 'classification algorithms' are employed to categorize data values into distinct categories. Specifically, an ensemble of LSTM models is utilized to categorize review data into different opinion polarities. Initially, the dataset undergoes preprocessing where it is converted into word vectors. These word vectors serve as the initial input to the classifier. The model leverages both lexicon features and deep aspect-level features extracted from the data to train the classifier for polarity determination. The entire process is depicted in Figure 3.4.

The research involves dataset preparation and simulation using the proposed algorithm. For performance evaluation, ensemble classifiers are employed, which will be detailed further:

Ensemble (LSTM) in Training

After clustering the data samples, they are inputted into a deep classifier network composed of an ensemble of LSTM models. Traditional LSTM networks typically use a softmax layer in their final layer, but its effectiveness can be limited. In this study, the softmax layer is replaced with a random forest classifier to enhance the analysis of protocol data types.

Figure 3.5 illustrates the block diagram of the proposed training architecture. LSTM (Long Short-Term Memory) is a type of recurrent neural network widely used in deep learning. The memory cell, inputs unit, outputs unit, and forget unit are the four primary components that make up each node in an LSTM network (Figure 3.6).

The input, output, and forget units control the data flow used to evaluate the output, while the memory cell unit continuously maintains internal parameter values. To control the information flow via the network, these units—input gate it, forget gate, output gate oto_tot, and memory cell—are initialized at each time sample t.

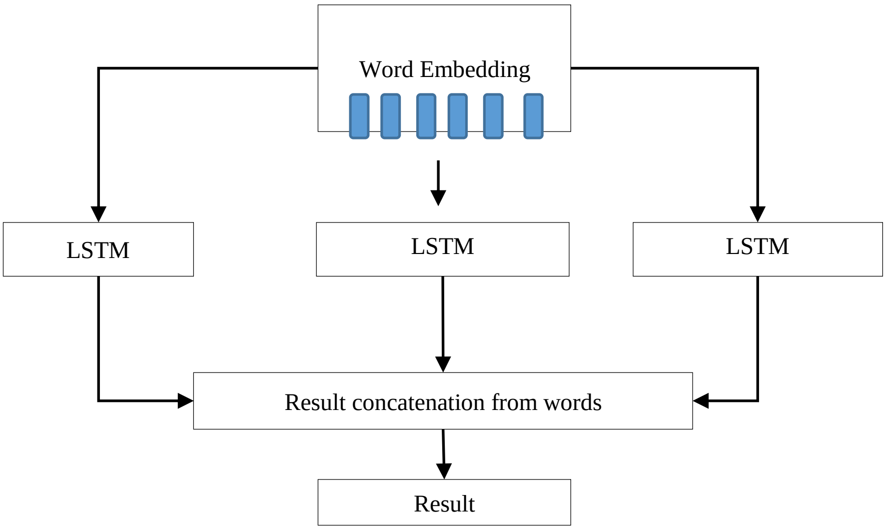

Figure 10 Feature Classification' for 'Proposed Work'

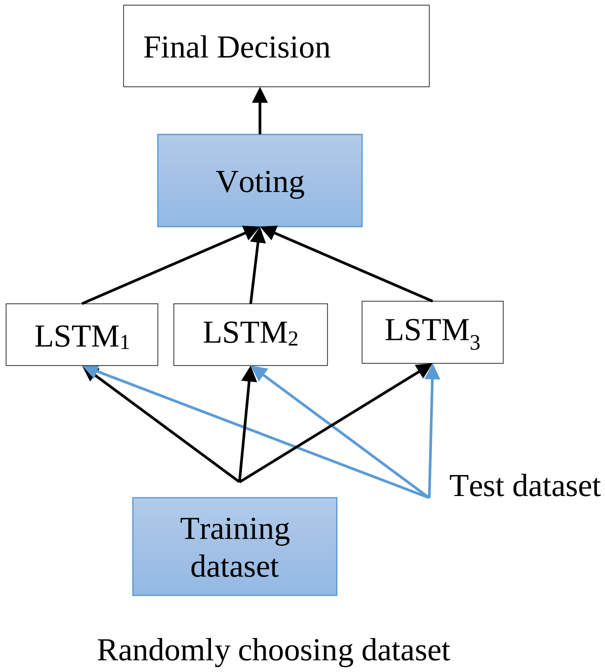

Figure 11 Proposed Training Architecture

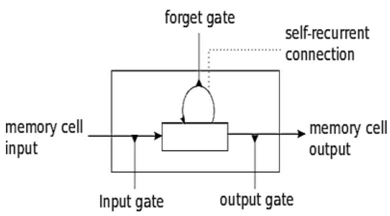

Figure 12 Long Short-Term Memory (LSTM) Units

All these together are used to compute the output of the hidden layer ht as follows:

$$f_t = \sigma(W_f * x_t + U_f * h_{t-1} + b_f) \quad (3.3)$$

$$i_t = \sigma(W_i * x_t + U_i * h_{t-1} + b_i) \quad (3.4)$$

$$\hat{C}_t = tanh(W_c * x_t + U_c * h_{t-1} + b_c) \quad (3.5)$$

$$C_t = i_t * \hat{C}_t + f_t * C_{t-1} \quad (3.6)$$

$$o_t = \sigma(W_o * x_t + U_o * h_{t-1} + b_o) \quad (3.7)$$

$$h_t = o_t * \tanh(C_t) \quad (3.8)$$

In this model, σ\sigmaσ represents the sigmoid activation function, tanh⁡\tanhtanh denotes the hyperbolic tangent activation function signifies the input at time t, Wi, WC, Wf, Wo, Ui , UC , Uf , Uo,Wo are weight matrices controlling the input, and Ui,UC,Uf,UoU_i, U_C, U_f, U_oUi,UC,Uf,Uo are weight matrices managing the recurrent connections. Additionally, bi, bC, bf, bo are bias vectors incorporated into the computation.

V. Simulation And Result Analysis

Implementation Details

In this chapter, implementation details about proposed algorithm is given. In this chapter performance evaluation platform, performance evaluation parameters as well as result analysis is discussed.

Following system configuration to implement proposed methodology are discussed as following:

Hardware Requirement

- Intel Core i5 CPU @ 2.11GHz
- 8 GB RAM
- 1 TB HDD

Software Requirement

- Windows 64 bit OS
- MATLAB R2020a

MATLAB is a sophisticated programming language and platform tailored for technical computing tasks. It boasts a robust set of features and integrates seamlessly with various toolboxes. Offering high-level functionality, MATLAB supports object-oriented programming principles and is equipped with comprehensive debugging and editing tools. Originally developed for research and educational purposes, MATLAB excels in mathematical computations thanks to its extensive library of functions and toolboxes. Its user-friendly graphical interface tools and bundled applications enhance usability across diverse technical fields.

Key aspects of MATLAB include:

- MATLAB facilitates meticulous documentation and step-by-step recording of image processing stages, ensuring traceability and verification in applications like forensic evidence handling.
- Known for its numerical precision, MATLAB guarantees accuracy throughout data processing and analysis phases, surpassing many commercial software solutions.
- MATLAB excels in integrating computation with graphical representation, enabling interactive data exploration and visualization. Being an interpreted language (not compiled), MATLAB offers flexibility for error correction and iterative refinement.

MATLAB supports numerous toolboxes that cater to specialized domains such as digital communication. Examples include the Communication Toolbox and Image Processing Toolbox, which provide essential functions for simulation, analysis, and experimental testing in research and development. These toolboxes bolster MATLAB's versatility and applicability across a wide spectrum of scientific and engineering disciplines.Top of FormBottom of Form

Image vision Toolbox is a package of standard or traditional image processing algorithms. This package provides the toolbox to implement traditional algorithms with set of comprehensive tools, analytical tools, visualization tool, development tools etc. Anyone who wants to perform processing over image then these toolboxes provide image processing, segmentation, enhancement, object detection, etc. This toolbox also supports the GPU implementation and C code generation.

Along with vision toolbox machine learning toolbox and deep learning toolbox are also available that can provide a wide range to application to be implemented and analysis. The most of the application now-a-days are implemented using image processing toolboxes including deep learning toolbox. This helps in improvement of analysis and visualization of data.

Result and Discussions

The analytical and experimental explanation of the suggested sentiment analysis methodology is included in this part. The MATLAB platform is used to run the simulation and assess performance. The study is concentrated on extracting aspect-level features for sentiment analysis from reviews and lexical features for the simulation output. To carry out the simulation, evaluations from various categories are taken out and gathered from datasets, such as the Stanford Sentiment Treebank review data (Richard Socher, 2013) and the movie review data (Andrew et al., 2011). On the other hand, several reviews were gathered via the TripAdvisor website. Performance results are covered in section 4.2.2 and the performance parameters are covered in section

Performance Parameters

Accuracy

It is the one of the most important parameters for determination of efficiency of the classifier. It represents the total correctly classified output either positive or negative data. The mathematical representation of accuracy is represented as in eqn (4.1):

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \qquad (4.1)$$

P (True Positive): This refers to the total number of test samples that are predicted as positive and whose actual labels are also positive.

TN (True Negative): This denotes the total number of test samples that are predicted as negative and whose actual labels are also negative.

FP (False Positive): This represents the total number of test samples that are predicted as positive but whose actual labels are negative.

FN (False Negative): This indicates the total number of test samples that are predicted as negative but whose actual labels are positive.

Precision

Similarly, another parameter for performance evaluation is precision that determines all correct positive classification out of all predicted positive samples. Mathematically, precision is represented as in eqn (4.2):

$$Precision = \frac{TP}{(TP + FP)} \qquad (4.2)$$

Recall

Recall is a further performance evaluation metric that establishes an advantage prediction from all real positive samples. It is expressed mathematically as in eqn (4.3):

$$Recall = \frac{TP}{(TP + FN)} \qquad (4.3)$$

F_Measure

The harmonic mean between recall and precision is termed as f_measure. Mathematically it is represented as in eqn (4.4):

$$(F_{measure} = \frac{2 * Recall * Precision}{(Recall + Precision)}) \qquad (4.4)$$

Result Analysis

The suggested algorithm's performance assessment over datasets, both in and out of optimization, is displayed in Table 1. Based on the result analysis, it was determined that the classification produced the best outcome through optimization.

Table 1: 'Performance Evaluation of Proposed Algorithm'

Algorithms	**'Accuracy'**
With Optimization	94.46
Without Optimization	86.35

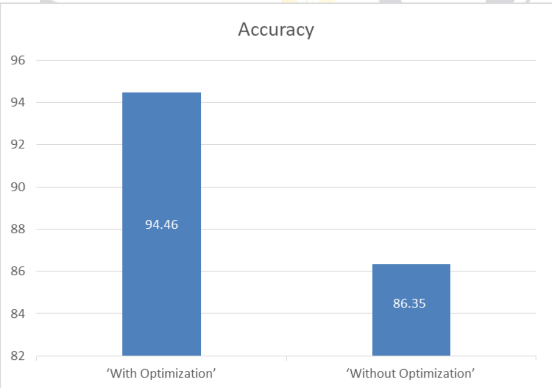

Figure 13 Performance Comparison of Accuracy with and Without Optimization

Table 2 shows the methodology's evaluations of performance that is suggested in this work. In this work, machine learning is used to evaluate sentiment analysis. Recall, measure, accuracy, and precision are used to assess performance. Various testsets are used to demonstrate the model's efficacy.

Table 2: Performance Evaluation on IMDB Data from Different Sources

	IMDB	**Average**	**Semeval**	**SST**
Accuracy	90.62	90.92	90.29	91.85
Recall	91.65	91.923	92.23	91.89
Precision	90.34	90.84	92.20	92
F_Measure	91.49	91.74	90.76	92.97

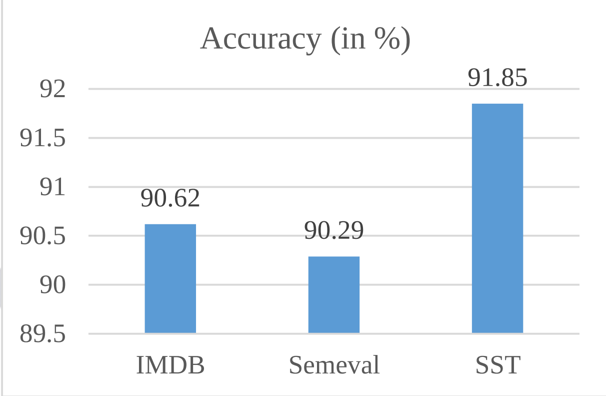

Figure 14 Performance Evaluation of Accuracy

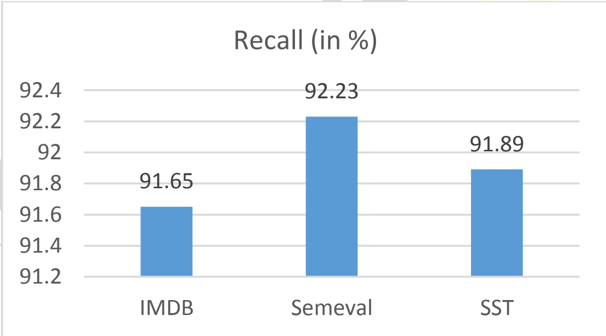

Figure 15 Performance Evaluation of Recall

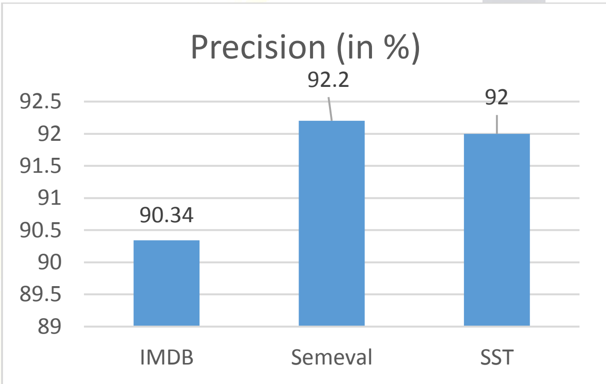

Figure 16 Performance Evaluation of Precision

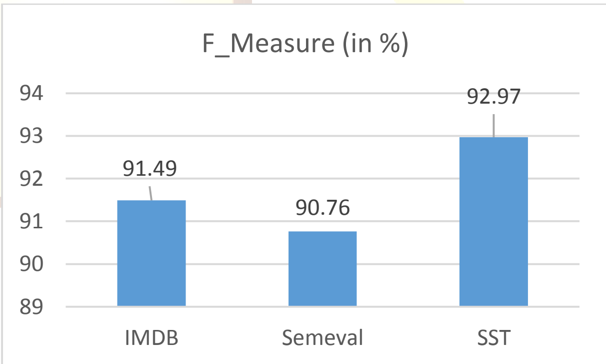

Figure 17 Performance Evaluation of 'Accuracy F_Measure'

The comparative performance evaluation with the research work reported by Lin et al. (2020) is shown in Tables 3 and 4. Bidirectional LSTM network for sentiment analysis on many domains was presented by Lin et al. (2020).

Table 3: Comparative Accuracy Assessment with Previous Research

(Datasets)	(Lin et al. 2020)	(Proposed)
IMDB	90.6	92.63
Semeval	81.5	92.30
SST	74.6	93.86
Average	82.14	92.93

Table 4: Comparative Assessment of Precision with Current Work

Datasets	Lin et al. (2020)	Proposed
IMDB	93.10	92.35
Semeval	71.4	92.21
SST	74.3	94
Average	79.9	93.52

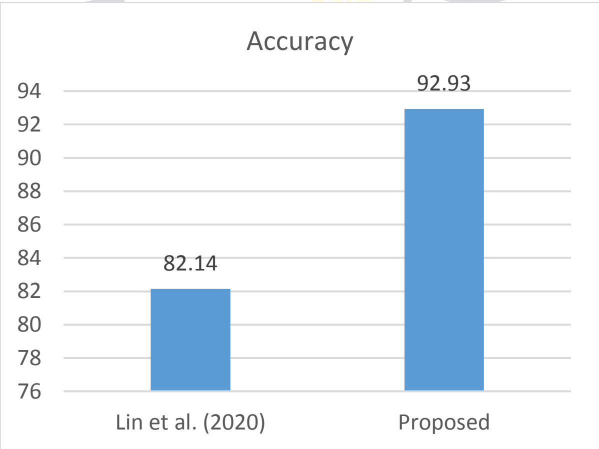

Figure 18 Accuracy Comparative Performance Evaluation

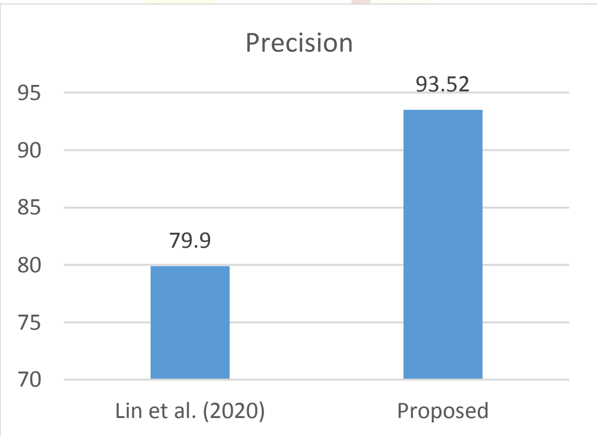

Figure 19 Precision Comparative Performance Evaluation

VI. CONCLUSION

This study introduces an optimized sentiment analysis framework that integrates swarm intelligence for feature reduction and ensemble machine learning for sentiment polarity determination. The proposed framework addresses scalability issues associated with large feature sets in sentiment analysis datasets. Experimental results highlight its effectiveness across diverse review datasets, showcasing improved accuracy compared to existing methodologies. Future research directions include exploring additional optimization techniques and extending the framework to handle real-time sentiment analysis applications.

REFERENCES

[1] Wu, C., Yang, H., He, X., Hu, C., Yang, L., & Li, H., "Principle, development, application design and prospect of fluidized bed heat exchange technology: Comprehensive review." *Renewable and Sustainable Energy Reviews*, *157*, 112023, 2022.

[2] Abhishek Gupta, Prashant Sharma, Research scholar, Associate professor Department of Mechanical engineering UIT, RGPV, Bhopal, "A Review on Heat Exchanger Having Different Types Of Baffles Used To Enhance." The Heat Transfer Rate, © IJRTI | Volume 3, Issue 6 | ISSN: 2456-3315, 2018.

[3] Elshafei EAM, Safwat Mohamed M, Mansour H, Sakr M., "Experimental study of heat transfer in pulsating turbulent flow in a pipe." International Journal of Heat and Fluid Flow, 29, 1029–38, 2008.

[4] Ravindra M.Ghogare1, Vijay G.Gore2, A.S.Shaikh3, "A Review Of Passive Technique Used For Heat Transfer Enhancement In Heat Exchanger," International Research Journal of Engineering and Technology (IRJET) (2018).

[5] Nwokolo, N., Mukumba, P., & Obileke, K., "Thermal performance evaluation of a double pipe heat exchanger installed in a biomass gasification system." Journal of Engineering, 2020, article ID 6762489, 2020. https://doi.org/10.1155/2020/6762489

[6] Kim, Myung-Ho, Van Toan Nguyen, Sunghyuk Im, Yohan Jung, Sun-Rock Choi, and Byoung-Jae Kim., "Experimental Validation of Flow Uniformity Improvement by a Perforated Plate in the Heat Exchanger of SFR Steam Generator Energies 14," no. 18, 5846, 2021. https://doi.org/10.3390/en14185846

[7] Marzouk, S. A., Abou Al-Sood, M. M., El-Said, E. M., & El-Fakharany, M. K., "Effect of wired nails circular–rod inserts on tube side performance of shell and tube heat exchanger: experimental study," *Applied Thermal Engineering*, *167*, 114696, 2020.https://doi.org/10.1016/j.applthermaleng.2019.114696

[8] Pasupuleti, R. K., Bedhapudi, M., Jonnala, S. R., & Kandimalla, A. R., "Computational Analysis of Conventional and Helical Finned Shell and Tube Heat Exchanger Using ANSYS-CFD.," *International Journal of Heat & Technology*, *39*(6), 2021.

[9] Abdul Hussein, S.A., Shbailat, S.J., "Impact of bumpers position variation on heat exchanger performance: an experimental and predictive analysis using an artificial neural network," *J. Eng. Appl. Sci.* **70**, 6, 2023. https://doi.org/10.1186/s44147-023-00176-x

[10] Kumar, S., Dinesha, P., "Optimization of thermal parameters in a double pipe heat exchanger with a twisted tape using response surface methodology," *Soft Comput* **22**, 6261–6270, 2018. https://doi.org/10.1007/s00500-018-3374-8

[11] Bhattad, A., & Babu, S. S., "Thermal analysis of shell and tube type heat exchanger using hybrid nanofluid., *Trends in Sciences*, *19*(5), 2890-2890, 2022.

[12] Basavarajappa, S., Manavendra, G., & Prakash, S. B., A review on performance study of finned tube heat exchanger. In *Journal of Physics: Conference Series* (Vol. 1473, No. 1, p. 012030). IOP Publishing, (2020, February). **DOI** 10.1088/1742-6596/1473/1/012030

[13] Maghrabie, H. M., Elsaid, K., Sayed, E. T., Abdelkareem, M. A., Wilberforce, T., Ramadan, M., & Olabi, A. G., "Intensification of heat exchanger performance utilizing nanofluids." *International Journal of Thermofluids*, *10*, 100071, 2021.https://doi.org/10.1016/j.ijft.2021.100071