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A CONCEPTUAL AQUILA MERGED ARITHMETIC OPTIMIZATION (AIAO) INTEGRATED AUTO-ENCODER BASED LONG SHORT TERM MEMORY (AUE-LSTM) FOR SENTIMENT ANALYSIS

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ABSTRACT
Sentiment analysis is a branch of analysis that uses disorganized written language to infer the opinions and emotions of people's critiques and attitudes toward entities and its features. In order to produce acceptable results, the majority of sentiment analysis models that employ supervised learning algorithms require a large amount of labeled information during the training stage. This is typically costly and results in significant labor expenses when used in practical applications. In this study, an intelligent and unique sentiment prediction system is developed for accurately classifying the positive, negative, and neutral comments from the social media dataset. Data preprocessing, which entails noise reduction, tokenization, standardization, normalization, stop word removal, and stemming, is done to ensure that the data is of a high enough quality for efficient sentiment prediction and analysis. The preprocessed data is then used to extract a mix of features, including hash tagging, Bag of Words (BoW), and Parts of Speech (PoS). Consequently, in order to choose the best features and speed up the classifier, a new hybrid optimization method called Aquila merged Arithmetic Optimization (AIAO) is used. Furthermore, an Auto-Encoder based Long Short Term Memory (AuE-LSTM), an innovative and clever ensemble learning technique, is used to precisely anticipate and classify user feelings based on the chosen data. This study uses a variety of open source social media datasets to evaluate the performance of the suggested AIAO integrated AuE-LSTM model.
Keywords: *Sentiment Analysis, Opinion Mining, Bag of Words (BoW), Social Media, Aquila merged Arithmetic Optimization (AIAO), Auto-Encoder based Long Short Term Memory (AuE-LSTM)*

1. Introduction

Sentiment analysis and opinion mining is an intricate, multidisciplinary artificial intelligence challenge. Mitigating the disparity between humans and machines is its objective (Hossain et al., 2023; R. Singh & Singh, 2023). Thus, the language is mined to identify user emotions, choices, opinions, and desires using a combination of human and technological intelligence. There are several ways to access user-generated information, including discussion forums, blog posts, feedback, and articles. The social network revolution is vital to the collection of data pertaining to public opinion. Opinions from the public are extracted from this information in order to acquire factual and subjective information. Consequently, it is the process of forecasting implicit data regarding the intents, propensity, and preferences of the user. These social networking sites produce millions of bytes of data every week (Kheiri & Karimi, 2023). People and businesses both tend to be curious about the thoughts of others. For example, when someone want to buy a new product, they first look for reviews, or what other individuals think concerning the good or service, and then make their decision based on those reviews. In the same manner, businesses search across the globe for customer testimonials (Costola et al., 2023; Wilksch & Abramova, 2023). The digital ecosystem is overflowing with resources for the same, such as forums and weblog. Feature extraction is a fundamental stage in sentiment analysis and opinion mining, and its general procedure is graphically shown in Fig 1.

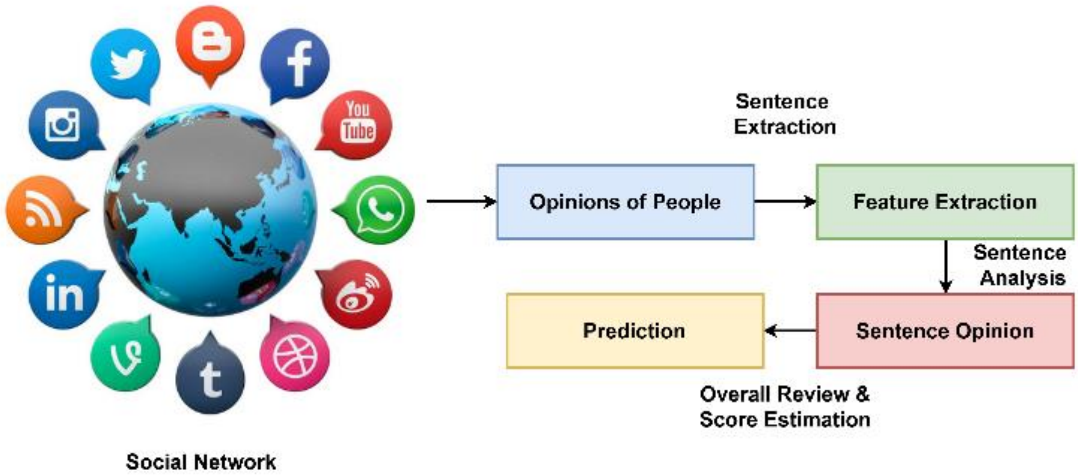

Fig. 1. Typical sentiment analysis framework

With the vast amount of text data (movie feedback, website conversations, posts on Twitter, and other shares in social networks) that is readily available and contains opinions, criticisms, and recommendations, sentiment analysis has experienced an upsurge in interest. The numerous scientific concerns that are brought up by the diversity of the data and the industrial uses of sentiment analysis by the employed systems remain unexplored (Kalbhor & Goyal, 2023; Rahman et al., 2023). The creation of opinion detection techniques based on these fresh viewpoints is a difficult field. In industrial sectors, the sentiment analysis-based opinion detection systems have been created to predict market value variations, target customers and assess the effectiveness of marketing initiatives, while gaining knowledge about the user experience with specific goods or businesses. Feedback from customers is becoming increasingly important in e-commerce platforms like Flipkart, eBay, Amazon, and so on. Potential consumers find it challenging when selecting a product online based on reviews or remarks made by previous customers about the product or supplier (A. V. Yenkikar & Babu, 2023). The assessment methodology for discovering the points of view, attitudes, and feelings of the public concerning any item, product, or vendor is called perception mining or sentiment analysis. The item might describe people, things, or subjects. Sentiment analysis is the process of utilizing machine learning, natural language processing, or statistics to mine, classify, analyze, and describe sentiments or feelings in the form of word-based data. Opinion mining and sentiment analysis are two more interchangeable terms. Opinion mining is a method that analyzes textual data to determine how the public feels about a particular object, while sentiment analysis categorizes and then investigates the sentiment expressed in a script (Dominic et al., 2023; Tufchi, Yadav, Rai, & Banerjee, 2023). Two types of sentiment analysis methodologies, including machine learning and lexicon-based models for sentiment categorization, have been applied in the studies that are currently available. In contrast to lexical approaches, machine learning models have become more and more popular recently because of their effectiveness in sentiment analysis and prediction. However, the main issues with the conventional algorithms were associated with higher prediction complexity, longer training and testing times, and worse efficiency. Therefore, the goal of the proposed work is to create a fresh and distinctive methodological framework for sentiment analysis based on deep ensemble learning. The following list includes the primary contributions to this research study:

- For accurately categorizing the positive, negative, and neutral comments from the social media dataset, an intelligent and unique sentiment prediction system is developed in this work.
- In order to prepare the data with high quality for an effective sentiment prediction and analysis, the data preprocessing is carried out, which includes the operations of noise reduction, tokenization, standardization, normalization, stop word removal, and stemming.
- Then, the combination of features such as hash tagging, Bag of Words (BoW), and Parts of Speech (PoS) are extracted from the preprocessed data.
- Consequently, the novel and hybrid optimization technique, named as, Aquila merged Arithmetic Optimization (AIAO) technique is implemented for selecting the most suited features to increase the speed of classifier.

- Moreover, an intelligent and unique ensemble learning algorithm, called as, Auto-Encoder based Long Short Term Memory (AuE-LSTM) is deployed for accurately predicting and categorizing the sentiments of users according to the selected features.
- For examining the performance of the proposed AIAO integrated AuE-LSTM model, the wide range of open source social media datasets are used in this study.

The remaining sections of this piece of writing are divided into the subsequent units: In Section 2, a comprehensive review of the literature is presented, looking at both deep learning and traditional machine learning techniques employed in this field for sentiment analysis and prediction. Based on the effectiveness and efficiency of the standard studies, it also addresses the drawbacks and difficulties associated with them. Furthermore, Section 3 provides a detailed description of the suggested sentiment classification model. In Section 4, the effectiveness and outcomes of the suggested technique are assessed and verified through the use of many assessment metrics. Section 5 concludes the paper by summarizing its benefits, conclusions, and outcomes

2. Literature Review

Semantic analysis and sentiment prediction techniques based on deep learning and traditional machine learning are reviewed and examined in this part. Additionally, it analyzes each mechanism's benefits and drawbacks in light of its performance and sentiment prediction outcomes.

Zhang et al., (2021) implemented an aspect level sentiment prediction methodology for effectively recognizing the sentiment polarities from the document or sentence. In this study, the word analysis is performed semantically as well as syntactically with the use of fusion mechanism. For this analysis, the Sem-Eval 2014 dataset has been used in this study. *Khan, et al* (Khan et al., 2020) developed a new semantic analysis mechanism for predicting the supporters' of political leaders using social media. In this study, the publicly available twitter dataset has been used to predict and test the results.

Geler et al., (2021) implemented a machine learning based sentiment prediction approach for analyzing the opinions and actions of people from the web sources and social media contents. The purpose of this study is to implement and examine different regression techniques for analyzing the reviews about the food services. The techniques considered in this work are Support Vector Machine (SVM) – regression, Random Forest (RF), Random Tree (RT), Regression Tree Learner (REPT), linear regression, and Multilayer Perceptron (MLP). Furthermore, the accuracy of these methods' predictions is assessed using various error metrics, including Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).

While examining the reviews, additional elements like taste, service, and atmosphere are also taken into account. In comparison to other models, the REPT model is found to provide less error, according to the conclusion. Aziz & Starkey (2019) applied a contextual analysis method for performing sentiment analysis from the unstructured social data. In this paper, the relationship among words are identified by using the Hierarchical Knowledge Tree (HKT), Tree Similarity Index (TSI), and Tree Difference Index (TDI) measures. Moreover, it comprises three levels of operations such as seed words extracted during level 1, and word embedding operations are carried in level 2. Finally, semantic prediction is performed with use of ANN algorithm at level 3. According to the best similarity value, the sentiment is exactly predicted from the given data. However, the performance of classifier need to be improved with high accuracy and efficiency. Zhang et al., (2020) utilized a standard machine learning technique for analyzing the opinions and posts about the pandemic situations from social media. Here, the n-gram and TF-IDF models are used for extracting the features from the given data.

Moreover, several classification approaches including k-nearest neighbors (KNN), RF, SVM, and neural network. Moreover, the public twitter social data has been used as the major source for analyzing the sentiments and opinions. After that, the standard data preprocessing is applied for noise removal and normalization. Then, the evaluation model is applied to predict the sentiment of words with high accuracy. However, the suggested machine learning classifiers consumes more time for training and validation, which could be the major drawback of this study.

In paper (Wankhade, Rao, & Kulkarni, 2022), the authors have used an Artificial Intelligence (AI) based classification approach to categorize the sentiment polarization of online messages. Here, a CNN has been trained for analysis of text-based sentiments and visual based sentiments with the help of vector words and neural network. The dataset was taken from media network of china including text information and various collections of images for the analysis (A. Yenkikar, Babu, & Hemanth, 2022). Analysis of sentiments had been done with respect to various websites of micro-blogging with the aid of learning models and machine learning. In work, an ANN with feed forward technique is applied to analyze the sentiments of micro-blogs and a comparison was done with respect to machine learning methodology. Qiu et al., (2019) stated that their method was more accurate than that of current methods. The deep neural networks are not used in most works in the field of YouTube sentiment analysis. The survey examines important contributions to employ Bayesian classifiers, lexical analysis, clustering, shallow neural networks and other classic data mining approaches according to a sentiment analysis of Blog comments. There was no combination of Blog comments, Sentiment analysis and deep neural network classifiers in the past. In the existing system, only minimal videos had been taken for sentimental analysis. So categorization of the output was not possible with this minimal number of videos. The three indications of categorization such as positive, negative and neutral were taken for analysis in the existing system which did not provide good classification results. Chakraborty et al., (2020) discussed different classification approaches such as SVM, Logistic Regression, Naïve Bayes and SGD for sentiment analysis. The category and the dataset used are public reviews and twitter respectively. A survey was made on discussing various models of deep learning with neural networks and the proposed method solved various types of situations connected with categorization and analysis of sentiments.

Table 1 - Comparative Analysis Among Conventional Sentiment Prediction Approaches

Ref	Methods	Type of dataset	Findings
(Wadawadagi & Pagi, 2020)	Deep Neural Network (DNN)	Amazon review and twitter	Capable of handling large datasets with good accuracy.
(Priyadarshini & Cotton, 2021)	Convolutional Neural Network (CNN)	IMDB, Amazon, and Kaggle	Improved prediction accuracy, and high time for classification.
(Abid, Alam, Yasir, & Li, 2019)	Recurrent Neural Network (RNN)	Twitter	Lower training and testing accuracy.
(Nurrohmat & Azhari, 2019)	Long Short Term Memory (LSTM)	News review dataset	Very low performance rate and efficiency.
(N. K. Singh, Tomar, & Sangaiah, 2020)	Linear Regression (LR)	Social media twitter and Stanford dataset	Good performance in sentiment prediction, and consistency.
(Han, Chien, Chiu, & Cheng, 2020)	Support Vector Machine (SVM)	Twitter dataset	Complexity in kernel estimation, and works well for large corpus data.
(Kalarani & Selva Brunda, 2019)	Artificial Neural Network (ANN)	Social media dataset	Reduced training speed, and high accuracy.
(Bibi, Qamar, Ansar, & Shaheen, 2019)	Decision Tree (DT)	Urdu news twitter dataset	Significant success rate in sentiment prediction.

It is clear from the literature review that several machine learning and deep learning algorithms were used in the previous studies to predict and analyze sentiment. However, most methods have the following drawbacks: poorer accuracy, inadequate testing and training, and mathematical modeling complexity. Therefore, the suggested study intends to analyze user opinions from the social media dataset by implementing a novel sentiment prediction technique.

3. Research Methods

This section includes an algorithmic flow diagram and a comprehensive explanation of the suggested sentiment prediction method. The paper's novel contribution is the development of a distinctive framework for classifying and recognizing the positive, negative, and neutral comments obtained from the social media data. In this study, a novel Aquila merged Arithmetic Optimization (AIAO) technique is created for this aim, which is merged with an Auto-Encoder based Long Short Term Memory (AuE-LSTM) mechanism. Fig. 1 depicts the flow of the suggested AIAO using AuE-LSTM model, which includes the sentiment prediction activities listed below:

- Data collection from social media
- Data preparation and preprocessing
- Feature extraction
- AIAO based feature optimization
- AuE-LSTM based sentiment prediction

Sentiment prediction is performed in this study using social media datasets that were sourced from open source websites. The raw social dataset is typically noisy and contains extraneous data such as stop words, hash tags, and other things. As a result, it undergoes initial preprocessing for data cleansing and preparation. Operations like noise reduction, tokenization, standardization, normalization, stop word removal, and stemming are carried out during this step. Following preprocessing, feature extraction is carried out, encompassing hash tagging, Bag of Words (BoW), and Parts of Speech (PoS). Following their extraction, the AIAO technique is used to optimize the features and lower the dataset's dimensionality. This type of optimization procedure aids in increasing classifier speed while consuming less time. Furthermore, a hybridized ensemble learning method known as the AuE-LSTM algorithm is used to accurately classify positive, negative, and neutral feedback.

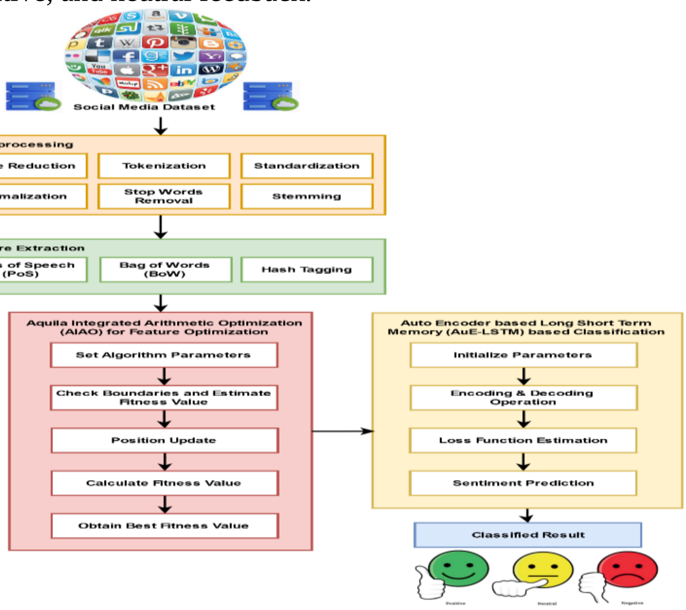

Fig. 1. Flow of the proposed AIAO with AuE-LSTM based sentiment prediction model

Data Preprocessing

Because of the intricacy of the data, data preparation and preprocessing are essential for each social network-based mining system because it directly affects sentiment analysis's efficacy. Typically, the social media information gathered from publicly accessible websites is taken into account when processing data. Since the raw social data contains so many hyperlinks, hashtags, distinctive symbols, emoticons, and other elements, so it considered as the noisiest types of data. Therefore, the following preprocessing techniques have been applied to clean and normalize the original data: noise reduction, tokenization, standardization, and stemming. During noise removal, the operations such as URL elimination, unique symbols or notations elimination, hashtag removal, and stop words removal are all performed to standardize the input data. Stop words are meaningless words in a dialect and have no utility in sentiment analysis, which is used to analyze the grammar structure of a spoken language. Articles, phrases, prefixes, some adjectives, and frequent terms like the, a, and, about, on in, in, and so forth are among the stop words that we have eliminated. In preprocessing, tokenization is the process of dividing lengthy text strings into smaller units called tokens. Paragraphs that can be further divided into small sentences, which are then separated into words, might contain such tokens. To improve the consistency of text preprocessing, the normalization stage involves transforming the content into a standard format. During this process, all content will be changed to be either uppercase or lowercase. Stemming is the stage that comes following tokenization. The process of stemming involves reverting the words back to their fundamental form, or stem form, in order to reduce the total number of word classes or types in the dataset. At the end of preprocessing, the standardized and normalized data is produced as the output, which is further used for sentiment prediction operation.

Feature Extraction

Following the data preprocessing, the features are taken out of the normalized dataset to guarantee a successful sentiment classification. This study uses the bag-of-words (BoW), feature hashing (FH), and POS feature extraction technique to extract and choose text features for appropriate classification. The most basic kind of syntactic analysis for disambiguation of word senses and parsing is offered by POS taggers. Every word in posts has a grammatical marking associated with it, such as an article of speech, phrase, adjective, adverb, conjunction, etc. Adjectives are excellent expressions of sentiment in semantic analysis. Word polarity determines whether an expression is neutral or subjective, and it has been used to inform feature selection in emotion classification. BoW employs an order-invariant array of properties for every single word in a post updates, as well as an exhaustive library of post terms for dictionary purposes. Hash-tagged words are labels of the creator's own thoughts and feelings. Hash tags are incredibly helpful for gleaning emotion from objective and humorous replies. The process of sentiment analysis and prediction is improved by this type of feature extraction.

Aquila Integrated Arithmetic Optimization (AIAO) Algorithm for Feature Selection

The most important and ideal characteristics are chosen using the AIAO technique once the pertinent features have been extracted. This helps to improve the classifier's overall speed with a short training period. Various optimization techniques have been used for feature selection in previous publications, but the conventional approaches typically suffer from low convergence, decreased efficacy, and excessive searching complexity. Therefore, the goal of the suggested study is to put into practice a complex and distinctive optimization algorithm for feature optimization. This technique is developed by integrating the functions of two distinct optimization algorithms such as Arithmetic Optimization Algorithm (AOA) and Aquila Optimization (AO). While the AOA outperformed most existing algorithms, its exploration and exploitation capabilities are not evident when optimizing certain complex issues and individuals within AOA swarms would also quickly become imprisoned in local optima. In this study, we offer a new enhancement that hybridizes the AOA with AO. The AOA still requires development. Typically, the AO technique comprises four predation strategies for finding the most optimal solution, in which soaring over the sky in quest of prey is the initial method. Then, brief glide assault combined with contour flight, slow-attacking low-altitude aircraft approaching its victim, and acquiring prey when on land are the consequent stages of operations. Similar to this algorithm, the AOA also comprises four distinct arithmetic operators for optimization. In the hybrid algorithm, the input parameters such as set of population, maximum number of iterations, dimension and position are initialized at first. The following algorithm illustrates the process of feature selection:

Algorithm 1 – AIAO based feature selection

Input: Extracted features F, set of population P, maximum number of iterations H, and problem dimension d;
Output: Optimized features OF;
Start
Initialize the input parameters;
Initialize the individual positions $M_i(i = 1,2 \dots P)$;
While $(h \leq H)$
Compute Math Optimizer Probability (MOP) and Math Optimizer Accelerated (MOA) as represented in the following equation:

$$MOP\ (h) = 1 - \frac{h^{\frac{1}{s}}}{H^{\frac{1}{s}}}$$

$$MOA\ (h) = Minimum + h \times \left(\frac{Maximum - Minimum}{H}\right)$$

(2)

//Where, h - current iteration, H – maximum iteration, s – sensitive coefficient.
Update the shape of search a and b as illustrated in the following equation:

$$a = (\alpha + 0.00565 \times \delta) \times \sin(-\partial \times \delta + \frac{3 \times \pi}{2})$$

$$b = (\alpha + 0.00565 \times \delta) \times \cos(-\partial \times \delta + \frac{3 \times \pi}{2})$$

//Where, α – count of searching cycles, δ – random integer, and ∂ – constant value.
For $i = 1\ to\ P$
If $|X| \geq 1$
If $q < 0.5$
Update the position $M(h + 1)$ as represented in the following equation:

$$M(h + 1) = M_b(h) \times \left(1 - \frac{h}{H}\right) + (M_g(h) - M_b(h) \times q)$$

Else

$$M(h + 1) = M_b(h) \times LF(d) + M_A(h) + (b - a) \times q$$

//Where, $M(h + 1)$ – individual position, $M_b(h)$ - current best solution, $M_g(h)$ - current mean position, q – random number, $M_A(h)$ - random position of Aquila, d – problem dimensionality, and LF – Levy function;
End if;
Else
If $q < MOA$
If $q > 0.5$
Perform position update as shown in below:

$$M(h + 1) = \begin{cases} M_b(h) \div (MOP + \sigma) \times \left((\mathrm{u} - \mathrm{l}) \times c + \mathrm{l}\right) & w < 0.5 \\ M_b(h) \times MOP \times \left((\mathrm{u} - \mathrm{l}) \times c + \mathrm{l}\right) & otherwise \end{cases}$$

//Where, u – upper bound, l – lower bound, σ – small integer, and c – control parameter;
End if;
End if;
If $q > 0.5$
Perform position update as show in the following equation:

$$M(h + 1) = \begin{cases} M_b(h) - MOP \times \left((\mathrm{u} - \mathrm{l}) \times c + \mathrm{l}\right) & z < 0.5 \\ M_b(h) \times MOP \times \left((\mathrm{u} - \mathrm{l}) \times c + \mathrm{l}\right) & otherwise \end{cases}$$

End if;

End if;
End for;
For $i = 1\ to\ P$
Compute the fitness function $M(h)$;
Update the value of $M_b(h)$;

End for;
$h = h + 1$;
End while;
Return $M_b(h)$;

$OF = M_b(h)$;

AuE-LSTM based Sentiment Prediction and Classification

At this point, sentiment prediction and classification are performed using the selected feature set as the input. In order to achieve this, the AuE-LSTM technique—an intelligent and ensemble-based learning algorithm—is used to provide an accurate sentiment analysis. When compared to other deep learning algorithms, the AuE-LSTM provides an improved prediction accuracy with less computational burden. The architecture model of the proposed AuE-LSTM technique is shown in Fig 3. This auto-encoder implementation combines the advantages of both models for sequential or time-series data by applying LSTM cells in an encoder-decoder architecture layer. The LSTM auto-encoder is used in the suggested model because it has certain advantages over ordinary auto-encoders. For example, an LSTM-AuE can handle sequences as input (time series data), whereas a standard AuE is unable to accept samples in succession as the input information. Furthermore, the typical AE model only accepts input data of a fixed size, whereas the LSTM AE model accepts a wide variety of input lengths. An input layer, one or more hidden layers, and an output layer make up the proposed AuE architecture. The output layer data is generated by the interconnected layers using LSTM cells. In order to compute and assess their influence on following sample data at a different sampling time, hidden layers use samples from several testing times. By combining and simulating these effects as a projected value, the output values will be obtained at the subsequent time point. The suggested model's overall sentiment prediction accuracy is significantly raised with the aid of the AuE-LSTM model.

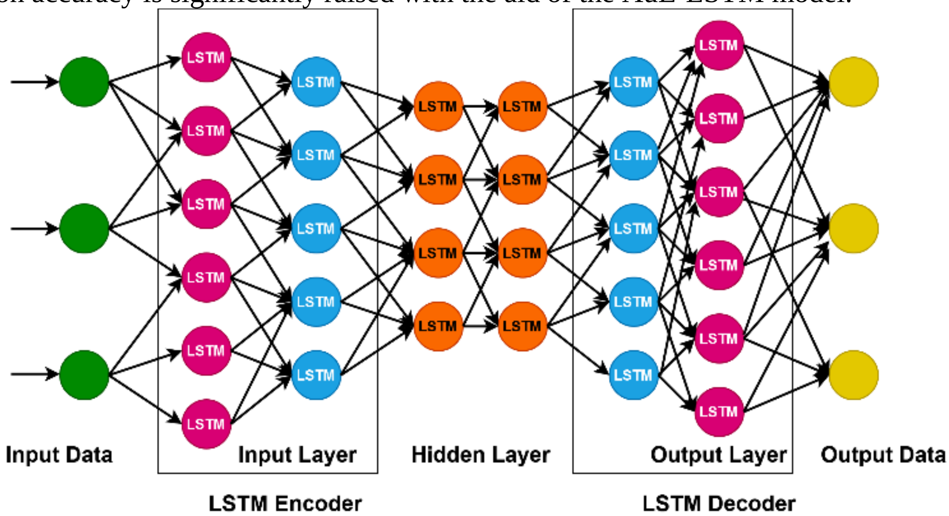

Fig. 3. Architecture model of AuE-LSTM model

4. Results and Discussions

This section outlines the research study's datasets as well as the statistical parameters that have been employed to assess the algorithms. Performance evaluation is a crucial step in the process of machine learning that we must undertake in order to verify the efficiency of the proposed approach. Here, a number of artificial intelligence and machine learning techniques are examined and compared with the proposed model in order to determine if a text is positive or negative. Model performance must be ascertained through evaluation. One of the most popular measures for assessing methods of classification is accuracy. It explains the frequency that an algorithm successfully identifies data. The amount of accurately anticipated data points relative to the total number of data points is known as accuracy. Accuracy can also be expressed as the total of TP and TN divided by the total of TP, TN, FP, and FN. Another well-liked statistic for problems relating to pattern recognition, data extraction, and identification is precision. It can be defined as the quantity of pertinent observations relative to the retrieved values. Additionally, TPs can be used to calculate precision in relation to the overall amount of TPs and FNs together. The ratio of real events that were beneficial to positively expected events functions as a visual representation of sensitivity. Another name for it is recall. Additionally, the actual value can be used to compute sensitivity in relation to the aggregate of TP and FN. The ratio of real negative to expected negatives can be utilized to define specificity. Moreover, TNs would compute specificity in relation to the overall amount of TN and FP. The F-1 score is a commonly used metric for assessing the accuracy of an algorithm on a dataset. The models' accuracy, precision, recall, sensitivity, specificity and F1-score are assessed using standard metrics, where TP stands for true positive, TN for true negative, FP for false positive, and FN for false negative, as demonstrated in the following equations:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN}$$

$$Precision = \frac{TP}{TP+FP}$$

$$Recall = \frac{TP}{TP+FN}$$

(11)

$$Sensitivity = \frac{TP}{TP+FN}$$

$$Specificity = \frac{TN}{TN+FP}$$

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

The performance of the suggested and traditional sentiment prediction models is contrasted in Fig. 4 using the metrics of recall, f1-score, and accuracy. Generally, the classifier's overall accuracy rate is used to evaluate its efficacy and enhanced performance. The results of this comparison study have been tested and evaluated using the publicly available, open-source dataset known as IMDB (Chiny, Chihab, Bencharef, & Chihab, 2021). The suggested AIAO integrated AuE-LSTM model performs better than alternative classification strategies, according on the prediction findings.

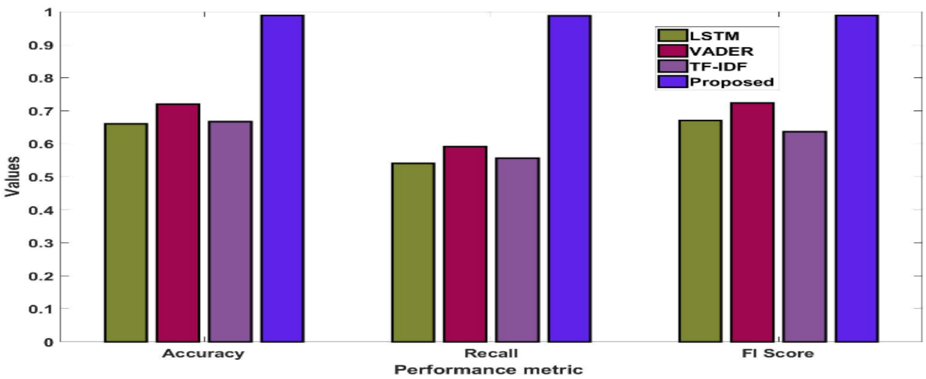

Fig. 4. Comparative analysis with feature extraction models

Similarly, using the IMDB dataset, Fig. 5 compares and validates the most popular machine learning techniques for sentiment prediction. The general-purpose classification techniques that are widely employed in several prediction application systems are LR, KNN, RF, SVM, and NB. This study compares the proposed existing classification methodologies to assess the effectiveness of the proposed AIAO integrated AuE-LSTM model. All things considered, the prediction results show that the suggested AIAO integrated AUE-LSTM performs better than alternative classification strategies with excellent results.

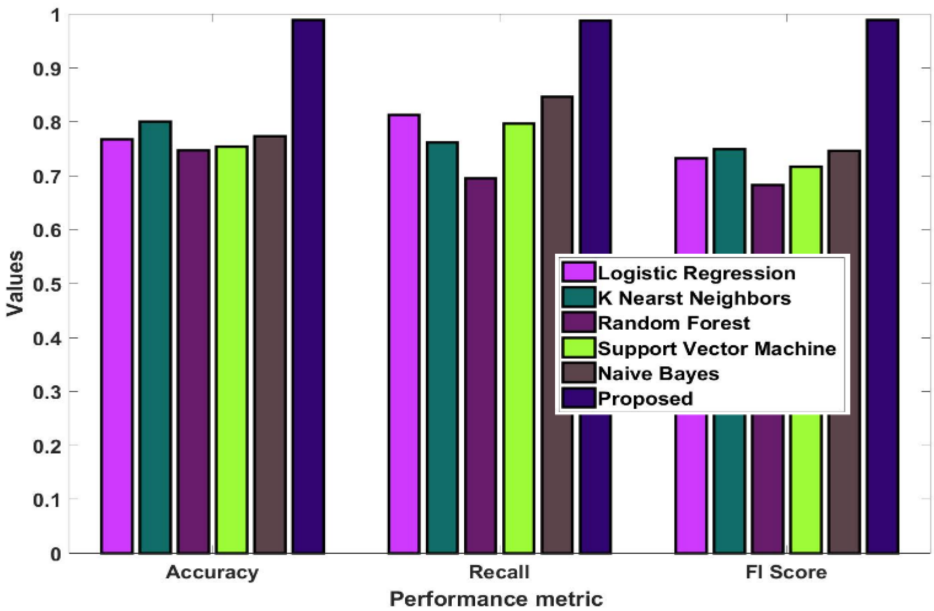

Fig. 5. Comparative Analysis With Other Machine Learning Techniques

Furthermore, utilizing a variety of social media datasets, Figures 6 and 7 contrast the most recent cutting edge deep learning classification techniques with the suggested AIAO integrated AuE-LSTM model. Parameters like accuracy and precision are considered for this analysis. Additionally, major open source review datasets including sentiment 140, airline tweets, SemEval, IMDB, Cornell movie, book, and music reviews are used in this investigation to verify the effectiveness of the suggested AIAO integrated AuE-LSTM approach. When compared to other deep learning classification methods (Dang, Moreno-García, & De la Prieta, 2021; Goularas & Kamis, 2019), the suggested model offers higher accuracy and precision values, according to the overall comparison.

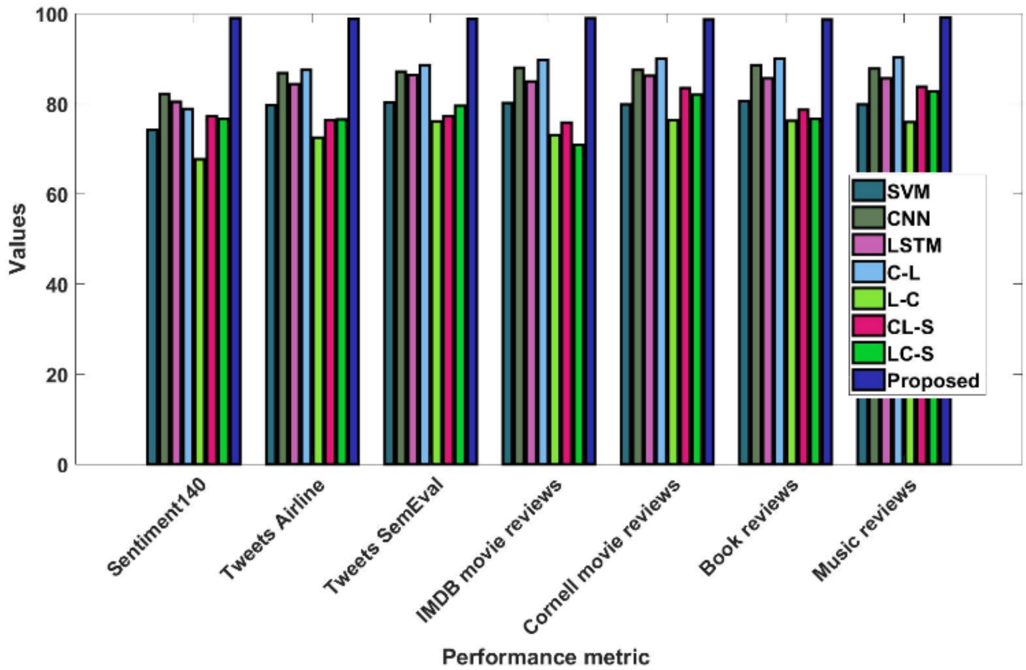

Fig. 6. Accuracy Analysis Using Different Social Media Datasets

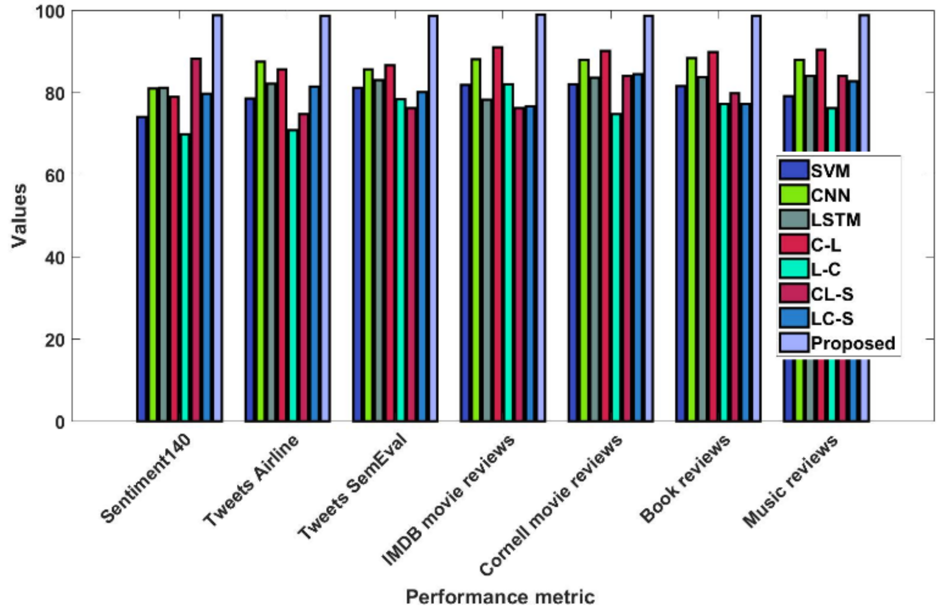

Fig. 7. Precision Analysis Using Different Social Media Datasets

The Area under Curve (AUC) performance of various deep learning methods for sentiment analysis and prediction is compared in Fig. 8. The LSTM and hybridized LSTM approaches are taken into consideration for comparison analysis in this work. This comparison shows that the suggested AIAO integrated AuE-LSTM model performs better than alternative deep learning methods with higher AUC.

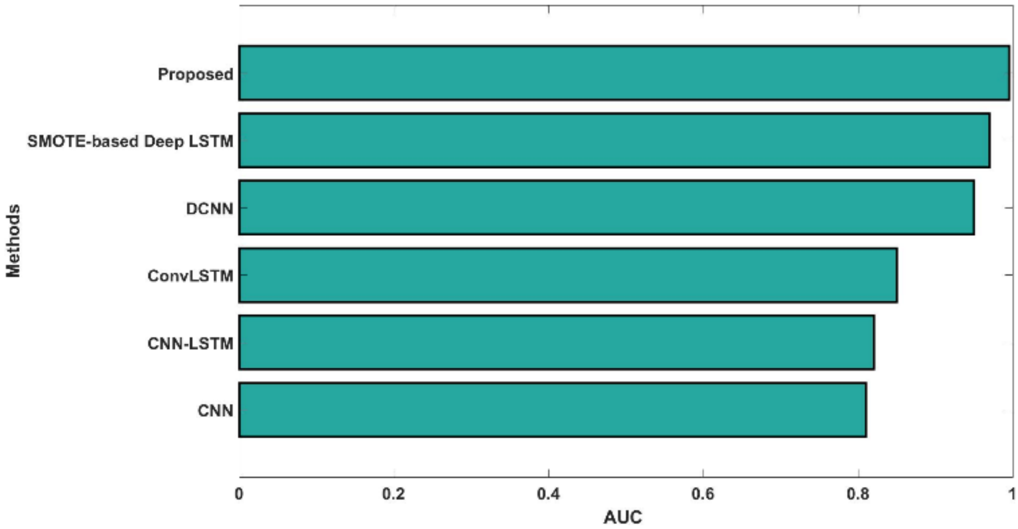

Fig. 8. Comparative Analysis with Other Deep Learning Techniques Based On AUC

The kappa and Root Mean Squared Error (RMSE) values of the suggested AIAO integrated AuE-LSTM and conventional deep learning approaches, respectively, are validated in Figures 9 and 10. In addition to accuracy, kappa and RMSE are regarded as the most crucial critical parameters for evaluating the classifier's performance. This comparison analysis shows that the suggested sentiment prediction system outperforms alternative models with higher kappa values and lower error rates. The efficiency and sentiment prediction accuracy of the proposed classifier in this work are significantly boosted with appropriate preprocessing and feature extraction techniques. Furthermore, using the movie review dataset, as illustrated in Fig. 11, the overall effectiveness of the most recent state-of-the-art model techniques is verified and contrasted with the suggested technique. When compared to other models, the results show that the total prediction performance rate and accuracy have increased to 99%.

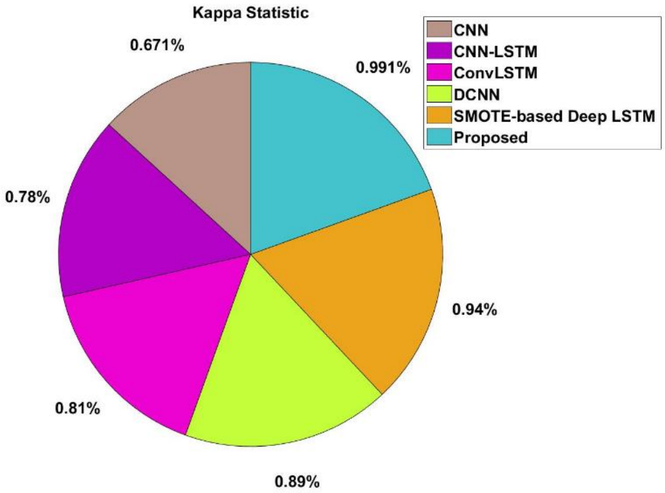

Fig. 9. Kappa analysis

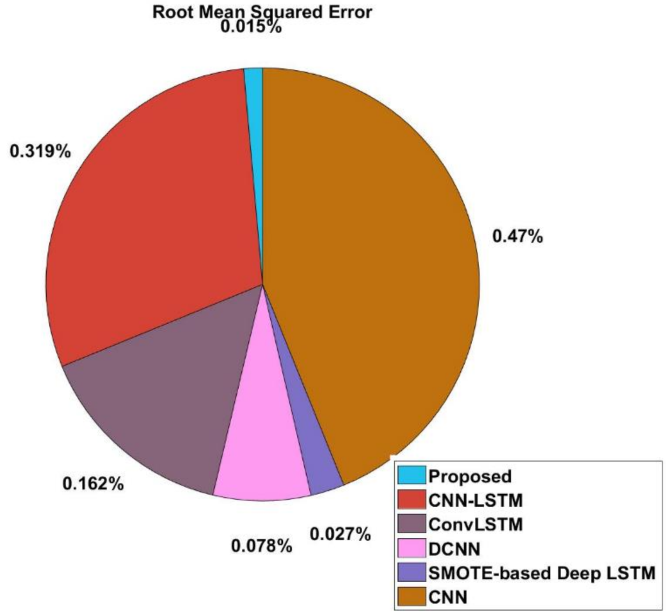

Fig. 10. RMSE analysis

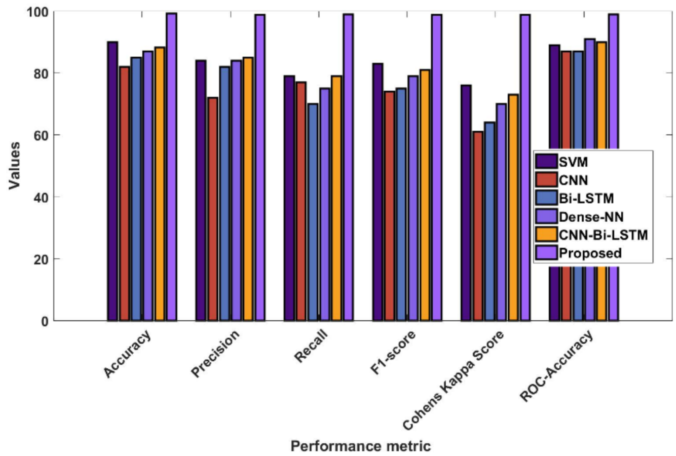

Fig. 11. Overall Performance Analysis with Movie Review Dataset

Tables 2 and 3 use the Amazon and movie review datasets, respectively, to compare the suggested technique with a few different machine learning and deep learning techniques. As a result, Table 4 uses the Stanford and Twitter datasets to evaluate the effectiveness of many categorization strategies integrated with feature extraction models. The suggested system achieves a significant improvement in sentiment prediction performance by combining the AIAO model with an ensemble deep learning technique.

Table 2 - Comparative Analysis with Several Deep Learning Models Leveraging Amazon Dataset

Methods	Accuracy	Precision	Sensitivity	Specificity	F1-Score
KNN	77.9	83.5	86.7	92.8	85
NN	89.7	90	90	91.5	90
CNN	92.7	92.2	91.8	91.3	92.8
LSTM	90.5	91.2	89.7	92.9	91.5
CNN-LSTM	94.5	93.9	92.5	92.5	93.1
CNN-LSTM-GS	96.4	94.3	93.3	94.9	93.9
Proposed	99.1	98.8	99	98.9	99

Table 3 - Comparative Analysis with Several Deep Learning Models Leveraging Movie Review Dataset

Methods	Accuracy	Precision	Sensitivity	Specificity	F1-Score
KNN	88.9	89.6	89.1	91.8	88.9
NN	89.2	91.8	91.1	92	91.1
CNN	92.7	91.8	92	92.7	92

LSTM	91.5	90.9	92	91.9	91
CNN-LSTM	93.8	92.9	93.6	92	92
CNN-LSTM-GS	97.8	98.2	98.9	99	97.2
Proposed	99.1	99	98.8	98.9	99

Table 4 - Comparative Study Based On Accuracy Using Twitter And Stanford Dataset

Methods	Twitter corpus data	Stanford data
NB	53.77	48.45
SVM	49.71	45.23
RF	54.51	51.37
LR	55.12	52.23
NB + PoS	83.13	80.12
SVM + PoS	83.27	81.34
RF + PoS	81.15	78.34
LR + PoS	79.45	76.45
NB + BoW	79.82	71.31
SVM + BoW	82.43	67.41
RF + BoW	79.24	66.57
LR + BoW	77.45	64.90
NB + HT	54.25	54.32
SVM + HT	49.75	47.63
RF + HT	55.64	47.63
LR + HT	56.94	55.71
Proposed	98.8	99.21

5. Conclusion

The main purpose of this paper is to develop an intelligent and unique sentiment prediction system is created for accurately classifying the positive, negative, and neutral comments from the social media dataset. This study uses social media datasets that were obtained from open source websites to do sentiment prediction. The unprocessed social dataset is usually noisy and includes irrelevant information like hash tags and stop words. It therefore goes through preliminary preprocessing for data preparation and purification. This step includes tasks like stemming, stop word removal, standardization, normalization, noise reduction, and tokenization. After preprocessing, feature extraction is performed, which includes parts of speech (PoS), bag of words (BoW), and hash tagging. The AIAO technique is used to optimize the features and reduce the dimensionality of the dataset after they are extracted. This kind of optimization process helps to speed up classifiers in a shorter amount of time. Moreover, the AuE-LSTM algorithm, a hybridized ensemble learning technique, is employed to precisely categorize positive, negative, and neutral feedback. The performance of the proposed AIAO integrated AuE-LSTM model is examined in this study using a variety of open-source social media datasets. The proposed system combines an ensemble deep learning method with the AIAO model to obtain a notable improvement in sentiment prediction performance. The results demonstrate that the overall prediction performance rate and accuracy have increased to 99% when compared to other models.

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