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Understanding Public Opinions on Social Media About ChatGPT – A deep Learning Approach for Sentiment Analysis

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ABSTRACT

User-generated multimedia content—photos, text, videos, and audio—is becoming more and more common on social networking sites to allow individuals to express their thoughts. One of the largest and most advanced social media platform discussing ChatGPT is Twitter. This is because Twitter updates are constantly being produced and have a limited duration. The deep learning method for sentiment analysis of Twitter data about ChatGPT evaluation is presented in this research. This study used 4-class labels (sadness, joy, fear, and anger) from public Twitter data stored in the Kaggle database. The proposed deep learning strategy significantly improves the efficiency metrics determined by the use of the attention layer in current LSTM-RNN approaches, increasing accuracy by 20% and precision by 10-12%, but recall only 12-13%. Out of 18000 ChatGPT-related tweets, positive, neutral, and negative sentiments accounted for a respective 45%, 30%, and 35%. It is determined that the suggested deep learning technique for ChatGPT review sentiment categorization is effective, realistic, and fast to deploy.

Keywords: Categorization, Deep Learning, ChatGPT, Sentiment Analysis.

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INTRODUCTION

An artificial intelligence (AI) Chabot named ChatGPT has astonishing competence, sensitiveness, and usefulness when it comes to naturally understanding and producing human language [1] . The *OpenAI*[1] foundation's cutting-edge computational language AI model, GPT-3 (Generative Pretrained Transformer 3), which can make text that resembles human speech, is used in ChatGPT. Contrary to conventional catboats, ChatGPT prohibits improper queries and disputed incorrect answers [2]. It also recalls whatever the user stated previously in the interaction for subsequent inquiries. ChatGPT offers responses, approaches, and explanations to challenging issues, providing possible solutions to layout issues, code creation, and optimizing queries [3]. Considering the benefits, ChatGPT has over conventional catboats; it has over one million customers in the first week of its existence, outpacing other well-known online platforms like Netflix, Facebook, and Instagram in terms of adoption rates [4]. Additionally, many analysts believe ChatGPT will overtake Google shortly [5].

Early users of ChatGPT predict it will ultimately supplant several knowledge creation-related professions, including developers, instructors, playwrights, and journalists [1]. For instance, it has been shown that ChatGPT has the potential to deliver outstanding responses to a range of problems, such as resolving coding problems and creating precise answers to test questions [6]. "Sentiment analysis" investigates personal information derived from human sentiments to determine a person's viewpoint toward a given subject or the larger context of an event [7]. People can now express their opinions, emotions, and thoughts regarding everything due to the growth of social networking sites [8]. Sentiment analysis or sentiment mining is the computer investigation of people's opinions, feelings, emotions, evaluations, and perspectives towards entities, including products, offerings, businesses, individuals, problems, concepts, and characteristics [9]. When analyzing Twitter data, deep learning systems might help recognize sentiments. Still, there must be a technological problem regarding how deep learning algorithms may be modified and tweaked to achieve high efficiency, considering the challenges associated with textual analysis.

According to [10], it is essential to comprehend how people perceive things. For instance, a human feeling assessor could show corporations that customers feel comfortable purchasing goods they believe would be crucial in a previously unseen period. According to [11], considering social media emotions might aid organizations in reevaluating their company's framework since consumer exposure to news and knowledge may cause an organizational shift. Different methods for assessing user sentiment in social media information have been reported in earlier publications [12] , [13] , [14] , [15].[16]explain how a hybrid machine learning method might be used, for example, to categorize customer sentiment as positive or negative.[17] Use natural language processing (NLP) to examine customer sentiment on set of user analysis.

[18] Employ a Bayesian graphical model to assess Twitter data. This techniques, nevertheless, may be computationally hard, over-due, only sometimes offer high accuracy. Additionally, Twitter is a well-known and significant social networking small –-blogging platform [19]. With Twitter's growing appeal, academics and professionals increasingly utilize Twitter data to gather new consumer information [20]. Twitter is a social networking website that was established in 2006 because of its absence of limitations and regular posting. Tweets are the name for messages, and a tweet can only be 140 characters long. Due to the character's restriction and widespread use of Twitter for expressing thoughts on many topics, Twitter data is an increasingly common choice for text analysis employment. It is possible to get a sense of people's emotional states and the causes of those feelings by retrieving text from Twitter and analyzing individual tweets [21]. Automatic emotion recognition from tweets is

challenging due to the complexity of human emotions and the nature of Twitter data. Different learning techniques, such as lexicon-based [22], machine/deep learning [23], a combination of linguistic and machine learning [24], and concept-based learning approaches [25], and others, are used by sentiment analysis systems to extract sentiment from textual input. The study of sentiment has grown in significance for machine learning applications. Particularly during the present COVID-19 pandemic, social media sentiment analysis has been one of the primary areas of research [26]. In these studies, the evaluation of social sentiment analysis has been the main focus of obtaining knowledge for developing suitable healthcare solutions. In the current study, sentiment analysis of Twitter data related to public evaluation and understanding of the ChatGTP was conducted using a deep learning approach. Further investigation is warranted since deep learning systems with racially mixed observation mechanisms, as suggested in this study, exhibit great promise for sentiment analysis. This article discusses the Twitter dataset that fills this research gap. Also introduced are the LSTM and recurrent neural networks (LSTM-RNN), which map features utilizing the attention layer. We test the method using a publicly accessible dataset of tweets and categorize the tweets according to different attitudes.

To the best of the authors' knowledge, no previous approaches have implemented Weighting features with attention mechanism using semantic sequences with LSTM the suggested deep learning strategy, especially in understanding sentiments from Tweets related to ChatGTP. The main goal is to use attention learning with LSTM to improve efficient weight by word semantic relation. This study made a sentiment analysis on Twitter related to ChatGPT. Overall, this study provides a brief evaluation of several approaches that could be used to look at user comments regarding ChatGPT that have been posted online. In the next section, related work will be examined. Afterward, research methods will be explained, and findings and discussion will be stated. Finally, conclusions will be discussed along with limitations and future studies.

LITERATURE REVIEW

Since ChatGPT is an emerging technology, we have yet to find much comprehensive information about this. However, studies have been conducted on the GPT family of text-generating AIs, such as GPT-2 and GPT-3. Additionally, we discovered sufficient studies on Twitter data mining to examine user sentiment. Consequently, in the parts afterward, we discuss a few incredibly comparable studies to the current research.[27] Examined Twitter data to determine how people felt regarding the Internet of Things (IoT). They employed sentiment evaluation and topic modeling to identify prevalent subjects and the general public's attitudes regarding every question. They found that, compared to other IoT categories, consumers have good opinions regarding IoT and are more intrigued by business and technology. [28] Created the Robustly Optimized BERT Pre-training Method (RoBERTa) to study public opinion on hybrid work arrangements using tweets. Many customers support a combined work framework, according to the RoBERTa. Another investigation [29] claimed that movie box office performance could be forecast via Twitter temporal data mining. The researchers proposed a time-varying product popularity algorithm and an assessment prediction framework to indicate user satisfaction and consumer interest in films. Parallel to this, [30] prediction model were proposed for estimating the outcomes of Pakistan's political election. The authors' algorithm identified outcomes from Twitter data with 98% effectiveness and precision compared to other approaches. [31] Merge the CNN and RNN frameworks for sentiment analysis. The results show that the technique can significantly boost classification efficiency [32]. [33] Analyze SentiStrength, NLTK, Stanford, and Alchemy match hand sentiment tagging as examples of sentiment analysis algorithms. According to the researchers, these tools are different from manual labeling. However, it is found that NLTK performs better. On data gathered from Twitter,[23] use SVM to analyze sentiment. Using the TF-IDF technique, two SVM models are used to identify the feelings after obtaining characteristics. In this sense, we find that linear

SVM is more accurate than kernel SVM. [34] Use machine-learning techniques to classify positive and negative reviews. [35] Study enhanced propagation of information across layers of neural networks for sentiment analysis. [36] Combined SVM classifier with SentiWordNet (SWN) based feature vectors for sentiment analysis of Twitter dataset. The hybrid strategy using machine learning and lexicon-based approaches is noted being quite effective by [37], who use multilevel machine learning to extract sentiments from opinions about HPV vaccines on Twitter. With the help of 23 variables and an analysis of 280,000 tweets, [38] predicted sensitive tweets. They use auto-encoders enhanced by word-encoding techniques, individually categorize tweets, and model the susceptivity of different tweets using RNN. They note that softmax and ReLU architecture achieves a high degree of efficiency in tweet identification. The model is confirmed using several activation features, including sigmoid, softmax, and ReLU [39]. with a sensitive nature. CNN's ability to conceptualize semantics from training data is tested by [40], who also point out some of the model's shortcomings. This study is the inaugural attempt to analyze feelings in ChatGPT data and provide feedback. By presenting an overview of consumers' initial reactions to this most recent technology, we add to the literature. Using an LSTM-RNN technique may enhance efficiency during sentiment analysis by improving the ability to conceptualize phrase sequences. Therefore, in this paper, we propose a deep learning method. Sentiment analysis to understand audience perception of ChatGTP on social media.

METHODOLOGY

The dataset, which included more than 18000 tweets, was compiled and tested using the proposed method. To pinpoint precise and accurate feelings about how the general public regarded and interpreted the ChatGPT, the study focused on sentiment analysis of tweets. We collected tweets from March 1, 2023, through March 5, 2023. Only those with the term "ChatGPT" were considered when we gathered the tweets. Additionally, we got solely English-language tweets. The dataset additionally contains distinct columns for user id, location, and other data in addition to the tweet and user ratings, such as the number of people who designated the tweet as a favorite. The tweet content and the user ratings, sometimes known as the "user likes" portion, are two of these to which we devote special attention. Evaluations with a user-favorite column value of 0–100 are deemed unfavorable, 100–2000 are considered impartial, and reviews with a value of 2000 or higher are deemed favorable. Such categorization labels and the attributes created are the specimens given to the classification methods utilized in this study, as detailed in the stage below. The first phase in the current study is to clean and preliminary processing of the written information to eradicate duplication while performing precautions to ensure safety: the appearance of both uppercase characters has been changed to lowercase; all internet slang has been erased; all sentences which effectively omitted in the paragraph, like an a, as, etc., gap have been eradicated; redundant terms have been compressed; and the text of the hashtags has been left isolated. The second step then comprises extracting features by (a) listing term incidence alongside keyword frequency, sorting them while avoiding grammatical errors like typos, and (b) analyzing the parameter matrices using deep learning-based categorization technologies.

The Term Frequency-Inverse Document Frequency (TF-IDF) is determined below applying the formulas given in [42–44]:

$$t\,f\,id\,f\,(t, d, D) = t\,f(t, d) \times id\,f\,(t, D) \qquad (1)$$

Where t f (t, d) = Term frequency; id f (t, D) = Inverse document frequency.

Steps in LSTM-RNN

As was already mentioned, this research aims to investigate the method of DL using attention layers to comprehend the precision of sentiment categorization from tweet information. There are hence certain computation phases of a suggested LSTM-RNN architecture. Initially, convolution is there for attributes. Public opinion on ChatGPT tweets is incorporated into the LSTM-RNN model during this time. The goal of this step is to take important semantic components out of the term's order. The LSTM-RNN model also generates feature vectors and establishes the temporal relationship between features. In order to train the dataset, A second set of labels with values corresponding to the expressed emotions (fear = 0, sadness = 1, anger = 2, joy = 3) is also considered. The goal is to create a matrix layer that can be input to the LSTM-RNN. In order to provide results for sentiment analysis, taking into account that the assignment of emotion labels is random. RNN model is shown in Figure 1.

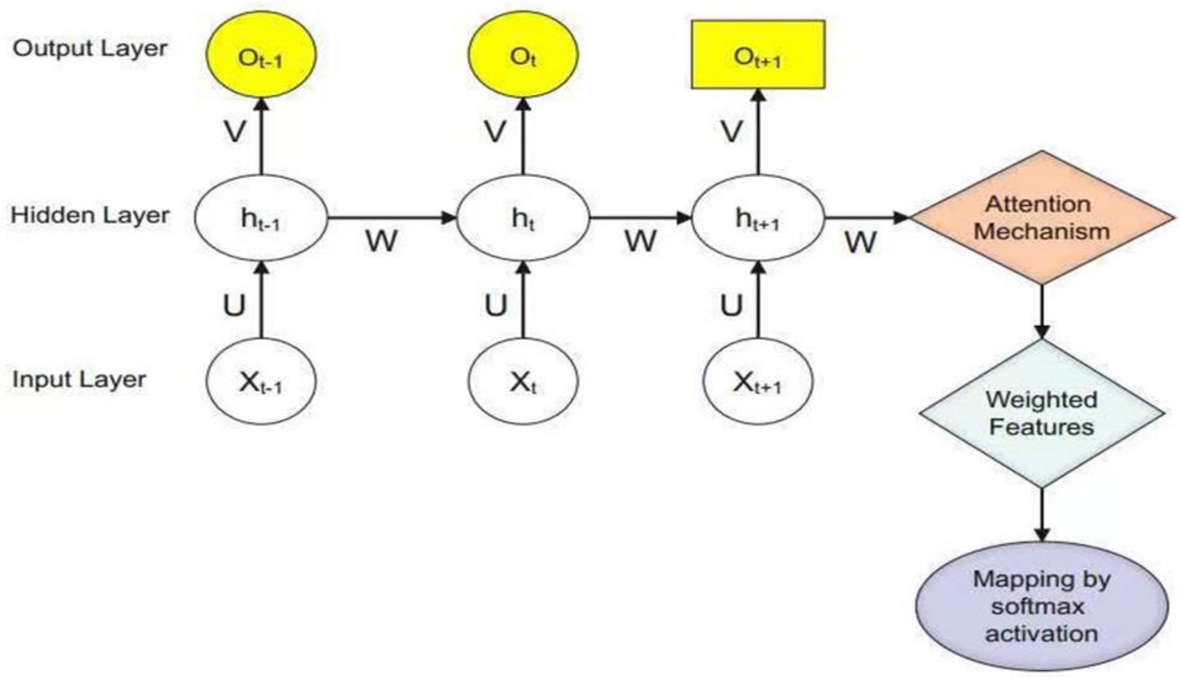

Figure 1: A graphical model of RNN and presented change

Figure 1 shows that the RNN model takes a sequence of pixels' x = x1, x2, ..., xn generates hidden states H = H1, H2. . ., Hn and indicates O = O1, O2. . ., Turn it on as follows. [41], [42]:

$$Ot = \sigma(Wt * Ht = bt) \quad (2)$$

$$H_t = \sigma(WHt - 1 * Ht + Ht - 1 + Wxt * HtXt + bHt) \quad (3)$$

The angle between the output unit Ot and the hidden unit Ht is expressed by WHtOt. In this case, Ht1 designates the hidden unit of the sequence t − 1 pixels. bHt and bt are biased. WH t −1 Ht is the weight vector from Ht-1 to Ht for sequence time t.The graphical depiction for RNN in Figure 1 displays the changed composition of the LSTM-RNN in addition to recommendations for adjustments. The time sequence characteristics of problems requiring a single series of measurements can also be learned using the LSTM stack. These characteristics are crucial for a model to acquire knowledge to forecast the following value in order. [43],

$$ig_t = \tanh(Wxt * igtxt + WHt - 1 * igtHt - 1 + bigt \quad (4)$$

$$pt = \sigma(Wxt * pt - 1 * xt + WHt - 1 * pt - 1 * Ht - 1 + bpt) \quad (5)$$

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$$fgt = \sigma(Wxt * fgt * xt + WHt - t * fgt * Ht - 1 + bfgt \quad (6)$$

$$opt = \sigma W_{xtopt} x_t + W_{Ht-1opt} H_{t-1} + b_{opt} \quad (7)$$

$$C_{et} = {}_{cet-1} O_{fgt} + {}_{igt} O_{pt} \quad (8)$$

$$H_t = \tanh(C_{et}) O_{opt} \quad (9)$$

where *big*, *bp*, *b f g*, *bop* is the bias vector; *igt* stands for input gate; p_t for anticipation in the initial layers; $f\,g_t$ for the forget gate; H_t for data about outputs; Ce_t for the cell's state; and W_{xx} for the weighting vector. Contextual information from the input tweets can be extracted using a combination of the LSTM and RNN models.

We apply the attention layer in the study primarily to improve the comprehension of characteristics and component weights, as indicated in [44]. To acquire phrase sequences, the LSTM-RNN generates characteristics weighted by the attention process. Additionally, learners are able to acquire more domain knowledge more easily when secondary indicators are used in conjunction with LSTM-RNN. According to the research, the focus calculation for the attention layer computes an assortment for the different layers and tests weight distribution. [45] Stated otherwise, given an input of Xi, the features derived from the second layer are f(Xi, Xiplus1), while the characteristics derived from the Lth layer are f(Xi, Xi+1, · · ·, Xi + These feature values, or Xi unigrams and Xi bigrams, are the responses of multi-scale n-grams.Xi L-grams and Xi+1 Xi+1 + Xi + L 1. The filtering assembly and the focusing mechanism work together to rebalance the system. In addition, scale reweigh utilize signifier like input to compute the SoftMax distribution of attention weights and generates weighted attribute weights for reweighing. [43] , [44].

$$S^i l = FL_{ensm} X^i l \quad (10)$$

$$X^i{}_{atten} = \sum{}^{L}{}_{j=i} \alpha^i{}_L X^i{}_L \quad (11)$$

$$\partial^L{}_i = soft\max(MLP(X^i{}_{atten})) \quad (12)$$

The three performance benchmarks that are utilized to assess the efficacy of the proposed deep-learning technique are recall, accuracy, and precision. The attention layer technique's ability to improve feature weighting is what makes the suggested approach unique. The suggested technique takes a sequence that has been mapped by LSTM-RNN and extracts textual information from it by having the LSTM generate a set of annotations for each input. The attention layer approach then fine-tunes the features using the vector representations used in this work, which are a concatenation of the encoder's hidden states. The attention mechanism's help with feature weighting is greatly enhanced by the activation feature of softmax.

Sentiment polarity

Information was gathered on the Tweets with the keywords ChatGPT in terms of the number of comments received for each. WordNet is one of the many lexicons used as a foundation for lexicon-oriented approaches that identify the polarity of emotion. An existing WordNet lexicon and a curated list are used in sentiment analysis performed on user comments. The detailed list includes many terminologies and phrases. These terminologies and phrases are used to convey the thoughts of users. The SentiWordNet assigns polarity to every word and phrase included in WordNet. WordNet is used to assess the feelings expressed by users in their comments.

The Sentiment Architecture of Study

There are five steps in the design. The initial step requires entering the text collection of tweets. Next, pre-processing is done on the tweet text, which lowers distortion by removing unnecessary symbols and

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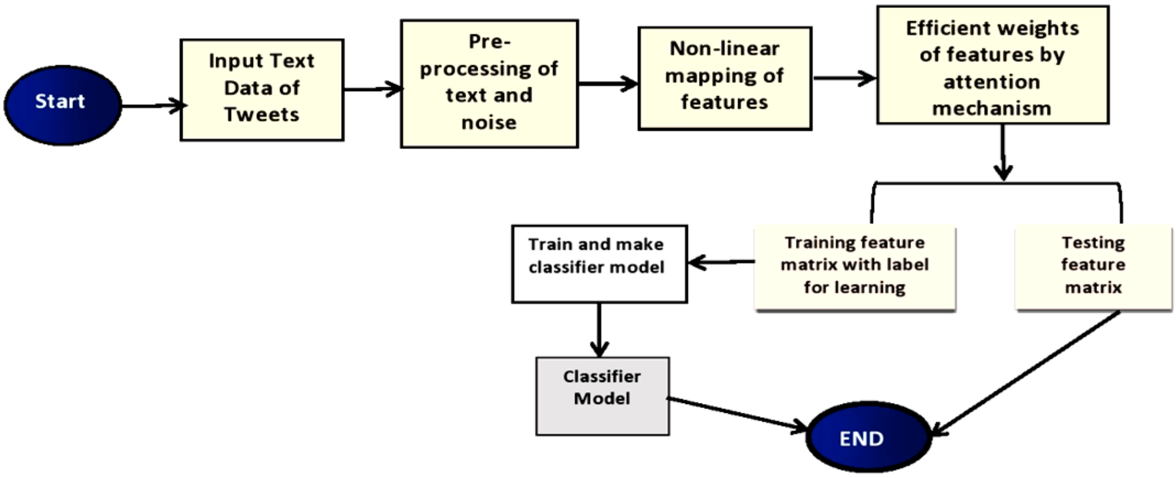
words from the content. The text is converted into a value at the pre-processing phase according to its occurrence. The fourth stage involves feature mapping, where weights supplied by LSTM-RNN



mapping features are modified to lessen feature overlaps. They are utilizing the attention method to improve weights aids in selecting appropriate data. The fifth stage in the suggested technique involves applying a fundamental softmax classifier. The recommended strategy's Recall, accuracy, and precision are utilized to gauge its effectiveness. Attention layer distributes effective weights, and the suggested approach primarily emphasizes choosing or designing features via the LSTM-RNN function. The model and suggested technique offer practical methods for determining and weighing valuable characteristics in the nonlinear domain. The attention layer in Figure 2 is Tweet classification topology serves a purpose for deep learning since it can improve the efficiency of neural networks and lead to advancements.

Figure 2: Tweet classification sentiment architecture

The "long-term dependencies" between word sequences can be captured by the LSTM model. The layer can focus extra attention on a specific, very significant portion of the input sequence thanks to the attention mechanism. Combining such a technique with LSTM can be beneficial since it makes it easier to concentrate on the sentences or documents that textual analysis, such as the one employed in this study, is conducted on. The attention mechanism aims to break down intricate duties into smaller attention areas that are then processed sequentially. By breaking a big problem into smaller pieces and concentrating on solving each one at a time, the model executes visual attention in an approach similar to how a human being accomplishes. Attention mechanisms are frequently employed in software programs such as machine translation, speech recognition, sentiment analysis, and emotion detection because they enable neural networks to function better by concentrating on key elements of a pattern. This has made them prevalent in the past decade. Another advantage of attention mechanisms is their adaptability and effectiveness in solving complex issues.

The formulas for calculating accuracy, precision, and recall are as follows:

$$Accuracy = (Po+Ne)/\ (Po+Ne+Fpo+FNe)$$

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Where Po denotes accurately marked positive specimens, Ne denotes appropriately tagged negative models, Fpo denotes incorrectly classified unfavorable samples, and FNe denotes incorrectly categorized positive examples.

Precision = Po/ (Po+Fpo) represents precision, and
Recall= Po/ (Po+FNe) represents recall.

EXPERIMENT

Sentiment Analysis on ChatGPT Topics

We conducted sentiment analysis for each of the ChatGPT subjects we had chosen. The library labeled specific bad tweets that we detected as neutral (discussing both positive and negative elements of ChatGPT). Additionally, many tweets included visuals (such as screenshots) and text. For a more comprehensive understanding of the tweet's content, we found it preferable to examine the tweet in its entirety along with these photographs. Lastly, our earlier work [45], which discussed the most current developments in this field's solutions and trends, demonstrated how qualitative analysis offers a more thorough and sophisticated data analysis. As a result, we decided to analyze the tweets for quality manually. To evaluate overall trends over time, we intend to expand on this work in the future by including an additional data set and using an automated analysis method. All five writers did the instructions for labeling and qualitative assessment of our data. In this instance, two authors labeled each data set for every topic.

Support vector machine hyper parameter tuning

Three classification methods are taken into account in this study: SVM (support vector machine), RF, and the suggested method-utilizing layer of attention. Employing search grids, the classifiers' characteristics are adjusted. The Support-Vector-Machine-Radial-Basis-Function (S-V-M-R-B-F), which contains two primary hyper parameters, C and gamma, presents the results of variable modification in Table 1. The settings strike an appropriate equilibrium between overestimation and adaptation. The value of gamma aids lowering spiral since collection of information would rise without it, and the learning method's polynomiality would suffer. Lesser collection matched with the C lesser point to lessen this over-fitting and data mugging. Table-1 demonstrates that gamma low and high C produced outstanding results versus other conditions. The SVM hyper parameter tuning reveals that the most effective model for this classifier for the taken variables has accuracy, precision, recall, and F-score values of 63.12%, 63.14%, and 65% at C = 10, and gamma = 0.01.

Table-1: Support vector machine optimize parameter

C	Gamma	Accuracy	Precision	Recall	F-Score
0.2	1	56.14	57.32	51.12	60.14
1	0.1	58.21	60.13	61.23	57.32
10	0.01	63.12	63.14	64	65
100	0.001	62	64	56	58
500	0.0001	61.23	56.21	5.12	56.23
1000	0.0001	61	53.22	51.12	50
1	0.5	45.12	46	50	53.21

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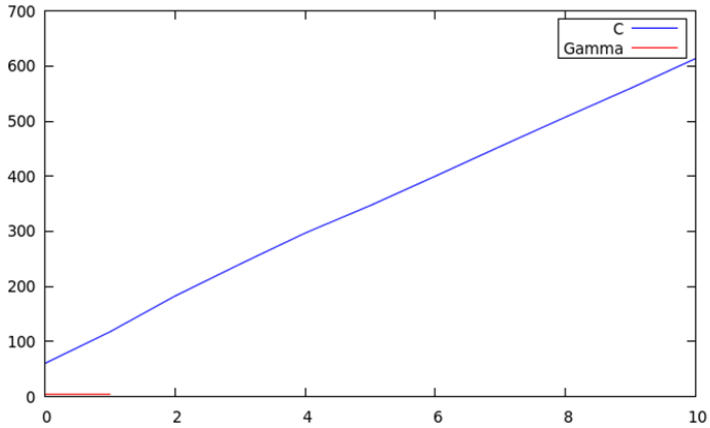
10	0.25	34.23	56.23	54.12	54.12
100	0.125	52.12	53.12	52.12	53.12
500	0.0625	57.21	58.23	54.23	52.12
1000	0.0325	58.12	54.12	50.23	54.12



Random forest hyper parameter adjustment is shown in Table 2. The hyper-parameters considered include max depth, estimates, and splits. These variables indicate the highest possible number of forests formed throughout the framework's growth, the lowest number of information in nodes before a split happens, and the depth of forests. When the lowest split is five, the highest depth is 10, and there are 600 estimations, the model's accuracy, precision, recall, and F-score are all 61%, 62%, 64%, and 61%, respectively, presented in the following table 2. For the variety of factors examined, this model works the best.

Table-2: Tabular description of RF-Hyper-parameter adjustment

Estimations	Max. Depth	Min. Split	Accuracy	Precision	Recall	F-Score
200	10	3	46.19	49.22	55.34	57.23
300	20	6	46.21	48.22	50.12	58.12
400	30	10	60	56.22	50.21	53.23
500	40	2	54.2	57.22	49.11	50.23
600	50	5	61	62	64	61
700	60	10	51.89	52	50.98	54.62
800	70	2	56.58	56.82	53.37	56.38
900	80	5	57.6218	56.8215	54.0185	55.4612
1000	90	10	57.4188	56.8321	54.8122	56.0125

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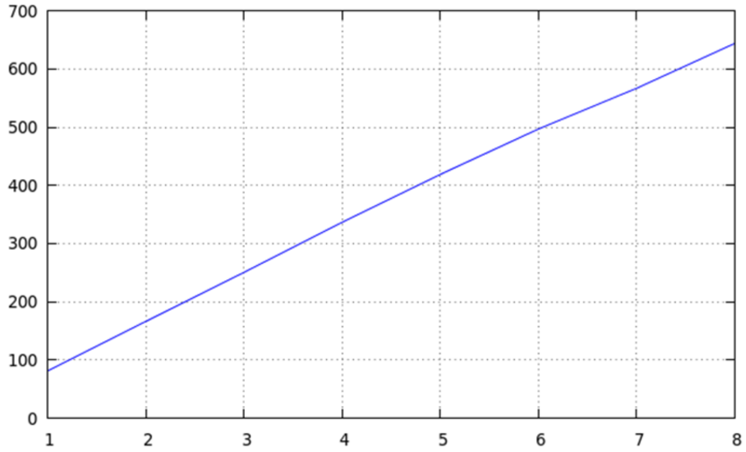
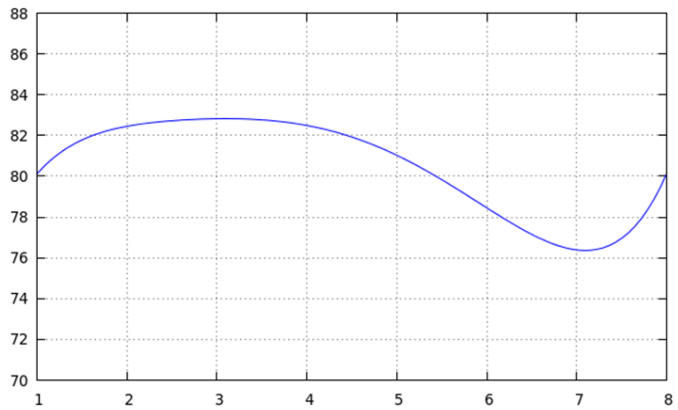


Hyper-parameter tuning is shown in Table 3 for various attention layer counts and as a function of activation. Although CNN layers dramatically boost the consumption of resources, the total number of CNN layers in the research, as mentioned above, is restricted. There are 1 and 8 attention layers. The framework's efficiency improves from one to 4 attention layers, as shown in the table; its efficiency then deteriorates. The accuracy, precision, recall, and F-score of the model are 87.12%, 85.23%, 86.23%, and 86.12%, respectively, 4. This is showing superior to the previous ones that have been seen.

Table 3: Hyper-parameter tuning for AL

CNN Layer	Attention Layers	Accuracy	Precision	Recall	F-Score
4	1	82.23	81.23	80.12	81
4	2	86.12	83.12	85.13	85.12
4	3	83.12	85.23	80.12	84.23
4	4	87.12	85.23	86.23	86.12
4	5	81.12	82.23	81.12	82.12
4	6	83.12	82.12	81	78
4	7	79.12	70.23	70	70
4	8	82.23	81	80.12	77.12



Next, we used four attention layers with epochs to test the hyper-parameter tuning of our suggested technique to see which produced the most effective outcomes. Table 4 demonstrates that epoch 18 made the most favorable outcome. Table 5 compares the proposed methods against various deep learning and machine learning methods such as SVM, random forest with the most accurately detected hyper-parameters, LR, & LSTM-RNN to baseline hyper-parameters. Comparatively, it is found that the presented technique for deep learning outperformed the other methods that were already in use.

Table 4: Epoch tuning

Epochs	Accuracy	Precision	Recall
1	81.04	81.01	81.09
2	82.12	78.12	77.34
3	81.23	80	80
4	81.34	81.23	78
5	82.34	80.45	81.2
6	83	81.23	82
7	83.23	83.23	80
8	83.13	81.228	79.967
9	83	81.472	79.929
10	84.12	81.522	80.156
11	82.34	81.736	80.179
12	83.164	81.838	80.490
13	83.150	82.559	81.388
14	83.154	81.626	80.158
15	83.186	81.656	80.181
16	82.998	81.683	80.214
17	83.130	81.672	80.255
18	84.55	82.34	82.12
19	83.406	81.795	80.534
20	83.456	81.830	80.556

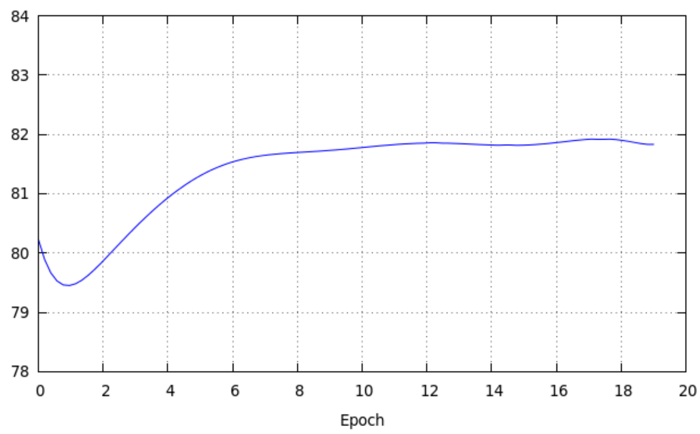
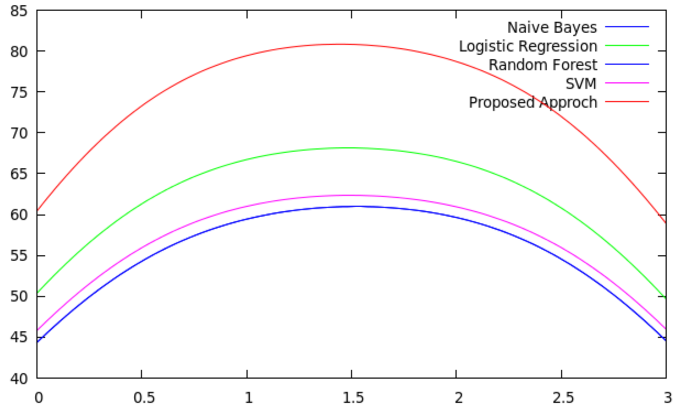


Table 5: Outcomes of the suggested method and contrast with other methods currently in use

Classifier	Accuracy	Precision	Recall	F-Score
NB	68	67.99	68.33	69
Random Forest	61	62	63	61
SVM	63.13	64.12	63	64
Logistic Regression	71.21	68.32	72	68.43
LSTM-RNN	74.31	72.22	77.55	76.82
Proposed Approach	80.66	81.13	83.24	81.88



CONCLUSION AND RECOMMENDATIONS

Various methods have been developed throughout analyzing social media content sentiment analysis. Due to the vast volume of information and the need for accuracy, this sentiment analysis procedure is typically complicated and exhausting. As a result, this study suggests using deep learning to analyze the sentiment of Twitter data on ChatGPT. The method's cornerstone is an LSTM-RNN-based system with higher emphasized weighting from an attention layer. This method considers a better modification to the features topology by using an attention mechanism. This experiment employed four class labels—sad, joy, fear, and anger—from publicly accessible Twitter data stored in the Kaggle database. With advantages of 20% accuracy and 10% to 12% precision, but only 12–13% recall, the suggested deep learning approach dramatically improved its efficacy metrics, especially when compared to earlier approaches. Positive, neutral, and negative tweets made up 45%, 30%, and 35% of the total number of tweets relating to ChatGPT.

In conclusion, the suggested DL strategy to categorizing the way of thinking about ChatGPT evaluations has been demonstrated to be effective, practical, and readily implementable. The research has both academic and practical significance.

REFERENCES

Crawford, J., M. Cowling, and K.-A. Allen, Leadership is needed for ethical ChatGPT: Character, assessment, and learning using artificial intelligence (AI). Journal of University Teaching & Learning Practice, 2023. 20(3): p. 02.

Chen, T.-J., ChatGPT and other artificial intelligence applications speed up scientific writing. Journal of the Chinese Medical Association, 2023. 86(4): p. 351-353.

Cooper, G., Examining science education in chatgpt: An exploratory study of generative artificial intelligence. Journal of Science Education and Technology, 2023. 32(3): p. 444-452.

Bozkurt, A., et al., Speculative futures on ChatGPT and generative artificial intelligence (AI): A collective reflection from the educational landscape. Asian Journal of Distance Education, 2023. 18(1).

Dahmen, J., et al., Artificial intelligence bot ChatGPT in medical research: the potential game changer as a double-edged sword. Knee Surgery, Sports Traumatology, Arthroscopy, 2023. 31(4): p. 1187-1189.

Polonsky, M.J. and J.D. Rotman, Should Artificial Intelligent Agents be Your Co-author? Arguments in Favour, Informed by ChatGPT. 2023, SAGE Publications Sage UK: London, England. p. 91-96.

Wankhade, M., A.C.S. Rao, and C. Kulkarni, A survey on sentiment analysis methods, applications, and challenges. Artificial Intelligence Review, 2022. 55(7): p. 5731-5780.

Weismueller, J., et al., What makes people share political content on social media? The role of emotion, authority and ideology. Computers in Human Behavior, 2022. 129: p. 107150.

Xing, Y., et al., Research on opinion polarization by big data analytics capabilities in online social networks. Technology in Society, 2022. 68: p. 101902.

Chaturvedi, V., et al., Music mood and human emotion recognition based on physiological signals: a systematic review. Multimedia Systems, 2022. 28(1): p. 21-44.

Bilro, R.G., S.M.C. Loureiro, and J.F. dos Santos, Masstige strategies on social media: The influence on sentiments and attitude toward the brand. International Journal of Consumer Studies, 2022. 46(4): p. 1113-1126.

Airani, R. and K. Karande, How social media effects shape sentiments along the twitter journey? A Bayesian network approach. Journal of Business Research, 2022. 142: p. 988-997.

Yin, F., et al., Sentiment mutation and negative emotion contagion dynamics in social media: A case study on the Chinese Sina Microblog. Information Sciences, 2022. 594: p. 118-135.

Chandrasekaran, G., et al., Visual sentiment analysis using deep learning models with social media data. Applied Sciences, 2022. 12(3): p. 1030.

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Pellert, M., et al., Validating daily social media macroscopes of emotions. Scientific reports, 2022. 12(1): p. 11236.

Balli, C., et al., Sentimental analysis of Twitter users from Turkish content with natural language processing. Computational Intelligence and Neuroscience, 2022. 2022.

Chang, S.W., D.Y. Rhee, and H.J. Jun, A natural language processing framework for collecting, analyzing, and visualizing users' sentiment on the built environment: case implementation of New York City and Seoul residences. Architectural Science Review, 2022. 65(4): p. 278-294.

Ruz, G.A., P.A. Henríquez, and A. Mascareño, Bayesian constitutionalization: Twitter sentiment analysis of the chilean constitutional process through bayesian network classifiers. Mathematics, 2022. 10(2): p. 166.

Haque, M.U., et al., " I think this is the most disruptive technology": Exploring Sentiments of ChatGPT Early Adopters using Twitter Data. arXiv preprint arXiv:2212.05856, 2022.

Laor, T., My social network: Group differences in frequency of use, active use, and interactive use on Facebook, Instagram and Twitter. Technology in Society, 2022. 68: p. 101922.

Wang, J. and Y.-L. Liu, Deep learning-based social media mining for user experience analysis: A case study of smart home products. Technology in Society, 2023. 73: p. 102220.

Peng, S., et al., A survey on deep learning for textual emotion analysis in social networks. Digital Communications and Networks, 2022. 8(5): p. 745-762.

AlBadani, B., R. Shi, and J. Dong, A novel machine learning approach for sentiment analysis on Twitter incorporating the universal language model fine-tuning and SVM. Applied System Innovation, 2022. 5(1): p. 13.

Sham, N.M. and A. Mohamed, Climate change sentiment analysis using lexicon, machine learning and hybrid approaches. Sustainability, 2022. 14(8): p. 4723.

Heidemann, L., M. Monnet, and K. Roscher. Concept Correlation and Its Effects on Concept-Based Models. in Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision. 2023.

Yin, H., et al., Sentiment analysis and topic modeling for COVID-19 vaccine discussions. World Wide Web, 2022. 25(3): p. 1067-1083.

Jassim, M.A., D.H. Abd, and M.N. Omri, Machine learning-based new approach to films review. Social Network Analysis and Mining, 2023. 13(1): p. 40.

Sirusstara, J., et al. Clickbait Headline Detection in Indonesian News Sites using Robustly Optimized BERT Pre-training Approach (RoBERTa). in 2022 3rd International Conference on Artificial Intelligence and Data Sciences (AiDAS). 2022. IEEE.

Biradar, S.H., J. Gorabal, and G. Gupta, Machine learning tool for exploring sentiment analysis on twitter data. Materials Today: Proceedings, 2022. 56: p. 1927-1934.

Ali, H., et al., Deep learning-based election results prediction using Twitter activity. Soft Computing, 2022. 26(16): p. 7535-7543.

Chiha, R., M.B. Ayed, and C.d.C. Pereira, A complete framework for aspect-level and sentence-level sentiment analysis. Applied Intelligence, 2022. 52(15): p. 17845-17863.

Trisna, K.W. and H.J. Jie, Deep learning approach for aspect-based sentiment classification: a comparative review. Applied Artificial Intelligence, 2022. 36(1): p. 2014186.

Nurkholis, A., D. Alita, and A. Munandar, Comparison of Kernel Support Vector Machine Multi-Class in PPKM Sentiment Analysis on Twitter. Jurnal RESTI (Rekayasa Sistem Dan Teknologi Informasi), 2022. 6(2): p. 227-233.

Onan, A., Bidirectional convolutional recurrent neural network architecture with group-wise enhancement mechanism for text sentiment classification. Journal of King Saud University-Computer and Information Sciences, 2022. 34(5): p. 2098-2117.

Kathuria, A., A. Gupta, and R. Singla, AOH-Senti: Aspect-Oriented Hybrid Approach to Sentiment Analysis of Students' Feedback. SN Computer Science, 2023. 4(2): p. 152.

Han, S., R. Mao, and E. Cambria, Hierarchical attention network for explainable depression detection on Twitter aided by metaphor concept mappings. arXiv preprint arXiv:2209.07494, 2022.

Gong, B., et al., Temperature forecasting by deep learning methods. Geoscientific Model Development, 2022. 15(23): p. 8931-8956.

Shaila, S., et al. Twitter Data-based Sarcastic Sentiment Analysis using Deep Learning Framework. in 2022 International Conference on Artificial Intelligence and Data Engineering (AIDE). 2022. IEEE.

Yan, Y., Y. Wang, and P. Zheng, A graph-based pivotal semantic mining framework for rumor detection. Engineering Applications of Artificial Intelligence, 2023. 118: p. 105613.

Shijaku, R. and E. Canhasi, ChatGPT Generated Text Detection. Publisher: Unpublished, 2023.

Pegoraro, A., et al., To ChatGPT, or not to ChatGPT: That is the question! arXiv preprint arXiv:2304.01487, 2023.

Lamichhane, B., Evaluation of chatgpt for nlp-based mental health applications. arXiv preprint arXiv:2303.15727, 2023.

Nair, K., et al. Bitcoin price prediction using sentimental analysis-a comparative study of neural network model for price prediction. in 2022 2nd Asian Conference on Innovation in Technology (ASIANCON). 2022. IEEE.

Biswas, S., The Function of chat GPT in social media: According to chat GPT. Available at SSRN 4405389, 2023.