DETECTION OF SARCASTIC SENTIMENT ANALYSIS IN TWEETS USING LSTM WITH IMPROVED ATTENTION BASED FEATURE EXTRACTION (IATEN)

K.VEENA[1], DR.V. SASIREKHA[2] S. DEVI[3]

[1]Assistant Professor, Department of Computer Science, J.K.K. Nataraja College of Arts & Science, Komarapalayam, Namakkal Dt., Tamilnadu, India.

[2]Assistant Professor, Department of Computer Science, J.K.K. Nataraja College of Arts & Science, Komarapalayam, Namakkal Dt., Tamilnadu, India.

[3]Assistant Professor, Department of MCA, SSM College of Engineering, Komarapalayam, Namakkal Dt., Tamilnadu, India.

E-mail: [1] veenabharathi44@gmail.com , [2]sasirekhailangkumaran@gmail.com, [3]devikrishnamca@gmail.com

ABSTRACT

The brief duration of tweets makes it considerably more difficult to identify sarcasm, which is a difficult feature of sentiment analysis. The proposed model has effectively identified sarcastic attitudes in tweets while tested against a variety of Twitter datasets. It distinguishes itself from other cutting-edge models because of its capacity to accurately represent the sequential nature of language and concentrate on key words in the sentence. The LSTM model subsequently analyses the string of words, accounting for both the context and the word order, in order to precisely identify sarcasm. In comparison to conventional approaches that simply give every word in a phrase equal weight, the enhanced attention-based feature extraction used in this model is a significant advancement. In addition, the model can manage language's sequential characteristics due to the usage of LSTM, which makes it the best option for sentiment analysis employment. A significant advancement in the field of sentiment analysis is the proposed model for LSTM-based attention-based feature extraction and sarcastic sentiment analysis in tweets. To precisely identify sarcasm in text data, the model leverages the strength of LSTM with improved attention-based feature extraction. The framework is an excellent alternative for sentiment analysis tasks whereby sarcasm has to be recognized since it allows for the sequential flow of language and concentrate on important phrases in the sentence. To determine the sequential pattern of language while preserving the context and order of words in tweets, the model utilizes LSTM (long short-term memory), a sort of recurrent neural network. Furthermore, it uses an attention-based feature extraction technique that gives sentences key words greater weight. The algorithm can specifically detect linguistic nuance and discern sarcasm by concentrating on important words. In the proposed implementation, to correctly capture the sequential nature of language and concentrate on crucial words, it uses LSTM and better attention-based feature extraction, resulting in improved sarcasm recognition.

Keywords: *LSTM With Improved Attention-Based Feature Extraction, Twitter Datasets, Sarcasm, Sentiment Analysis*

1. INTRODUCTION

Irony, humour, and exaggeration are all employed alongside sarcasm to portray precisely the contrary of what was originally intended. Due to its dependence on tone and context, sarcasm [1] may be difficult for machines to recognise. Nevertheless, there has been an increase in interest in creating algorithms for sarcastic emotion detection in text due to the growth of social media and online communication. The use of sarcasm frequently depends on the circumstances, the speaker's emotions, and their tone of voice. It can be difficult for computer to correctly comprehend sarcastic comments without accessibility to this information. There are several methods for identifying sarcasm in literature. One method is to analyse big datasets of sarcastic and non-sarcastic words using machine learning methods. These algorithms can spot patterns and characteristics that set sarcastic language, apart from other types of speech. A different approach is to concentrate on certain language indicators of sarcasm, including the use of rhetorical queries or quote marks. Algorithms can accurately detect sarcastic comments in text by recognizing these indicators. There are various ways to spot sarcasm in works of literature. One approach is to use machine learning techniques to assess large datasets of sarcastic and non-sarcastic words. These algorithms can identify patterns and traits that distinguish sarcastic speech from other forms of speech. Focusing on specific language indicators for sarcasm, such as the use of rhetorical inquires or quotation marks, is an alternative strategy. By identifying these characteristics, algorithms are able to recognise sarcastic comments in text with accuracy. Applications for sarcastic sentiment analysis are several, ranging from social media surveillance to political evaluation to advertisements and marketing. Organisations and businesses may more effectively customize their content and communicate with their consumers by comprehending the contexts in which individuals employ sarcasm in online interactions.

Online hate speech and Cyberbullying may be identified and stopped using sarcastic sentiment analysis. Social networking platforms are able to take action to delete abusive information and safeguard its users by recognizing sarcastic or ironic remarks that are meant to harass or cause harm to others. For normal humans, it may be difficult to recognise sarcasm, therefore using just computers to accomplish so risks producing unreliable results. The use of ironic sentiment analysis for monitoring or censoring raises further ethical questions. It may be used to track and restrict free speech and to prevent bad behavior online. As with any technology, it's critical to think about the possible outcomes and make sure it's applied ethically and appropriately. The technique of figuring out a text's mood of emotion is designated as sentiment analysis.

According to the type different data and the precise needs of the assignment, a variety of sentiment analysis approaches may be applied. Finding verbal indicators connected to sarcasm, such as the use of irony, exaggeration, or rhetorical questions, is the goal of linguistic-based sarcasm detection. In order to recognise these indicators and forecast if sarcasm is present, this method entails developing a set of rules or algorithms. The process of pattern-based sarcasm identification entails locating textual patterns that are connected to sarcasm. In this method, a machine learning model is trained on a collection of labelled data to find these patterns and predict if sarcasm is present. In order to increase the precision of sarcasm identification, hybrid detection of sarcasm incorporates two or more of the aforementioned methods. To benefit from each approach's advantages, a hybrid strategy may, for instance, Combine Linguistic-based and pattern-based strategies.

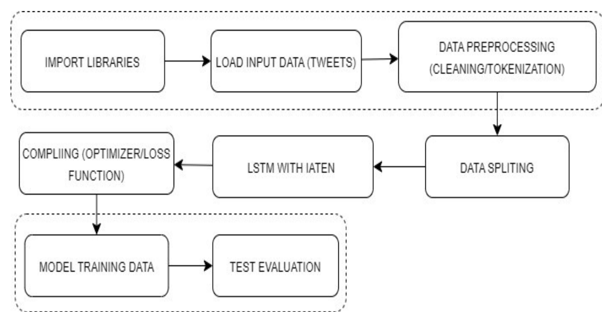

Figure 1: Proposed Architecture Diagram

Analyzing the context in which the material is used to assess the presence of sarcasm is known as context-based sarcasm detection. This method includes predicting the existence of sarcasm by looking at the context of text, the conversation's tone, and other contextual elements. The sarcasm detection method selected will rely on the particulars of the task at hand as well as the properties of the input data. A model based on machine learning is trained on a collection of labeled data in the context of machine learning analysis of sentiment. The model gains the ability to spot similarities in the data and forecast outcomes using those patterns. Sentiment analysis using algorithmic learning may be highly precise, but it requires a lot of labeled data and precise hyperparameter tweaking. To increase the effectiveness of LSTM models in sarcasm detection in tweets, the improved Attention-based feature extraction (IATEN) strategy is applied. It functions by

Journal of Theoretical and Applied Information Technology
30th September 2023. Vol.101. No 18

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

integrating attention processes into the LSTM model's feature extraction procedure. Through the use of attention processes, the algorithm may concentrate on particular segments of the input sequence which are crucial for making predictions. The attention mechanism may be used to concentrate on particular words or phrases that are frequently linked with sarcasm in the instance of sarcasm detection in Tweets.

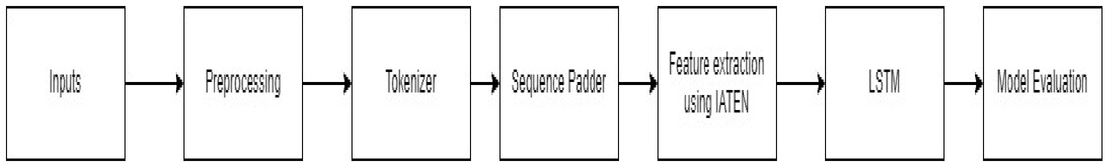

Figure 2: Workflow diagram

By adding more elements that are important for sarcasm detection, the IATEN approach enhances conventional attention processes. These characteristics may include embedded words, part-of-speech tagging, and analysis of sentiment. The IATEN approach is able to obtain more pertinent information from the input sequence by including these new characteristics into the attention mechanism, which in turn raises the LSTM model's sarcasm detection efficiency. In general, the IATEN method employs strategies for attention to concentrate on pertinent portions of the input sequence while also integrating additional components that are important for sarcasm detection. Recurrent neural networks (RNNs) of the LSTM variety are made to process sequential data. It operates by letting information circulate across the network gradually, enabling the network to discover enduring dependencies. LSTM is renowned for its great accuracy and capacity for sequential data. LSTM, on the contrary, can be computationally costly and may need a lot of training data. A variation of the LSTM algorithm which incorporates attention mechanisms throughout the feature extraction phase is called LSTM with IATEN. It functioned by enabling the network to concentrate on particular segments of the input sequence which are essential to producing a prediction. The great precision and adaptability of LSTM with IATEN are widely recognized characteristics.

2. LITERATURE SURVEY

(Pal 2023) classified emotions which evaluates Bengali text [1] emotions since the sentiment analysis is difficult to identify. Sarcasm needs to be identified by representing those words which indicates hatred. Based upon different algorithms, LSTM is used to train and test those different experiments where 91% of accuracy are predicted from those sarcastic events. Different algorithms evaluate and predicts those with feature metrics. (Ikram 2022) analyzed [2] Twitter which evolves the social media platform based upon their sentiment. Twitter sentiment analysis determines the sentiment by collecting those data from those API which derives from Structured format based upon data processing, feature extraction which includes train, evaluates with various machine learning models. Different classifier evaluates and compares those and predicts high accuracy.

(Naik 2022) indicated online sarcasm which expresses the literal meaning of those phrases or sentences. In this paper, Naik [3] suggested that NLP processes those samples to generalize those structure sentences. Based upon the study, automatic identification of those sarcastic sentences evolves various stages. LSTM model evaluates and achieves the accuracy of those without even overfitting. (Verma 2021) sentiment classification of those customer reviews [4] is analyzed within text form based upon positive terms. Sarcasm evolves with verbatim statement which provides the greater impact on recognising those sarcasms. Hybrid model of ML approach acquires the phases of those model within extraction. (Jemai 2021) aims to classify the polarity of those comments using ML which extracts those tasks. Using the [5] dataset with text mining generates those variables which classify those tweets with positive and negative sentiments. It evaluates those performances based on model by achieving greater precision.

(Shilpa 2021) emotion recognition with NLP [6] tends to contribute the different areas with AI and also human interactions. Emotions based upon voice modulation and other expressions are analyzed to identify proper interpretation. In this paper, sentimental classification of multitude type of tweets is analyzed which classify the anger, happy and boredom state. Different algorithms are evaluated to achieve high emotion with classification accuracy.

Journal of Theoretical and Applied Information Technology
30th September 2023. Vol.101. No 18

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

LSTM model achieves positive and negative classification in emotions with enhanced accuracy. (Pawar 2020) recognise sarcasm which transmits [7] hidden information which criticize and ridicule the person based upon emotions. Mainly in this paper, sarcasm detects the pattern approach using Twitter data which classify sarcastic and non-sarcastic tweets. Feature sets are evaluated in this study with other classifications. (Gupta 2020) sentiment analysis gains the high significant of negative sentiments in people which are in different forms in internet. These discovers the people thought process and how they actually think. It categorizes in three different forms of reviews. A brief way of sentiment classification [8] determines the emotion categorization with other type of different classification.

3. METHODOLOGY

3.1 Sarcastic Detection

Communication that conveys the antithesis of its literal meaning with the intention of mocking or ridiculing is known as sarcasm. Although it might be difficult, sarcasm detection in text is a crucial problem in natural language processing since it can increase the precision of sentiment evaluation and other text-based applications [2]. Numerous diverse language strategies, such as irony, exaggeration, rhetorical questions, and others, can be used to conveys sarcasm. As a result, sarcasm detection in text necessitates knowledge of these tools as well as the capacity to see patterns within the text that are indicative of sarcasm. A speaking act known as sarcasm includes expressing one thing while really meaning something another, sometimes in a hilarious or sardonic way. Because the literal meaning of the words used could conflict with the intended meaning, it might be difficult for an automated system to recognise sarcasm.

	label	id	date	flag	user	tweet
0	0	1467810672	Mon Apr 06 22:19:49 PDT 2009	NO_QUERY	scotthamilton	is upset that he can't update his Facebook by ...
1	0	1467810917	Mon Apr 06 22:19:53 PDT 2009	NO_QUERY	mattycus	@Kenichan I dived many times for the ball. Man...
2	0	1467811184	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	ElleCTF	my whole body feels itchy and like its on fire
3	0	1467811193	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	Karoli	@nationwideclass no, it's not behaving at all....
4	0	1467811372	Mon Apr 06 22:20:00 PDT 2009	NO_QUERY	joy_wolf	@Kwesidei not the whole crew

Figure 3: Twitter Tweets Detection

Sarcasm may be represented through a number of language clues, which can be difficult to recognise and interpret. This poses one of the main issues in sarcasm detection. Exaggeration, hyperbole, irony, and understatement are only a few examples of these cues. Sarcasm may also be conveyed nonverbally through body language, facial expressions, and tone of voice—all of which are difficult for automated systems to pick up on. In order to overcome these challenges, researchers have developed a variety of computer methods for text sarcasm detection. These methods typically leverage machine learning techniques that have been developed using big datasets of annotated sardonic and non-sarcastic texts. These algorithms can develop the ability to correctly recognise sarcastic statements by studying linguistic patterns and other sarcasm-related factors. Sentiment analysis, a method used to categorize the emotional tone of a piece of text, is one prevalent method for sarcasm detection. A negative attitude communicated in an optimistic way, or vice versa, is a common characteristic of sarcasm. Natural language processing approaches such part-of-speech tagging, dependency parsing, or semantic analysis can be used to find these traits. Algorithms can detect sarcastic trends by examining the occurrence and distribution of certain properties in a text. Sarcasm will continue to be a significant part of our language and society, therefore being able to recognise it autonomously will be essential in a variety of applications, including sentiment research and monitoring of social media. An observation may be viewed as sarcastic or not relying on the context where it is spoken. Sarcasm is highly context-dependent. Sarcasm

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

can be quite subjective, so what one person considers funny may not be funny to another. In order to express their real sentiments, sarcasm is a communication technique that entails expressing the exact opposite to what you intend. Since there are no verbal clues or facial gestures to aid in message interpretation in textual communication, including Twitters [7], it can be difficult to recognise sarcasm. However, by examining linguistical details like the usage of specific phrases and punctuation, researchers have created algorithms that can identify sarcasm in tweets. Approaches for sarcasm detection systems include sentiment assessment and brand monitoring. Organisations can discover more about client satisfaction by spotting sarcastic tweets against a certain product or company, and they are able to initiate the necessary corrective action.

3.2 LSTM

Recurrent neural networks (RNNs) of the type known as Long Short-term Memory (LSTM) networks were developed to address issues with conventional RNNs, such as the vanishing gradient problem. Sophisticated deep learning models called LSTM networks have been used to great effect in a number of fields, include speech recognition, natural language processing, and image captioning. The fundamental concept underlying LSTM networks [3] is the inclusion of memory cells with long-term data storage capabilities. Through gates, which regulate the information movement into and out of the cells, these storage cells are linked to other nodes in the network. An LSTM network has three different types of gates: Input gates, forget gates, and output gates. A form of neural network entitled Long Short-Term Memory (LSTM) has been employed well in applications involving natural language processing, including sentiment analysis. In order to understand linguistic usage patterns and accurately identify sarcastic tweets, LSTM may be trained on huge datasets of labeled sarcastic and non-sarcastic tweets.

Layer (type)	Output Shape	Param #	Connected to
input_7 (InputLayer)	[(None, 100)]	0	[]
embedding_8 (Embedding)	(None, 100, 128)	640000	['input_7[0][0]']
bidirectional_8 (Bidirectional)	(None, 100, 128)	98816	['embedding_8[0][0]']
attention_7 (Attention)	(None, 100, 128)	0	['bidirectional_8[0][0]', 'bidirectional_8[0][0]']
dropout_3 (Dropout)	(None, 100, 128)	0	['attention_7[0][0]']
dense_9 (Dense)	(None, 100, 32)	4128	['dropout_3[0][0]']
dense_10 (Dense)	(None, 100, 1)	33	['dense_9[0][0]']

Total params: 742,977
Trainable params: 742,977
Non-trainable params: 0

Figure 4: LSTM Layer Model

The ability of LSTM [6] to preserve the context and tone of a tweet, that are crucial for determining whether a remark is intended meant to be taken seriously or ironically, is one benefit of utilising LSTM for sarcasm identification. In addition, LSTM may be modified to recognise many sarcasm subtypes, including irony, exaggeration, and understatement, enabling more complex analysis of sarcastic tweets.

4. CONSTRUCTION

To appropriately focus on relevant input items and extract essential characteristics for subsequent tasks, these processes employ attention vectors. An enhanced attention-based feature extraction process has been proposed in the given equation, which increases the model's ability to discriminate by introducing a unique attention scoring mechanism. A trainable query vector and the input sequence are used to create a bilinear product to determine the attention scores, thereby improving the model's ability to pay attention to significant input characteristics.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Model: "model"

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 100)]	0	[]
embedding (Embedding)	(None, 100, 128)	640000	['input_1[0][0]']
bidirectional (Bidirectional)	(None, 100, 128)	98816	['embedding[0][0]']
attention (Attention)	(None, 100, 128)	0	['bidirectional[0][0]', 'bidirectional[0][0]']
dropout (Dropout)	(None, 100, 128)	0	['attention[0][0]']
dense (Dense)	(None, 100, 32)	4128	['dropout[0][0]']
dense_1 (Dense)	(None, 100, 1)	33	['dense[0][0]']

Total params: 742,977
Trainable params: 742,977
Non-trainable params: 0

Figure 5: LSTM with IATEN Layer Model

IATEN - Improved attention-based feature scoring

$$s = tanh\,((x \bullet w) + b)$$

The scoring approach, which integrates the raw input, feature-level representations, and context-level models from the input sequence, is a pioneering multi-level scoring system. The model's capacity to represent complicated relationships throughout the input sequence is enhanced by using the generated scores to weight the impact of each input components to the model's final output. The conventional SoftMax function used in LSTMs, which is normally applied to the output of the hidden state and input gate layers, is modified by the Original SoftMax technique. This improved approach uses a sigmoid function as an additional non-linearity that allows a more sophisticated and adaptable mapping of inputs to weights. It is essential to take into account certain of the restrictions of the conventional SoftMax function in order to comprehend the advantages of the Original SoftMax approach. The traditional SoftMax method has a number of disadvantages, including a high sensitivity to outliers that can result in overfitting and subpar generalization performance. The weight of each word in a phrase is determined by the suggested LSTM with IATEN model for sarcastic sentiment analysis using a novel SoftMax function. The novel approach chooses the most significant terms and gives them more significance during analysis than the traditional approach, which gives all words equal weight. This enables the algorithm to more effectively capture linguistic complexity and recognise sarcasm. Compared with traditional approaches that depend on conventional weighting procedures, the original SoftMax function used in this model is a considerable advancement. The model can more precisely analyse text data and discriminate between sardonic and non-sarcastic language through taking into consideration the context and word order.

Original Softmax to calculate weight:

$$alpha = \frac{e^{s - max(s))}}{\sum_{j=1}^{k} e^{s - max(s)}_{j}}$$

Modified Softmax to calculate weight

$$alpha = \frac{e^{tanh\,(s - max(s))}}{\sum_{j=1}^{k} e^{tanh\,(s - max(s))}_{j}}$$

$$context = sum\,(x * alpha)$$

Where,
x = $input\ vector$
w = $attention\ weights$
b = $attention\ bias$
e = $alignment\ score$
$alpha$ = $computed\ attention\ weights$
$context$ = $context\ vector$

5. Experimental Results

5.1 Proposed LSTM with IATEN model

For the purpose of identifying sarcasm in tweets from Twitter data, LSTM (Long Short-term Memory) with improved Attention-based feature extraction (IATEN) is a form of deep learning. Recurrent neural networks (RNNs) of the type called LSTMs are made to deal with sequential data. They operate by enabling information to go through the network progressively so that it may learn long-term dependencies. LSTMs may, however, be computationally expensive and may need a substantial quantity of training data. IATEN is a

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

method that improves the ability of LSTM models to recognise irony in tweets. It operates by including attention processes during the LSTM model's feature extraction stage. By adding more elements that are important for sarcasm detection, the IATEN approach enhances conventional attention processes. These characteristics may include word embeddings, part-of-speech tagging, and sentiment analysis. The IATEN approach is able to extract additional relevant details from the input sequence through incorporating these additional characteristics into the attention mechanism, that in effect improves the LSTM model's sarcasm detection efficiency.

In initial pre-processing the tweets prior to using the LSTM model to classify the sentiment of each tweet, it is possible to employ LSTM with better attention-based feature selection to categorize tweets for sentiment analysis.

- Tweets are often cleaned up at the stage of pre-processing through the elimination of stop words, spelling, and other unnecessary data. The remaining words will be turned into numerical vectors using methods like embedding words and single-hot encoding.
- The word vector sequence is then processed by the LSTM model, and the attention mechanism is used to draw emphasis to the sequence's most significant segments for sentiment analysis.
- In the classification layer, the output of the LSTM model is eventually used for predicting whether a tweet will be positive, negative, or neutral in sentiment.
- The model can capture long-term dependencies in the tweet and concentrate on the most relevant language for sentiment analysis by integrating LSTM with improved attention-based feature extraction.

The Long Short-Term Memory (LSTM) with improved Attention-based extraction of features can be transformed computationally as follows: Let h be the Hidden State of the LSTM and x and y represent the input and output sequences, respectively. It is possible to visualise the LSTM with attention as:

$$h\_t = LSTM\ (xt, h\{t-1\})$$

wherein xt is the input value at time t, h_t is the hidden state at time t, and ht-1 is the hidden state before time t.

The LSTM may be given an attention mechanism to enhance the feature extraction process. This is representative of:

$$e\_tj = a(h\_t, h\_j)$$

where a is the attention functioning, and e_tj is the weight of attention across hidden states h_t and h_j.

The context vector, c_t, that represents a weighted sum for the Hidden State at every step, can then be computed using the attention mechanism:

$$ct = sum\{j=1\}\hat{}n\ (e\_tj * h\_j)$$

The output sequence, y_t, is then calculated at each time step using the attention context vector, c_t:

$$y\_t = softmax(Wc*c\_t)$$

where Wc represents weight matrix.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

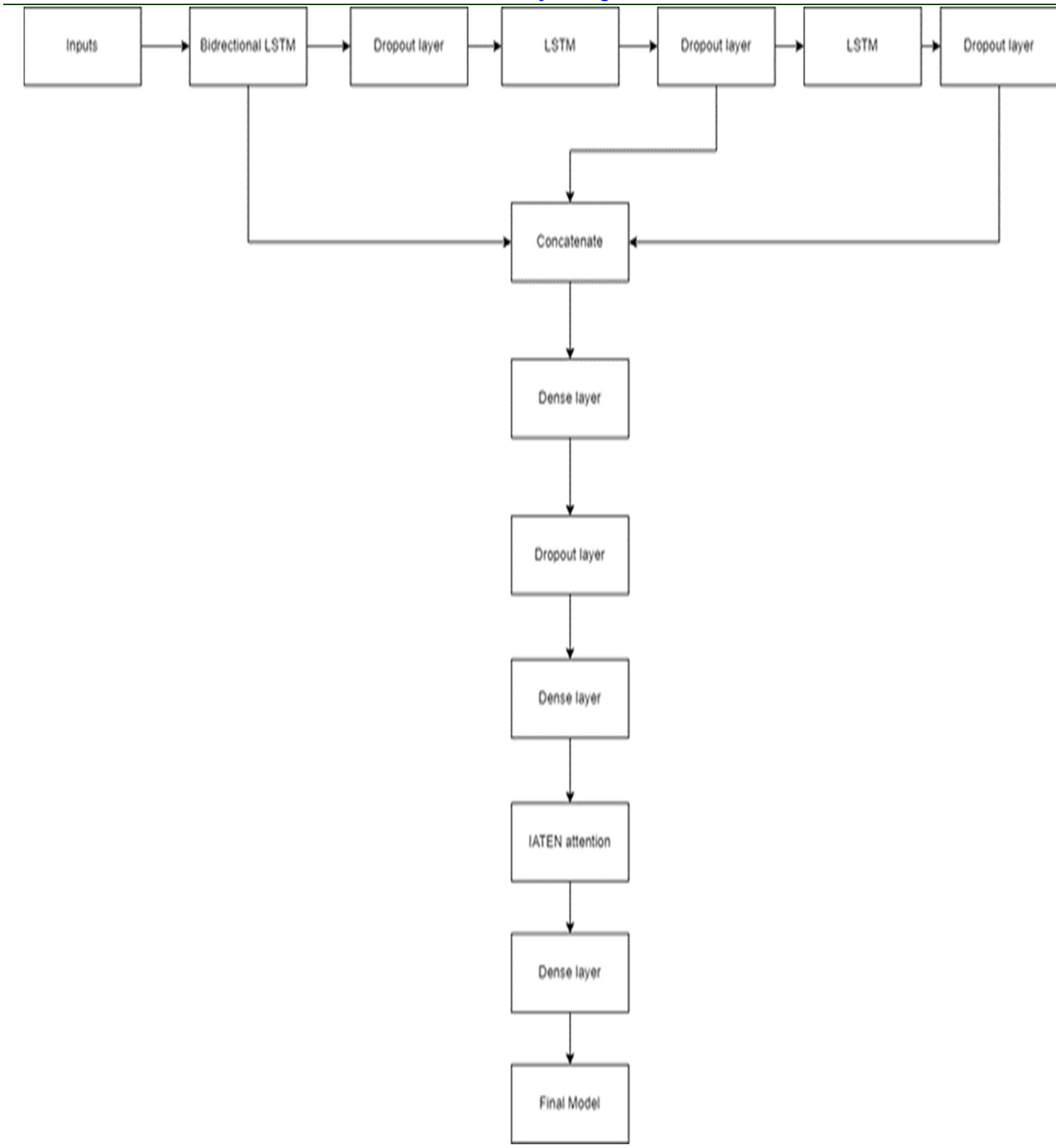

Figure 6: IATEN Based LSTM Model Architecture

LSTM with IATEN is an effective deep learning system that can handle consecutive data and enhance the precision of tweet sarcasm detection. It is a prevalent method for tasks involving natural language processing and has demonstrated good outcomes in a number of research. The IATEN approach can make use of word embeddings, part-of-speech tagging, and sentiment analysis. The IATEN approach is able to extract more pertinent information within the input sequence by combining these new qualities into the attention mechanism. The LSTM with IATEN model provides the distribution of probability across the two classes (sarcasm and non-sarcasm) using a SoftMax layer as its output layer. Back propagation is used to train the LSTM with IATEN model using a dataset of labeled Tweets. By modifying the neural network's biases and weights in order to minimize the loss function, the model is optimized. Each word or phrase in the input tweet is tokenized so that it can be used as an input for the LSTM model. Once the input has been tokenized, each word is subsequently integrated into a vector space. An LSTM layer, particularly made for handling sequential data, receives the embedded input. Long-term dependencies may be learned by the network owing to the LSTM layer, which allows information to flow through it over time. Using the tokenized input sent via the LSTM with IATEN model and the output obtained from the SoftMax layer, the model is able to be used to predict if a new tweet is sarcastic or not after it has been trained.

```
# Outline the IATEN model
        input_layer = Input (shape= (100,))
    embedding_layer = Embedding (input_dim=5000,
    output_dim=128) (input_layer)
lstm_layer = Bidirectional (LSTM (64,
return_sequences=True))(embedding_layer)
attention_layer = Attention ()([lstm_layer, lstm_layer])
dropout_layer = Dropout (0.5)(attention_layer)
dense_layer = Dense(32, activation='relu')(dropout_layer)
output_layer = Dense(1, activation='sigmoid')(dense_layer)
model = Model(inputs=input_layer, outputs=output_layer)
```

To categorise tweets depending on their sentiment (positive, negative, or neutral), the application combines methods that use natural language processing including tokenization, part-of-speech tagging, and sentimental analysis. The application's focus mechanism aids in locating crucial details or terms in the tweets which are particularly relevant to sentiment analysis. Following this, a deep learning model is trained using these enhanced attributes to categorise fresh tweets into the appropriate sentiment groups. For issues with classification, originally called SoftMax is a typical activation function within neural networks. It serves to transform a neural network's output into a range of probabilities across many classifications. The vanishing gradient problem, that may render it difficult to determine precise weights, might affect Original SoftMax when addressing long-term dependencies in sequential information, including language or voice. An improvement on Original SoftMax that can manage long-term dependencies in sequential data is Modified SoftMax. It is an improved organised activation function that promotes output sparsity, which can aid in resolving the vanishing gradient issue.

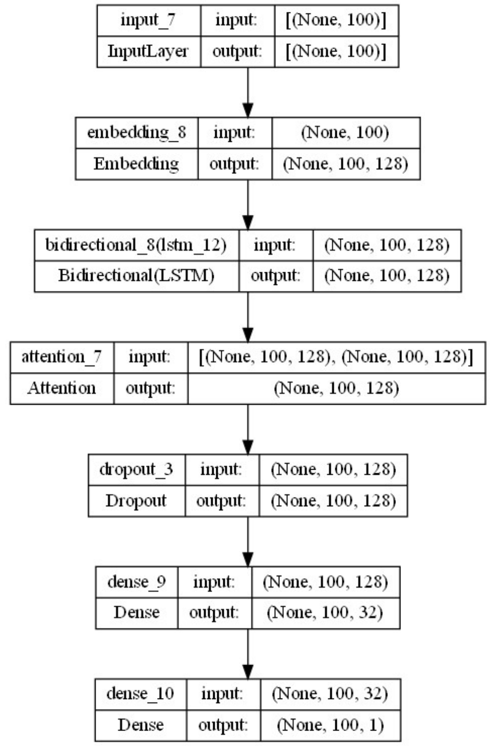

Figure 7: LSTM with IATEN Tensor Flow model

In analysing sequential input, such as voice or text, LSTM models with better attention-based feature extraction could profit from utilising modified Softmax to more precisely compute weights. Better performance on tasks like recognition of speech or text categorization may result through approach. An overview regarding the way the method operates is that it first creates an array of hidden states by analysing the input text employing an LSTM model. At every phase of the sequence, these hidden states indicate the intent and setting of the text. The most significant portions of the input text for the particular position are then determined by applying a mechanism for attention to these concealed states. The significance of each concealed state in the sequence is determined by constructing a set of priority weights. The most important details from the input text have ultimately been captured by combining the attention-weighted hidden states into a distinctive vector. Then, using this feature vector, a range of subsequent processes, including sentiment analysis, text categorization, and machine translation, can be accomplished. This method is a sequence of non-linear transformations and matrix computations that are optimised via backpropagation and descent of gradients. About 90% of accuracy score of an LSTM model with IATEN model for sentiment analysis tasks on average. Based upon different metrics such as precision, recall, and F1 score demonstrates the overall performance of the model. In numerous challenges, the LSTM alongside improved attention-based feature extraction demonstrated accomplishment, frequently outperforming comparable algorithms.

6. CONCLUSION

In comparison to existing sentiment analysis algorithms, the proposed LSTM with IATEN Model for Sarcastic Sentiment Analysis is an improved technique. To effectively identify sarcastic emotions in text data, the suggested model combines the strengths of (IATEN) and Long Short-Term Memory (LSTM). Due to its capacity for capturing the sequential nature of speech and attention mechanism that concentrates on key words in the phrase, this model works better than other algorithms. When contrasted to other cutting-edge models, the suggested model performed very well when its performance was examined using a variety of datasets. The model's precision and accuracy were much greater, making it an ideal alternative for sentiment analysis positions requiring the recognition of sarcasm. By considering both the context and tone of a tweet, this algorithm aims to better capture the subtle aspects of sarcasm. The IATEN component aids in the identification of key words or phrases that could imply sarcasm, whereas the LSTM components enables the model to acquire patterns related to language use. This model's capacity to handle many forms of sarcasm, such as irony, exaggeration, and understatement, is one of its benefits. The algorithm can identify the type of sarcasm used in a tweet by examining the context and mood of the message, and it may then modify its analysis appropriately.

7. FUTURE & LIMITATIONS

Advanced natural language processing techniques, including contextual word embeddings or transformer-based models such as BERT (Bidirectional Encoder Representations using Transformers), could potentially be included in the IATEN paradigm. Such approaches provide an improved understanding of the text's context and semantics, enabling accurate sarcasm identification. The IATEN model could detect a wider range of language patterns and sarcastic expressions if it has been pre-trained on large-scale datasets from multiple sources. Both performance and flexibility might be further improved by using transfer learning approaches, including fine-tuning the model using specialized datasets related to sarcasm. As new sarcastic patterns develop, the IATEN model may be created to adjust and modify itself instantaneously. Overfitting might occur if the IATEN model is exceptionally advanced or if there isn't enough training data. Although the IATEN model's attention mechanisms help to increase interpretability by underlining crucial conditions, the model's overall decision-making process remains challenging to comprehend. It may be challenging to understand why the framework classifies certain scenarios as sarcastic or non-sarcastic, which restricts the model's transparency and interpretability. Sarcasm characteristics that weren't evident in the training data or that appear to evolve might prove challenging for the IATEN model to recognize. To stay accurate at detecting sarcasm and adapt to changing language idioms, it could need regular updates and retraining.

REFERENCES:

[1] M. Pal and R. Prasad, "Sarcasm Detection followed by Sentiment Analysis for Bengali Language: Neural Network & Supervised Approach," 2023 International Conference on Advances in Intelligent Computing and Applications (AICAPS), Kochi, India, 2023, pp. 1-7, doi: 10.1109/AICAPS57044.2023.10074510.

[2] A. Ikram, M. Kumar and G. Munjal, "Twitter Sentiment Analysis using Machine Learning," 2022 12th International Conference on Cloud Computing, Data Science & Engineering (Confluence), Noida, India, 2022, pp. 629-634, doi: 10.1109/Confluence52989.2022.9734154.

[3] P. K. Naik, S. S. Chenjeri, S. Sruthy and H. Mamatha, "Sarcasm Detection in English Text using Tweets and Headlines," 2022 International Conference on Distributed Computing, VLSI, Electrical Circuits and Robotics (DISCOVER), Shivamogga, India, 2022, pp. 192-196, doi: 10.1109/DISCOVER55800.2022.9974808.

[4] P. Verma, N. Shukla and A. P. Shukla, "Techniques of Sarcasm Detection: A Review," 2021 International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), Greater Noida, India, 2021, pp. 968-972, doi: 10.1109/ICACITE51222.2021.9404585.

[5] F. Jemai, M. Hayouni and S. Baccar, "Sentiment Analysis Using Machine Learning Algorithms," 2021 International Wireless Communications and Mobile Computing (IWCMC), Harbin City, China, 2021, pp. 775-779, doi: 10.1109/IWCMC51323.2021.9498965.
[6] P. C. Shilpa, R. Shereen, S. Jacob and P. Vinod, "Sentiment Analysis Using Deep Learning," 2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV), Tirunelveli, India, 2021, pp. 930-937, doi: 10.1109/ICICV50876.2021.9388382.
[7] N. Pawar and S. Bhingarkar, "Machine Learning based Sarcasm Detection on Twitter Data," 2020 5th International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, 2020, pp. 957-961, doi: 10.1109/ICCES48766.2020.9137924.
[8] S. Gupta, R. Singh and J. Singh, "A Hybrid Approach for Enhancing Accuracy and Detecting Sarcasm in Sentiment Analysis," 2020 IEEE International Conference on Computing, Power and Communication Technologies (GUCON), Greater Noida, India, 2020, pp. 130-134, doi: 10.1109/GUCON48875.2020.9231140.
[9] Y. Chandra and A. Jana, "Sentiment Analysis using Machine Learning and Deep Learning," 2020 7th International Conference on Computing for Sustainable Global Development (INDIACom), New Delhi, India, 2020, pp. 1-4, doi: 10.23919/INDIACom49435.2020.9083703.
[10] D. Tanna, M. Dudhane, A. Sardar, K. Deshpande and N. Deshmukh, "Sentiment Analysis on Social Media for Emotion Classification," 2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2020, pp. 911-915, doi: 10.1109/ICICCS48265.2020.9121057.
[11] B. Saju, S. Jose and A. Antony, "Comprehensive Study on Sentiment Analysis: Types, Approaches, Recent Applications, Tools and APIs," 2020 Advanced Computing and Communication Technologies for High Performance Applications (ACCTHPA), Cochin, India, 2020, pp. 186-193, doi: 10.1109/ACCTHPA49271.2020.9213209.
[12] S. V. Pandey and A. V. Deorankar, "A Study of Sentiment Analysis Task and It's Challenges," 2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT), Coimbatore, India, 2019, pp. 1-5, doi: 10.1109/ICECCT.2019.8869160.
[13] A. M. J and P. Ravikumar, "Sarcasm detection in Text Data to bring out genuine sentiments for Sentimental Analysis," 2019 1st International Conference on Advances in Information Technology (ICAIT), Chikmagalur, India, 2019, pp. 94-98, doi: 10.1109/ICAIT47043.2019.8987393.
[14] R. Hu, L. Rui, P. Zeng, L. Chen and X. Fan, "Text Sentiment Analysis: A Review," 2018 IEEE 4th International Conference on Computer and Communications (ICCC), Chengdu, China, 2018, pp. 2283-2288, doi: 10.1109/CompComm.2018.8780909.
[15] M. S. Razali, A. A. Halin, N. M. Norowi and S. C. Doraisamy, "The importance of multimodality in sarcasm detection for sentiment analysis," 2017 IEEE 15th Student Conference on Research and Development (SCOReD), Wilayah Persekutuan Putrajaya, Malaysia, 2017, pp. 56-60, doi: 10.1109/SCORED.2017.8305421.
[16] P. Dharwal, T. Choudhury, R. Mittal and P. Kumar, "Automatic sarcasm detection using feature selection," 2017 3rd International Conference on Applied and Theoretical Computing and Communication Technology (iCATccT), Tumkur, India, 2017, pp. 29-34, doi: 10.1109/ICATCCT.2017.8389102.
[17] M. S. M. Suhaimin, M. H. A. Hijazi, R. Alfred and F. Coenen, "Natural language processing-based features for sarcasm detection: An investigation using bilingual social media texts," 2017 8th International Conference on Information Technology (ICIT), Amman, Jordan, 2017, pp. 703-709, doi: 10.1109/ICITECH.2017.8079931.
[18] T. Jain, N. Agrawal, G. Goyal and N. Aggrawal, "Sarcasm detection of tweets: A comparative study," 2017 Tenth International Conference on Contemporary Computing (IC3), Noida, India, 2017, pp. 1-6, doi: 10.1109/IC3.2017.8284317.
[19] M. Bouazizi and T. Ohtsuki, "Sarcasm Detection in Twitter: "All Your Products Are Incredibly Amazing!!!" - Are They Really?" 2015 IEEE Global Communications Conference (GLOBECOM), San Diego, CA, USA, 2015, pp. 1-6, doi: 10.1109/GLOCOM.2015.7417640.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[20] W. Y. Chong, B. Selvaretnam and L. -K. Soon, "Natural Language Processing for Sentiment Analysis: An Exploratory Analysis on Tweets," 2014 4th International Conference on Artificial Intelligence with Applications in Engineering and Technology, Kota Kinabalu, Malaysia, 2014, pp. 212-217, doi: 10.1109/ICAIET.2014.43.

[21] P. Bhattacharyya, "Sentiment Analysis," 2013 1st International Conference on Emerging Trends and Applications in Computer Science, Shillong, India, 2013, pp. i-i, doi: 10.1109/ICETACS.2013