Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

An effective framework for monitoring Depression (A Mental Disorder) using Sentiment Analysis and Affective Computing

Aurobind Ganesh [1*], R. Ramachandiran [1]
[1] *Dept. of Computer Science & Engineering, Sri Manakula Vinayagar Engineering College (SMVEC), Madagadipet Puducherry*
**Corresponding author – aurofindsyou@gmail.com*

ARTICLE INFO

Received: 18 Dec 2024

Revised: 10 Feb 2025

Accepted: 28 Feb 2025

ABSTRACT

The technique efficiently tracks depression, a mental illness, using sentiment analysis and affective computing. It offers reliable and prompt identification, beneficial assistance, and interventions for at-risk people by analyzing reactions and communication in digital situations. The framework's drawback is its reliance on textual data processing, which could ignore invisible indicators and variation regarding the way depression symptoms are expressed, reducing accuracy in some situations. In this paper, we offer Attribute-attention based LSTM (AALSTM) for strengthening an effective framework for monitoring depression to overcome this crucial issue. Initially, we gather the tweets dataset and preprocess the collected data to remove duplicates and guarantee homogeneity. The subsequent stage involves extracting pertinent features from the pre-processed data. We simulate trials with Python 3.11 software to assess the efficiency of the suggested algorithm. In terms of accuracy (99.53%), precision (99.58%), recall (99.51%), and F-Measure (99.56%), our results show that the AALSTM technique outperforms other methods in effectiveness. Our suggested AALSTM technique provides exciting outcomes for securing an effective framework for monitoring depression using Sentiment Analysis and Affective Computing.

Keywords: Depression, Affective computing, mental disorder, Attribute-attention based LSTM (AALSTM).

INTRODUCTION

Depression is one of the most common mental disorders, and they pose a serious threat to the health of millions of individuals around the world. Debilitating effects of depression might include decreased life satisfaction, difficulty working properly, and, in extreme situations, suicidal thoughts [1]. For prompt assistance and management, better patient outcomes, and less strain on medical systems, initial identification and ongoing monitoring of depression are crucial. Artificial intelligence (AI) and technology developments in the past decade have created new treatment options for mental illness [2-3]. Sentiment analysis and affective computing, two potent AI subfields, are gaining traction as potential methods for reliably assessing and tracking people's mental wellness. As opposed to affective computing, which tries to identify and analyze emotions from various sources such as text, images, and speech, sentiment analysis involves the automated interpretation of human emotions and regards from written information [4-5].Sentiment analysis and affective computing are used in the approach we propose for effectively tracking depression. It recognizes emotional cues and indications for depressive disorders by scrutinizing electronic communications and social networking posts. It gives mental health practitioners real-time mood tracking and insightful data using machine learning algorithms. This non-intrusive strategy attempts to help at-risk people get timely support and individualized solutions [6]. Ultimately, it improves mental health outcomes and raises the standard of living for depressed people.

This study aimed to propose a novel approach called Attribute-attention based LSTM(AALSTM) for monitoring depression using sentiment analysis and affective computing.Part 2: Related work; Part 3: Methodology; Part 4: Results and Discussion; Part 5: Conclusion makes up the balance of the content of this study.

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RELATED WORK

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RELATED WORK

Study [7] presented a machine learning-based classifier architecture to detect despair in internet-based texts utilizing 90 distinct variables as input. These features can deliver outstanding outcomes for depressive identification since they originate from several feature collection methodologies combining emotional lexicons and textual content. Though the effectiveness of the various component groupings differed, the sum of all the attributes produced accuracy levels of more than 96% for all individual conventional classifiers, with gradient booster, a collective algorithm, achieving a precision of over 98%.

A study [8] proposed a structure-based attentiveness networking circuit layout for multidimensional emotional computing that can be applied to monitoring mental health. In particular, an inexpensive memory was created utilizing albumin proteins, and the required testing was done to ensure the device's efficacy and durability. Additionally, an approach that monitors psychological wellness that was low in resource use, low in cost to produce, and soft in privacy invasion can be created using mobile devices and adaptable electronics. The present user's emotional well-being can be tracked using a correlation between multidimensional psychological computing and mental wellness.

The study's primary objective [9] was to disseminate knowledge regarding the different interconnected domains influencing affective computing. These fields comprise their concepts, simulations, and a few approaches that are very helpful in the operations of affective computing.

A study [10] examined emotional computing from the perspective of continuous learning. In a more particular utilization of cross-cultural multimodal recognition of emotions, they suggested the flexible weighted consolidation (EWC) continuous learning method. Although emotional computers are multimodal and changing, the findings will make it easier to create and apply them in a real-world setting.

A study [11] presented a useful technique for assessing Twitter users' levels of depression. To improve the approach for calculating depression ratings, sentiment assessments might be mixed with additional feelings. The different components of depressive disorder that weren't previously recognized will be brought to light by this approach. The major goal was to give a sense of understanding about the levels of sadness in various users along with the way the scores might be associated with the primary data.

Study[12] proposed a unique multi-level attention network for multipurpose depressive predictions that integrates data from audio, video, and text modalities while recognizing the between and intermodality significance. The multifaceted attention supports overall learning by choosing the most important Attributes from every approach for making choices. They conduct extensive testing to develop several regression equations for audio, video, and text mediums. To comprehend the effects of every characteristic and method of instruction, several fusing simulations

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with different configurations are created. Regarding root mean squared error, they outperform the present baseline by 17.52%.

Study [13] suggested a brand-new classifier called Cost-sensitive Boosting Pruning Trees (CBPT), which exhibits promising results on two data sets for identifying Twitter sadness that are available to individuals. They use three additional datasets from the UCI machine learning library to assess CBPT's categorization capabilities fully, and when compared to many cutting-edge enhancing methods, CBPT achieves commendable classification outcomes.

Study [14] examined two mathematical models that try to capture the existence and evolution of the feelings displayed by social networking users. Two recently available information collections for two significant psychological disorders—depression and anorexia—are used in our analysis. The findings obtained imply that the availability and variety of sentiments, reflected by the suggested visualizations, enable the identification of important facts about social media users who are anorexic or depressed.

Study [15] examined the original structure for emotional evaluation, which analyzes users' facial expressions using their facial photos to understand and automatically recognize users' emotions. The system comprised three components: autonomous expression analysis, image preliminary processing, and input of facial expressions films. Through automatic facial expression analysis, the findings presented in the study show that the suggested technique performs better than it told the device might work as a clever, inexpensive, and intuitive cognition aid to recognize, path, and overall diagnosis the psychological well-being of a person by outperforming alternative approaches about of effectiveness and precision.

METHODOLOGY

Figure 1 illustrates the many stages that were performed to help explain the various actions which were completed. This study will answer an open question by developing a distinctive model for a practical framework for monitoring depression. In this work, real-time datasets are the main focus. We utilized feature extraction and data preparation.

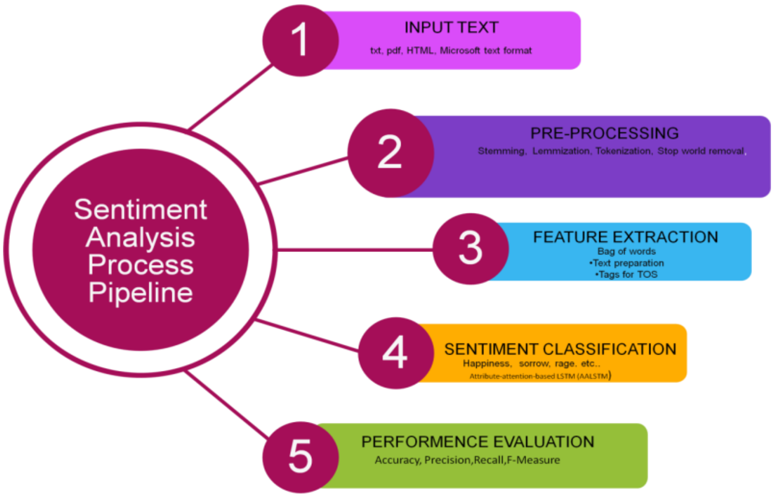

Figure 1: Sentiment analysis process pipeline

DATASET

The dataset [16] is presented in Table 1.

Table 1: Dataset

Category	**Details**
Date Range	March 21, 2020, to April 16, 2020
Total Tweets	43,3 billion the COVID-19 tweets
Total Users	37.6 billion clients, probably

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Depression Group	2575 unique Twitter users identified as having depression
Comparison Group	2575 individuals were randomly selected without depression-related phrases in their recent statements/profiles
Depression Identification Method	Regular expression search based on patterns in tweets and user profiles
Hashtags Used	"#Corona," "#Covid_19," and "#coronavirus"
Search Criteria	Tweets containing phrases "corona," "covid19," "covid-19," and "coronavirus"
Depression Indicators	Language and user profile information, e.g., users identifying as "depression fighters."
Additional Indicators	Expressions like "I have/developed/got/suffer(ed) from X depression," "my X depression," "I'm healing from X depression," "I'm diagnosed with X depression," and keywords like "depression fighter/sufferer/survivor."
Exclusion Criteria	Users with descriptions containing "practitioner" and "counselor" words were excluded
Twitter API	Applications program interfaces (API) are twee
Tweets Retrieved	afterward, the depressing tweeting, public tweets sent by selected persons throughout the past three months
Tweets per User	Capped at 200 tweets per user (average number of tweets published in 3 months)
Human Annotations	86% of randomly selected users in the depression group had positive annotations assigned by humans

Data preprocessing

Preprocess the data by taking out noise and unimportant knowledge and concealing sensitive data. Perform stemming/lemmatization, deletes stop words, and tokenizes the text.

Stemming or Lemmatization

By combining variations of the same word, stemming or lemmatization lowers words to their simplest form, reducing sparseness. This increases the precision of sentiment analysis and pattern detection. The structure then evaluates the text's psychological overtones to help with a mental wellness evaluation. For thorough depressive observing, it integrates research of emotions with additional elements.

Tokenization

Tokenization aids in providing the text with analysis in an organized fashion, enabling us to comprehend the emotions behind every sentence and the way it contributes to the text's mental tone. We can identify whether the text reflects happy, detrimental, or neutral feelings by giving these tokens expression ratings, which can reveal important details about the person's state of mind. Implementing a solid foundation for tracking distress and promoting mental well-being assessment and treatment requires proper data preparation, especially tokenization.

Stop and Removal

Eliminate non-emotionally significant words (such as "the," "and," or "us") from data preprocessing when employing sentiment analysis to detect sadness to reduce noise and conserve computer resources. This process removes meaningless phrases from the text data. Tokenize the text to separate it into words so that you may analyze it more

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thoroughly. While emotion dictionaries link words to emotions and aid in analyzing feelings, applying stemming or lemmatization assures word coherence. This process improves the accuracy of the depression monitoring system by reducing distortion and unimportant information.

There are some key tools for initial processing of the text data included in the Keras deep learning packages.The subsequent stages make up this procedure:

Step1: By using fundamental normal expressions to remove backlinks and special characters.

Step 2: To separate phrases, use text to create word sequencing.

Step 3: Put a space between every phrase (split="").

Step 4: filters='!"#$%&()*+,-./:;=>?@[]_'|tn' eliminates whitespace.

Step 5: Lowercase=True transforms uppercase content.

Step 6: Tokenizers' API

Step 7: Tokenizer is a class in Keras that can be used to prepare text files for deep learning purposes. It is necessary to create the Tokenizer before using it on plain text or text that has been integer-encoded.

Step 8: Stopword removal - Stopwords are often used words in a language, such as "the," "a," "of," "I," "it," "you," and so on.

Step 9: Originating is a technique that strips words of intonation by removing extraneous individuals, usually a suffix, from the beginning of the phrase.

Feature extraction using a bag of words

Feature extraction is used to transform words into a matrix of vectors. Unlike supervised algorithms or a network of deep neural networks, this level is not implemented the same way.

Bag of Words (BoW) is a popular method for extracting features from text input in language processing and information recovery. The BoW method transforms written documents into quantitative feature vectors that show how frequently each word appears in the text. An instruction manual for performing the extraction of features using the Bag of Words method is provided below:

- **Text preparation**

Lowercase: To ensure that word counts are not affected by the case, convert all text to lowercase.

Tokenization: The division of the text into tokens, or single words. Whitespace characters are typically employed to separate words, but more sophisticated tokenization strategies can also be applied.

Punctuation Removal: Remove all non-alphanumeric characters, including punctuation.

Remove common words (such "the," "and," and "in") that have little to no significance due to the fact they tend to appear regularly in all writings.

- **Tags for TOS**

Utilise tools from NLTK or SpaCy to determine the parts of speech (POS) tags for each word in the preprocessed text. Include specific markers, such as "N_" for nouns, "V_" for verbs, "A_" for adjectives, etc. to indicate the different parts of speech for each word in the bag of words vector. When "dog" is designated as a noun, the result is "N_dog."

Sentiment Analysis

A broad phrase used in the framework of text categorization is sentiment evaluation. It describes the method of analyzing and categorizing emotion in text utilising artificial intelligence and natural language processing. We classify the tweets about COVID mental health as positive, bad, or neutral using deep learning algorithms.

Attribute-attention-based LSTM (AALSTM)

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- **LSTM with Attribute Embedding (AE-LSTM)**

When categorizing the opposite sides of a specific Attribute in one statement, Attribute facts are essential. When numerous variables are taken into account, we could obtain polarities that are opposite. We suggest learning encoding vectors for every component to make the most of the Attribute information.

Using the portion of the i incorporation, a vector v_(a_i)∈Rd^ais shown, where da is the dimension of the component encapsulation. Every element integrating makes up A∈ R 〖d^a〗^(×|A|). To the greatest extent of our knowledge, this is the initial occasion that component integration has been proposed.

- **Attention-based LSTM (AT-LSTM)**

Standard LSTMs are unable to identify the crucial information for Attribute-level sentiment categorization. We suggest creating a mechanism for attention that can identify the essential portion of an argument in its reaction to a specific component to solve this problem. The structure of an AT-LSTM, or attention-based LSTM, is shown in Figure 2.

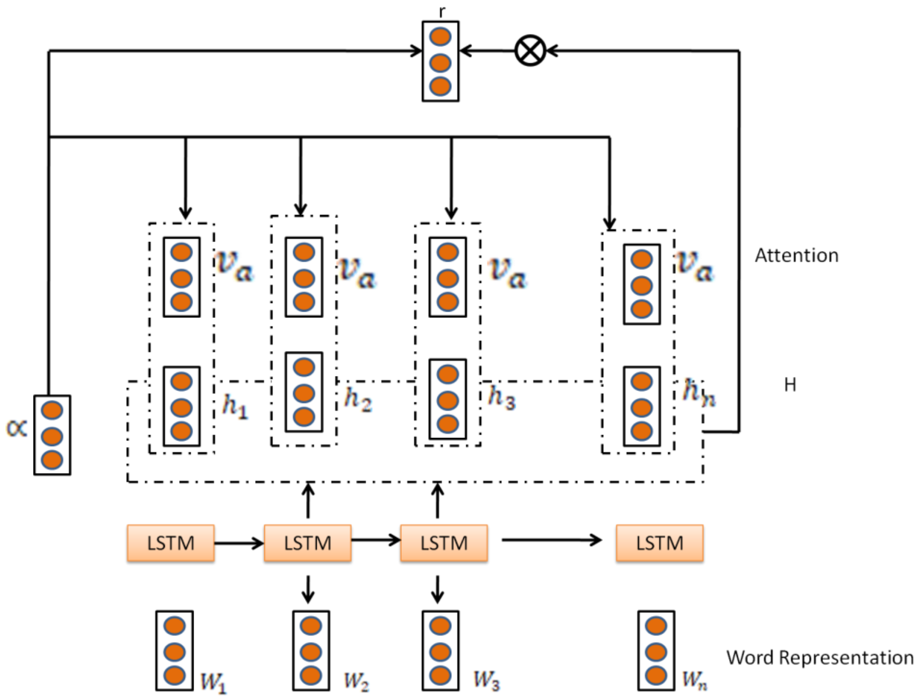

Figure 2: Structure of Attention-based LSTM

Let $H \in \mathbb{R}^{d\times|A|}$ be a matrix made up of the hidden vectors (h1,...,hN) that the LSTM generated, where d is the number of hidden layers and N is the sentence's total length. Additionally, v_a denotes the encapsulation of perspective, and similar $e_N \in \mathbb{R}^N$ is a representation of one. A balanced concealed Markov model and a concentration strength vectors will result from the concentrating process representation r.

$$M = \tanh\left(\begin{bmatrix} W_h H \\ W_v v_a \otimes e_N \end{bmatrix}\right) \quad (1)$$

$$\propto = softmax(W^T M) \quad (2)$$

$$r = H \propto^T \quad (3)$$

where, $M \in \mathbb{R}^{(d+d_a)\times N}$ $\propto \in \mathbb{R}^N$, $r \in \mathbb{R}^d W_h \in \mathbb{R}^{d\times d}$, $W_v \in \mathbb{R}^{d_a\times d_a}$ are projection parameters. α is a vector made up of concentration measurements, and r is a weighted illustration of the statement with the specified feature. The

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e-ISSN: 2468-4376
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symbol in the number 7 (abbreviated OP here) means $v_a \otimes e_N = [v; v; \ldots; v]$, The function, wherein e_N is an ordered vectors with N 1s, combines u for N times in this manner. $W_v v_a \otimes e_N$ is equal to the number of words in the expression periods the vertically translated u_a..

The last phrase in the example is provided by:

$$h^* = \tanh(w_p r + w_x h_N) \quad (4)$$

where $h^* \epsilon \mathbb{R}^d$, w_p and w_x are projected characteristics that can be trained on. We discover that adding $W_x h_N$ to the ultimate illustration of the statement makes it substantially more effective.

When several factors are taken into account, the process of attention enables the simulation to remember an especially significant portion of an expression.

The characteristic of the depicting the phrase provided a specified facet is thought to be h^*. To transform phrase vectors into e, a real valued vectors having a dimension equivalent the classification numbers |C|, that we add an inverse linear layer. The next step is to apply a softmax layer to convert e to a contingent likelihood density.

$$y = softmax(W_8 h^* + b_s) \quad (5)$$

Attention-based LSTM with Attribute Embedding (ATAE-LSTM)

Feature integration is used in the AE-LSTM to compute attention weighting to leverage component knowledge. We add the supplied component encapsulation into every syllable output vector so that component knowledge can be used more effectively. Three is an illustration of this algorithm's construction. In this method, the supplied component u_aability can be included in the resultant hidden representations (h1,h2,...,hN).The relationship between phrases and the input Attribute can thus be modeled in the subsequent phase that computes interest evaluations.

Affective Computing regarding emotion recognition

Figure 3 illustrates the many stages that were performed to help explain the various actions which were performed. Put emotional computing methods to use by implementing a feelings recognition system. To recognize sentiments such as happiness, sorrow, rage, etc., from written material, this could entail retraining machine algorithms using labeled emotion data.Assign emotional labels to each text entry to indicate the main feeling conveyed.

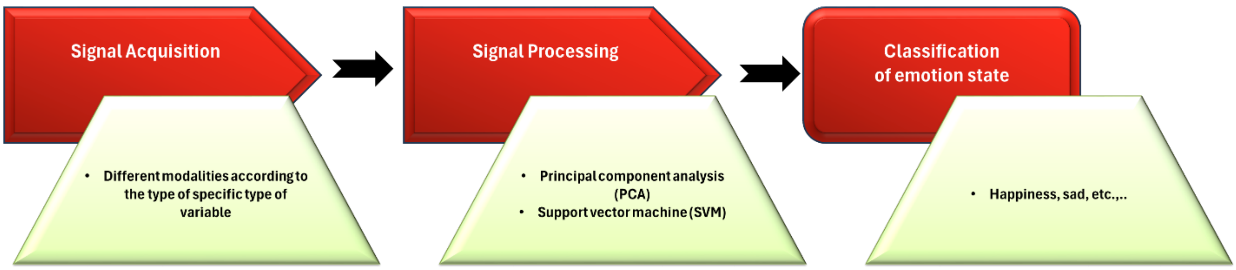

Figure 3: The Affective Computing process pipeline

Principal component analysis (PCA)

PCA may tangentially increase the health care system's security by identifying abnormalities, choosing characteristics, visualizing information, de-identifying information, and encryption data.This informal method of PCA and other AI approaches relies on information that reduces a particular database. By implementing the provided associations (positive or negative) and the accuracy of the key components (PCs) to the aggregate available, the results of such modifications can be used for a greater account of a specific event to uncover obscure facts. The jth Utilising, the PC vector (Fi) is calculated. The starting matrices M have observations of $m \; x \; n$ and a unit-weighting columns (Uj).

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e-ISSN: 2468-4376
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$$Fi = UTjM = \sum i = 0UjiM \tag{6}$$

U is the stress coefficient, while M and U are n-dimensional informational matrices. By providing N to V, variation vectors $M(Var(M))$ are created and need to be maximized subsequently:

$$Var(M) = 1n(UM)(UM)T = 1nUMMTU \tag{7}$$

$$MaximumV(M) = Maximum((1n)UMMTU) \tag{8}$$

Since $M(cov(M))$ and $1nMMT$ have the same correlation matrices, $Var(M)$ can be expressed in this manner:

$$Var(M) = UTcov(M)U \tag{9}$$

The Lagrange multiplier method can be used to figure out the Lagrangian function as follows:

$$Lg = U^T \tag{10}$$

$$Lg = UTcov(M)U - \delta(UTU - 1) \tag{11}$$

"UT U- 1" be assumed near be equivalent to zero because the scaling vector in Equation (11) is an integer variable. The absolute maximum of $Var(M)$ can therefore be discovered by contrasting the combined value (L) of the translational functional with regard to U as shown below.

$$\frac{dL}{dU} = 0 \tag{12}$$

$$c(M)U - \delta U = (cov(M) - \delta I)U = 0 \tag{13}$$

Where δ represents $cov(M)$ where U's eigenvector equals their amplitude.

Depression detection and monitoring

Using software and hardware technology, affective computing can recognize a person's emotional state. Recent effective systems are built on the gathering of several biosignals, including:

- Physical characteristics and factors, such as appearance, language, gestures, and activity.
- Physiological indicators include eye tracking, breathing, Heart Rate (HR), EEG, ECG, and Galvanic Skin Response (GSR).

Prepared unprocessed signals are first used to increase SNR (Signal Noise Ratio). It can be split depending on events or stimulus after the background noise has been removed, making it easier to analyze them later. The signals must then be calculated in order to identify specific characteristics. Handling affective signals in the time, duration, temporal frequency, or power domains is possible. Figure 4 illustrates the architecture of the depression monitoring.

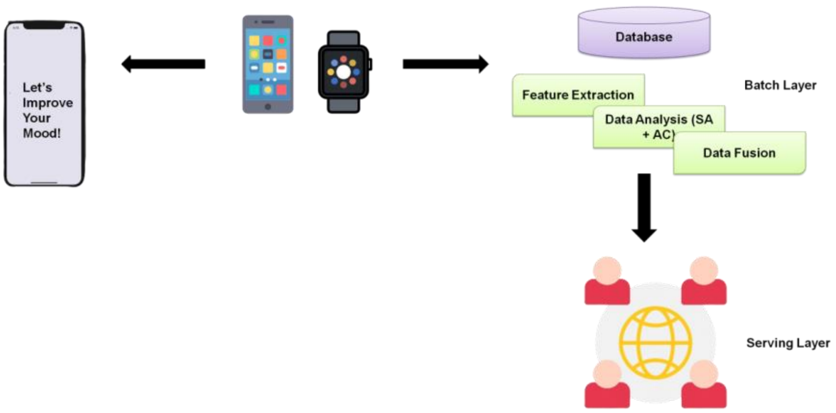

Figure 4: The architecture of the depression monitoring

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Support Vector Machines (SVM)

Support Vector Machines (SVM) can be used for this. SVM is employed in this situation as a binary classifier to differentiate between positive and negative emotions. We give a condensed explanation of SVM's operation for depression evaluation.

Consider that we possess a collection of text samples, each of which has been classified as either positive (+1) or negative (-1) in terms of emotion. Given that N is the total number of samples, let's refer to the feature vectors of these samples as xi and their related labels as y_i.

Finding a hyperplane (decision border) that distinguishes the samples that are positive from those that are negative with the biggest distance is the objective of SVM. The hyperplane's equation(1) can be written as:

$$w \cdot x + b = 0 \tag{14}$$

Where, the weight vector w is parallel to the hyperplane. The feature vector input is x. The bias factor, b, determines the offset of the hyperplane from the origin.

The signature distance (margin), which measures the separation between a data point x_i and the hyperplane, can be determined.

$$distance\ (x_i) = y_i(w \cdot x + b = 0) \tag{15}$$

RESULTS AND DISCUSSION

In this study, the Python 3.11 platform has been used to implement the Attribute-attention based LSTM (AALSTM) technique. A Windows 10 laptop with an Intel i7 processor and 32 GB of RAM. This section examines the metrics of accuracy, precision, recall, and F-measure. The proposed method outperforms the already existing methods (simpleRNN, LSTM, GRU) [17].

The framework's accuracy in identifying depression (true positives) and non-depression (true negatives) is measured in depression monitors accuracy. It analyses the congruence between predictions and the actual state of mental health, which is essential for assessing how well the system works. Better discriminating between people with and without depression is indicated by higher accuracy. Equation (16) considers how well a method estimates its position based on the available information. Figure 5 and Table 2 depicts the comparative evaluation of the existing and proposed method. When compared with the existing method Simple RNN(86.25%), LSTM(96.29%), GRU(99.47%) our proposed methods achieves AALSTM(99.53%), it shows that our proposed method is superior than the existing method for monitoring depression.

$$Accuracy = (NumberofTruePositives + NumberofTrueNegatives) \,/\, TotalNumberofCase \tag{16}$$

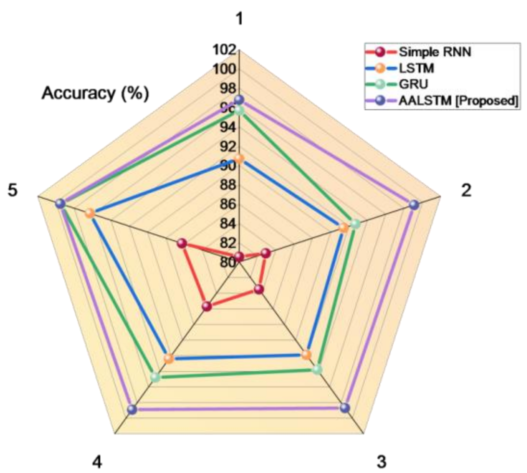

Figure 5: Accuracy

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2025, 10(40s)
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Table 2: Accuracy

Epochs	Accuracy (%)			
	Simple RNN[16]	LSTM[16]	GRU[16]	AALSTM [Proposed]
1	80.54	90.7	95.7	96.8
2	82.9	91.4	92.7	99.1
3	83.5	91.9	93.8	98.7
4	85.7	92.4	94.8	98.9
5	86.25	96.29	99.47	99.53

The percentage of accurately recognised true positive depression cases across all the positive forecasts provided by the surveillance architecture is known as precision in depression monitoring. Equation (17) assesses how well a method estimates its position based on the available information. Figure 6 and table 3 depicts the comparative evaluation of existing and proposed method. When compared with the existing method Simple RNN(92.71%), LSTM(96.29%), GRU(99.47%) our proposed methods achieves AALSTM(99.58%), it shows that our proposed method is superior than the existing method for monitoring Depression

$$Precision = True\ Positives / (True\ Positives + False\ Positives) \quad (17)$$

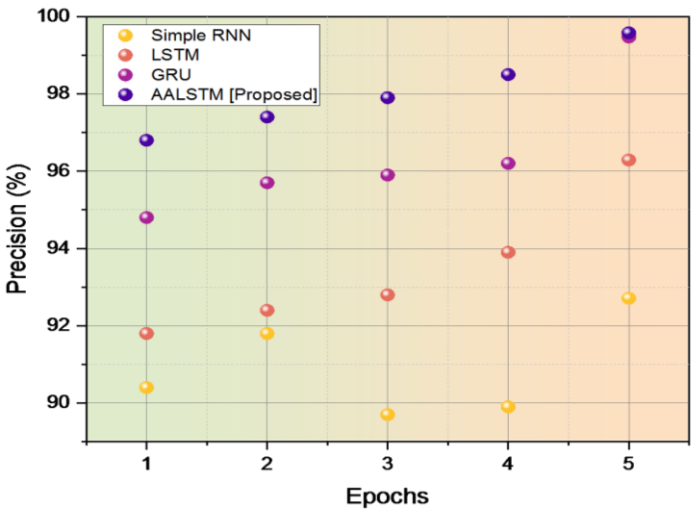

Figure 6: Precision

Table 3: Precision

Epochs	Precision (%)			
	Simple RNN[16]	LSTM[16]	GRU[16]	AALSTM [Proposed]
1	90.4	91.8	94.8	96.8
2	91.8	92.4	95.7	97.4
3	89.7	92.8	95.9	97.9
4	89.9	93.9	96.2	98.5
5	92.71	96.29	99.47	99.58

Recall, also referred to as sensitivities or the percentage of true positive estimates made out of all real positive cases in a binary classification issue, is a performance parameter. It shows how successfully a model can detect positive occurrences. Equation (18) assesses how well a method estimates its position based on the available information. Figure 7 and table 4 depicts the comparative evaluation of existing and proposed method. When compared with the existing method Simple RNN(80.95%), LSTM(95.24%), GRU(99.47%) our proposed methods achieves

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AALSTM(99.51%), it shows that our proposed method is superior than the existing method for monitoring Depression.

$$Recall = True\ Positives\ /\ (True\ Positives + False\ Negatives) \quad (18)$$

Figure 7: Recall

Table 4: Recall

Epochs	Recall (%)			
	Simple RNN[16]	LSTM[16]	GRU[16]	AALSTM[Proposed]
1	80.4	90.8	95.8	96.8
2	79.5	91.6	94.7	97.5
3	78.4	92.7	92.8	98.4
4	78.9	93.4	93.8	99.1
5	80.95	95.24	99.47	99.51

F-measure is a metric used to assess a binary classification model's efficacy, such as in the monitoring of depression using sentiment analysis and affective computing. It creates a single score by combining precision (the percentage of accurate positive predictions among all positive predictions) and recall .Equation (19) assesses how well a method estimates its position based on the available information. Figure 8 and table 5 depicts the comparative evaluation of existing and proposed method. When compared with the existing method Simple RNN(86.36%), LSTM(95.75%), GRU(99.47%) our proposed methods achieves AALSTM(99.56%), it shows that our proposed method is superior than the existing method for monitoring Depression.

$$F - measure = 2 * (precision * recall) / (precision + recall) \quad (19)$$

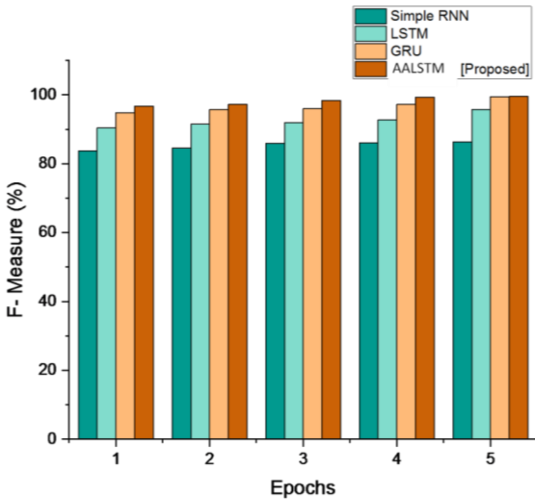

Figure 8: F-Measure

Table 5: F-Measure

Epochs	F- Measure (%)			
	Simple RNN[16]	LSTM[16]	GRU[16]	AALSTM[Proposed]
1	83.74	90.4	94.84	96.7
2	84.6	91.5	95.7	97.2
3	85.9	91.9	96.1	98.4
4	86.1	92.7	97.2	99.3
5	86.36	95.75	99.47	99.56

Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
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CONCLUSION

An effective method for tracking depression that uses sentiment analysis and affective computing to accurately diagnose and measure mental health.For sentiment classification, we used Attribute-attention based LSTM(AALSTM). In this work, real-time datasets are the main focus. We utilized feature extraction and data preparation.From the 43,3 billion the COVID-19 tweetssent by 37.6 billion clients, probably between March 21 and April 16, 2020, we first determined which users had depression. For the proposed method's performance, we were able to obtain values for in terms of accuracy (99.53%), precision (99.58%), recall (99.51%), and F-Measure (99.56%). The proposed method was compared to the one that is currently being used, and the results of the experiments showed that the proposed strategy was more effective. Consistently collecting complicated feelings and mental conditions during text analysis presents challenging in properly monitoring depression with sentiment analysis and affective computing. Future study will focus on improving and fusing sentiment analysis and affective computing to build an exhaustive structure for precise and timely surveillance of sorrow as a psychological condition.

Conflicting interests
There is no conflict of interest relating to this research.

Funding
This research received no specific grant from any funding agency

Ethical approval
Not applicable

Guarantor
Not applicable

Contributorship
Not applicable

Acknowledgements
Not applicable

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