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BeWell: An Integrated Mental Health Application Using LSTM Neural Network Model and Vader Sentiment Analysis for Emotional Well-Being

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ABSTRACT

The burgeoning field of mental health has significantly benefited from advancements in Artificial Intelligence (AI), particularly in emotion recognition and analysis. This paper presents the "BeWell" application, a pioneering tool designed to leverage the synergy between Long Short-Term Memory (LSTM) neural networks with the proposed Emotional Support System (EMS) algorithm and Vader sentiment analysis for enhanced mental health support. The application aims to provide users with an interactive platform for emotion tracking and mental well-being assessment, utilizing vocal and textual inputs. By analyzing speech patterns and text input, "BeWell" identifies emotional states and provides tailored responses and recommendations. We detail the application's development, emphasizing its robust AI-driven backend, which combines LSTM-EMS models known for their efficacy in sequence prediction tasks with the nuanced sentiment detection capabilities of the Vader algorithm. Our experimental results demonstrate the system's precision and reliability in real-world scenarios, offering a versatile and user-friendly approach to managing mental health. The "BeWell" application stands as a testament to the potential of integrating multiple AI techniques to create sensitive and adaptive mental health technologies.

KEYWORDS
Artificial Intelligence, BeWell, Neural Network Model, Confusion Matrix, Emotion Classification, Machine Learning, Long Short Memory Model, Vader Sentiment,

1. INTRODUCTION

Emotion recognition involves the intricate process of comprehending and articulating an individual's existing cognitive state or mental disposition. The exploration of this realm has witnessed a surge in scholarly investigation in recent times, primarily focusing on accurately identifying emotions through analyzing brain signals [1–3]. Scholars from diverse domains such as neuroscience, computer science, cognitive sciences, and medicine are converging on the recognition of emotions as a topic of paramount importance, particularly in advancing artificial intelligence [4-9].

The complex process of understanding emotions through different means, and then emphasizes the unique value of using electroencephalogram (EEG) data for convergence of various avenues for conveying Emotional States, Facial Expressions [10-12] where these studies explain the emotions related to face impressions, bodily movements [13,14] where the body language contributes to emotional communication, Gestures [15,16] where the hand and arm movements, or other types of gestures, are additional non-verbal cues to emotions.

After discussing these external indicators, the above passage shifts focus to the significance of EEG data for emotional analysis. Unlike the observable means mentioned earlier, EEG offers a direct window into brain activity. EEG data is considered crucial due to the direct reflection of brain signals where the EEG captures the electrical activity of the brain, which is directly influenced by our mental states [17] and the Intricate Tapestry of Human Thoughts and Emotions where our thoughts and emotions are complex and interwoven, affecting brain signals in a way that is perhaps more nuanced and profound than external expressions can fully capture. The distinct advantage of EEG data in emotional analysis, arguing that brain signals offer a more direct and potentially deeper understanding of emotional states because they are directly tied to our thoughts and feelings. This emphasis on EEG data suggests a belief in the value of neuroscientific approaches to emotion research, proposing that such methods can uncover aspects of emotional states that might not be as readily apparent through external expressions alone.

Artificial Intelligence (AI) is revolutionizing the way we understand and interact with human emotions by providing advanced computational methods. These methods are adept at mining valuable insights from a variety of inputs, ranging from facial expressions and the tone of voice to the sentiment embedded in text and physiological signals. Such a broad spectrum of inputs necessitates the development of sophisticated algorithms [18,19] and models [20,21], each tailored to suit different types of data and their unique application contexts. This customization allows for a nuanced approach to emotion recognition, enabling technologies to cater to specific emotional understanding requirements across diverse scenarios.

The significance of this paper lies in its introduction of a pioneering system, dubbed "Be-Well." "Be-Well" stands out for its innovative integration of a Long Short-Term Memory (LSTM) model with Vader sentiment analysis. This combination is not merely additive but synergistic, enhancing the system's ability to recognize and interpret emotional states with remarkable precision. The LSTM model contributes its strength in processing and remembering information over long periods, making it ideal for understanding complex emotional patterns. Meanwhile, Vader sentiment analysis offers a robust framework for interpreting the emotional tone from textual data, providing a comprehensive emotional analysis.

2. LITERATURE REVIEW

India's vast and varied demographic landscape is facing a critical mental health challenge that requires immediate and focused attention [22]. Mental health disorders transcend age, socioeconomic status, and geographic boundaries, affecting people from diverse backgrounds. The impact of these disorders is profound, leading to personal distress, hindered daily functioning, and significant costs to society [22]. The frequency of mental health issues in India has been on an upward trajectory, marking a serious concern for the nation's public health infrastructure. It is estimated that around 15% of India's population is battling some form of mental health condition, including but not limited to anxiety, depression, bipolar disorder, schizophrenia, substance abuse, and neurodevelopmental disorders [23].

The societal impact of mental health challenges is extensive. At the individual level, those suffering from mental health conditions face severe personal suffering and a diminished capacity to live fulfilling lives. This often translates into difficulty in maintaining social relationships, pursuing educational or employment goals, and engaging in community activities [24]. On a larger scale, mental health issues significantly undermine community and national functioning. Economic repercussions include decreased productivity in both professional and domestic settings. Specifically, mental health conditions contribute to absenteeism, lower work efficiency, and long-term disability, thereby negatively influencing workforce productivity and stalling economic progress [25,26].

In India, a significant portion of the population is affected by mental health issues, with reported prevalence rates ranging from 9.5 to 370 per 1000 individuals [27]. These figures indicate a wide array of mental health challenges prevalent across the country, underscoring the complexity of the issues faced by its citizens [27]. Such high prevalence rates underscore the critical need for robust interventions and support mechanisms to cater to the mental health needs of the Indian populace. Commonly encountered conditions include depression, anxiety disorders, bipolar disorder, schizophrenia, and substance use disorders, highlighting the variety of mental health challenges that need to be addressed [27].

Depression, a widespread mental health condition, manifests as persistent feelings of sadness and despair, coupled with a diminished interest or pleasure in daily activities. It has been noted that 3.5% of all deaths can be linked to anxiety or depression at a global level [28]. Anxiety disorders involve intense, prolonged worry, fear, or anxiety that disrupts everyday life. Specifically, Generalized Anxiety Disorder is marked by ongoing, excessive anxiety about various life situations [29,30]. Bipolar disorder features cycles of mood elevation (mania or hypomania) and depressive episodes. During manic phases, individuals might experience increased energy, reduced need for sleep, rapid thought processes, overly confident self-esteem, reckless actions, and an inflated sense of importance [31]. Schizophrenia, a serious mental illness, leads to distorted perceptions of reality, affecting how a person thinks, feels, and acts, with profound impacts on their interaction with the world [32].

In Indian society, mental health is profoundly affected by factors such as societal stigma and discrimination [33,34], gender inequalities [35], poverty and socioeconomic disparities [36], rapid urbanization and migration [37], family dynamics and societal pressures [38], and varying cultural beliefs surrounding mental illness [39]. These elements contribute to a pervasive environment where mental health conditions are stigmatized, leading to isolation and hindering access to care. Women, in particular, face heightened vulnerability due to systemic gender biases and related stressors. Economic challenges further exacerbate the mental health crisis, limiting access to necessary services and support. Urbanization and migration introduce additional stress and disconnection, while familial and societal expectations can amplify anxiety and stress, impacting individuals' well-being. Cultural attitudes towards mental health can deter individuals from seeking evidence-based treatments, perpetuating cycles of mental distress. Collectively, these issues impose a significant burden on individuals, characterized by diminished life quality and increased suicide risk, and society, marked by economic losses and a strained healthcare system [40,41,42], underscoring the urgent need for comprehensive mental health interventions in India.

In order to lessen all the factors above, we have developed an application-based model named as “Be Well” that combines the both applications of LSTM model along with Vander Sentiment analysis in order to predict the emotional responses for mental health responses. "Be-Well" is designed with a clear focus on mental health support, recognizing the crucial need for personalized and effective interventions in this area. By accurately identifying and interpreting emotional states, "Be-Well" aims to facilitate the delivery of targeted mental health assistance, bridging the gap between emotional recognition technology and practical mental health solutions. This system represents a significant leap forward in leveraging AI to enhance mental well-being, offering a promising tool for both individuals and mental health professionals.

3. BASIC DESCRIPTION OF BE-WELL

3.1 Front End

The Be-Well Android application, developed through the integration of Java and XML technologies, aims to assist users in managing their mental health effectively. It features an AI-powered chatbot that initiates interactive conversations, offering users a platform to articulate their feelings. Based on the users' expressed emotional conditions, the chatbot delivers customized advice and empathetic responses, carefully aligned with the users' current emotional states.

Moreover, the application is enhanced by the incorporation of advanced speech recognition and sentiment analysis technologies, which enable it to process and understand both text and voice inputs from users, assessing their emotional states.

This capability allows the app to adeptly generate suggestions, guiding users to consult with mental health professionals if signs of depression or anxiety are detected. As committed data science students, our interest in exploring the nuanced dynamics of emotions has led us to engage in predictive analyses within our research. This approach provides foresight into the expected results of our study. Through this journey of gathering and analyzing information, we aim to deepen our understanding of emotional complexities, striving to make a significant contribution to the field of emotional well-being.

3.2 Back End

The program is developed in Python and utilizes Google Colab as its compiler. It employs the RAVDESS dataset, sourced from a reputable website, which includes audio files from various actors for analysis. The Be-Well initiative leverages state-of-the-art technologies to provide personalized mental health support to its users. By analyzing chat and audio data, the software employs LSTM models—a type of recurrent neural network—to more accurately predict users' emotional states. Additionally, it utilizes VADER sentiment analysis to understand the emotional tone of text, enhancing its ability to deliver tailored responses. Speech recognition models further refine the system's ability to detect nuances in voice intonation and tone, improving mood analysis accuracy.

Furthermore, the Be-Well initiative incorporates machine learning techniques to refine the precision of its predictive models and enhance its ability to offer personalized assistance. The software learns and adapts from each interaction by identifying patterns in user data, becoming increasingly effective over time.

The approach includes analyzing audio files to identify different emotions, focusing on emotion representation, sample rate, and the entity of the audio segment within each file. Normalization of sample rates leads to the extraction of 13 Mel-frequency cepstral coefficients (MFCCs). Emotion labeling involves distinguishing emotional content from silence and using padding to standardize audio lengths. Noise reduction is achieved through low-pass filtering, enabling the identification of 15 unique features per audio sample, as illustrated in Fig.1.

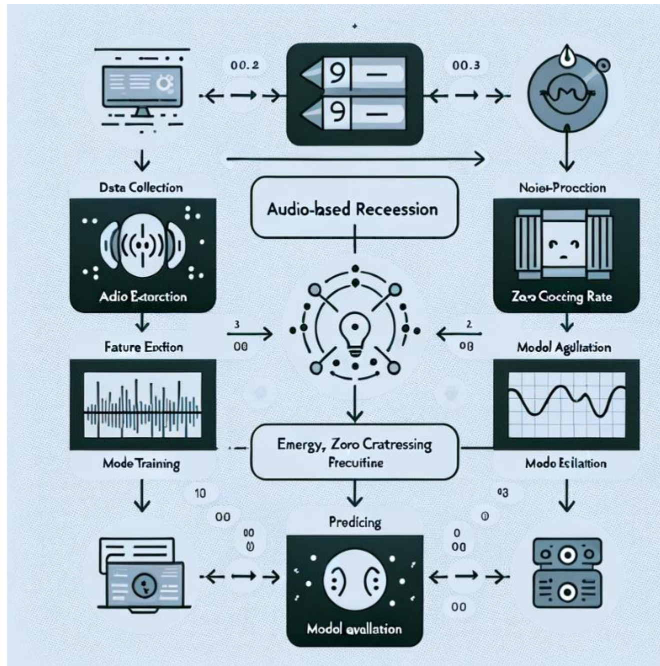

Fig. 1 Proposed Methodology

3.3 The proposed Emotional Support (EMS) Algorithm

The proposed algorithm is outlined in a structured process as follows:

1. Collection of User Inputs: This step involves gathering inputs from users, which could be in the form of voice recordings or text messages.
2. Analysis of Sentiment: Utilize tools for sentiment analysis to determine the overall emotional tone from the user's text chats and voice submissions.
3. Classification of Mood via Machine Learning: A machine learning model is trained with annotated data to identify the user's current emotional state, categorizing it into emotions like happiness, sadness, anxiety, or depression.
4. Generation of Responses Based on Mood: Depending on the mood identified by the model, craft suitable replies to address the user's emotional needs. For instance, comforting phrases might be provided for someone deemed sad, or uplifting messages for an individual feeling down.
5. Tracking and Monitoring Mood: This involves ongoing observation of the user's mood, paying attention to significant mood fluctuations that could signal changes in emotional health.
6. Referral for Professional Assistance: Should the algorithm identify a potential for depression or anxiety through mood trends, it advises the user to consult a qualified mental health expert.
7. Enhancement of the Model with Continuous Learning: The machine learning model is periodically updated and refined with new, labeled data to improve its precision in mood categorization.

This proposed EMS algorithm, by weaving together sentiment analysis, machine learning, and natural language processing, assesses and responds to the user's emotional state in a supportive and understanding manner, aiming for enhanced user interaction.

3.4 Mathematical Representation of proposed EMS

Let X be the set of user inputs,

$$X = \{x_1, x_2, ..., x_n\} \quad (1)$$

where each x_i can be a text message or voice recording. For text analysis, let $S(x_i)$ be the sentiment score of input x_i.

$$S: X \rightarrow R \quad (2)$$

where each sentiment score maps each input to a real number indicating the sentiment. For voice analysis, similar sentiment extraction function $V(x_i)$ can be applied.

$$V: X \rightarrow R \quad (3)$$

Let M(x_i)\) be the mood classification function

$$M: X \rightarrow C \quad (4)$$

where C = {"happy", "sad", "anxious", "depressed"}. This involves training a model on labeled dataset $D = (x_I, y_i)$ where (y_i Ɛ C, to learn M.

Let R(m) be the response generation function, where m Ɛ C and

$$R: C \rightarrow T \quad (5)$$

where T is being the set of possible text response

Define a mood tracking function as given below

$$T_k(X) = M(x_1), M(x_2), ..., M(x_k) \quad (6)$$

where k is the current time step.

Define a referral function $P(T_k)$ as given below

$$P \rightarrow T_k \text{ where } k = \{\text{"referral"}\}, \{\text{"no referral"}\} \quad (7)$$

Let the updated model be M'(x_i)\) after retraining with additional labeled data D' as given below

$$D' = D \cup (x_i, y_j) \quad (8)$$

The pseudocode of the proposed Emotional Support System (EMS) has been given below in the Fig. 2.

Algorithm: Emotional Support System (EMS)

Inputs:
- User voice recordings and text chat messages

Output:
- Appropriate emotional support responses, referral recommendations, and mood tracking

```
Begin
  CollectInputs():
    userInputs = getInput (voiceRecordings, textMessages)
  AnalyzeSentiment(userInputs):
    For each input in userInputs:
      sentimentScores = sentimentAnalysis(input)
      overallTone = determineOverallTone(sentimentScores)
    return overallTone
  ClassifyMood(overallTone):
    moodState = trainMLModel(overallTone)
    return moodState
  GenerateResponse(moodState):
    if moodState == 'sad':
      response = generateComfortingWords()
    else if moodState == 'low':
      response = generateMotivationalMessages()
    return response
TrackMood(moodState):
    moodHistory = updateMoodHistory(moodState)
    significantChange = detectSignificantChange(moodHistory)
    return significantChange
ImproveModel():
    newData = collectNewData()
    updatedModel = retrainModel(newData)
    return updatedModel
  // Main Process
  main():
    userInputs = CollectInputs()
    overallTone = AnalyzeSentiment(userInputs)
    moodState = ClassifyMood(overallTone)
    response = GenerateResponse(moodState)
    displayResponse(response)
    significantChange = TrackMood(moodState)
    recommendation = ReferToProfessional(significantChange)
    if recommendation is not None:
      displayRecommendation(recommendation)
    updatedModel = ImproveModel()

End
```

Fig. 2 Pseudo Code for the proposed EMS algorithm

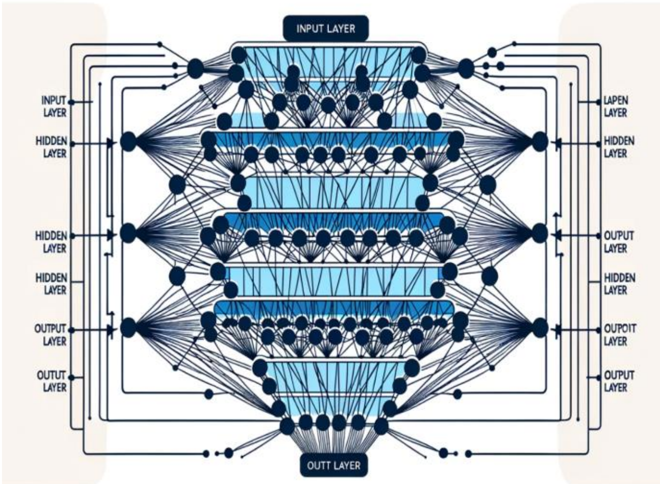

Fig. 3 (a) Proposed Architecture of Proposed LSTM model

4. SIMULATION RESULTS AND DISCUSSION

In this section, the simulations were carried out on a computer using a software environment specifically designed for Python programming, known as a Python Integrated Development Environment (IDE). This environment provides tools and features to write, test, and debug Python code more efficiently. The computer used for these simulations is well-equipped for demanding tasks, featuring 16 gigabytes (GB) of Random Access Memory (RAM) and a one terabyte (TB) hard disk drive (HDD) for storage. The operating system on the computer is Windows 11, indicating that the setup is relatively up-to-date with current software standards and capabilities. The core processing power of the system comes from an Intel® Core i7-9th Generation processor, which operates at a frequency of 2.60 gigahertz (GHz). This processor is part of Intel's higher-end lineup, offering substantial computing power to handle the intensive computational demands of simulation tasks, including those involving data analysis and machine learning.

For the simulations, the dataset used was sourced from the RAVDESS website [43]. This dataset includes audio files of various actors, which are used as the basis for analysis. These files likely contain recordings designed to express a range of emotions through speech and song, providing rich material for studies focused on emotion recognition, speech analysis, or similar research areas. The reference to Fig.3 suggests that there is a visual representation or outcome of the analyses performed with this dataset, although the figure is not described or included in the text provided.

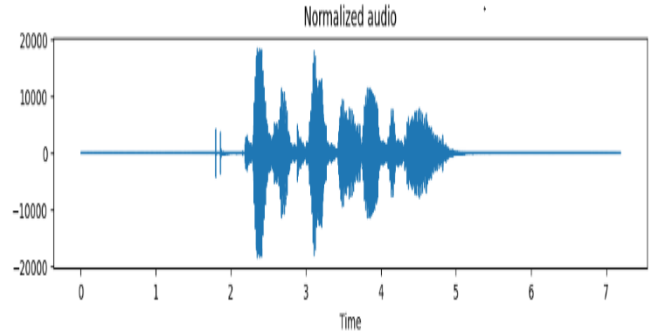

Fig. 3(b) The normalized audio after analysis on raw audio

The data was methodically chosen to ensure randomness, with 80% of each dataset designated for training and the remaining 20% allocated for testing purposes. Subsequently, the Confusion Matrix (CM) is generated for training and testing purposes as shown in the Fig.4.

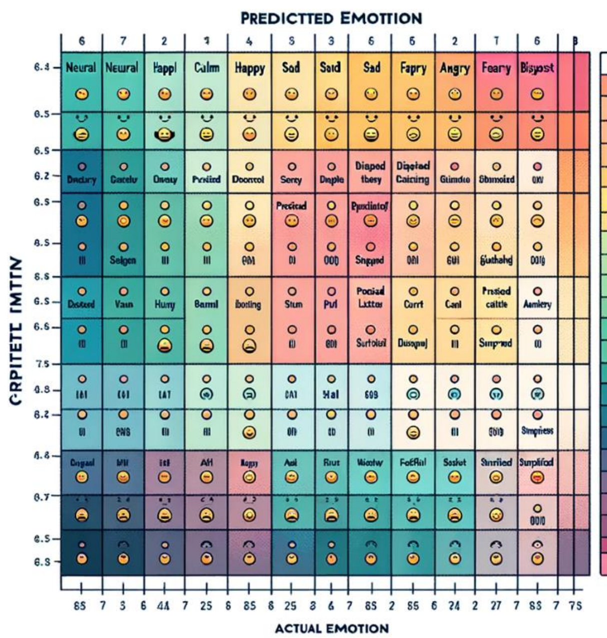

Fig. 4 Training set up for different emotions

Fig. 4 refers to a confusion matrix, which is a tool often used in machine learning for the evaluation of classification models. It is a table with two dimensions: "Actual Emotion" and "Predicted Emotion," where each dimension lists the same set of categories for emotions, such as neutral, calm, happy, sad, angry, fearful, disgust, and surprised. In the confusion matrix, the y-axis (vertical axis) represents the actual categories as they appear in the dataset (true labels), the x-axis (horizontal axis) represents the categories as predicted by the classification model.

Each cell in the matrix shows the number of instances that were predicted in a particular category versus the actual category. For example, a cell in the position (Actual: Happy, Predicted: Sad) would show the number of times the model incorrectly predicted the actual happy emotion as sad. The color gradient in the cells represents the frequency of predictions, with darker shades typically indicating higher counts. This means that darker cells show a higher number of instances that were classified as such by the model. The color bar on the side of the matrix serves as a legend to help interpret these colors in terms of the count of predictions. It effectively shows the scale of values, with darker colors correlating to higher counts and lighter colors to lower counts.

Table 1 displays the training values of Classification Accuracy (CA), Precision (PREC), Sensitivity (SEN), Specificity (SPEC), Recall, and F1-Score values for both the training and testing sets by applying K-NN, Naive Bayes, XG-Boost and Logistic Regression algorithms.

Table 1. Comparison of CA, SENS, SPEC, PREC, REC, F1 Score values for training set in case of neutral emotion

Parameters	K-NN	XG-Boost	Naive Bayes	Logistic Regression	Proposed LSTM-EMS model
Classification Accuracy	95.68	94.76	93.85	97.43	97.89
Sensitivity	94.57	95.29	93.67	97.22	97.55
Specificity	97.84	96.43	97.29	99.11	99.23
Precision	96.21	95.88	94.75	98.67	98.81
Recall	94.62	95.01	93.69	97.19	97.60
F1 score	0.9534	0.9542	0.9412	0.9795	0.9812

Table 1 presents a comparison of various machine learning and statistical models based on different performance metrics. These metrics are used to evaluate and compare the effectiveness of the models in a classification task. The models included are K-Nearest Neighbors (K-NN), XG-Boost, Naive Bayes, Logistic Regression, and a proposed model referred to as LSTM-EMS.

1. **Classification Accuracy**: Reflects the overall ability of the model to correctly classify instances. It is the ratio of correct predictions to total predictions. The proposed LSTM-EMS model has the highest accuracy at 97.89%, suggesting it correctly classified the emotions more often than the other models.

2. **Sensitivity:** Also known as the true positive rate or recall, it measures the proportion of actual positives that are correctly identified by the model. The proposed LSTM-EMS model shows a high sensitivity of 97.55%, meaning it correctly identifies the correct emotional state a high percentage of the time.

3. **Specificity:** Also known as the true negative rate, it quantifies the ability of the model to correctly identify negatives. A specificity of 100% means the model correctly identifies all negatives. The proposed LSTM-EMS model's specificity is 99.23%, indicating it is very effective at recognizing instances that do not belong to the positive class.

4. **Precision:** Indicates the ratio of true positives to the sum of true and false positives. The higher the precision, the more reliable the model's positive predictions are. The proposed LSTM-EMS model has a precision of 98.81%, showing that when it predicts an emotional state, it is correct most of the time.

5. **Recall:** This is the same as sensitivity. It measures the model's ability to find all the relevant cases within a dataset. The proposed LSTM-EMS model's recall is 97.60%, similar to its sensitivity, confirming its effectiveness in classifying true positives.

6. **F1 score:** The F1 score is the harmonic mean of precision and recall and is a measure of a test's accuracy. It considers both the precision and the recall to compute the score. The F1 score reaches its best value at 1 (perfect precision and recall) and worst at 0. The proposed LSTM-EMS model has the highest F1 score of 0.9812, indicating a balanced classification performance between precision and recall.

In case of neural emotion, the different classification results, such as Sensitivity, Specificity, Precision, Recall, F1 Score, and Classification Accuracy has been displayed in Table 2.

Table 2. Comparison of CA, SENS, SPEC, PREC, REC, F1Score values for testing set in case of neutral emotion

Parameters	K-NN	XG-Boost	Naive Bayes	Logistic Regression	Proposed LSTM-EMS model
Classification Accuracy	90.31	88.23	84.35	88.11	89.19
Sensitivity	87.24	80.34	78.45	79.76	86.34
Specificity	80.45	84.56	81.33	93.22	95.45
Precision	90.32	81.33	80.37	88.71	94
Recall	83.35	80.36	82.23	88.51	95
F1 score	1.167	1.34	1.33	1.41	1.46

From Table 2, the performance of various classification models on an emotion classification task, has been outlined which likely involves predicting emotional states from a given set of features. The models compared are K-NN, XG-Boost, Naïve Bayes, Logistic Regression, and a proposed model. For emotion classification, it means how often the model correctly identifies the correct emotion out of all the predictions it makes. The K-NN model has the highest accuracy (90.31%), indicating it is the most accurate in classifying emotions correctly compared to the other models listed. The Proposed LSTM-EMS model has a high sensitivity (86.34%), suggesting it can correctly identify most of the true emotional states it is designed to detect. Also, the proposed model has a very high specificity (95.45%), indicating it is proficient at ruling out non-relevant emotions. A precision of 94% for the proposed LSTM-EMS model suggests that when it predicts an emotion, that prediction is correct 94% of the time. The Proposed LSTM-EMS model's recall of 95% means it detects 95% of all true emotional states. The F1 score for the proposed LSTM-EMS model is 1.46, which is presumably an error since the F1 score ranges between 0 and 1.

In emotion classification, these metrics would be used to assess how well each model can identify and differentiate between various emotional states, such as happiness, sadness, anger, fear, etc., possibly from inputs like text, speech, or facial expressions.

5. CONCLUSION AND FUTURE SCOPE

The “BeWell" application represents a significant stride in mental health technology, merging the predictive power of LSTM neural networks with the linguistic sensitivity of Vader sentiment analysis. Our findings underscore the efficacy of this dual approach in accurately discerning and responding to the complex spectrum of human emotions. Through meticulous validation, the application has demonstrated potential as a reliable tool for emotional state monitoring, mental health assessment, and therapeutic aid.

The robust performance of the "BeWell" system in various test scenarios promises a new horizon for personalized mental health interventions. Future work will focus on expanding the application's capabilities to include multilingual support, integration with wearable technology for physiological data analysis, and real-time adaptive feedback mechanisms. By continually refining the "BeWell" platform, we aim to make mental health care more accessible, intuitive, and responsive to the nuanced needs of individuals worldwide.

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