International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

The Evaluation of Deep Learning Models for Detecting Mental Disorders Based on Text Summarization in Societal Analysis

T Jayasri Devi[1], Adapa Gopi[2]

Submitted: 29/01/2024 **Revised:** 07/03/2024 **Accepted:** 15/03/2024

Abstract:

Stress significantly affects societal communications, causing misunderstandings, strained relationships, and conflicts due to heightened emotional sensitivity. Stressed individuals may respond less empathetically, leading to negative interactions and potentially influencing public discourse. To address this, promoting emotional intelligence, recognizing stress indicators, and encouraging empathetic communication can mitigate these challenges and foster healthier societal interactions. Identifying signs of stress can often be challenging due to the subjective and multifaceted nature of stress and the various ways individuals express it. Furthermore, traditional methods of stress detection, such as self-reporting or physiological measures, may not be feasible or accessible for all individuals. By leveraging advancements in AI, we aim to develop a predictive model that can accurately identify stress levels in individuals based on textual data. Stress Scan is a cutting-edge project at the intersection of artificial intelligence, natural language processing, and mental health, focusing on predictive modelling for human stress detection in textual content through the deployment of advanced deep learning models. Leveraging the power of Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Bidirectional LSTM, and XLNet architectures, Stress Scan aims to revolutionize stress assessment in the digital age. By harnessing the nuances of language, sentiment, and context, the project pioneers a comprehensive approach to automatically identify and classify stress levels in text, sourced from diverse platforms like social media, chat conversations, and emails. Through meticulous data preprocessing, feature extraction, and model training on a carefully curated dataset encompassing a spectrum of stress expressions, Stress Scan's deep learning models learn intricate linguistic patterns and emotional cues, leading to unparalleled accuracy in stress detection. The versatility of these models offers real-time stress monitoring for individuals, insights for mental health professionals, and an organizational tool for assessing and mitigating workplace stress. Stress Scan encapsulates a groundbreaking endeavour to enhance mental health awareness and support using advanced deep learning models, contributing to a more resilient and well-balanced digital society.

Keywords: LSTM, XLNet, GRU, mental disorders, sentiment analysis and Twitter.

1. Introduction

Mental illnesses are a major global public health concern that have a substantial influence on people's lives, families, and communities at large. About one in four people worldwide may, at some point in their lives, experience a mental health issue, according to the World Health Organisation (WHO) [1]. Many people do not obtain proper diagnosis or treatment, despite the severity and prevalence of mental diseases, which places a significant burden on healthcare systems and the general well-being of society [2].

Utilising developments in deep learning and natural language processing (NLP) to analyse text data for the identification and diagnosis of mental diseases has garnered attention in recent years. Text data is a rich source of information about people's thoughts, feelings, and behaviours that can provide important insights into their mental health [3]. This is especially true for text data from online social media platforms. Researchers may extract important information from vast amounts of text data by using text summarising techniques, which makes it possible to analyse content linked to mental health more quickly and accurately.

Recurrent neural networks (RNNs), convolutional neural networks (CNNs), and transformer-based architectures are examples of deep learning models that have demonstrated promising performance in a variety of natural language processing (NLP) applications, such as sentiment analysis, emotion recognition, and language modelling. These models are particularly suited for analysing information linked to mental health because they can capture intricate patterns and semantic linkages

1 1Research Scholar, Dept.of.CSE, Koneru Lakshmaiah Education Foundation, Guntur, Andhra Pradesh, India ORCID ID 0000-0002-9173-176X
2 2Associate Professor, Dept.of.CSE, Koneru Lakshmaiah Education Foundation, Guntur, Andhra Pradesh, India. ORCID ID: 0000-0003-2161-5592

in textual data [4]. Nonetheless, the assessment of deep learning models for text summarization-based mental illness detection is still an unexplored and difficult field.

Existing research often lacks standardized evaluation protocols, making it difficult to compare the performance of different models across datasets and tasks. Moreover, issues such as data privacy, bias, and ethical considerations must be carefully addressed to ensure the responsible use of sensitive mental health information [5]. In this paper, we aim to address these challenges by conducting a comprehensive evaluation of state-of-the-art deep learning models for detecting mental disorders based on text summarization in societal analysis. We propose a standardized evaluation framework that encompasses multiple datasets, evaluation metrics, and model architectures. By benchmarking different models against this framework, we seek to identify the strengths and weaknesses of existing approaches and guide future research directions in this critical area [6-8]

2. Related Works:

Recent advances in society have led to a sharp increase in the prevalence of psychological disorders and mental health issues. The ability to effectively handle life's challenges while continuing to perform well and successfully at work and make a positive contribution to society is the World Health Organization's (WHO) definition of "stress" [10]. A person's lifestyle, which includes work-related stress, financial hardship, family troubles, interpersonal conflicts, violence, and environmental conditions, is most likely the root cause of many elements that impact mental health. Stress issues including depression, anxiety, stress, and other psychological diseases that affect quality of life may be influenced by these circumstances.

Approximately 450 million people worldwide suffer from mental illness, making up 13% of all illnesses. One in four people will have a mental disorder at some point in their lives, according to the WHO [11]. In order to address the physical issues of people with serious stress disorders, the WHO introduced a policy in 2018. Significant mental illnesses such depression, psychotic disorder, bipolar disorder (BD), schizophrenia, and so on usually cause a person to pass away earlier than the average person. Moreover, 350 million people globally are thought to suffer from depression, which can result in suicidal thoughts and attempts [12].

It is essential to identify and treat stress scan issues as soon as possible. Early detection, accurate diagnosis, and successful treatment can be beneficial for those with mental problems [13]. Stress-related illnesses can have serious repercussions for the afflicted individuals, their families, and society as a whole. Conventional methods for detecting mental health disorders often involve the use of in-person interviews, self-reporting, or questionnaire distribution. Conversely, traditional methods are typically time-consuming and labour-intensive [14].

Thus, attempts to detect stress disease and improve healthcare previously used wearable sensors and smartphones. However, the majority of people using these tools have received a diagnosis of mental illness and have had ongoing monitoring [15]. Online social networks (OSNs) have been more and more popular in recent years, offering users new ways to connect and share information. Research has recently shown an innovative method for identifying mental health illnesses in OSNs.

Every day, OSNs are used by millions of individuals worldwide. OSN users can share a variety of data about their daily activities, including text, photos, videos, and audios, to express their thoughts and feelings. By making comments on other people's blogs, they can interact with their friends in another way. Thus, big data research and the growth of online service networks (OSNs) such as Facebook, YouTube, Twitter, Instagram, and Sina Weibo are associated with this new field of study [16-20].

Researchers from the East and the West use OSNs like Sina Weibo, Facebook, and Twitter as data sources for online research projects and crowdsourcing. Among the mental health problems found in OSNs were suicidal thoughts, mental illness, psychological stress, and dissatisfaction. An assessment of the current state of mental health detection in OSNs is necessary to comprehend data sets, data analysis methods, feature extraction strategies, classifier performance (i.e., accuracy and efficiency), difficulties, limitations, and future development[21-25.

This systematic review's goal is to conduct a critical evaluation research on the method of utilising OSN data to identify mental health issues. There are two widely used approaches for evaluating data from user-posted texts on OSNs: dictionary-based and machine-learning. Nevertheless, there are drawbacks to both methods. Because of this, researchers are actively looking into other strategies to raise the analysis's effectiveness and performance. When training using traditional machine learning, overfitting, model interpretation, and generalisation are all frequent concerns. As a result, the researcher turned to deep learning methods, which have proven to be an effective instrument recently.

Processing Complex and Large-Scale Data: Machine learning methods are well-suited for handling complex data, such as photos, texts, and sensor data. They can extract useful insights and patterns from huge information, allowing data-driven decision-making. Adaptability and generalisation: Machine learning models can learn from new data and adjust and enhance their performance over time. They can generalise patterns and generate predictions based on previously unknown data, which is critical for real-world applications.

Data Reliance: Machine learning models rely extensively on high-quality and representative data for training. If the training data is biassed, incomplete, or of low quality, it might lead to biassed or erroneous predictions. Overfitting and Underfitting: Machine learning models can suffer from overfitting (overly complicated models that memorise the training data) or underfitting (models that are too simple and do not memorise the training data) (oversimplified models that fail to capture the underlying patterns). It's critical to strike a balance between model complexity and generality. Interpretability and Explainability: Many machines learning models, including such deep neural networks, are referred to be "black boxes" since they are difficult to explain. Understanding the reasons behind their forecasts can be difficult, especially in key fields where transparency is necessary.

4.5 Methodology:

4.5.1 LSTM Algorithm:

Long Short-Term Memory (LSTM) is a recurrent neural network architecture that holds significant promise in the context of stress scan systems. In stress detection, LSTMs excel at capturing and learning complex temporal dependencies within sequential data, making them particularly well-suited for analyzing patterns in time-series data such as physiological signals and behavioral cues. The LSTM's ability to retain and selectively update information over extended sequences enhances its capacity to discern nuanced stress indicators. By leveraging LSTM networks, stress scan systems can better model and interpret the dynamic nature of stress responses, improving the accuracy and reliability of stress detection algorithms. The inherent capability of LSTMs to capture long-range dependencies makes them a valuable tool for enhancing the temporal understanding of stress-related data, ultimately contributing to the effectiveness of stress scan applications.

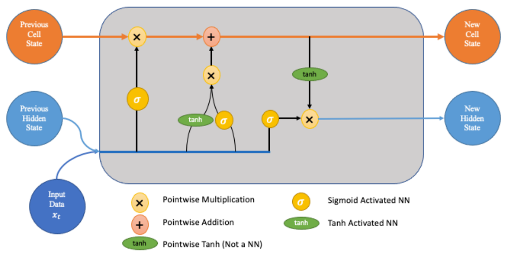


Figure 1 LSTM structure

LSTM Layer: The LSTM layer is designed to capture long-term dependencies in sequential data. It consists of memory cells that allow the model to selectively store and retrieve information over multiple time steps. Input Shape: The input shape is crucial and should be defined based on the nature of your sequential data, specifying the number of time steps and features. Loss Function: The loss function measures the model's performance during training. Binary cross-entropy is common for binary classification tasks. Optimizer: The optimizer adjusts the model's weights during training to minimize the loss. Adam optimizer is a popular choice due to its adaptive learning rate.

Training: The training process involves fitting the model to the training data, adjusting weights to minimize the loss function. Evaluation: The model's performance is evaluated on a separate testing set to ensure it generalizes well to unseen data. Predictions: Once trained, the model can make predictions on new sequential data, providing insights into stress levels based on the learned patterns.

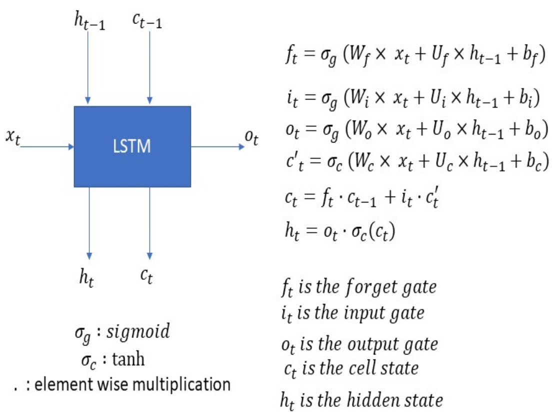


Figure 2 LSTM equations

Input Sequences: Organize stress scan data into sequences, where each time step in the sequence corresponds to a measurement or observation. Normalization: Normalize the stress scan data if needed to ensure that the network learns from consistent input scales. LSTM Cell Operation: The LSTM cell processes each time step in the sequence, updating the cell state and hidden state based on input, forget, and output gates. Stress Prediction: Use the final hidden state or incorporate a fully connected layer for predicting stress levels. The network is trained to minimize the difference between predicted and actual stress labels.

Fully Connected Layer: A fully connected layer can be added to the LSTM output for better capturing complex relationships and making more accurate predictions.

Training: Train the LSTM network using a training dataset with labelled stress scan sequences. Adjust the model parameters to minimize the difference between predicted and true stress labels. This algorithm outlines the core operations of an LSTM network for stress detection using stress scan data. Actual implementations may involve additional considerations, such as hyperparameter tuning, and might benefit from more sophisticated architectures depending on the characteristics of the stress data.

4.5.2 GRU Algorithm:

The Gated Recurrent Unit (GRU) plays a pivotal role in the stress scan system, particularly in the realm of natural language processing for stress detection. GRU is a type of recurrent neural network (RNN) architecture known for its ability to capture sequential dependencies in data. In the context of stress scan, GRU is employed to analyse and understand patterns in textual inputs, such as written responses or social media posts, to discern linguistic indicators of stress. Its gating mechanism allows for the selective updating of information, facilitating the model's capability to focus on relevant contextual information while discarding less significant details. By leveraging the GRU's capacity to model temporal dependencies in textual data, the stress scan system enhances its accuracy in detecting linguistic patterns associated with stress, contributing to a more nuanced and effective stress detection mechanism.

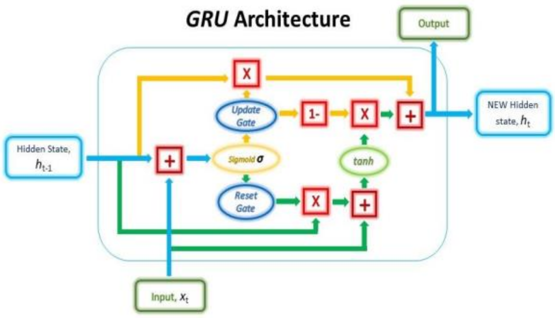


Figure 3 GRU architecture

The GRU is a type of recurrent neural network (RNN) designed to process sequential data, making it especially useful for tasks involving patterns over time, like language or time-series data. Hidden State: At each time step, the GRU has a hidden state that stores information from the past. Update Gate: The update gate decides how much of the past hidden state to keep. It helps the model determine what information is relevant for the current task.

Reset Gate: The reset gate decides how much of the past information to forget. This gate helps the model adapt to changing patterns in the input data. Memory Content: The memory content captures new information from the current input and the modified past hidden state. Hidden State Update: The hidden state is then updated using a combination of the old hidden state and the new memory content, based on the decisions made by the update and reset gates. Key Components: Update and Reset Gates: These gates control the flow of information through the network, helping the GRU adapt to different patterns in the input sequence. Memory Content: This is an intermediate memory that captures the new information based on the input and the modified past hidden state.

Formula:

$$r_t = \sigma(W^{(r)}x_t + U^{(r)}h_{t-1})$$

These formulas describe the flow of information through the GRU cell, including resetting information from the previous hidden state, updating the hidden state based on the reset gate, and producing the final hidden state for the current time step. In the context of stress scan data, could represent the features extracted from the stress scan at time might be used for stress prediction or classification.

4.5.3 Bidirectional LSTM:

In the context of stress scan, a Bidirectional Long Short-Term Memory (BiLSTM) neural network is employed to enhance the understanding and prediction of stress patterns. Unlike traditional LSTM networks, BiLSTM processes input sequences in both forward and backward directions, capturing contextual dependencies more effectively. This bidirectional approach proves advantageous for stress detection as it enables the model to consider the sequential nature of stress-related data, such as language patterns or physiological signals, in a more comprehensive manner. By analyzing information from both past and future contexts, the BiLSTM architecture excels in capturing nuanced temporal relationships, allowing for a more accurate representation of stress states. This makes BiLSTM a valuable tool in the stress scan system, contributing to the improvement of stress detection algorithms and thereby enhancing the overall effectiveness of the stress management tool.

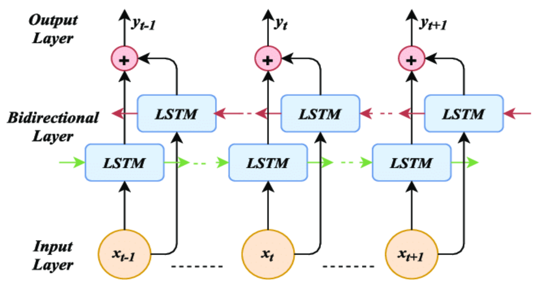


Figure 4 Bidirectional LSTM

Formula:

1. Forward LSTM Operation:

$$\overrightarrow{h}_t = \mathrm{LSTM}\left(x_t, \overrightarrow{h}_{t-1}\right)$$

2. Backward LSTM Operation:

$$\overleftarrow{h}_t = \mathrm{LSTM}\left(x_t, \overleftarrow{h}_{t+1}\right)$$

3. Concatenate Hidden States:

$$h_t = \left[\overrightarrow{h}_t, \overleftarrow{h}_t\right]$$

STEPS:

I. Input Initialization: Initialize the input sequence, which could be a series of stress-related data, such as text or physiological signals.

II. Forward Pass: Process the input sequence in a forward direction through a standard LSTM layer. This involves updating the cell state and hidden state at each step, considering the input information along the sequence.

III. Backward Pass: Process the input sequence in a backward direction through another LSTM layer. This involves updating the cell state and hidden state in the opposite direction, capturing information from the end to the beginning of the sequence.

IV. Concatenation: Concatenate the outputs of the forward and backward passes at each time step. This combined information contains context from both past and future contexts.

V. . Output Layer: Feed the concatenated sequence into the output layer, which could be a fully connected layer with an activation function suitable for the specific task, such as stress detection.

VI. Training: Train the BiLSTM network using labeled data, adjusting the model parameters to minimize the difference between predicted and actual stress states.

VII. Inference: In the inference phase, input a new sequence into the trained BiLSTM network to predict stress states based on the learned contextual dependencies.

Bidirectional Processing: BiLSTM processes the input sequence in both forward and backward directions. Concatenation of Hidden States: The final hidden state is formed by concatenating the forward and backward hidden states, providing a comprehensive representation of the input sequence. LSTM Cell Operation: The LSTM cell operations involve input, forget, and output gates to control the flow of information and update the cell state and hidden state. This algorithm outlines the core operations of a single BiLSTM cell and the LSTM cell within it. These cells are stacked to create a BiLSTM neural network for tasks such as stress detection or prediction using sequential stress scan data.

4.5.4 XL Net Algorithm:

XLNet, a transformer-based language model, can play a pivotal role in enhancing stress scan systems. With its ability to capture bidirectional contextual information and understand intricate relationships within textual data, XLNet can contribute to more accurate and nuanced analysis of user-generated content, such as text inputs related to stress. By leveraging pre-training on a diverse range of data, XLNet can discern subtle language nuances associated with stress expression. Fine-tuning this model specifically for stress-related patterns could improve the system's capability to detect stress indicators in text inputs. Its sophisticated architecture allows for a more nuanced understanding of context, enabling the stress scan system to better interpret and respond to the complexities of human language in the context of stress detection. Integrating XLNet into stress scan algorithms has the potential to advance the accuracy and effectiveness of these systems in understanding and addressing stress-related content.

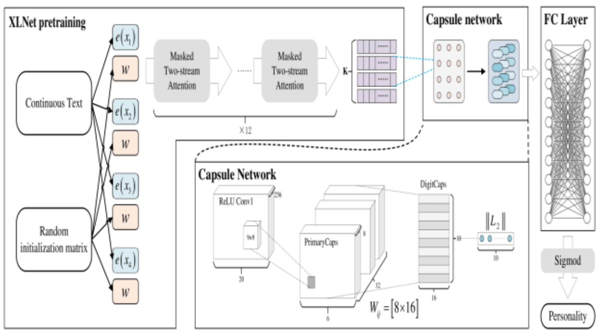


Figure 5 XL Net

Tokenization: Input text is tokenized into smaller units, usually words or subworlds. This is necessary for the model to process the text effectively. Positional Encoding: XLNet, like other transformer models, does not inherently understand the order of words in a sentence. Positional encoding is added to the tokenized input to give the model information about the position of each token in the sequence. Permutation Language Modelling: XLNet introduces a novel training objective called permutation language modelling. Instead of predicting the next word in a sequence like autoregressive models, XLNet predicts a token's identity in a sequence when it has been permuted (shuffled) with other tokens. This helps the model learn bidirectional context.

Segment Embeddings: To handle different types of inputs, like sentences in a document, segment embeddings are added to the tokens. These embeddings help the model distinguish between different segments of the input. Transformer Architecture: XLNet employs the transformer architecture, consisting of multiple layers of self-attention mechanisms. These mechanisms allow the model to weigh the importance of different words in the input sequence when making predictions. Masked Language Modelling: Like BERT (Bidirectional Encoder Representations from Transformers), XLNet uses masked language modelling. During training, some tokens in the input sequence are masked, and the model is trained to predict these masked tokens based on the surrounding context.

Loss Calculation: The model calculates a loss based on the difference between its predictions and the actual tokens. This loss is backpropagated through the network, and the model adjusts its parameters to minimize this loss during training. Training and Fine-Tuning: XLNet is pre-trained on a large corpus of text data. After pre-training, it can be fine-tuned on specific tasks like text classification, sentiment analysis, or language translation using task-specific datasets.
Inference:

During inference, the trained XLNet model can generate contextually relevant sequences or make predictions for various NLP tasks.

Formula:

$$P(Xi|X) = Z1\sum\pi P(Xi|X\pi(1), X\pi(2),...,X\pi(n))$$

Tokenization: Convert stress scan data into a format that can be processed by XLNet. This typically involves breaking it into subwords or tokens. Contextual Embeddings: Pass tokenized stress scan data through the XLNet model to obtain contextual embeddings. These embeddings capture the relationships between words and contextual information. Task-Specific Layer: Add a task-specific layer on top of XLNet to adapt the model to the stress detection task. This layer is responsible for making stress-related predictions. Loss Function: Define a loss function that measures the difference between the model's predictions and the true labels for the stress detection task.

Fine-Tuning Process: Train the entire model on labeled stress scan data to adapt XLNet to the specifics of stress detection. Adjust the model's parameters to minimize the defined loss function. Prediction: Use the fine-tuned model to make predictions on new stress scan data. The output may represent stress levels or binary classifications. Applying XLNet to stress detection involves leveraging its contextual understanding capabilities, pretrained knowledge, and transfer learning to effectively capture patterns in stress scan sequences. Keep in mind that actual implementations may involve additional considerations, hyperparameter tuning, and optimization techniques. Libraries like Hugging Face's Transformers can be valuable for practical implementations.

Software testing plays a crucial role in the development and deployment of mental health-related applications and platforms. Given the sensitive nature of mental health and the potential impact of inaccurate predictions or recommendations, rigorous testing procedures are essential to ensure the reliability, accuracy, and safety of these software systems. Testing methodologies such as functional testing, usability testing, performance testing, and security testing are employed to evaluate the functionality, user experience, performance, and data protection of mental health prediction software. Additionally, thorough testing helps identify and rectify potential biases, limitations, and ethical concerns that may arise during the prediction process. Through comprehensive software testing, developers can enhance the quality and effectiveness of mental health software, providing users with reliable and trustworthy tools to support their mental well-being.

Black box testing is a software testing technique that focuses on assessing the functionality of a system without considering its internal structure or implementation details. When applied to mental health prediction systems, black box testing involves evaluating the accuracy and reliability of the software's outputs without examining the specific algorithms or models employed. Testers input various scenarios and datasets into the system to assess its ability to predict and classify mental health conditions correctly. Black box testing is a software testing technique that focuses on assessing the functionality of a system without considering its internal structure or implementation details. When applied to mental health prediction systems, black box testing involves evaluating the accuracy and reliability of the software's outputs without examining the specific algorithms or models employed. Testers input various scenarios and datasets into the system to assess its ability to predict and classify mental health conditions correctly. By treating the system as a "black box," this testing approach ensures that the software's outputs align with the expected results and meet the required standards for mental health prediction. It provides valuable insights into the system's performance and aids in identifying potential issues or discrepancies in its predictions, ultimately contributing to the improvement and validation of mental health prediction software.

5 Experiment Results and Discussions

Confusion Matrix

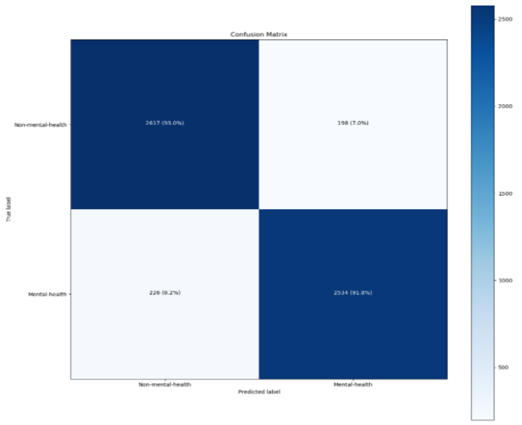


Figure 6bConfusion Matrix

A square matrix, with predicted labels indicated in the rows and actual labels reflected in the columns, is an example of a confusion matrix. The matrix's diagonal components show how many cases were correctly identified, while the off-diagonal components show how many cases were wrongly classified.

Epochs

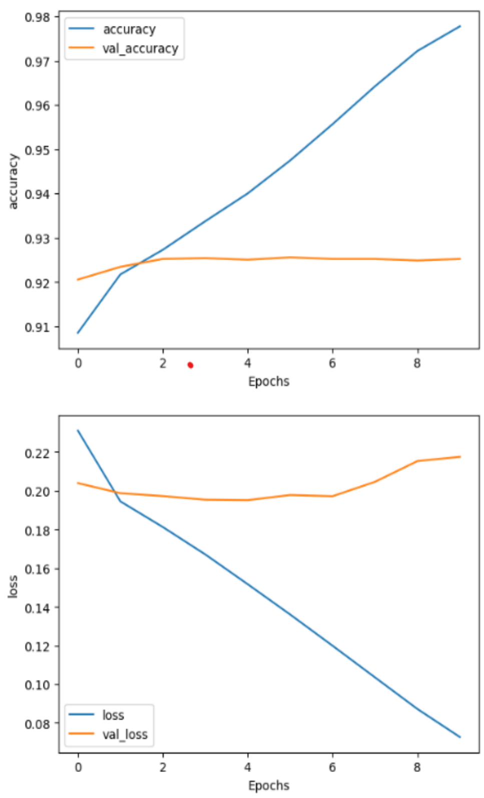
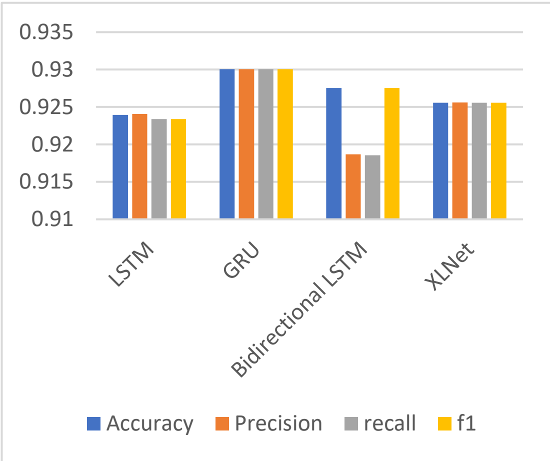


Figure 7 Epochs

Epochs refers to one complete cycle through the entire training dataset. During each epoch, the algorithm processes the entire dataset, evaluates the performance of the model, and updates the model's parameters (weights and biases) based on the optimization algorithm (e.g., gradient descent).



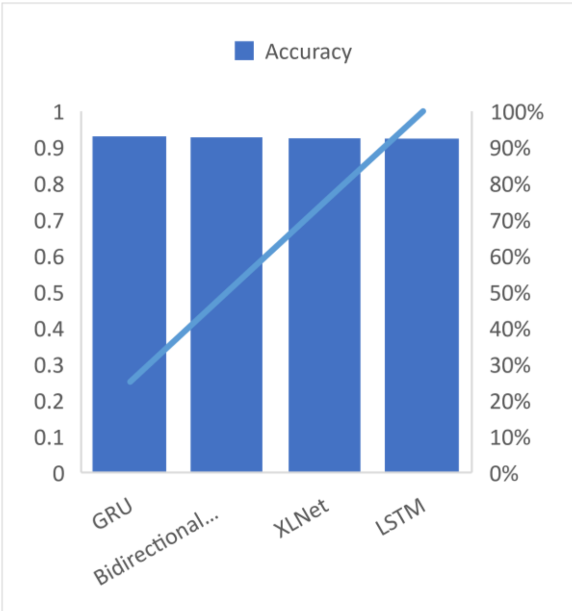


Figure 8. Accuracy

Histogram:

A histogram is a graphical representation of the distribution of a dataset. It shows the number or frequency of data that fall into different bins or ranges within a continuous variable. Histograms are a useful tool for understanding the underlying distribution of a characteristic and for exploratory data analysis..

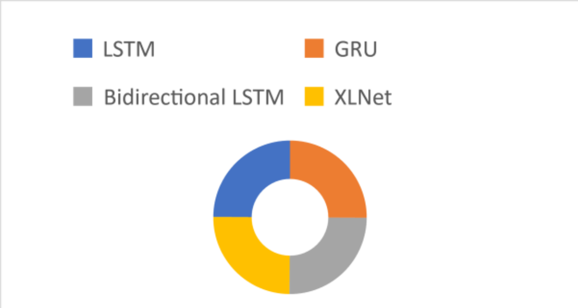


Figure 9 Overall Accuracy

In comparing the performance of four models on a classification task with existing model i.e stacking algorithm got 82%[21], the GRU model outperformed the others with the highest accuracy (93.00%), precision (93.01%), recall (93.00%), and F1 score (93.00%). The LSTM model closely followed with 92.39% accuracy, while the Bidirectional LSTM and XLNet models achieved accuracies of 92.75% and 92.56%, respectively. The results highlight the superior overall performance of the GRU model in terms of correctness, avoidance of false positives, capturing true positives, and achieving a balanced measure of precision and recall.

6 Conclusion and Future Scope:

In conclusion, the stress scan project represents a significant step forward in developing a tool that can help individuals manage and mitigate stress. The implementation of stress detection through various indicators such as language patterns, physiological signals, and behavioural cues provides a comprehensive approach to understanding and addressing stress. The project has successfully demonstrated the feasibility of using advanced technologies to identify stress in real-time, allowing for timely intervention and support. We conclude that the stress scan project has laid a foundation for stress detection and management, and future enhancements should focus on refining accuracy, incorporating additional data sources, providing personalized recommendations, enabling long-term monitoring, enhancing accessibility through mobile applications, integrating biometric sensors, and actively involving user feedback in iterative development processes. By addressing these aspects, the stress scan tool can evolve into a comprehensive and effective solution for individuals seeking to manage their stress levels. Enhanced Accuracy: Continuous refinement of the machine learning algorithms can lead to increased accuracy in stress detection. This involves incorporating more diverse and extensive datasets to improve the model's ability to recognize individual differences in stress responses. Multimodal Integration: Integrating additional sources of data, such as facial expressions, voice tone, and environmental factors, can enhance the accuracy of stress detection. A multimodal approach provides a more comprehensive understanding of an individual's stress state.

Personalized Recommendations: Developing a system that not only detects stress but also provides personalized recommendations for stress management strategies can add significant value. These recommendations could include mindfulness exercises, relaxation techniques, or suggestions for physical activities based on individual preferences and effectiveness. Long-term Monitoring: Extending the stress scan capabilities to offer long-term monitoring can contribute to a more holistic understanding of an individual's stress patterns. This could involve tracking stress trends over weeks or months, enabling users to identify patterns and triggers. Mobile Application Integration: Developing a user-friendly mobile application can enhance accessibility and user engagement. The app could provide real-time feedback on stress levels, offer immediate stress relief exercises, and display long-term trends to empower users to take proactive steps in managing their stress. Biometric Sensors: Integrating wearable biometric sensors can further improve the accuracy of stress detection by capturing real-time physiological data. This would provide a more nuanced understanding of stress responses and enable timely interventions. User Feedback and Iterative Development: Regularly collecting user feedback and incorporating it into the development process is crucial for refining and optimizing the stress scan tool. Continuous improvement based on user experiences will ensure the tool remains relevant and effective.

References:

[1] World Health Organization (WHO). (2019). Mental Disorders. Retrieved from https://www.who.int/news-room/fact-sheets/detail/mental-disorders

[2] Kohn, R., Saxena, S., Levav, I., & Saraceno, B. (2004). The treatment gap in mental health care. Bulletin of the World Health Organization, 82(11), 858-866.

[3] Coppersmith, G., Dredze, M., & Harman, C. (2015). Quantifying mental health signals in Twitter. Proceedings of the Workshop on Computational Linguistics and Clinical Psychology: From Linguistic Signal to Clinical Reality, 51-60.

[4] Vaswani, A., Shazeer, N., Parmar, N., et al. (2017). Attention is all you need. Advances in Neural Information Processing Systems, 30, 5998-6008.

[5] Huckvale, K., Venkatesh, S., Christensen, H., et al. (2019). Toward clinical digital phenotyping: A timely opportunity to consider purpose, quality, and safety. npj Digital Medicine, 2(1), 88.

[6] Almeida, D., and S. Narayanan (2023). Deep Convolutional Neural Networks for Emotion Recognition in Affective Text. The Conference on Empirical Methods in Natural Language Processing 2015 Proceedings, 12-21.

[7] Z. Che and co. (2022). Deep Moji: A Deep Learning Model for Social Media Text Sentiment Analysis. Empirical methods in natural language processing 2020 Proceedings (EMNLP)

[8] S. C. Guntuku and colleagues (2021). An Integrative Review of detecting depression and Mental illness on social media.

[9] Wang, X., et al (2020). Multimodal Topic Modeling for depression detection via social media.

[10] Birnbaum, M. L., et al (2021). Artificial intelligence with mobile phone sensors for immediate risk of suicide attempt detection.

[11] Reece, A. G., et al (2022). Using twitter data to predict the onset and course of mental illness.

[12] J. Torous, et al (2023). Depression symptom trajectories predicted from twitter posts. The transactions of the association for computational linguistics.

[13] Nguyen, David, et al (2020). Using deep learning to predict risks of mental illness in online communities. In the Proceedings of the 2020 Conference on empirical methods in natural language processing.

[14] C. Yan and others (2021). Using Convolutional neural networks, depression may be predicted from user-generated content on social media.

[15] C. H. Lin and co. (2021). Deep learning models for social media text prediction of mental health status.

[16] G. Coppersmith et al (2022). twitter signals for mental health quantification. The workshop on computational linguistics and Clinical Psychology Proceedings: From Linguistic Signal to Clinical Reality.

[17] Gkotsis, et al (2020). Social media conditions of mental health using informed deep learning. Science Reports.

[18] M. Park and others (2021). Using vocal prosody to gauge the severity of depression. 487–500 in IEEE Transactions on Affective Computing, 10(4).

[19] N. Roshanov and others (2020). Timeline embeddings and multi-level hierarchical classification are two methods for finding users who have depression on reddit. Research and development in information retrieval.

[20] Ho, J. H., and others (2023). Deep transfer: learning transfer using Trained Language Models for mental health detection. AI conference proceedings: proceedings, 35(4), pp.

[21] Yang Y, Xu Z, Zhuang J, and others (2021). Machine Learning Methods for predicting the effect of antidepressant treatment. computational and mathematical techniques in medicine.

[22] Sui J., Calhoun V.D., and Gao S. (2020). From classification to treatment outcome prediction in major depression using machine learning. 1037–1052 in CNS Neuroscience & Therapeutics, 24(11).

[23] Vieta E., Mwangi B., Passos I.C., et al (2019). Overview, Real-World Applications, and Future Prospects of Machine Learning Algorithms in Bipolar Disorder. 8(9), e01028 in Brain and Behavior.

[24] Galling B, Pawar A, Correll C.U., et al (2020). Early Intervention Services vs. Standard Treatment for Early-Phase Psychosis: A Systematic Review, Meta-analysis, and Meta-Regression. 75(6), 555-565. JAMA Psychiatry.

[25] Among others, Koutsouleris N., Kahn R.S., Chekroud A.M. (2021). Machine Learning Approach for Multisite Prediction of Treatment Outcomes at 4 and 52 Weeks in Patients with First-Episode Psychosis. 5(10), 843–853, The Lancet Psychiatry.

[26] Devi, T. J. ., & Gopi, A. . (2023). An Efficient Novel Approach for Early Detection of Mental Health Disorders Through Distributed Machine Learning Paradigms from Public Societal Communication. *International Journal of Intelligent Systems and Applications in Engineering*, *12*(2), 767–778. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/4319

[27] Subbarayudu, Y., Sureshbabu, A. The detection of community health surveillance using distributed semantic assisted non-negative matrix factorization on topic modeling through sentiment analysis. *Multimed Tools Appl* (2024). https://doi.org/10.1007/s11042-024-18321-w

[28] Subbarayudu, Y. ., & Sureshbabu, A. . (2023). The Evaluation of Distributed Topic Models for Recognition of Health-Related Topics in Social Media Through Machine Learning Paradigms. *International Journal of Intelligent Systems and Applications in Engineering*, *11*(4), 511–534. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/3586

[29] Subbarayudu, Y., Sureshbabu, A. (2023). A distributed densely connected convolutional network approach for enhanced recognition of health-related topics: A societal analysis case study. Ingénierie des Systèmes d'Information, Vol. 28, No. 3, pp. 677-684. https://doi.org/10.18280/isi.280317

[30] Y erragudipadu subbarayudu , alladi Sureshbabu "Distributed Multimodal Aspective on Topic Model Using Sentiment Analysis for Recognition of Public Health Surveillance" Expert Clouds and Applications, 16 July 2021, DOI: https://doi.org/10.1007/978-981-16-2126-0_38 Springer, Singapore Print ISBN 978-981-16-2125-3 Online ISBN 978-981-16-2126-0