# A Novel technique for the early diagnosis of Mental Health using Natural language processing

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**Abstract.** In this work, we delve into the critical issue of mental health, particularly focusing on depression, a condition affecting over 264 million individuals of all ages globally, as reported by the World Health Organization (WHO). The pervasive nature of depression establishes it as a leading cause of disability on a worldwide scale. Recognizing the immense impact of mental health disorders, our research is centered around the imperative of early diagnosis as a crucial preventive measure to address this global concern. At the intersection of linguistics, Artificial Intelligence (AI), and computer science, Natural Language Processing (NLP) emerges as a pivotal field. Our study seeks to leverage NLP in addressing the challenges associated with the early diagnosis of mental health issues. NLP is fundamentally concerned with enabling computers to interpret, analyze, and approximate human speech, offering a sophisticated avenue for understanding the nuances present in mental health-related text data. To contextualize the practical applications of NLP in mental health, we draw attention to the emergence of chatbots such as Woebot, Wysa, Joyable, and Talkspace. These chatbots, available as Android/iOS apps or websites, have the capacity to perform mental health assessments using natural conversation. By integrating NLP techniques, these chatbots exemplify the potential for technology to contribute to mental health assessments in an accessible and user-friendly manner. In summary, our research paper aims to contribute to the intersection of mental health and technology, emphasizing the significance of early diagnosis using NLP techniques.

**Keywords:** Mental Health, Natural Language Processing, LSTM, Word Embeddings, Artificial Intelligence.

## 1 Introduction

### 1.1 Background

Mental health issues, with depression as a prominent example, afflict a staggering 264 million individuals globally, as highlighted by the World Health Organisation (WHO) in 2020. This widespread prevalence positions depression as a leading cause of disability on a global scale (Vashishtha, Yadav and Agrarwal, 2021). The imperative of early diagnosis emerges as a crucial preventive measure to address the far-reaching impacts of mental health concerns. Notably, a telephone survey conducted in Germany revealed unique challenges, emphasizing shame and self-stigmatization as primary barriers hindering individuals from seeking psychiatric help for depression. This insight adds nuance to the complexities surrounding mental health, indicating that addressing the issue requires a multifaceted approach, considering not only perceived stigma but also internalized factors.

Technology, particularly within the intersection of Natural Language Processing (NLP) and neural networks, offers a promising avenue for addressing the complexities of mental health assessment. Our focus extends beyond traditional diagnostic approaches, aiming to create a user-centric solution that aligns with the evolving dynamics of mental health conversations. Chatbots and conversational agents, such as Woebot and Wysa, exemplify the potential of technology to engage users in meaningful mental health dialogues. Many health classification algorithms exists to solve real world health conditions- breast cancer (Gupta et al., 2023) and medical segmentation (Beniwal and Vashishtha, 2022). Our research aspires to contribute to this trajectory by developing an algorithm that facilitates users in expressing their mental health concerns in a manner akin to a conversation with a therapist.

The integration of NLP techniques, coupled with Long Short-Term Memory (LSTM) networks, forms the core of our technological approach. NLP enables the system to understand and process the natural language expressions of users, while LSTM, a type of recurrent neural network, facilitates the modeling of temporal dependencies within the narratives. This combination aims to enhance the algorithm's ability to discern nuanced patterns and contextual intricacies within users' explanations, thereby enabling more accurate and sensitive mental health classifications.

The present study applied NLP techniques to process patients' explanations of their mental health issues and used neural networks to classify their issues into distinct categories. Such a classification system can help identify problem areas and direct patients to appropriate therapists for their particular issues. The data used for this research was extracted online from the repository by Nicolas Bertagnolli, who received the data from CounselChat.com (Bertagnolli, 2020).


**Fig. 1.** Mental Illnes

### 1.2 Objective

The primary aim of this research is to employ advanced sequence modeling techniques for the classification of user-written text into distinct categories of mental health issues. Recognizing that user-generated text is essentially a sequence of words, the research advocates for the application of sequence-to-sequence neural network architectures as a fitting solution. The selection of recurrent neural networks (RNNs) is motivated by their inherent capability in sequence modeling tasks. However, acknowledging the potential limitations of RNNs in processing long sequences, the research strategically incorporates long short-term memory (LSTM) cells. This dual approach seeks to optimize the accuracy and efficiency of mental health issue classification, particularly when dealing with extended textual sequences. By integrating state-of-the-art sequence modeling techniques, this research aims to contribute to the advancement of intelligent methods, paving the way for more effective and nuanced early detection and intervention strategies in the field of mental health.

The structure of the remainder of the paper is as follows: Section 2 provides a comprehensive literature review, delving into existing research on mental health classification, NLP, and related technologies. Section 3 outlines the dataset used in our research, laying the foundation for the empirical aspects of our study. Section 4 articulates our proposed methodology, detailing the integration of NLP and neural networks for mental health issue classification. The subsequent sections delve into experimental results, discussion, and conclusions, providing a holistic view of our research findings and their implications.

## 2 Literature Review

### 2.1 Mental Health in the Tech Industry

The intersection of mental health and the technology industry has become a subject of increasing concern and scholarly attention. Tech workers face a unique set of challenges that can impact their mental well-being. The demanding nature of the industry, characterized by tight project deadlines, high-stakes decision-making, and a constant need for innovation, contributes to an environment where stress and burnout are prevalent. Studies have shown that tech workers often grapple with imposter syndrome, a phenomenon where individuals doubt their accomplishments and feel like frauds despite evidence of success. This psychological burden, coupled with the expectation of continuous learning and adaptation, places tech professionals at an elevated risk for mental health issues.

Moreover, the pervasive culture of long working hours, intense competition, and a lack of clear work-life boundaries further exacerbates mental health challenges. As the technology sector continues to expand, it becomes imperative to understand the psychological toll on its workforce and explore effective interventions to mitigate these challenges.

## 2.2 Natural Language Processing in Mental Health Assessment

The utilization of Long Short-Term Memory (LSTM) cells has emerged as a prominent and well-received technique in the realm of Natural Language Processing (NLP), particularly due to their ability to effectively process longer sequences of data. In a study conducted by Wang et al. (2018)[1] that delved into the application of LSTM networks on social media data, the researchers experimented with a sequence of word embedding vectors derived from social media content. Their findings demonstrated the superiority of the LSTM model compared to both the naïve Bayes model and the extreme learning machine (ELM) model. The LSTM's outperformance was attributed to its proficiency in capturing complex patterns within the context of social media language. Importantly, this study emphasized that the success of deep learning methods, particularly those utilizing LSTM and word embeddings, hinged on the availability of sufficient training data. This observation underscores the robustness of LSTM networks in learning and retaining word usage patterns, especially in the context of social media language nuances.

While these studies provide a strong foundation for the use of LSTM networks in text classification, it is crucial to acknowledge the nuanced considerations raised by Wang et al. (2018). Specifically, the quantity of training data is highlighted as a critical factor influencing the effectiveness of LSTM networks. This insight directs attention to the importance of dataset size in harnessing the full potential of LSTM-based approaches in NLP and text classification tasks. Consequently, the literature review establishes LSTM networks as a promising avenue for addressing challenges in processing longer sequences, offering valuable insights into their applications and considerations in the context of NLP.

The history of NLP dates back to 1950 when Alan Turing proposed a test for artificial intelligence evaluating whether a computer can use language to fool humans to believe it is human (Ganegedara, 2018). However, besides approximating human speech, NLP has a wide range of other applications that include sentiment analysis ((Vashishtha, Gupta and Mittal, 2023); (Vashishtha and Susan, 2022)), the detection of spam emails and bias within the text, breast cancer detection (Gupta et al., 2023), improving accessibility for people with special needs, question answering, and language translation, among others. Based on recent research (Vashishtha and Susan, 2021; Vashishtha and Susan, 2019), it is understood that NLP aims to create a machine that can pass the Turing test. To accomplish this, researchers have broken down several intermediate tasks within NLP, including tokenization, word-sense disambiguation, named entity recognition, part-of-speech tagging (Vashishtha and Susan, 2021), sentence classification, language generation, question answering, and machine translation. This project utilizes a few of these tasks, which are described in this section.

The Normalization Approach is suggested by Brigitte Bigi (2014) ,in a Multilingual Text Normalization Approach. Which deals with unrestricted text need the text to be normalized. Text normalization is a very important issue for Natural Language Processing applications. This paper presented a text normalization system entirely designed to handle multiple languages and/or tasks with the same algorithms and the same tools.

In the realm of Natural Language Processing (NLP), text normalization plays a crucial role, especially when dealing with diverse and unstructured textual data. Bigi's work addresses this by presenting a text normalization system designed to handle multiple languages and tasks with the same algorithms and tools.
The workflow of this project is greatly influenced from the work of .Nicolas Bertagnolli [4] (2020),Counsel Chat: Bootstrapping High-Quality Therapy Data. Counselchat.com is an example of an expert community. It is a platform to help counselors build their reputation and make meaningful contact with potential clients. On the site, therapists respond to questions posed by clients, and users can like responses that they find most helpful. It's a nice idea and lends itself to some interesting data.
The data is verified by the therapists posting the responses.If someone is using Reddit data the person providing advice could be anyone. But on Counselchat the individuals providing the advice are qualified counselors. It is important to keep in mind that in-person interactions with a therapist are often very different from what we see publicly online. Another thing, this is not a dialogue between a therapist and a patient. It only involves a single talk turn.
In the Projects in Computing and Information Systems, by [5] Dawson, C.W., 2009. Author has explores various aspects of managing and executing projects in the field of computing and information systems. Which include topics like project planning, requirements analysis, system design, implementation, testing, and project management methodologies. It also explains upon issues such as team collaboration, risk management, and the integration of technology into broader organizational goals.
It states all projects have five elements that require managing to some extent as the project progresses: time, cost, quality, scope and resources. These elements need to be balanced against one another so that you achieve your project's aims and objectives.
In the paper BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding, [6] Devlin, J., 2019. addresses the challenge of capturing contextual information and bidirectional dependencies in language understanding tasks, which previous models struggled with. BERT achieves state-of-the-art results on various benchmark NLP tasks, including question answering, sentiment analysis, and named entity recognition. The bidirectional context understanding proves crucial for tasks requiring a deep understanding of language semantics.
The various concepts of machine learning used in this paper are formulated from the book by [7]Geron, A., 2019. Hands-on Machine Learning with Scikit-Learn, Keras and Tensorflow. The book covers both the theoretical concepts of machine learning and practical implementation using hands-on examples. It includes topics of Introduction and Basics of machine learning concepts. In-depth coverage of Scikit-Learn library for classical machine learning algorithms. Detailed explaination of Keras library for building neural networks, Creation and training deep learning models using Keras. Deep dive into TensorFlow, an open-source machine learning library developed by Google.
Implementing BERT has turned out to be far less complicated than implementing the traditional methods. Paper by [8]Gonzalez-Carvajal, S. and Garrido-Merchan (2020). Comparing BERT against traditional machine learning text classification, they have introduced four different NLP scenarios where we have shown how BERT has

outperformed the traditional NLP approach, adding empirical evidence of its superiority in average NLP problems w.r.t. classical methodologies.
In Sentiment Analysis using Simplified Long Short-term Memory Recurrent Neural Networks by [9] Gopalakrishnan, K. and Salem (2020) perform sentiment analysis on a GOP Debate Twitter dataset. To speed up training and reduce the computational cost and time, six different parameter reduced slim versions of the LSTM model (slim LSTM) are proposed. They evaluate two of these models on the dataset. The performance of these two LSTM models along with the standard LSTM model is compared. The effect of Bidirectional LSTM Layers is also studied. The work also consists of a study to choose the best architecture, apart from establishing the best set of hyper parameters for different LSTM Models.
In paper Sentiment Analysis using LSTM, by [10] Tholusuri, A. (2019).They Classify the movie reviews using LSTM . The reviews dataset is taken from the IMDB movie review dataset. Here they classify a review based on the memory in the neural network of a LSTM cell state. Movie reviews often contain sensible content which describe the movie. One can manually decide whether a movie is good or bad by going through the reviews. Using machine learning approach they are classifying the movie reviews such that one can say that a movie is good or bad. They prove that LSTM is effective than many other techniques like RNN and CNN.

## 3 Dataset and Implementation

In this work, Counselchat Dataset is used which is a counseling data available to use from public GitHub repository. Initially, the data was scraped from www.counselchat.com. There are 31 topics on the forum, with the number of posted responses ranging from 317 for the topic of “depression” to 3 for “military issues”. There are 307 therapist contributors on the site, most of whom are located on the West Coast of the US (Washington, Oregon, California). They range in licensing from Ph.D. level psychologists, social workers, and licensed mental health counselors. The dataset is presented as a CSV with 9 columns : questionID, questionTitle, questionText, questionLink, topic, therapistInfo, therapistURL,answerText, upvotes , split. This work was implemented in the Python programming language. The Tensorflow library by Google Inc and its Keras API were used as the backend of the neural networks.

## 4 Methodology

### 4.1 Initial Data Analysis

The data were loaded into a Pandas DataFrame from a CSV file (available in Nicolas Bertagnolli’s public Github repository). Upon loading the dataset, the author noted that it contained some sensitive information such as therapist names and URLs as well as the text and category data required for the project. Moreover, additional columns existed regarding upvotes, answer text and question ID, which were considered unnecessary. All of the sensitive and unnecessary columns were first removed from the dataset before progressing into further processing to comply with the ethical considerations. Once the aforementioned columns were removed, the only two columns that remained were ‘questionText’ and ‘topics’.

The dataset included 1482 samples. Through data exploration, it was noticed that there were 99 null values in ‘questionText’ and 10 null values in ‘topics’. The rows containing these null values were simply removed from the dataset since there was no alternative method to impute missing values. Thereafter, 1376 samples remained in the dataset.

Some samples were labelled with multiple topics. A Keras LSTM model was implemented with multi-labels, however the model failed to converge even with multiple attempts. Thus, it was decided that only the first label of the multi-label samples would be kept. A plot was then created to observe the distribution of questionText by topics defined within the dataset.

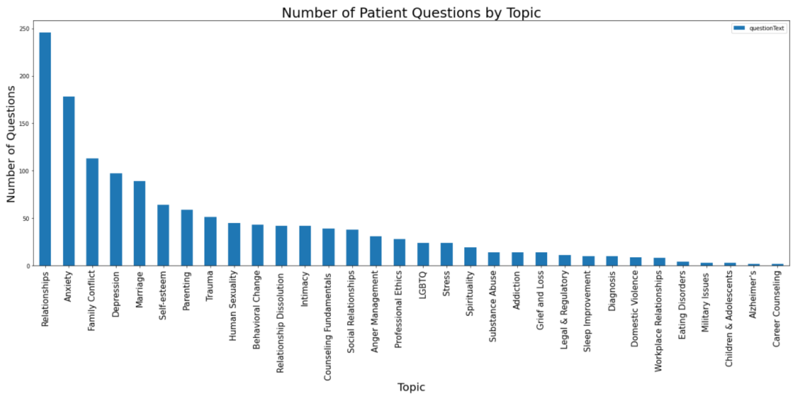


**Fig. 2.** Plot of patient questions by topic and number of questions

As seen in Fig.2, the data were not equally distributed across all categories. This implies that the model may be biased toward some categories within the dataset. To check for model bias, various classification metrics were employed on the trained models.

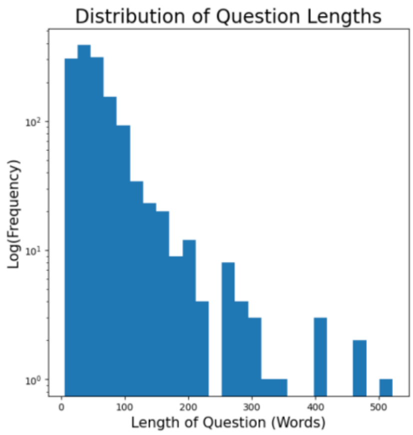


**Fig. 3.** Distribution of Question Lengths

## 4.2 Text Processing

In this section, the step-by-step process of text data processing is explained.

### 4.2.1. Noise removal

The data samples were checked individually and it was noted that the samples contained capitalizations, punctuation marks and some HTML tags. These elements are considered noise within a natural language dataset since they do not contain actual meaning. Noise removal was performed using regular expressions (Regex).

### 4.2.2. Tokenization

Following noise removal, tokenization was performed for each sample. This process simply involved breaking the text into its word tokens.

### 4.2.3. Lemmatization

The tokenization provided individual word tokens for each sample. However, in the English language, some word tokens take different forms according to their usage within a sentence. Therefore, it was necessary to convert those tokens into their root forms so that the learning model did not treat them as different tokens.

### 4.2.4. Stop word removal

The samples within the dataset had several commonly occurring words that were necessary to remove so that the learning model would not focus on their presence within each sample. Words such as 'is', 'am', 'are', 'has', 'had', 'have', 'my', 'their', 'what', 'that', 'it' and 'they' were commonly observed.

### 4.2.5. Conversion to numerical data

Once the samples were stripped of their stop words, they were converted to numerical data. This was performed using the Keras preprocessing library. The trained learning model will be able to identify the location of the tokens within the feature space using the indices. After creating this dictionary, the next step was to take in the samples individually and map them to their token indices based on the dictionary created.

#### 4.2.6. Padding

The token lengths for each sample were different, which is the case in most NLP projects. Therefore, the maximum sequence length was determined by checking the length of each sample. The longest sample included 220 tokens. Therefore, all other sequences shorter than 220 tokens were post-padded with zeros to make up for the shortcoming.

#### 4.2.7. Word embeddings

To create word embeddings of tokens for each sample within the dataset, a Keras embedding layer was used. In this case, the length of the word index dictionary is 2417. This means that the tokens converted as one-hot vectors would be 2417 dimensions long for each token. This would increase the processing time for each sample and the learning model would take a long time to train and predict. The implemented Keras embedding layer was parameterised to 200-dimensional vectors, meaning each token had only 200 dimensions instead of 2417. GloVe is a word vector technique. The advantage of GloVe is that, unlike Word2vec, GloVe does not rely just on local statistics (local context information of words), but incorporates global statistics (word co-occurrence) to obtain word vectors.

### 4.3. Neural Network Design

As previously stated, this is a sequence classification project. Therefore, an LSTM network was chosen as the core neural network structure. Moreover, a bidirectional LSTM with 100 neurons and dropout of 0.1 was chosen for sequence modelling so that the learning model would go through the sequence from start to end and vice versa. A dense layer with 500 neurons and ReLU activation was added after the LSTM network to allow for further featurization. Finally, a 32-neuron dense layer with softmax activation was chosen as the final layer for classifying the samples into 32 categories. Overall, 30,055,1282 total weight parameters were optimized during training.

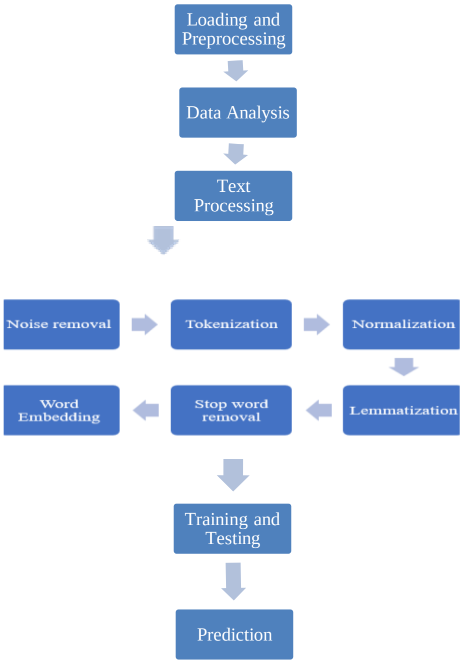


**Fig. 1.** Work flow of proposed model

# 5 Results

The LSTM model was trained for 30 epochs. The training accuracy continuously increased and ultimately reached 81%. However, the test accuracy stabilized at approximately 65%. This is a great result considering the size of the dataset. It is possible that with more data, the test accuracy could be increased further since there will be more word tokens available for the network to rely on. The F1 score provides insights into how well the model generalizes to new, unseen data. it is evident from graph that both training and testing f1 values are increasing after each epoch indicating that model performs well on both unseen as well as unseen data.

Fig. 4. a) graph displays two different colored lines, blue and orange, representing two different sets of data. The blue line represents the accuracy plot of training data, while the orange line represents the accuracy plot of test data. The two lines are plotted against each other, allowing for a comparison of the model's performance with the actual test results. Fig. 4.b) the above graph shows categorical crossentropy loss, which is a measure of the difference between the predicted and actual values of the training data. The plot shows the difference between the predicted and actual values for both

datasets. The orange line represents the validation dataset, and the blue line represents the training dataset.

The training loss is a metric used to assess how a deep learning model fits the training data. That is to say, it assesses the error of the model on the training set. Note that, the training set is a portion of a dataset used to initially train the model. Computationally, the training loss is calculated by taking the sum of errors for each example in the training set.

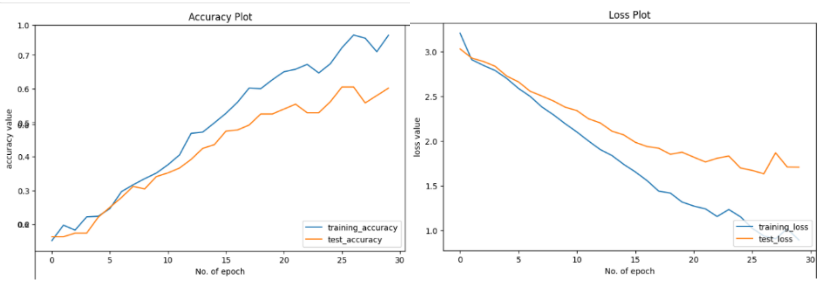


**Fig. 4.** a) Accuracy Plot of LSTM model b) Loss Plot of LSTM model

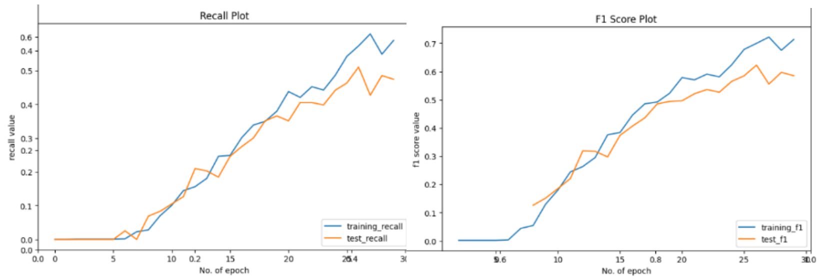


**Fig. 5.** a) Recall Plot of LSTM model b) F1 score Plot of LSTM model

Fig. 5. a) Graph displays recall plot. Recall, also known as sensitivity or true positive rate, is a metric used to evaluate the performance of a classification model. It measures the proportion of actual positive cases that were correctly identified by the model among all the actual positives.

The recall values on the training dataset might show how well the model is performing during the training phase as the threshold or settings are varied. It gives insights into how the model is learning to classify the training examples across different parameter values.

The recall values on the testing or validation dataset help assess the model's generalization capability. It indicates how well the model performs on unseen data. This is crucial to understand whether the model has learned patterns that can be applied to new, unseen examples it is evident from graph that both training and testing recall values are increasing after each epoch indicating that model performs well on both unseen as well as unseen data.

| Dataset | Precision | Recall | f1-score |
|---|---|---|---|
| Addiction | 0.00 | 0.00 | 0.00 |
| Alzheimer's | 0.00 | 0.00 | 0.00 |
| Anger Management | 0.17 | 0.13 | 0.15 |
| Anxiety | 0.47 | 0.26 | 0.33 |
| Behavioral Change | 0.04 | 0.07 | 0.05 |
| Career Counseling | 0.00 | 0.00 | 0.00 |
| Children & Adolescents | 0.00 | 0.00 | 0.00 |
| Counseling Fundamentals | 0.27 | 0.67 | 0.39 |
| Depression | 0.34 | 0.10 | 0.16 |
| Diagnosis | 0.42 | 0.80 | 0.55 |
| Domestic Violence | 0.31 | 0.44 | 0.36 |
| Eating Disorders | 0.67 | 0.50 | 0.57 |
| Family Conflict | 0.47 | 0.06 | 0.11 |
| Grief and Loss | 0.00 | 0.00 | 0.00 |
| Human Sexuality | 0.07 | 0.07 | 0.07 |
| Intimacy | 0.00 | 0.00 | 0.00 |
| LGBTQ | 0.06 | 0.17 | 0.09 |
| Legal & Regulatory | 0.00 | 0.00 | 0.00 |
| Marriage | 0.45 | 0.46 | 0.46 |
| Military Issues | 0.00 | 0.00 | 0.00 |
| Parenting | 0.30 | 0.44 | 0.36 |
| Professional Ethics | 0.33 | 0.07 | 0.12 |
| Relationship Dissolution | 0.50 | 0.24 | 0.32 |
| Relationships | 0.45 | 0.36 | 0.40 |
| Self-esteem | 0.12 | 0.14 | 0.13 |
| Sleep Improvement | 0.01 | 0.10 | 0.03 |
| Social Relationships | 0.09 | 0.39 | 0.14 |
| Spirituality | 0.19 | 0.63 | 0.29 |
| Stress | 0.14 | 0.21 | 0.17 |
| Trauma | 0.60 | 0.29 | 0.39 |
| **Macro average Accuracy** | 0.27 | 0.23 | 0.21 |
| **Weighted average Accuracy** | 0.34 | 0.25 | 0.26 |

**Table 1.** Category wise performance metrics for mental health classification

Fig. 5 b) The F1 score is another metric commonly used in classification tasks that combines both precision and recall. It's the harmonic mean of precision and recall, providing a single value that represents a balance between these two metrics. blue curve shows the F1 scores obtained by the model during different iterations or epochs of training. It helps visualize how the F1 score changes as the model learns from the training data orange curve illustrates the F1 scores achieved by the model when evaluated on a separate set of data (validation) that it hasn't seen during training. It provides insights into how well the model generalizes to new, unseen data. it is evident from graph that both training and testing f1 values are increasing after each epoch indicating that model performs well on both unseen as well as unseen data.

## 6 Conclusion and Limitations

In conclusion, this project has provided an algorithm that can be used in systems that analyse natural language data to understand patients' mental health issues. Users would simply have to explain their issue as they would to a therapist and the system would process that explanation using NLP techniques and classify them into a particular category. Such a system can be used in multiple areas. A counselling therapy provider could choose to have their patient perform an initial assessment online, which would help them automatically direct the patient towards an appropriate therapist. This means that providers could save on costs related to initial assessments. Second, it could also be used in mental health counselling applications where the system tries to consolidate patients by constantly analysing their natural language descriptions of the issues they are dealing with. Classifying each conversation that patients make within the app would further help the application to maintain overall records of patients' issues. The project highlights the development of a functional AI system for classifying natural language descriptions of mental health issues. The LSTM model gave 81% accuracy while BERT model gave 59% accuracy.

## References


1. Wang, J., Liu, T., Luo, X and Wang, L., 2018. An LSTM Approach to Short Text Sentiment Classification with Word Embeddings, The ROCLING Confer-ence on Computational Linguistics and Speech Processing, pp. 214-223.
2. Ganegedara, T., 2018. Natural Language Processing with Tensorflow. Birming-ham: Packt Publishing Ltd.
3. Bigi, B., 2014. A multilingual text normalization approach. Human Language and Technology Challenges for Computer Science and Linguistics, vol. LNAI8387, pp. 515-526.
4. Bertagnolli, N., 2020. Counsel Chat: Bootstrapping High-Quality Therapy Da-ta, [online] Available at:https://towardsdatascience.com/counsel-chat-bootstrapping-high-quality-therapy-data-971b419f33da
5. Dawson, C.W., 2009. Projects in Computing and Information Systems, Harlow: Pearson Education Ltd.
6. Devlin, J., 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding, ArXiv, [PDF] Available at: https://arxiv.org/pdf/1810.04805.pdf
7. Geron, A., 2019. Hands-on Machine Learning with Scikit-Learn, Keras and Tensorflow. Sebastopol: O'Reilly Media Inc.
8. Gonzalez-Carvajal, S. and Garrido-Merchan, E.C., 2020. Comparing BERT against traditional machine learning text classification, ArXiv, [PDF] Available at: https://arxiv.org/pdf/2005.13012.pdf
9. Gopalakrishnan, K. and Salem, F.M., 2020. Sentiment Analysis using Simpli-fied Long Short-term Memory Recurrent Neural Networks, Department of Electrical and Computer

Engineering - Michigan State University, ArXiv, [PDF] Available at: https://arxiv.org/ftp/arxiv/papers/2005/2005.03993.pdf

10.Tholusuri, A., Anumala, M., Malapolu, B. and Lakshmi, G.J., 2019. Sentiment Analysis using LSTM, International Journal of Engineering and Advanced Technology, 8(6S3), pp. 1338-1340.

11.Berndtsson, M., Hansson, J., Olsson, B and Lundell, B., 2008. Thesis Projects: A Guide for students in Computer Science and Infromation Systems, London: Springer-Verlag.

12.Vashishtha, S., Gupta, V., & Mittal, M. (2023). Sentiment analysis using fuzzy logic: A comprehensive literature review. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 13(5), e1509.

13.Vashishtha, S., & Susan, S. (2022). Neuro-fuzzy network incorporating multi-ple lexicons for social sentiment analysis. Soft Computing, 26(9), 4487-4507.

14.Vashishtha, S., & Susan, S. (2019). Sentiment cognition from words shortlist-ed by fuzzy entropy. IEEE Transactions on Cognitive and Developmental Sys-tems, 12(3), 541-550.

15.Vashishtha, S., & Susan, S. (2021). Highlighting keyphrases using senti-scoring and fuzzy entropy for unsupervised sentiment analysis. Expert Systems with Applications, 169, 114323.

16.Gupta, V., Gaur, H., Vashishtha, S., Das, U., Singh, V. K., & Hemanth, D. J. (2023). A fuzzy rule-based system with decision tree for breast cancer detec-tion. IET Image Processing, 17(7), 2083-2096.

17.Beniwal, N., & Vashishtha, S. (2022, September). Comparative Analysis of U-Net-Based Architectures for Medical Image Segmentation. In International Conference on Advances and Applications of Artificial Intelligence and Ma-chine Learning (pp. 715-725). Singapore: Springer Nature Singapore. https://doi.org/10.1007/978-981-99-5974-7_57

18. Vashishtha, S., Yadav, Y., & Agrarwal, Y. Impact caused by COVID-19 on Mental Health: word-level analysis.