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Detection of Stress and Anxiety on social media Using Tweets and Facebook Comments

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ABSTRACT:

Severe stress and anxiety pose significant challenges to individual and public health. Each year, about 10 million people suffer from anxiety, but only a small fraction receives appropriate treatment. This study aimed to investigate the ability to identify and diagnose major stress and anxiety disorders in individuals. To achieve this, machine learning algorithms were used to predict anxiety and stress levels. These algorithms were applied to tweets from various users during the first wave of the COVID-19 pandemic, collected using Twitter tweet IDs. In addition, relevant Facebook comments containing expressions of anxiety were also included in the dataset. The collected data is grouped into a single data set, which is modelled using various mathematical techniques. The most promising results were then selected by manual evaluation. Deep learning algorithms have been used to predict and detect stress and anxiety, making it easier to identify warning signs of these mental health problems. The findings suggest that social media platforms provide valuable indicators for understanding the occurrence of these problems in individuals, as evidenced by a decline in social activism and increased anxiety.

Keywords: Machine learning; LSTM; Deep Learning; random forest; support vector machine; stress; anxiety; tweets; Facebook; social media; Twitter

I. INTRODUCTION

Mental illness stands as a prominent contributor to global disability rates. An estimated 300 million individuals are affected by mental illness. According to the World Health Organization (2001), the lifetime prevalence rates for depression exhibit significant variation, with reported rates of 3% in Japan and 17% in the United States. In North America, the chances of experiencing a major depressive episode within a year range from 3% to 5% for males and 8% to 10% for females. Mental illness contributes significantly to global disability rates, affecting approximately 300 million people. Depression rates vary widely between countries, from 3% in Japan to 17% in the United States. In North America, the probability of experiencing a major depressive episode over the course of a year ranges from 3% to 5% for men and from 8% to 10% for women.

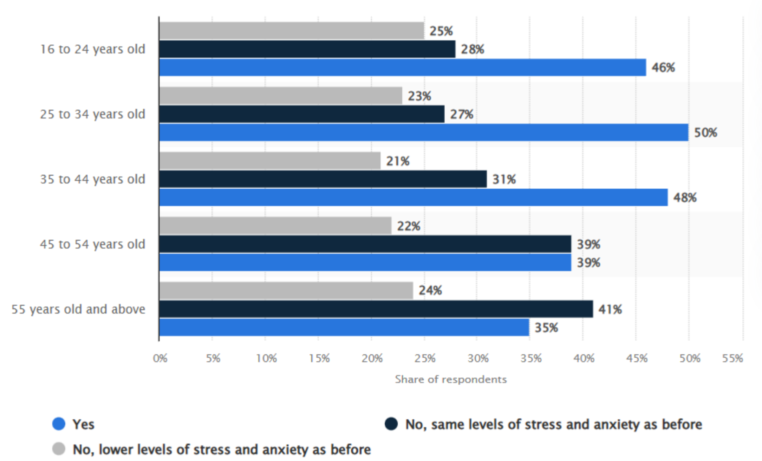

Figure 1. Stress and Anxiety in India amid covid age-wise.

However, universal services to identify, support and treat mental illness remain inadequate, with around 87% of governments providing primary health care but lacking specialized programs and budgets dedicated to mental health. Currently, there are no accurate laboratory tests to diagnose most mental illnesses, which typically rely on patient reports, comments from relatives or friends, and mental status examinations. Given these challenges, this study explores the potential role of social media in identifying and predicting emotional disorders in individuals. Symptoms of mental illness include memory difficulties, decreased ability to concentrate, impaired ability to make decisions, decreased interest in activities, changes in eating habits, feelings of guilt, Uselessness, helplessness, restlessness, irritability and thoughts of self-harm.

The study noted an increase in stress and anxiety levels during the Covid-19 pandemic, with 74% and 88% of Indians reporting feeling stressed and anxious respectively. Recent findings show a shift in therapy practice since the pandemic, with an increase in therapy sessions and new people seeking therapy. Social media platforms such as Twitter and Facebook provide information about individuals' cognition, mood, communication, activities, and social interactions.

The language and emotions expressed in social media posts may indicate emotions associated with major depression. Additionally, changes in social media use may reflect behavioural changes related to depression, such as withdrawal from social activities. The combination of changes in language, activity, and social connections on social networks could lead to effective detection and even prediction of major depressive disorder (MDD), complementing other studies traditional diagnostic methods.

The article focuses on analysing the traumatic experiences of people in India during the first wave of the coronavirus pandemic to determine the extent to which people suffering from mental health problems such as stress and anxiety detect. The main contributions of the study include compiling a dataset from Facebook tweets and comments, identifying behavioural patterns in users with mental health problems, and developing a comprehensive model using Advanced natural language processing techniques to detect stress and anxiety in users worldwide. about their content on social networks.

II LITERATURE REVIEW

Several researchers have invested significant time and resources in gathering and categorizing data from blog posts using sophisticated machine learning algorithms such as Random Forest Trees (RFT), Support Vector Machines (SVM), and Convolutional Neural Networks (CNN) [4], [9], [10]. Various text representation methods, including topic modelling, Bag-of-Words (BOW), and Term Frequency - Inverse Document Frequency (TF-IDF), were applied [4], [6], [11]. The modelling experiments were conducted using Python programming, and the CNN classifier demonstrated the highest level of success, attaining precision and recall scores of 78% and 0.72, respectively [1].

In the field of anxiety and depression screening, a variety of machine learning algorithms, including Logistic Regression, Catboost, Naive Bayes, Random Forest Trees (RFT), and Support Vector Machines (SVM), have been utilized [5], [6]. In a specific study involving 470 seafarers, data related to occupational, socio-demographic, and health factors were gathered from 16 different variables [6]. Among all the classifiers employed, Catboost demonstrated the highest accuracy and precision, achieving rates of 82.6% and 84.1%, respectively [6].

A study conducted by Leightley, Williamson, Darby, and Fear (2019) aimed to identify potential cases of post-traumatic stress disorder (PTSD) in a cohort of UK military personnel using supervised machine learning classifiers [7]. Multiple supervised machine learning classifiers achieved satisfactory sensitivity levels in the study; however, the presence of false negative diagnoses posed certain limitations to the outcomes [7].

Generalized Anxiety Disorder (GAD) is characterized by various symptoms such as irritability, nervousness, fatigue, sleep disturbances, gastrointestinal issues, panic, a sense of impending danger, elevated heart rate, sweating, rapid breathing, and difficulties in concentration [2]. Symptoms associated with stress include feelings of restlessness, inability to relax, low energy levels, chronic headaches, frequent exaggerated reactions, and recurring colds or infections [2]. As a result, stress, anxiety, and depression exhibit several overlapping symptoms, including sleep problems, chest pain, fatigue, elevated heart rate, and difficulties in concentration [2].

In the field of sociolinguistics, Oxman and colleagues (1982) conducted a study showing that linguistic analysis of speech could distinguish between individuals with depression and paranoia. Additionally, the utilization of the LIWC program for computerized analysis of written text has been successful in identifying predictive indicators linked to neurotic tendencies and psychiatric disorders [3].

Author(s)	**Year**	**Contribution**
Xinyu Wong, Chunhong Zhang, Li Sun et al [1]	**2013**	**Improved model for depression detection in micro-blog social network using machine learning algorithms and achieving high precision and recall scores**
Jetli Chung, Jason Teo [2]	**2021**	**Comprehensive review on mental health prediction using machine learning, discussing taxonomy, applications, and challenges**
Saha, B., Nguyen, T., Phung, D., Venkatesh, S. [3]	**2016**	**Framework development for classifying online mental health-related communities with an interest in depression**
Braithwaite, S. R., Giraud-Carrier, C., West, J., Barnes, M. D., Hanson, C.L. [4]	**2016**	**Validation of machine learning algorithms for Twitter data against established measures of suicidality**
Rohizah Abd. Rahman, Khairuddin Omar, Shahrul Azmad Mohd Noah et al [5]	**2020**	**Systematic review on the application of machine learning methods in mental health detection, providing insights into various approaches and their effectiveness**

Sau, A., Bhakta, I. [6]	**2018**	**Screening of anxiety and depression among seafarers using machine learning technology, demonstrating high accuracy and precision rates**
Leightley, Williamson, Darby, and Fear [7]	**2019**	**Identification of potential cases of post-traumatic stress disorder (PTSD) in UK military personnel using supervised machine learning classifiers, highlighting sensitivity levels and limitations of the outcomes**
Oxman and colleagues [8]	**1982**	**Linguistic analysis of speech distinguishing between individuals with depression and paranoia, contributing to the field of sociolinguistics**
Rude, Gortner, & Pennebaker [9]	**2004**	**Utilization of LIWC program for computerized analysis of written text to identify predictive indicators linked to neurotic tendencies and psychiatric disorders, enhancing understanding of linguistic markers**

Table 1. Research works summary of Stress and Anxiety Detection

III. METHODOLOGY

The main objective of this study was to detect anxiety and stress using the Depression, Anxiety and Stress Scale (DASS 21) questionnaire. The initial dataset includes tweet IDs, which are used to collect all available tweets in the dataset. Tweets were hydrated using Twitter Hydrator to create the provided dataset, which includes 25,424 Twitter comments and responses from various people in India. The text column of the dataset contains the entire text of the user's message or response, which will be used to perform natural language processing (NLP) and detect early signs of stress and anxiety settle.

A. Data Preprocessing

Data hydration, also referred to as data lake hydration, refers to the process of importing data into an object. When an object is awaiting data, it is in a state of readiness to be hydrated. The source of this hydration can be a data lake or another data repository. To ensure the proper selection and population of objects with the relevant data, multiple methods for data hydration are available. Successful data hydration extends beyond mere data extraction or storage and is significantly improved by the efficient migration of data into the correct location and format. As data and applications progressively transition to the cloud, the storage and processing of large-scale data will inevitably follow the same trajectory. To prepare the data for labelling, several tasks of Natural Language Processing (NLP) were applied. These tasks included the removal of URLs and emails, the conversion of all text to lowercase, the elimination of punctuation signs, the elimination of stop words, and the lemmatization of the text.

B. Data Vectorization

In machine learning, there exists a concept of an optimization algorithm that aims to reduce errors and compute the best parameters for the machine learning model. By utilizing a vectorized implementation in an optimization algorithm, the computation process becomes much faster compared to an un-vectorized implementation. This step is crucial, as models that can only interpret numerical data would not be able to process text without proper vectorization.

C. Topic Modelling

Topic Modelling is a statistical modelling approach that employs unsupervised machine learning to detect clusters or collections of comparable words in a given text corpus. This technique in text mining leverages the semantic structures present in the text to comprehend unstructured data without the need for pre-defined labels or training data.

i. Latent Dirichlet Allocation

To assign topics to each document in LDA (Latent Dirichlet Allocation), the process involves executing the following steps:

For each document, each word is randomly assigned to one of the predefined subjects.

1. For every document d:

• For every word w in the document, the following calculations are performed:

• The computation of the proportion of words in document d that are assigned to topic t is expressed as P (topic t | document d).

• The computation of the proportion of assignments to topic t across all documents from words that come from w is represented as P (word w | topic t)

• Topic T' is reassigned to word w based on the probability p (t' | d) * p (w | t'), taking into account the probabilities of all other words and their respective topic assignments.

2. The final step is iterated multiple times until reaching a steady state, where the topic assignments cease to change any further.

3. Based on the topic assignments, the proportion of topics for each document is subsequently determined.

Cluster of document by topic

Figure 2. Latent Dirichlet Allocation

ii. Non-Negative Matrix Factorization

Non-Negative Matrix Factorization (NMF) is an unsupervised technique that does not require topic labelling for model training. The main concept behind NMF involves decomposing or factorizing high-dimensional vectors into a lower-dimensional representation. Importantly, these lower-dimensional vectors and their coefficients are non-negative. Given the original matrix (A), NMF performs the factorization and generates two matrices (W and H). The matrix W signifies the discovered topics, while the matrix H contains the coefficients or weights associated with those topics. Essentially, matrix A represents the articles represented by words in its original form, matrix H represents the articles represented by topics, and matrix W represents the topics represented by words. During the entire process, NMF adjusts the initial values of W and H iteratively, aiming to minimize the approximation error until it reaches convergence or reaches the maximum number of iterations specified.

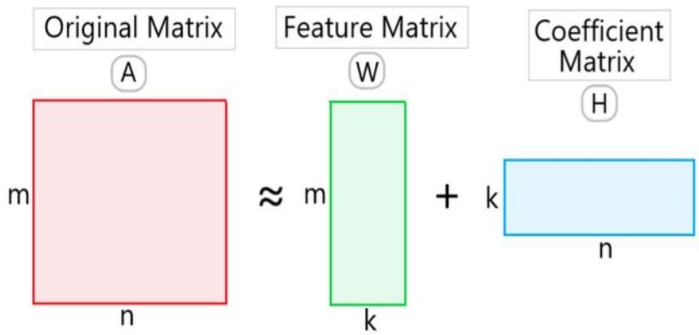

Figure 3. Non-negative matrix factorization

D. Topic Classification

i. Support Vector Machine

The Support Vector Machine (SVM) is a versatile machine learning algorithm capable of being utilized for both regression and classification tasks. However, its primary application is focused on classification purposes. This classifier has gained significant attention in recent times due to its remarkable ability to classify data effectively and its capability to produce high-quality results. The SVM algorithm separates the data into two distinct classes, often referred to as hyperplanes, by establishing a linear division. Moreover, it aims to maximize the distance between the two classes, emphasizing the separation between them.

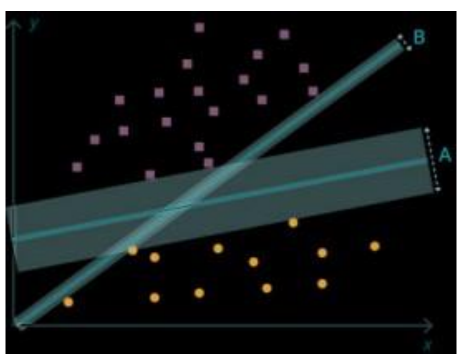

Figure 4. Support Vector Machine representation

ii. Random Forest Tree

The Random Forest classifier generates multiple decision trees by randomly selecting subsets from the training dataset. It subsequently combines the decisions made by these individual trees to determine the final class of test objects. In the context of random forest classification, a variation was proposed that involves using a reduced number of trees compared to the standard approach.

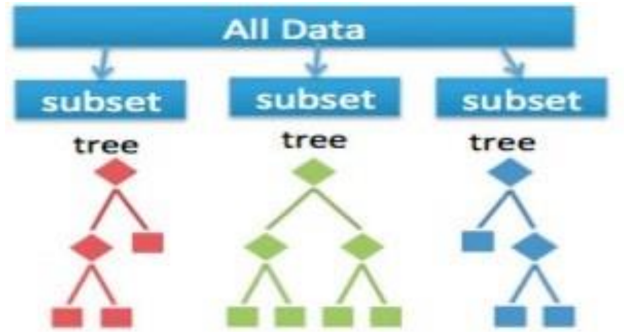

Figure. 5. Random Forest tree

E. Deep Learning Based Classification

A recurrent neural network (RNN) is a specialized type of neural network that is designed specifically to process sequential data, such as time series or natural language. It is widely recognized as an effective model for handling sequences. In contrast to traditional feedforward neural networks, RNNs are characterized by their loop-like connections, allowing them to maintain an internal memory or state. This memory capability enables RNNs to process input data sequentially, taking into consideration the context and dependencies of previous inputs. RNNs excel in tasks that involve sequence modelling and prediction, as they can capture temporal dependencies and learn patterns across different time steps. At each step of an RNN, it receives an input, updates its internal state, and generates an output. This output, along with the updated state, is then fed back into the network as input for the subsequent step.

An extensively used variation of RNN is the Long Short-Term Memory (LSTM) network, specifically designed to tackle the problem of vanishing gradients by integrating specialized memory cells. LSTMs are highly efficient in capturing long-term dependencies in data and have found extensive application in tasks like speech recognition, machine translation, and sentiment analysis. Overall, RNNs and their variants serve as powerful tools for processing sequential data, enabling the modelling of intricate temporal relationships. They have proven useful in tasks such as language generation, speech synthesis, and time series prediction.

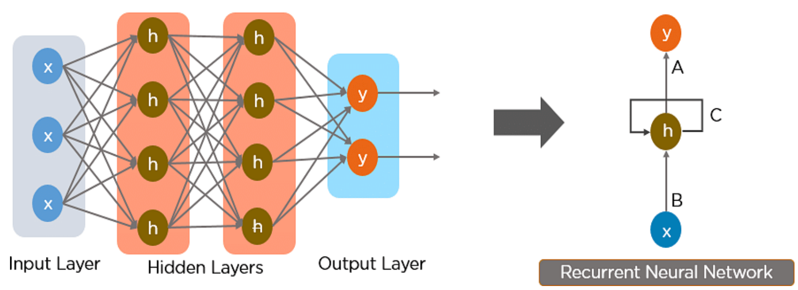

Figure 6. recurrent Neural Network

i. Long Short-Term Memory

The Long Short-Term Memory (LSTM) is a specialized variant of recurrent neural network (RNN) that effectively overcomes the issue of vanishing gradients and excels at capturing long-term dependencies in sequential data. Unlike traditional RNNs that struggle to retain information over lengthy sequences, LSTMs utilize memory cells with specialized components. The core element of an LSTM is the memory cell, which consists of a cell state and three gating mechanisms: the input gate, forget gate, and output gate. These gates are responsible for controlling the flow of information into, out of, and within the memory cell.

The input gate is responsible for determining which parts of the input should be stored in the memory cell, allowing relevant information to be preserved. The forget gate controls what information is discarded from the memory cell, preventing irrelevant details from persisting. The output gate regulates the output of the memory cell, taking into account the current input and internal state. By leveraging these gating mechanisms, LSTMs can selectively update the memory cell and adjust the information flow.

This capability allows LSTMs to efficiently learn and retain long-term dependencies in sequential data, making them well-suited for tasks like speech recognition, language translation, and sentiment analysis. The architecture of LSTM networks empowers them to retain information over extended sequences, effectively mitigate the vanishing gradient problem, and capture dependencies across different time steps. Consequently, LSTMs have been widely adopted in various applications that require modelling complex temporal relationships and handling long-term dependencies.

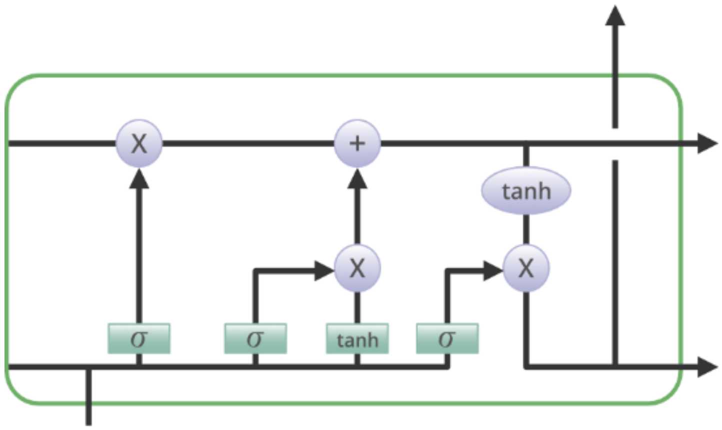

Figure 7. Long Short-Term Memory

A model based on Deep Learning usually comprises several layers, each with a specific role in the learning process. Our model is constructed with three layers: an Embedding Layer, an LSTM Layer, and a Dense Layer.

• The Embedding Layer is a specialized component frequently employed in deep learning models specifically created for natural language processing (NLP) tasks. Its purpose is to convert discrete input data, such as words or categorical variables, into continuous vector representations called embeddings. During training, the embedding layer learns to assign each input word or category a fixed-size dense vector, known as the embedding dimension. These vector representations are learned in a way that encourages similar words or categories to have similar embeddings, enhancing the model's capability to generalize to data it has not encountered before.

• The LSTM Layer, also known as the Long Short-Term Memory layer, is a specialized form of recurrent neural network (RNN) layer that effectively handles the issue of vanishing gradients and captures long-term dependencies in sequential data. At the core of an LSTM layer lies the LSTM cell, which consists of a cell state and three gating mechanisms: the input gate, forget gate, and output gate. These gates play a crucial role in controlling the flow of information within the LSTM cell. The usage of LSTM layers is widespread across various tasks involving sequential data, including NLP, speech recognition, and time series analysis. They offer powerful capabilities for modelling intricate temporal relationships and managing long-term dependencies, making them a vital element in many deep learning models.

• The Dense Layer, also referred to as a fully connected layer, is a fundamental component present in deep learning models. It is distinguished by the fact that every neuron within the layer is connected to all neurons in the preceding layer. In a dense layer, each neuron receives input from all the neurons in the previous layer and generates an output value. This is accomplished using a set of weights, one for each connection between input neurons and neurons in the dense layer. Additionally, a bias term may be included, which is a constant added to the weighted sum of inputs. Dense layers play a crucial role in deep learning models by enabling them to learn and represent high-level features and patterns in the data. Through connecting each neuron from the preceding layer to the current layer, dense layers facilitate the model in capturing and processing complex relationships present in the data.

F. Streamlit

Streamlit is a Python library that is open-source and allows the creation of interactive web applications for tasks such as data analysis, machine learning, and visualization. It offers a simplified approach to developing web apps by providing a user-friendly and intuitive interface for Python scripts. Streamlit aims to be user-friendly and facilitates the transformation of data analysis or machine learning code into interactive web applications. It can be utilized to develop interactive dashboards, tools for data exploration, and prototypes for machine learning models. Our website features a homepage that includes a form enabling users to input their name, comment, and age. Once the comment is entered, users can click a predict button to obtain a result indicating whether they are experiencing stress or anxiety. Additionally, there is a feedback and suggestions section where users can share their experience using the website and propose valuable improvements. For users who are suffering from stress or anxiety, there are links available that redirect them to websites where they can seek further assistance and guidance.

IV. RESULT AND ANALYSIS

Confusion matrices were generated for stress and anxiety classification using the Random Forest Tree (RFT) and Support Vector Machine (SVM) techniques. These matrices consist of rows representing the actual classes and columns representing the predicted classes. Several formulas were employed to calculate accuracy and error rates, precision, recall, and specificity for each confusion matrix.

The classification of anxiety and stress was performed using the Support Vector Machine (SVM) and Random Forest (RF) algorithms, achieving accuracies of 88.06% and 87.47%, respectively. It is worth mentioning that the Support Vector Machine demonstrated the highest accuracy, indicating its superior performance in identifying anxiety and stress. As a result, the SVM algorithm was chosen as the preferred method for the given dataset, consisting of diverse tweets from India during the COVID-19 pandemic. Subsequently, a deep learning model was implemented, yielding improved accuracies. Specifically, a single LSTM-based deep learning approach achieved a remarkable accuracy of 93.4% and a loss rate of 17%, accompanied by a significantly improved Confusion Matrix.

Figure 8. Single Layer LSTM: Accuracy – 95.2% Loss – 12.2%

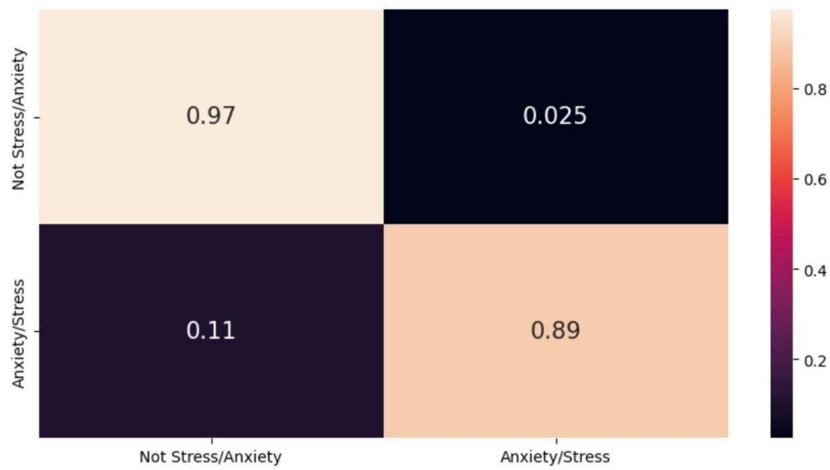

Figure 9. Double Layer LSTM: Accuracy – 95.6% Loss – 11.4%

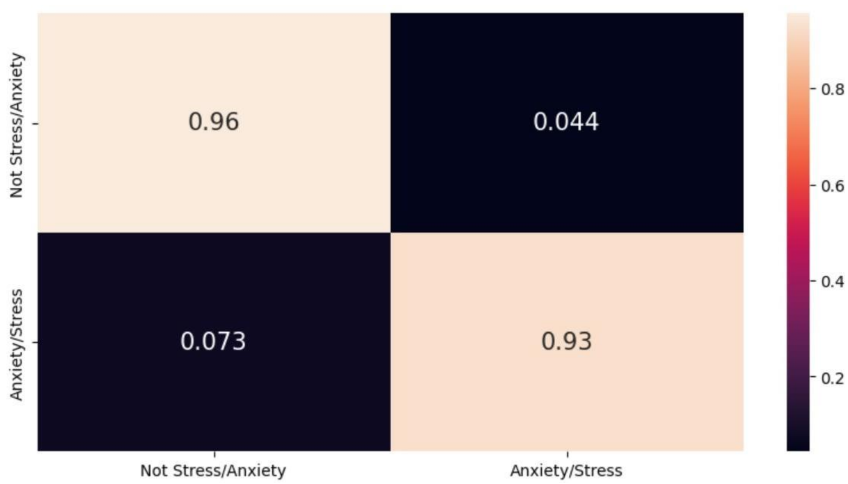

Figure 10. Bidirectional LSTM: Accuracy – 94.9% Loss – 15.9%

By utilizing this approach, it was possible to identify early indicators of stress and anxiety among Twitter users based on the content of their tweets. This enabled the identification of individuals who may be experiencing stress or anxiety symptoms. With this knowledge, appropriate interventions and support measures, including suitable medications, could be provided to those individuals in a timely manner.

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