IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Emotional Stability Analysis: A Predictive Modeling Of Emotional Stability In Student Populations Based On Gated Recurrent Unit (GRU)

Vimala Thangavelu[1] , Pooja Sonawane[2] , Savkar Bhagyashree[3] , Badadhe Suyog[4] , Bhagat Sahil[5]
Assistant Professor[1] Student[2345] M.Sc.(Computer Science)
Dept. of Computer Science,Nowrosjee Wadia College(Autonomous), Pune, Maharashtra, India

Abstract: Emotional stability plays a vital role in personal well-being and everyday functioning. This research explored the use of data analytics to evaluate and comprehend emotional stability, concentrating on psychological, behavioral, and environmental elements like stress. By examining survey responses, communication trends, and psychological evaluations, the study compared the reliability of the Cronbach and Omega methods. Gated Recurrent Unit (GRU) models were employed to forecast stress levels among student groups. The research developed predictive models for outcomes such as overall emotional stability, the risk of mental health problems, academic satisfaction, perceived social support, and stress levels. The analysis aimed to identify significant connections between input features and predicted outcomes, assess model performance using relevant metrics, and determine the importance of individual attributes in predicting students' well-being. It also offers valuable insights into the quantitative measurement of emotional stability and its variations in different situations.

***Keywords* :** Cronbach's Alpha, Omega method, Psychometric Analysis, RNN, LSTM,GRU.

I. INTRODUCTION

In recent years, student mental health has become a growing concern across educational institutions worldwide [2]. Emotion is complex set of interactions among subjective and objective factors, medicated by neural hormonal system, which can give rise to affective experience such as feelings of arousal, pleasure, displeasure; generate cognitive process such as emotionally relevant perceptual effects, appraisals, labeling processes; activate widespread physiological adjustments to the arousing conditions and lead to behavior that is often, but not always expressive, goal directed, and adaptive [5].With the increasing demands of academic performance, social expectations, and personal challenges, many students experience heightened levels of stress, anxiety, and emotional imbalance. Among various psychological factors, emotional stability plays a crucial role in shaping a student's ability to cope with pressure, maintain focus, and achieve academic success.

Emotional stability refers to an individual's capacity to remain calm, composed, and resilient in the face of emotional stressors [11]. Students with higher emotional stability tend to demonstrate better learning outcomes, effective communication, and stronger interpersonal relationships. In this paper we have tried to understand the emotional stability of students, using the deep learning concept, on data collected through an online survey.

The paper is structured as follows: Section II talks about the background and related data, followed by a conclusion and future directions in Section III.

II. BACKGROUND AND RELATED WORK

Emotional instability can lead to mental health issues, reduced academic engagement, and even dropout risks. Based on the findings of scientists in the area of social-psychological adaptation, Emotional stability is measured as a process of interaction between a personality and social environment, leading to effective adaptation or customization to the social environment [4][1]. A study investigated the relationship between emotional stability, motivation, and online study skills among first-year undergraduate students at a public university in eastern Malaysia during the COVID-19 pandemic. The research aimed to understand these factors in the context of online learning from home where both male and female students reported low levels of emotional stability (mean = 2.20 and 2.19, respectively) [10].

The Gated Recurrent Unit (GRU) algorithm, a variant of RNNs, further enhanced the capabilities of emotion recognition from EEG data. GRUs introduced specialized gating mechanisms that regulate the flow of information within the network, addressing the vanishing and exploding gradient problem encountered in standard RNNs [14].Emotion recognition from electroencephalogram (EEG) signals is a thriving field, particularly in neuroscience and Human-Computer Interaction (HCI) which aims to understand and improve the behaviour pattern) as the framework for the textual analysis of apprehensions/themes floodlit the predictive accuracy of emotional state classification through metrics such as valence, arousal, dominance, and likeness by applying a Long Short-Term Memory (LSTM) network to analyze EEG signals [15]. A research based on employers; stability engaged a qualitative method with reliance on secondary data; the study also used the self-efficacy theory (ability to execute a particular discussion, conclusion, and recommendations [12]. Emotional intelligence has been used to determine emotional stability [9].

A. METHODOLOGY

Data science is a process of analysing massive amounts of data to extract valuable knowledge from it. Figure 1 depicts the data science process:

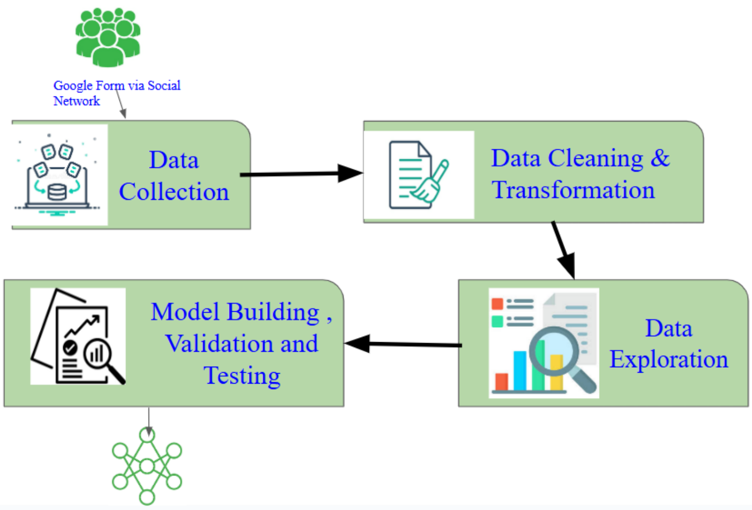


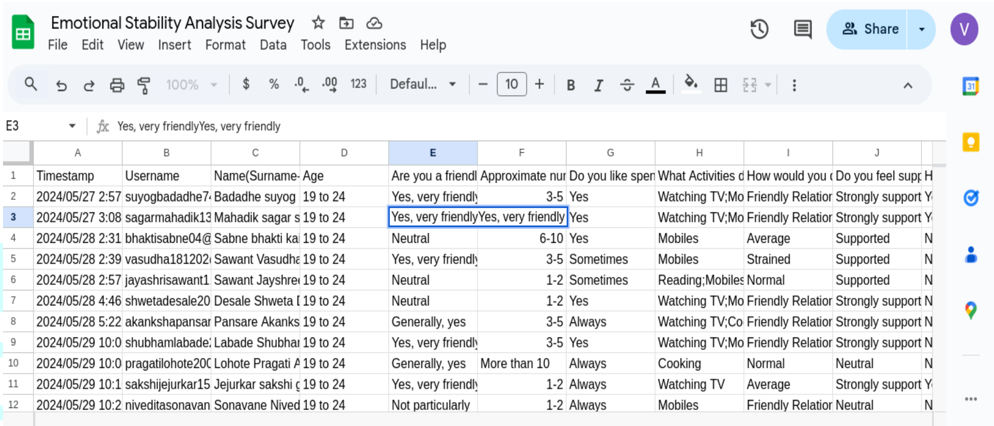
Figure 1: Data Science Process

1. Data Collection Method

An online survey was conducted to assess students' emotional experiences, stress levels, coping mechanisms, and mood fluctuations. Initially with above 200 responses(secondary data), we checked the reliability by using Cronbach’s Alpha and McDonald's Omega method. Statistical analysis involved gaining proficiency in using statistical software (e.g., Excel, Python, SPSS, Jamovi 2.6.2) to analyze survey data and applying descriptive and inferential statistical techniques to interpret the data. Table 1 depicts the Survey Design table and Figure 2 depicts the screenshot of the response sheet.

Table 1 : Survey Design Table

Target Population	Adults aged 16-35
Sample Size	700 participants
Survey Tool	Online questionnaire comprising 25 items
Metrics	Likert scale (1-5), where 5 indicates 'strongly disagree' and 1 indicates 'strongly agree'
Analysis Technique for Survey Data	Import the survey data into a statistical software (e.g. Python, SPSS, Excel, Jamovi)



Emotional Stability Analysis Survey

File Edit View Insert Format Data Tools Extensions Help

E3 Yes, very friendlyYes, very friendly

	A	B	C	D	E	F	G	H	I	J	
1	Timestamp	Username	Name(Surname-	Age	Are you a friendl	Approximate nur	Do you like spen	What Activities d	How would you (	Do you feel supp	H
2	2024/05/27 2:57	suyogbadadhe7	Badadhe suyog	19 to 24	Yes, very friendly	3-5	Yes	Watching TV;Mo	Friendly Relatior	Strongly support	Y
3	2024/05/27 3:08	sagarmahadik13	Mahadik sagar s	19 to 24	Yes, very friendlyYes, very friendly		Yes	Watching TV;Mo	Friendly Relatior	Strongly support	Y
4	2024/05/28 2:31	bhaktisabne04@	Sabne bhakti kai	19 to 24	Neutral	6-10	Yes	Mobiles	Average	Supported	N
5	2024/05/28 2:39	vasudha181202	Sawant Vasudha	19 to 24	Yes, very friendly	3-5	Sometimes	Mobiles	Strained	Supported	N
6	2024/05/28 2:57	jayashrisawant1	Sawant Jayshre	19 to 24	Neutral	1-2	Sometimes	Reading;Mobiles	Normal	Supported	N
7	2024/05/28 4:46	shwetadesale20	Desale Shweta I	19 to 24	Neutral	1-2	Yes	Watching TV;Mo	Friendly Relatior	Strongly support	N
8	2024/05/28 5:22	akankshapansar	Pansare Akanks	19 to 24	Generally, yes	3-5	Always	Watching TV;Co	Friendly Relatior	Strongly support	N
9	2024/05/29 10:0	shubhamlabade	Labade Shubhar	19 to 24	Yes, very friendly	3-5	Yes	Watching TV;Mo	Friendly Relatior	Strongly support	N
10	2024/05/29 10:0	pragatilohote200	Lohote Pragati A	19 to 24	Generally, yes	More than 10	Always	Cooking	Normal	Neutral	N
11	2024/05/29 10:1	sakshijejurkar15	Jejurkar sakshi g	19 to 24	Yes, very friendly	1-2	Always	Watching TV	Average	Strongly support	Y
12	2024/05/29 10:2	niveditasonavan	Sonavane Nived	19 to 24	Not particularly	1-2	Always	Mobiles	Friendly Relatior	Neutral	N

Figure 2 : Screenshot of the Response Sheet

We checked the reliability of the questions with two methods : Cronbach's Alpha and McDonald's Omega.

a) Cronbach's Alpha Method:

Cronbach's alpha (CA) presents significant potential in environmental health assessment. This metric plays a crucial role in ensuring the reliability of measurement instruments, guaranteeing that they consistently capture the intended constructs across various situations and over time. This review centers on exploring the capabilities of measures of internal consistency [9]. Cronbach's alpha is a statistic that measures how well a set of items in a survey or test are correlated, and therefore how reliable the items are. How to improve Cronbach's alpha Reword ambiguous questions, Refine the content to better match the construct, Remove redundant items, and Introduce new itemsThe Cronbach's alpha is the most widely used method for estimating internal consistency reliability.[2]

b) McDonald's Omega(Omega coefficient)Method:-

McDonald's omega (ω) is a method for estimating the reliability of a test or questionnaire. Omega is less likely to be affected by deviations from assumptions. It's considered more robust than Cronbach's alpha.Using methods such as the Omega coefficient to assess the consistency of the data.

Cronbach's Alpha and McDonald's Omega are commonly used for reliability estimations. The alpha uses inter-item correlations while omega is based on a factor analysis result [8]. Figure 3 depicts the comparison of Cronbach and Omega method by using Jamovi tool:

Reliability Analysis

Scale Reliability Statistics

	Cronbach's α	McDonald's ω
scale	0.715	0.721

Figure 3: Comparison of Cronbach and Omega method

The same online survey comprising 25 questions was circulated again to assess students' emotional states. The survey was distributed widely, resulting in approximately 700 responses. This substantial dataset served as the foundation for our analysis. To predict students' emotional stability, we implemented a Gated Recurrent Unit (GRU) model, a type of recurrent neural network known for its effectiveness in processing sequential data. The GRU model was trained on the collected responses, allowing it to identify patterns and correlations between various factors and emotional stability outcomes.

2. Data Cleaning and Transformation

The data preprocessing pipeline for the student emotional survey involves several key steps. Value Replacement transforms categorical responses into numeric values using a predefined mapping dictionary. Data Type Inference automatically detects and converts columns to appropriate data types, enhancing data consistency. Numeric Column Selection retains only numeric columns, eliminating non-numeric data. Missing Value Imputation addresses data gaps by filling NaN values with the most frequent value in each column.

The process involves two key steps: calculating an Emotional Stability Score and categorizing emotional stability. First, the Emotional Stability Score is computed by summing the numerical values of all indicator columns (survey responses) for each participant. This calculation assumes that higher scores may correlate with lower emotional stability, depending on the defined response_map. Second, a function called categorize_stability is implemented to assign categorical labels ('High', 'Normal', 'Low') to participants based on their Emotional Stability Score. These labels are determined using predefined score ranges, allowing for a more intuitive interpretation of the numerical scores.

B. MODEL BUILDING AND CONCRETIZATION

Model building is a systematic process of creating a representation of reality using data and algorithms to gain insights, make predictions, or support decision-making. Figure 4 depicts the flow diagram of Model Building:

Figure 4 : Model Building

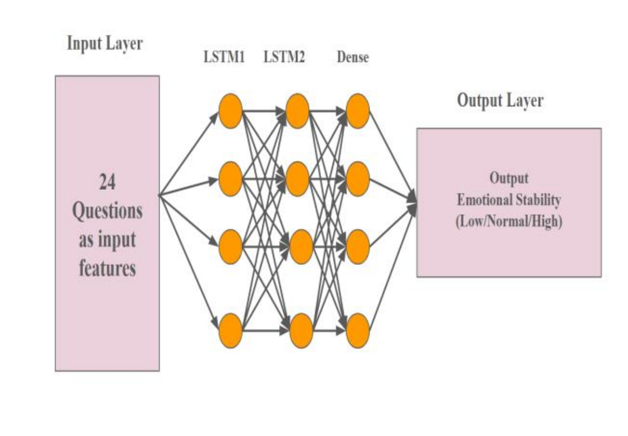
1. Model Selection

The LSTM block is composed of a state unit and three gating units: forget gate, input gate, and output gate. At a high level, the state unit handles the information transfer between the input and the output, and contains a self-loop. The gating units, which simply set their weights to a value between 0 and 1 via a sigmoid function, control the amount of information that is going to come from the input, go to the output, and be forgotten from the state unit [6].

Empirical work has shown that the key components of the LSTM are the forget gate and the output activation functions, and that there is no significant difference in terms of accuracy when comparing an LSTM with its other variants (Greff, Srivastava, Koutník, Steunebrink, & Schmidhuber, 2017). A variant of the LSTM is the gated recurrent unit (GRU; Cho et al., 2014), which simplifies the structure of the LSTM using a slightly different combination of gating units. Specifically, they lack the output gate, which exposes the full hidden content to the output [6].

LSTM and GRU- The combination of Long Short-Term Memory (LSTM) [13] with Gated Recurrent Unit (GRU) stands as the preferred choice among scientists for implementing Recurrent Neural Networks (RNNs) to handle time-dependent information originating from speech and text and physiological signals.

Experiments conducted with speech compounded with eight different types of noises reveal that GRU incurs an 18.16% smaller run-time while performing quite comparably to the Long Short-Term Memory (LSTM), which is the most popular Recurrent Neural Network proposed to date [3]. Figure 5 depicts the Neural Network of LSTM and GRU architecture:



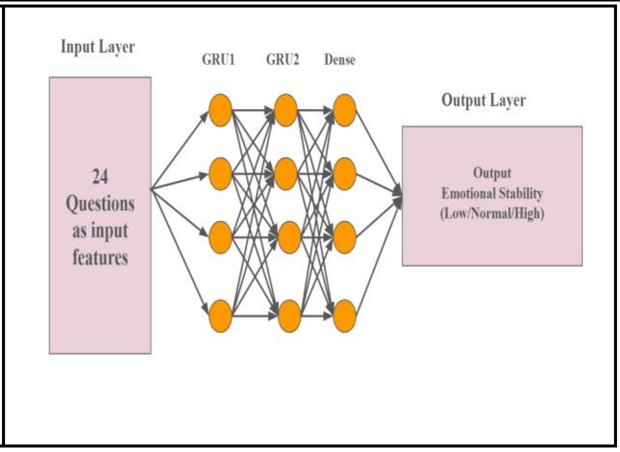


Figure 5 : Neural Network of LSTM and GRU

2. Model Validation

Model validation is the process of evaluating the performance of a machine learning model on data that was not used during its training. For validation we tried with two validation techniques which is given below:

i. **Stratified Sampling** - The train_test_split function from scikit-learn divides the dataset into training (80%) and testing (20%) subsets, with stratification and shuffling.

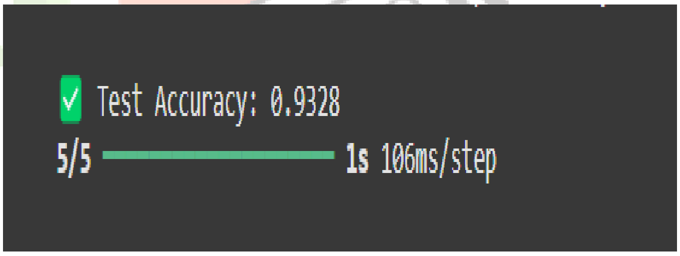
Using stratify=y ensures that the class distribution in y is preserved in both splits, which is crucial for imbalanced datasets. Setting random_state=42 fixes the random seed for reproducibility, guaranteeing the same split each time the code runs. It preserves class distribution, prevents ordering biases, and ensures reproducibility through a fixed random seed.

ii. **K-fold cross validation -** K-fold cross-validation is a technique used in machine learning to evaluate the performance of a model by splitting the dataset into K groups (folds).

3. Model Performance and Concretization

By using the K-Fold validation technique , the dataset is divided into two folds as K = 2 , the accuracy is very less compared with Stratify validation technique. So in this research we followed the Stratified validation. Figure 6 depicts the accuracy using K- fold validation and Stratified validation:

K - fold Validation



Stratified Validation

Figure 6 : Accuracy using K- fold validation and Stratified validation

a) Model Summary :

This model has been implemented with three main layers : Layer1, Layer2 and the Dense layer.The Summary of GRU model has been depicted in Figure 7.

Model: "sequential_4"

Layer (type)	Output Shape	Param #
gru_4 (GRU)	(None, 24, 128)	50,304
dropout_8 (Dropout)	(None, 24, 128)	0
batch_normalization_8 (BatchNormalization)	(None, 24, 128)	512
gru_5 (GRU)	(None, 64)	37,248
dropout_9 (Dropout)	(None, 64)	0
batch_normalization_9 (BatchNormalization)	(None, 64)	256
dense_4 (Dense)	(None, 3)	195

GRU Model Summary

Model: "sequential_5"

Layer (type)	Output Shape	Param #
lstm_4 (LSTM)	(None, 24, 128)	66,560
dropout_10 (Dropout)	(None, 24, 128)	0
batch_normalization_10 (BatchNormalization)	(None, 24, 128)	512
lstm_5 (LSTM)	(None, 64)	49,408
dropout_11 (Dropout)	(None, 64)	0
batch_normalization_11 (BatchNormalization)	(None, 64)	256
dense_5 (Dense)	(None, 3)	195

LSTM Model Summary

Figure 7 : GRU and LSTM Model Summary using Stratify Validation

The LSTM model achieved an accuracy of 87.31%, while the GRU model slightly outperformed it with an accuracy of 93.28%.The Figure 8 depicts the sample output of emotional stability analysis based on GRU.

```
📋 Emotional Stability Prediction per Student:
   Emotional Stability Score Emotional Stability Predicted Stability
0                       56.0              Normal            Normal
1                       45.0              Normal            Normal
2                       76.0                 Low               Low
3                       65.0                 Low               Low
4                       74.0                 Low               Low
..                       ...                 ...               ...
662                     69.0                 Low               Low
663                     62.0                 Low               Low
664                     74.0                 Low               Low
665                     59.0              Normal            Normal
666                     66.0                 Low               Low

[667 rows x 3 columns]
```

Figure 8: Sample Output of Emotional stability and Stress analysis based on GRU

III. CONCLUSION AND FUTURE SCOPE

This study explored the use of machine learning techniques—specifically Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks—for analyzing and predicting emotional stability among students. While both algorithms demonstrated the ability to capture temporal patterns and emotional fluctuations, GRU outperformed LSTM in terms of prediction accuracy, training efficiency, and computational simplicity. The final predictions generated by the GRU model effectively classified students into emotionally stable and emotionally unstable categories.

Emotional stability is linked to improved academic performance through better concentration, time management, and decision-making, with interventions based on emotional insights helping to improve focus, reduce exam stress, and boost outcomes. By tracking patterns of emotional instability, schools can detect mental health issues early, enabling proactive counseling and psychological intervention. Integrating emotional stability analysis with career guidance tools can recommend paths aligned with a student's temperament and stress-handling capacity, placing them in roles where they are likely to thrive emotionally and intellectually. Additionally, emotion-adaptive learning systems can personalize learning pathways by adjusting difficulty, pace, and style of content delivery based on a student's emotional readiness and mental resilience, with AI recommending learning materials or switching modes depending on stress or mood levels.

IV. ACKNOWLEDGMENT

We would like to express our sincere gratitude to Prof. Dr. Reena Bharathi for her valuable guidance and insightful feedback throughout this research project. We would like to thank our families and friends for their unwavering support and encouragement during the completion of this work.

V. REFERENCES

[1] Sheema Aleem , “Emotional Stability among College Youth” , July 2005.
[2] Sima Kalita , “Academic Achievement of High School Students in Relation to Their Emotional Stability”, Journal of process management and new technologies, 2016.
[3] Rajib Rana , “Gated Recurrent Unit (GRU) for Emotion Classification from Noisy Speech”, arXiv preprint arXiv:1612.07778, December 13, 2016.
[4] Tat'yana A. Serebryakovaa , Lyudmila B. Morozovaa , Elena M. Kochnevaa , Darya V. Zharovaa , Elena A. Kostylevab and Oxana G. Kolarkovaa, “Emotional Stability and Adaptation to Studying in a Higher Educational Institution”, International Journal of Environmental & Science Education, June 2016.
[5] Mohammad Amin Wani1 , Dr. R. Sankar , J. Angel , P. Dhivya , S. Rajeswari , K. Athirai , “Emotional Stability among Annamalai University Students” , The International Journal of Indian Psychology, July-September, 2016.
[6] S Mathew, D Danielle, WH Tok, “Deep Learning with Azure-Building and Deploying Artificial Intelligence Solutions on the Microsoft AI Platform”, Apress, 2018., 2018.
[7] G. O. Oriarewo, S. A. Ofobruku, K. Agbaezee, Z. A. Tor , “The Influence of Emotional Stability on Employees’ Performance: A Review”, South Asian Journal of Social Studies and Economics, August 30, 2018.
[8] Nelly Elsayed, Anthony S. Maida, Magdy Bayoumi ,Deep Gated Recurrent and Convolutional Network Hybrid Model for Univariate Time Series Classification , December 18, 2018.
[9] Amit Kumar Singh, Nongmeikapam Jinalee , “Emotional Stability, Age, and Work Experience: An Analytical Study”, Pacific Business Review International, March 2019.
[10] Mohd Tajudin Md Ninggal ,Nor Ezdianie Omar , Rohaizak Omar , Azleen Ismai,l “Relationship between Emotional Stability, Motivation, and Online Learning Skill of First-Year Undergraduates Learning Online During COVID-19 Pandemic”, AJODL, 28 Apr 2021.
[11] Sarita Devi , Pushpawati Kochrekar , “A Study on Emotional Stability Among Senior Secondary Students with Reference to Gender”, International Journal of Academic Research and Development, 27-June-2022.
[12] Dian Palupi Rini, Winda Kurnia Sari, Novi Yusliani, Deris Stiawan, Aspirani Utari , “Exploring Long Short-Term Memory and Gated Recurrent Unit Networks for Emotion Classification from Electroencephalography Signals”, Journal of the Indian Academy of Applied Psychology, 2023.
[13] Mohammad Saleh Khajeh Hosseini , Seyed Mohammad Firoozabad , Kambiz Badie, Praviz Azadfallah , “Personality-Based Emotion Recognition Using EEG Signals with a CNN-LSTM Network”, Brain Sciences, 14 June 2023.
[14] Sarthak Johari, Gowri Namratha Meedinti, Radhakrishnan Delhibabu, Deepak Joshi ,Unveiling Emotions from EEG: A GRU-Based Approach , July 2023.
[15] Shyam K Sateesh, Sparsh BK, Uma D , Decoding Human Emotions: Analyzing Multi-Channel EEG Data using LSTM Networks , August 2024.