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Mental Stress Prediction using Machine Learning on Real Time EEG Signal

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Abstract: - The primary cause of various health issues is mental stress. Experts and doctors have developed several devices to evaluate the degree of mental strain in the initial phase. The research has suggested several neurological imaging techniques for assessing mental strain at their work. This study uses electroencephalogram (EEG) signals and AI-based techniques to predict mental stress. Real-time EEG data was collected using a brain-computer interface (BCI) strategy with the Mindrove Bright Cap and analyzed using Transform to convert signals into the frequency domain. K-means clustering is used to group the data for stress prediction. Logistic Regression (LR) showed the highest accuracy of 99.77% and an F1-Score of 100% among the models evaluated. Measure the effectiveness of EEG signals and ML in predicting mental stress, with potential applications in identifying stress levels based on brain activity.

Keywords: Brainwave EEG Signals, Fast Fourier Transform (FFT), Clustering, Logistic Regression

I. INTRODUCTION

The brainwave signal, with its unique traits and characteristics, plays a crucial role in identifying individual identity. This uniqueness precludes the potential for similarity, making the sense of identity pivotal in recognizing distinct individual attributes [1]. The development of identity involves the use of biometric technologies, a significant aspect of this research, which aims to implant personality characteristics by leveraging diverse parts of a person's body or social behavior. The process of Identification Recognition utilizing Biometrics Technology allows individuals to authenticate their identity by employing certain anatomical features or patterns of human activity [2]-[3]-[4]-[5]. In [6], the author's work employs machine-learning algorithms to categorize EEG patterns, with a specific focus on the emotional states shown by participants during music listening. Out of 26 participants, the SVM technique achieved an accuracy of 82.29% when used to categorize four different emotional states. Vanitha [7] used the Hilbert-Huang Transform (HHT) method to clean up the EEG data and pull-out helpful time-frequency features. Afterwards, a SVM was used to identify stress levels produced attributes in a real-time stress detection situation.

EEG is an investigative tool in medicine. On the other hand, a broader use of the EEG entails the assessment of an individual's cognitive state, cognitive processes, or affective state. [8]-[9]. The authenticity of the visual observation of the EEG signal can be attributed to the remarkably short breadth of the EEG motion and the exquisite complexity of its pattern. Moreover, it is important to acknowledge that EEG signals can be influenced by several factors, including emotional states, general well-being, participant involvement, ambient conditions, interference from other physiological systems, and external stimuli [10]-[11]. A constant and discernible pattern of brain activity is a prerequisite for the effective beginning of the EEG signal. The observed pattern arose due to intentional stimulation administered by volunteers. EEG data provides a more comprehensive understanding of individuals' mental processes and reactions. The acquired EEG data will furnish insights into the characteristics of the waveform, duration, orientation, and rhythm of the signal [12]-[13].

The precise shape and spatial distribution of EEG signal patterns are currently undetermined owing to the inherent variety in both the signal patterns themselves and the reaction times of individuals' brains when subjected to external stimuli [14]. However, the potential of EEG data processing to identify and characterize these unique patterns of cerebral activity is a promising area of research [15]. Therefore, it is crucial to develop and utilize EEG data processing methodologies that can effectively capture and interpret these unique patterns.

The main contribution of this study is

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- Our study stands out for its innovative use of a BCI strategy, specifically the Mindrove Bright Cap, to collect real-time EEG data.
- We preprocessed the acquired data, extracted relevant features, and conducted a comprehensive Fast Fourier Transform (FFT)spectrum analysis. This thorough process ensured the conversion of EEG signals from the time domain to the frequency domain was accurate. We then clustered the data using the K-Means algorithm to predict stress levels.
- We built several ML models to classify the mental stress levels of subjects. After comparing and analyzing the models, we found one with the highest accuracy and F1 score, demonstrating its effectiveness in predicting stress levels.

Organization of the paper is: Section 2 presents reviews on EEG signal processing and predicting mental stress. Section 3 discusses the methodology. Section 4 discussed the performance analysis of the suggested models. Finally, Conclusion and future direction of the study is discussed in section 5.

II. Related Work

EEG serves as a diagnostic technique within the field of medicine. However, it has a broader range of applications, including analyzing an individual's mental state, cognitive patterns, and emotional state [8]-[9]. The visual inspection of the EEG signal is genuine, as it exhibits a remarkably low amplitude and intricate patterns. Moreover, various variables significantly impact EEG signals, including emotional states, physical well-being, participant engagement, surroundings, interference from neighboring organs, and external stimuli [10]-[11]. The successful initiation of the EEG signal necessitates the presence of a consistent and noticeable pattern of brain activity, which emerges as a result of deliberate stimulation provided by volunteers. EEG signals offer a greater understanding of individuals' emotional processes and reactions. The acquired EEG signals encompass the waveform, duration, signal direction, and rhythm [12]-[13]. The form and location of the EEG signal pattern data remain unknown due to the inherent variability in the signal patterns and reaction speeds shown by individuals' brains in response to stimuli [14]. Hence, an EEG signal processing technique is required to discern and characterize distinct patterns of brain activity [15].

The field of automated stress detection, which relies on analyzing EEG signals from the frontal lobe, is gaining significant traction within the stress research community. The increasing number of studies using EEG analysis to detect and evaluate mental stress underscores its growing importance and keeps the audience informed and up-to-date. Notably, the correlation between emotional states and EEG alpha-band activity within the frontal lobe has been a focus of attention. In a separate investigation, scholars examined the spectral strength, intricacy, and interconnections of EEG alpha, beta, and theta frequency bands inside the frontal cortex of two distinct cohorts. The initial cohort consisted of individuals with a moderate level of stress, while the second group consisted of people experiencing significant levels of stress. The trials demonstrated that the high-stressed group had more left prefrontal power than the moderate-stressed group.

Moreover, a method for detecting mental stress utilizing EEG data with clustering techniques has been previously introduced. We estimated stress levels by measuring perceived stress using the k-means approach and statistical analysis. In [19], the authors employed EEG brain signals to examine mental stress by applying classification approaches. However, many classifiers are utilized, with SVM achieving the highest level of accuracy. The stress categorization approach utilizing EEG data was introduced in a previous study [20]. During the feature extraction step, five primary characteristics are derived from the recorded EEG data. Ranjith et al. (2019) have presented a stress detection approach that uses an Improved Elman Neural Network (IENN). The feature extraction step involved applying PSE and GLDS approaches. The training phase involved using the IENN technique for categorization. One method proposed for stress detection is simultaneously looking at the duration and frequency domains. We used STFT and Empirical Mode Decomposition (EMD) to extract features from the recorded EEG data. The classification stage was then carried out using SVM. According to the authors, the proposed approach is better than the existing ones, and the actual results back this claim, instilling a sense of optimism and hope about the future of stress detection.

According to Bairagi et al. [22], hardware systems are designed for the detection of mental stress. This system utilizes EEG data and incorporates a preamplifier and filter. The researchers have concluded that the theta band, characterized by a frequency range of 4 Hz to 7 Hz, is associated with the frontal lobe. The accuracy achieved by the proposed technique was 88%. In a recent work, researchers presented a strategy for detecting mental stress using a multi-domain hybrid feature pool [23]. Statistical and wavelet-based analyses were used to extract characteristics from recorded EEG data. Subsequently, the KNN method was employed during the classification phase. This method obtained an accuracy of 73.38%. Also, the GA algorithm to identify mental stress based on the optimal features of EEG. This method employed GA for the dual objectives of obtaining and choosing features [24]. The KNN classifier, in contrast, was used for classification purposes. The proposed method obtained a 72% success rate. Priya et al. [26] introduced a stress detection methodology that relies on the power ratio analysis of EEG signals specifically targeting the frontal lobe. Power ratio analysis involves comparing the power of different frequency bands in the EEG signal, which can provide insights into the individual's mental state and stress level. The study analyzed and computed the PSD [27]-[28].

III. MATERIAL AND METHODS:

(a) Data Acquisition

The Mindrove EEG & EMG-based system is a wireless BCI device that connects to various devices, including computers and cellphones, using Bluetooth. This device is designed to capture information from human brain wave activity. This study utilized the Mindrove Bright EEG Band to measure brain activity. The device's use of occipital electrodes, which are intended to penetrate the hair and establish excellent contact with the skin, ensures dependable EEG recordings, providing reassurance about the quality of the data. The gadget exhibits a visual representation, as seen in Figure 2.

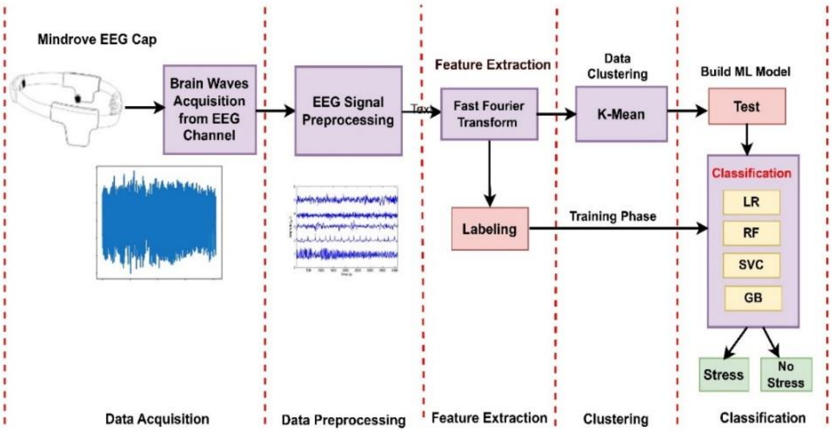

Figure 1 Architecture of Proposed Model

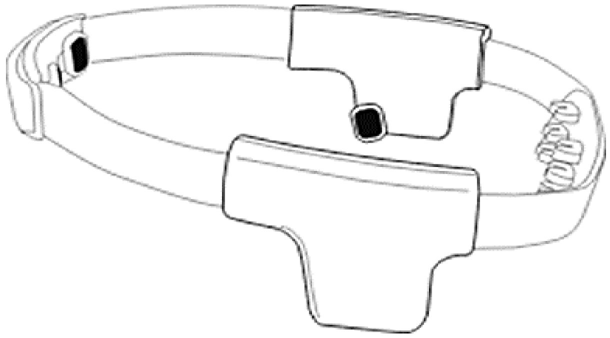

Figure 2 Visual representation of Mindrove Bright Device

Table 1. Technical Specification of Mindrove Bright Device

Parameters	Values
EEG Electrodes	4+2 channels
EEG Electrode's Locations	O1, O2, Fp1, Fp2
Reference Electrodes	Towards The Back of The Right Ear

Bias Electrodes	Not Far from The Left Ear
Electrode Material	Metallic Strands Woven into A Conductive Cloth
Electrode Type	Not Requiring Gel, Semi-Dry
Sampling rate	500 Hz
Resolution	24 bits
Bandwidth	0-250Hz

(b) Dataset Description

EEG Data were collected from 20 healthy adults aged 15 to 60. The experiment's goal was explained to all subjects, who were Indian civilians. A respondent's health was confirmed before data collection began.

Conducting the research in a serene and peaceful area makes subjects feel at ease and minimizes disruptions to the data acquisition phase. We will need at least four sessions over two days to collect 200 responses from 20 participants, with each data collection recording lasting seven minutes.

Figure 3. Different Age group Subject at Data Acquisition Phase

(c) Feature Extraction

Fast Fourier Transform (FFT): FFT is used in a wide range of disciplines, including digital signal processing, the resolution of partial differential equations, and techniques for performing large-scale integer multiplication. It is a computational technique that enables the rapid and efficient calculation of DFTs. The Fourier transform is necessary for representing the frequency domain due to the prevalence of continuous signals inside communication systems [24].

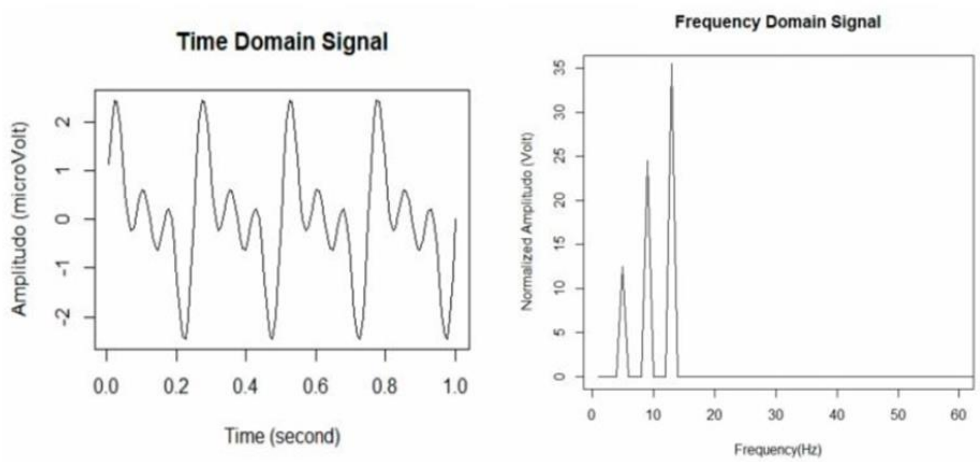

Figure 4. Time and frequency domain of EEG Signal [25]

Previous research into real-time applications has demonstrated that FFT is the most dependable approach for processing sine waves, which are EEG data. However, there are better fits for studying brief EEG signals [25]. To systematically express the EEG data using power spectral density (PSD) approximation, typically employed for determining the features of the obtained signal that need to be studied, the primary distinctive patterns of the EEG frequency are found within four band frequencies [18]. The predicted autocorrelation series, identified using nonparametric techniques, is then transformed by Fourier to determine the PSD. Some approaches, such as Welch's method, represent these patterns. Improved periodograms become available when signal windowing takes place to analyze the data stream [19]. The EEG data sequence $S_i(a)$ is represented as

$$S_i(a) = S(n + iD), \qquad a = 1,2,3, \dots, P-1$$

$$While\ i = 1,2,3, \dots Q-1 \tag{1}$$

Where iD represents the starting location of the i^{th} series. The created EEG data features were represented by Q of size 2P. The resultant periodograms that arise provide

$$\overset{\approx^{i}}{X}_{i}(f) = \frac{1}{AB} \left| \sum_{a=0}^{A} S_i(a)\, w(a) e^{-j2\pi f a} \right|^2 \tag{2}$$

Where, provides the power's normalizing coefficient for the window function which selects it in order to

$$B = \frac{1}{A} \sum_{a=0}^{A-1} w^2(a) \tag{3}$$

with the window parameter denoted by w(a). Welch's frequency spectrum is obtained by averaging these adjusted periodograms, and it looks like this:

$$X_{ss}^{W} = \frac{1}{Q} \sum_{i=0}^{Q-1} \overset{\approx^{i}}{X}_{i}(f) \tag{4}$$

(d) Clustering of Data

The EEG signals are acquired from the Mindrove cap through the software provided by Mindrove and stored in a .csv file format. The EEG data was clustered into two groups to predict and classify the subject's mental state as stressed or unstressed. To achieve this, K-mean clustering algorithm to convert this unsupervised data into supervised data. The following mathematical expressions describe the K-Means algorithm for clustering data points, specifically EEG signal features in this context. The process iterates between assigning data points nearer to centroid and update it until convergence.

$$d(x_i, \mu_k) = \sqrt{\sum_{j=1}^{n} \left(x_{ij} - \mu_{kj}\right)^2} \tag{5}$$

Where, x_{ij} is the jth feature of the EEG signal of point x_i and μ_{kj} is the jth feature of centroid μ_k

Assign the cluster of each feature data point

$$c_i = arg \min_k d(x_i, \mu_k) \tag{6}$$

Where, c_i is the cluster assignment for data point x_i

Update the centroid of data features

$$\mu_k = \frac{1}{|C_k|} \sum_{x_i \in C_k} x_i \tag{7}$$

The cluster visualization was done using graphical analysis and it is shown in figure 5.

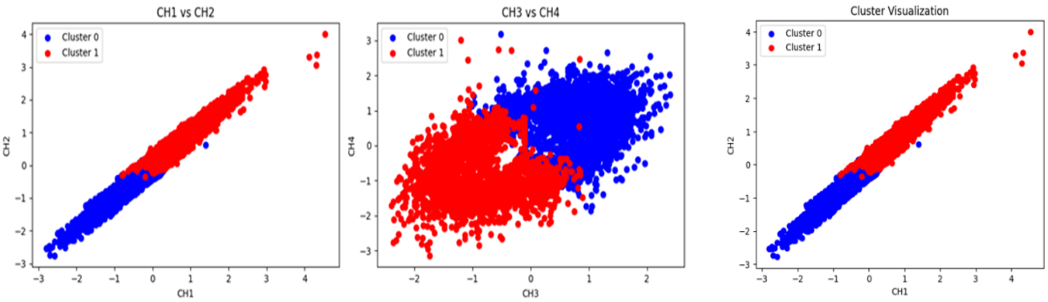

Figure 5. CH1 Vs CH2 and CH3 Vs CH4 Cluster Visualization of EEG Data

Figure 5 provides insight into the clustering of data collected via the four channels (CH1, CH2, CH3, CH4) of the Mindrove Bright EEG cap, showing CH1 vs CH2 and CH3 vs CH4.

Pseudo Code: K-Mean Algorithm

Step 1: Initialize the Parameters

- Select the number of Cluster K
- Randomly initialize K centroid $u1, u2, , , , uk$ from EEG signal Sample S

Step 2: Assignment

- For each data point $xi \in X$:
- Calculate the Euclidean distance $d(xi, \mu k)$ from xi to each centroid uk
- Assign xi to the cluster with the adjacent centroid.

Step 3: Update

- For every cluster k
- Revised the uk that all data values allocate to k.

Step 4: Goto Steps 2 and 3 until complete all cluster

(e) Build ML Models

After converting the data, classified it into two categories (Stress and No Stress) using various ML algorithms such as LR, SVC, RF, and GB.

Logistic Regression (LR): It simulates the likelihood that an input EEG signal falls into a specific class. Using a logistic operation, it maps anticipated values to probability among 0 and 1. The EEG signal features are used as input variables. The LR outputs the likelihood of mental stress. This model helps understand the influence of individual features on stress levels due to its interpretability.

$$P(y - 1|X) = \frac{1}{1 + e^{-\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n}} \quad (8)$$

Support Vector Classifier (SVC): It aims to obtain the hyperplane that classify stress and No stress in the feature space by using kernel functions.

Maximize the margin among the two classes.

$$min \frac{1}{2} \|w\|^2 \quad (9)$$

Subject to:

$$y_i(w.X_i + b) \geq 1$$

Random Forest (RF): While training the model, several decision trees are built using RF ensemble learning, which then classifies the features of the trees to indicate whether they are stressed or not stressed. Combining several decision trees learned on various subsets of the features minimizes overfitting. Random Forest is effective in handling large feature sets and capturing complex interactions between features.

Ensemble of N decision trees.

$$f(x) = \frac{1}{N}\sum_{i=1}^{N} T_i(x) \tag{10}$$

Where, $T_i(x)$ is the prediction of the i^{th} decision tree.

Gradient Boosting (GB): Gradient boosting is another ensemble learning technique that creates models one after another. Every new model seeks to fix the errors produced by the ones before it. It makes a robust predicted model by combining weak learners, typically decision trees. The residuals of earlier models serve to train succeeding versions. Sequentially fit N models.

$$f(x) = \sum_{i=1}^{N} \alpha_i h_i(x) \tag{11}$$

Where, $h_i(x)$are the individual models and α_i are the corresponding weights.

IV. RESULT AND DISCUSSION:

The suggested ML classifiers' performance was measured using various evaluation parameters. The models were built in Python using the Google Colab environment. After clustering, the classifiers fed the data to predict subjects' mental stress. A suggested classifier is used to find the best model for the dataset. The gathered EEG dataset was divided into 80% of the training set and 20% of the testing sets.

$$Accurcay = \frac{TP+TN}{TP+TN+FP+FN} \tag{12}$$

The fraction of data accurately identified as stress-free to all stress-free information (actual observed data) is referred to as sensitivity.

$$Sensitivity = \frac{TP}{FN+TP} \tag{13}$$

Specificity is defined as the percentage of under pressure data that is correctly classified out of all under stress data.

$$Specificity = \frac{TN}{TN+FP} \tag{14}$$

Precision accurately categorized as stress-free by the stress categorization method to the total data classified as stress-free.

$$Precision = \frac{TP}{TP+FP} \tag{15}$$

In this section, validate the performance of suggested ML model over the various parameters. Table 1 presents the performance of all models.

Table 2. Performance Analysis of ML Classifiers

Classifiers	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
LR	**99.77**	**100**	**100**	**100**
RF	**99.19**	**99**	**99**	**99**
SVC	**99.54**	**100**	**99**	**99**
GB	**99.31**	**99**	**99**	**99**

The performance analysis of ML models for mental stress prediction using EEG signals is shown in Table 2. This indicates that the LR outperforms the other classifiers, with an impressive accuracy score of 99.77%. It correctly predicts stress states with high reliability and consistency. RF achieves a strong performance with an accuracy of 99.19% and precision, recall, and F1-score of 99%, showing it as a robust model with slightly lower performance than LR. The SVC performs excellently with an accuracy of 99.54% and near-perfect precision (100%), along with high recall and F1-score (99%), making it a very effective classifier for this task. GB also demonstrates high accuracy at 99.31%, with precision, recall, and F1-score at 99%, showcasing its capability in handling the complexity of EEG data for stress prediction.

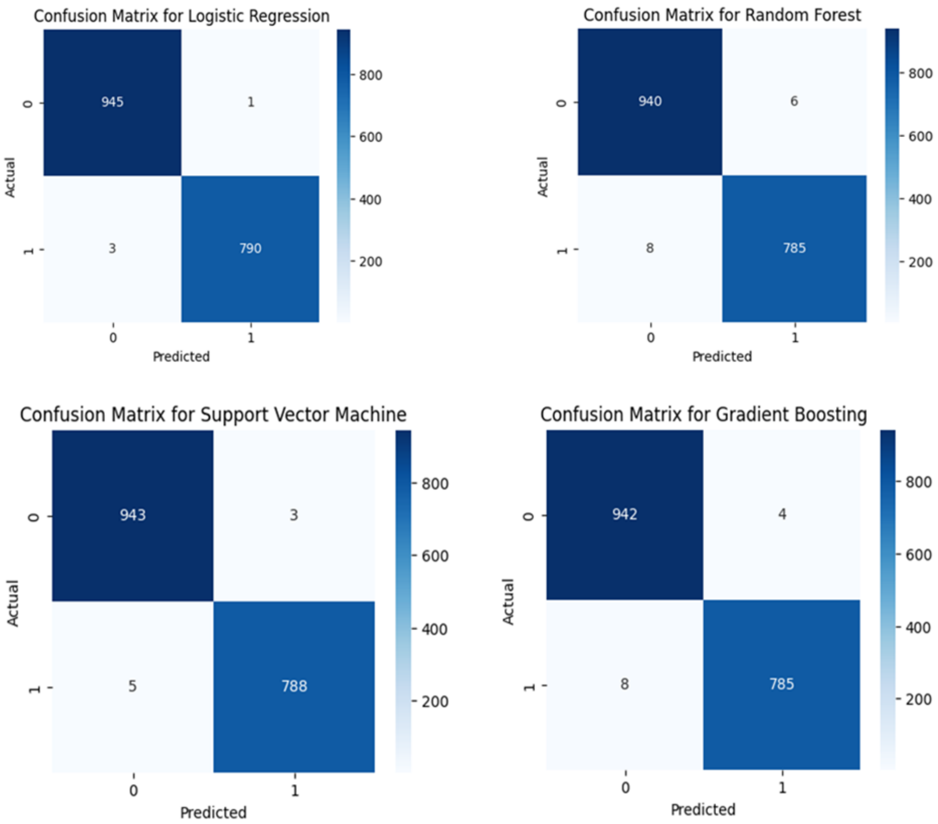

Figure 6. Confusion Matrix of ML Models

Figure 6 shows the confusion matrix of ML models. The LR performs best in predicting mental stress using EEG signals, with a high TP count of 945, the lowest FP count of 1, and an FN count of 3, resulting in a TN count 790. This indicates that LR has an excellent balance between sensitivity (recall) and specificity, making it highly reliable. With TP = 940, FP = 6, FN = 8, and TN = 785, RF demonstrates slightly lower performance, with more FP and FN compared to LR. The SVM also performs well, with TP = 943, FP = 3, FN = 5, and TN = 788, indicating slightly better precision and recall than RF but still not as optimal as LR. GB shows a TP count of 942, FP of 4, FN of 8, and TN of 785, placing it slightly behind SVM regarding precision and recall. Finally, it is concluded that LR has the highest accuracy and reliability, followed by SVM, GB, and RF, as reflected by their respective confusion matrix values.

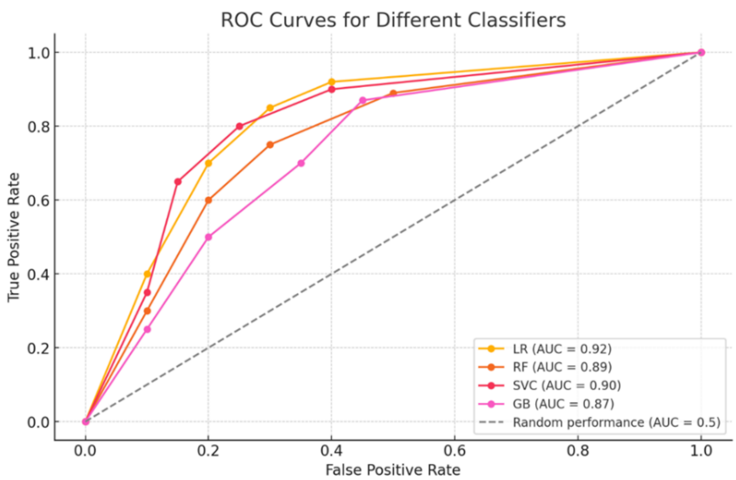

Figure 7. ROC-AUC Score of ML Models

Figure 7 shows the ROC AUC score for the different ML classifiers (LR, RF, SVC, GB). Each curve represents a classifier's performance, illustrating its respective TPR and FPR. The diagonal line indicates random performance (AUC = 0.5). This visualization helps compare the classifiers' ability to distinguish between Stress and No-Stress classes.

V. DISCUSSION

Due to its detrimental effects on people and society, stress is becoming an increasingly common issue in everyday life. Stress harms several bodily mechanisms, including the neurological, immunological, heart disease, and gastric organs. Whatever the type of stress, it significantly affects or changes the hippocampal region of the mind. This brain modification affects the person's capacity to remember things and make decisions. Additionally, it negatively impacts hormonal release, which is essential for the healthy functioning of the human defense mechanism. Therefore, mental stress assessment and evaluation constitute crucial processes that can be carried out to identify stress and stop serious health issues. There are several research that use EEG data to study this effect. However, comprehensive guidelines regarding the relationship between EEG features and their extraction techniques still need to be developed. A wide range of techniques exist for using EEG to measure mental stress. As said earlier, descriptors describing the ML model's functionality will be needed to fully understand neural processing since the brain operates as an interconnected system.

Table 3. Comparative Analysis of Proposed ML Classifiers with Existing Methods

Authors	Classifiers	Accuracy
Al-Shargie et. al. (2021)	**SVM**	**95.00%**
Attallah, O. (2020)	**linear SVM** **Cubic SVM** **KNN** **LDA**	**Acc= 98.60%** **Acc= 98.65%** **Acc= 98.98%** **Acc= 98.84%**
Devi, D. et. al. (2020)	**CNN**	**Acc = 92.01%**
Halim, Z. et. al. (2020)	**SVM** **NN** **RF**	**Acc= 91.55%** **Acc= 88.70%** **Acc= 86.00%**
Saeed, S.M.U et. al. (2020)	**SVM** **NB** **KNN** **LR** **MLP**	**Acc= 86.30%** **Acc= 81.69%** **Acc= 66.86%** **Acc= 86.25%** **Acc= 86.23%**
Baumgartl, H. et. al. (2019)	**RF**	**Acc = 82.00%**
Proposed	**LR** **RF** **SVC** **GB**	**Acc = 99.77%** **Acc = 99.19%** **Acc = 99.54%** **Acc = 99.31%**

Table 3 shows the comparative analysis of the accuracy of proposed machine learning classifiers with existing methods for mental stress prediction using EEG signals. Al-Shargie et al. (2021) achieved an accuracy of 95.00% using SVM. Attallah (2020) experimented with various classifiers, including linear SVM, cubic SVM, KNN, and LDA, with accuracies of 98.60%, 98.65%, 98.98%, and 98.84%, respectively. Devi, D. et al. (2020) used CNN and obtained an accuracy of 92.01%. Halim, Z. et al. (2020) utilized SVM, NN, and RF, achieving accuracies of 91.55%, 88.70%, and 86.00%. Saeed, S.M.U, et al. (2020) applied SVM, NB, KNN, LR, and MLP with respective accuracies of 86.30%, 81.69%, 66.86%, 86.25%, and 86.23%. Baumgartl, H. et al. (2019) achieved an accuracy of 82.00% using RF. The proposed study demonstrates superior performance with LR, RF, SVC, and GB classifiers, achieving accuracies of 99.77%, 99.19%, 99.54%, and 99.31%, respectively, indicating a significant improvement over the existing methods.

VI. CONCLUSION

The mental or emotional strain is a common experience for many individuals at different times. Anxiety negatively impacts an individual's health. As research on stress is still in its early stages, significant focus has been on defining and categorizing stress in the last decade. This study aims to determine the level of stress individuals experience in response to specific stimuli. Using the FFT method, features will be extracted from real-time data obtained from the Mindrove Bright Cap's brain wave recordings. The analysis will utilize the LR technique. The study aimed to assess the efficacy of several categorization models in analyzing real-time data. The LR model demonstrated the highest accuracy and F1-Score in predicting stress, with values of 99.77% and 100%, respectively, as indicated by the confusion matrix. The results suggest that the mean accuracy in the classification of brain waves was 99.77%. This study demonstrates the effectiveness of using the Fast FFT and LR algorithms for forecasting stress levels by analyzing real-time EEG signals.

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Data Availability:

This investigation does not generate or examine any new data. This paper does not apply to transferring data.

Conflict of interest:

The authors declare that there is no conflict of interest.

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