Stress Level Detection Using Hybrid Features and Meta Model Classifier with EEG Signal

Ankita Gandhi[1]*, Udesang K. Jaliya[2]

[1]Research Scholar, Gujarat Technological University, Ahmedabad, India, Email : anki.gandhi@gmail.com
[2]Birla Vishvakarma Mahavidyalaya, V.V. Nagar, India
*Corresponding Author

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ABSTRACT
Stress detection has become a critical area of study due to its significant impact on human health and productivity. This paper presents a novel approach to stress detection that leverages a hybrid Features and a hybrid classifier framework, integrating various machine learning techniques to enhance accuracy and reliability. Our hybrid features combines selected time domain & Frequency domain features for selected channel to improve the accuracy of the result. The hybrid classifier framework employs an ensemble of machine learning algorithms, including Support Vector Machines (SVM), Random Forests, and XGBoost, to improve classification performance through diversified model strengths. The proposed methodology was evaluated using benchmark datasets. Our results demonstrate that the hybrid approach significantly outperforms traditional single-source and single-classifier models, achieving higher accuracy, precision, and recall in stress detection. Using the proposed hybrid techniques, we achieved a higher accuracy by considering base classifiers and the meta-classifier.

Keywords: Stress Detection, machine Learning, EEG Signals, Supervised Learning, Mental Stress, Hybrid Techniques.

1. INTRODUCTION

Stress is a natural reaction to the stresses of daily life that can emerge positively or negatively. Short-term stress can produce pleasant emotions such as love, joy, and happiness, but when experienced over time, it can produce negative emotions such as hatred, fear, humiliation, or guilt. Prolonged stress is a major risk factor for mental health problems, including depression, and can indirectly lead to cardiovascular disease.
Stress can be divided into two categories: acute and chronic. Acute stress consider as a short term stress and chronic stress consider as a long term stress[1].Acute stress (Short-term stress): It is a type of short-term stress that does not create permanent harm. It is easy to spot, and it is also treatable. Chronic Stress (Long-term stress):This is considered a long-term stress, and it can cause severe damage. Finally, it is quite difficult to detect. Stress has a huge impact on millions of people's lives worldwide, causing a variety of health problems such as heart disease, cancer, and compromised immune systems. detecting stress early is critical for avoiding serious health problems [3].
As per Figure. 1, Stress can be measured both objectively and subjectively. Objective methods use physiological signals to assess stress levels, while subjective measures rely on questionable forms of detection. Traditionally, stress levels were assessed using psychological questionnaires completed by medical experts. However, recent advances in scientific methods have allowed for more effective and precise stress monitoring using physiological signals.These signals offer a continuous method for measuring stress levels, addressing the limitations of biochemical samples, which are both intrusive and impractical for real-time monitoring. To detect and characterise stress, this approach uses the electrical activity of the heart, as caught by ECG, and the variability in heart rate, as recovered by HRV, EEG signals and other methods can be used to extend the frequency band. These strategies offer accurate classification, making them useful for stress management and well-being[4]. EEG: it measures the brain's electrical activity. Since the brain is the origin of the stress response, EEG signal processing is a crucial technique for detecting and analyzing mental stress[5]. ECG-Measures the electrical activity of the heart rate and rhythm (Normal Resting rhythm and stress rhythm). An electrocardiogram (ECG) is a straightforward test that monitors the heart's rhythm and electrical activity. It involves placing sensors on the skin to detect the electrical signals produced by the heart with each beat. HRV- it assesses the fluctuations in the time intervals between consecutive heartbeats. Heart rate variability is the variance in time between successive heart beats. It's called RR Interval. GSR- Measures the electrical activity of Sweat

Secretion and when person is in stress the sweat glands will also be increased[6]& BVP- measuring the heart rate.

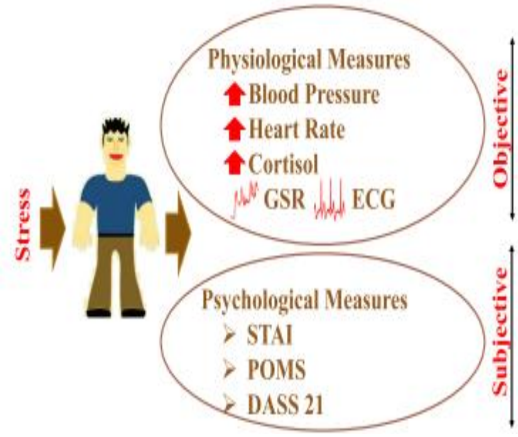

Figure 1. Objective and subjective measures of stress [7]

The electroencephalograph (EEG) signal is important in further research since it can be used to assess the level of human stress. Electroencephalography (EEG) is a non-invasive method of monitoring brain activity that provides precise and reliable data required for stress detection. It entails tracking and recording brain wave patterns with electrodes, which are small metal discs that gather electrical impulses from the brain and send them to a computer for further analysis. EEG signals are acquired from the central nervous system via electrodes. EEG measures human brain activity by detecting electrical activity in the cerebral cortex. These activities are mostly produced by neurons in the brain, which vary according to the level of human stress [8].

Raw EEG signal extraction approaches employ fourtypes of features: 1)frequency-domain, 2)time-domain, 3) time-frequency domain, and 4) spatial-time-frequency domain [9]. Three strategies are used to forecast stress levels based on EEG signals. They are listed below: preprocessing, feature extraction, and classification. Unwanted sounds in the recorded EEG signals will be removed during the preprocessing step using various filters. Following preprocessing, features would be extracted to represent the qualities or behaviour of EEG data. Finally, these features are classified to predict the degree of stress[8].

Machine learning classifiers are crucial in enhancing stress detection systems, as they enable the precise interpretation of complex physiological data.These classifiers, which include techniques like Support Vector Machines, Random Forest, and XGBoost, are trained using datasets comprising diverse physiological signals such as EEG, ECG, and GSR. Machine learning models can learn to distinguish between stressed and non-stressed states by extracting and selecting key signal properties such as mean, standard deviation, skewness, and kurtosis. The incorporation of machine learning algorithms enables real-time, non-invasive stress monitoring, allowing for prompt interventions.

In the proposed work, EEG signals are integrated with machine learning techniques to develop a hybrid model for detecting stress levels. Stress level 0 is classified as no stress, while stress level 1 is classified as stress. The proposed hybrid classifier model aims to enhance automated stress detection using EEG signals, addressing existing challenges and paving the way for new advancements in stress management and patient care. In the field of neuroscience and neurology, machine learning techniques have proven to be highly effective. Machine learning algorithms, especially ensemble methods such as Random Forest and XGBoost, have demonstrated exceptional abilities in analyzing complex data.

1.1. EEG Signals Morphology

EEG signals, or electroencephalography signals, represent the brain's electrical activity over time. It is a non-invasive method. It has low cost as compared to Magnetic Resonance Imaging (MRI). It has high temporal resolution and EEG waveforms are widely used to detect and analyze of the mental stress. In Figure. 2, you can see the standard 10-20 EEG electrode Placements.

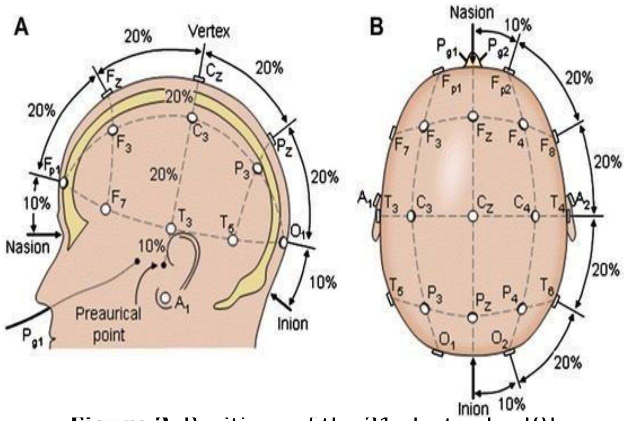

Figure 2. Positions of the 21 electrodes [9]

EEG signal shape typically consists of many major components as per given Table.1, Figure. 3& Figure. 4 as mention below.

1.1.1.Time domain features

In EEG signals, time-domain features indicate how the brain's electrical activity changes over time. These features are critical to understanding the dynamics and patterns of brain activity.

- Amplitude: The magnitude of the EEG signal at any given time point. Amplitude variations can indicate changes in neural activity.
- Frequency: The rate at which the EEG signal oscillates over time. EEG signals exhibit different frequency components, such as alpha, beta, delta, gamma and thetha waves, each associated with different states of activity performed in Brain.
- Phase: The relative timing of oscillatory components within the EEG signal. Phase relationships between different frequency bands can reflect coordinated neural activity.
- Power: The intensity or strength of the EEG signal within specific frequency bands. Power spectral density analysis quantifies the distribution of signal power across different frequencies.
- Inter-Channel Coherence: The degree of synchronization or coherence between EEG signals recorded from different scalp locations. Higher coherence indicates stronger functional connectivity between brain regions.

1.1.2. Frequency domain features

Frequency domain features in the EEG data provide useful information on the oscillatory patterns of brain activity. Researchers can leverage these capabilities to analyze the distribution of signal power across various frequency bands, including alpha, beta, theta, delta and gamma waves. Each frequency band is associated with distinct cognitive states and brain functions. Frequency domain research enables the identification of spectral features such as dominant frequencies, spectral power densities, and coherence across brain regions.

Table 1. Features representation of frequency domain [11]

Signal	**Frequency (Hz)**	**Amplitude (Micro Volt)**	**Activity**
Delta	Less than 4	20 -200	Power increase during stress
Theta	4 -8	Around 20	Power increase during stress
Alpha	8 -12	20 -200	Power supress during stress
Beta	13 -31	5 -10	Power varies during task activities

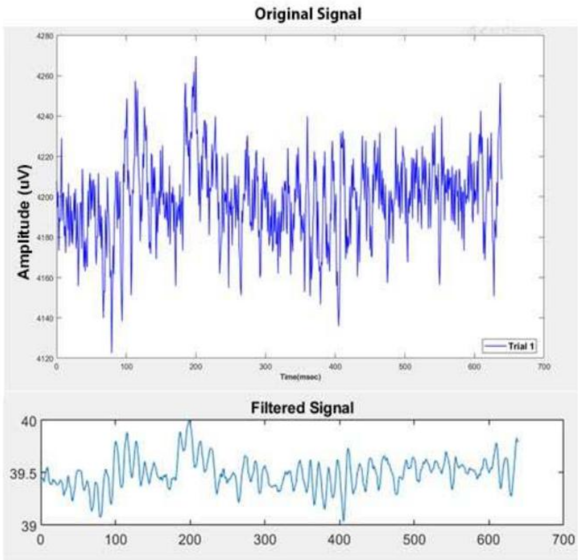

Figure 3. EEG Signals: Original Signal andfiltered Signal [10]

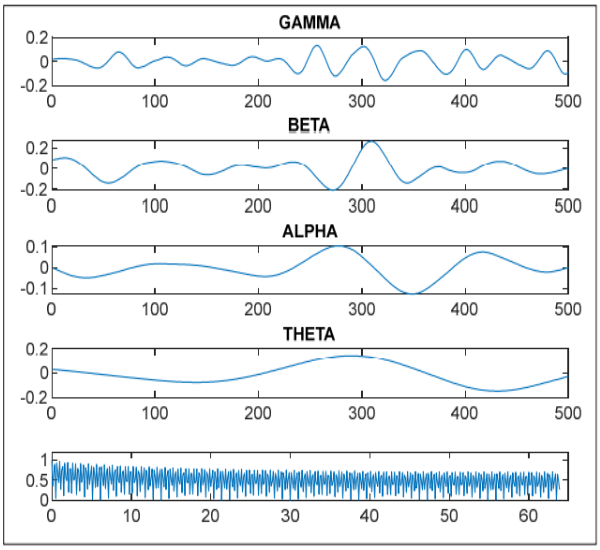

Figure 4. Frequency band of EEG Signals [10]

2. LITERATURE STUDY

According to the literature survey, EEG signals are effective in various domains for identifying stress levels. The recent trend in healthcare involves utilizing automated biomedical signal processing for enhanced and accurate diagnoses. In this context, we present an innovative approach for classifying stress and non-stress categories by analyzing multichannel Electroencephalogram (EEG) signals [12]. EEGs utilize small metal discs called electrodes, connected to gather electrical signals from the brain. These signals are then transmitted and stored by computer applications. Analysing stress levels in individuals throughout various tasks is a difficult subject with important potential applications in healthcare systems. Several research have highlighted the complexity and necessity of successfully utilising EEG data for stress detection, emphasising the need for sophisticated processing and analysis approaches to improve healthcare diagnosis and treatment[15].

An effective approach for recognizing stress markers in the frontal, temporal, central, and occipital lobes involves processing multimodal physiological signals. The Multilayer Perceptron (MLP) and Support Vector Machine (SVM) algorithms, both machine learning classifiers, are utilized to classify stress and non-stress categories.[16].Stress detection is crucial in today's fast-paced world, because brainwave recordings may accurately identify brain activity associated with stress. Due to the complexity of these signals, they have traditionally required highly skilled physicians to decipher them. This study presents a DWT-based hybrid deep learning model for stress detection that combines Convolution Neural Network (CNN) and Bidirectional Long Short-Term Memory (BLSTM). Using the Physionet EEG dataset for mental

arithmetic problems, the model eliminates noise from 19-channel EEG signals before decomposing them with the Discrete Wavelet Transform (DWT)[13].
Author[14] has developed an early detection framework using electroencephalogram (EEG) data to mitigate the risk of stress-related diseases. Traditional frameworks frequently split signals into smaller portions before feeding them into a deep neural network, which might result in data loss. To address this, a new multiclass classification framework introduced multibranch LSTM and hierarchical temporal attention for early detection of mental stress levels. This method reduces overfitting while increasing multiclass classification effectiveness. Furthermore, electrode placements are optimised to lower computational costs by reducing the number of important electrodes.Early identification of mental stress using machine learning techniques is crucial for illness prevention [17].
Author has explained about a specific approach to stress detection based on short-duration EEG signals has beenpresented. Entropy-based characteristics were recovered from EEG data that had been processed using thestationary wavelet transform. The selected features were then classified using a variety of supervised machine learning methods. In addition, various evolutionary-inspired methods were used to optimise support vector machine (SVM) parameters while also performing feature weighting[18].
This paper introduces a machine learning (ML) model designed to analyze electroencephalogram (EEG) signals from thirty-six participants for stress detection and classification of stress levels. The framework employs a hybrid feature set that feeds into five ML classifiers, leveraging a hybrid dataset and classifier approach to streamline model complexity and improve detection accuracy.

3. METHODOLOGY

3.1 Machine Learning Classifier

3.1.1.SVM (Support Vector Machine):it is considered as supervised learning technique for classification tasks. It locates an ideal hyperplane in an N-dimensional space that divides data points into different classifications. SVM tries to maximise the margin between classes, making it successful in high-dimensional spaces and applicable to both linear and non-linear data.
3.1.2.Random Forest (RF): Random Forest is considered as an ensemble method that generatesmany decision trees during training and outputs theirclassification or average prediction - regression. It enhances accuracy by reducing overfitting while being robust to noise and outliers.
3.1.3.K-Nearest Neighbour (KNN):it is a straightforward, instance-based learning technique for classification and regression. It categorises new data points based on how similar they are to the training data in feature space. KNN does not require training time, but it might be computationally expensive to forecast, especially on large datasets.
3.1.4.Decision Tree (DT):it is a supervised learning technique that divides data into subsets depending on defined criteria. It iteratively divides the data into branches depending on the feature that gives the best split at each node, resulting in a tree-like structure. Decision trees are simple to understand and visualise, but they are prone to overfitting.
3.1.5.Ensemble Classifier: An ensemble classifier combines many base classifiers to improve prediction performance and robustness compared to standalone models. Ensemble methods are classified into numerous categories, which include: Bagging (Bootstrap Aggregating): Creates several instances of the same basic classifier from various subsets of the training data (bootstrap samples). Final predictions are usually made by averaging (regression) or voting (classification) across all base classifiers.Boosting is the process of sequentially building an ensemble by training each base classifier to repair the faults of its predecessor. AdaBoost (Adaptive Boosting) and Gradient Boosting are two examples that focus on instances misclassified by earlier classifiers.
Stacking (Stacked Generalisation) is the process of combining predictions from numerous basis classifiers using a meta-classifier, which is commonly trained on the base classifiers' output.
Voting: Combines predictions from many base classifiers using simple majority voting (classification tasks) or averaging (regression tasks). It can be used with several procedures, including hard voting (counting votes) and soft voting (averaging probability).
Ensemble classifiers are commonly used in machine learning due to their ability to reduce bias and variance and enhance overall model performance by integrating the strengths of multiple base models.

3.2 Hybrid Feature Dataset Approach

A hybrid feature technique in machine learning combines data from multiple sources to improve model performance and resilience. This method integrates organised and unstructured data, numerous modalities such as audio and picture data, and may employ synthetic data generation or feature fusion algorithms. The hybrid dataset strategy seeks to capture complementary information, overcome data restrictions, and increase the model's capacity to generalise to new and unknown data by integrating a variety of data sources. This strategy is especially useful in dealing with complicated problems where a single form of data may not adequately capture all key characteristics, hence improving the overall effectiveness of machine learning models.

3.3 Hybrid-Meta Classifier Approach

In machine learning, using a hybrid meta-classifier approach, multiple base classifiers are combined to enhance predictive performance by leveraging their diverse strengths. The dataset is first trained with individual classifiers such as Random Forest and XGBoost, each contributing unique insights into the patterns within it. The predictions of these base classifiers are merged with those of a meta-classifier, like Support Vector Machine (SVM), to generate a final prediction. This layered approach capitalizes on the complementary advantages of the base classifiers, leading to improved accuracy and robustness in tasks like stress detection, where subtle and complex patterns in data, such as EEG signals, require sophisticated analysis.

4. PROPOSED SYSTEM

In the proposed system, EEG signals undergo initial preprocessing steps to enhance their quality. For preprocessing technchnoques Finite impulse response method is used in proposed work. Subsequently, feature extraction is performed using Power spectrum dencity for extracting the frequency domain features, focusing on extracting features from both Time and Frequency domains. Selected features from these domains are integrated into a hybrid features dataset. This hybrid features dataset is then analyzed to evaluate its effectiveness in mental stress detection. Finally, the performance of the hybrid features dataset is compared with that of a hybrid classifier using ensemble methods and a meta model, aiming to optimize classification accuracy and robustness.

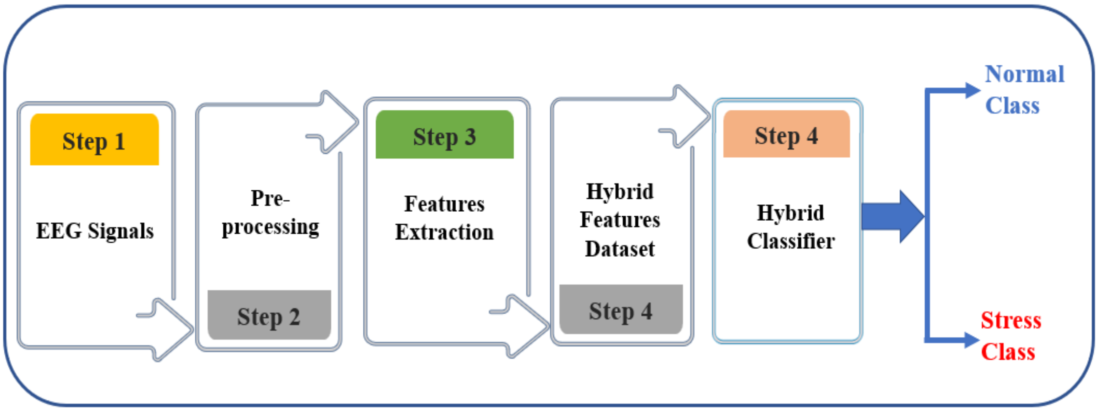

Figure 5. Proposed System

4.1. Dataset Description

In this research paper, publicly available dataset [9] was used to detect mental stress using Machine Learning classifiers. The EEG recordings were conducted using the Neurocom EEG 23-channel equipment. Electrodes made of silver/silver chloride were placed on the scalp according to the International 10/20 system, covering specific locations: symmetrical anterior frontal sites (Fp1, Fp2), frontal sites (F3, F4, Fz, F7, F8), central sites (C3, C4, Cz), parietal sites (P3, P4, Pz), occipital sites (O1, O2), and temporal sites (T3, T4, T5, T6). In this dataset a total of 36 subjects' data is available. Each subject has two EEG recording files. One file is before induced stress and the second file is after induced stress. The EEG data files are available in the European Data Format (EDF) within each folder. Each subject has two recording files: one labeled with "_1" indicating baseline EEG recorded before inducing stress, and the other labeled with "_2" indicating EEG recorded during stress induction. In total, there are 72 signal files provided for assessing the accuracy of the model.

4.2 Feature Selection Method

Feature importance ranking methods evaluate the importance of features in machine learning models by evaluating their impact on prediction accuracy and model performance metrics. These strategies help to identify key data features for effective model training and interpretation. Tree-based techniques (e.g., decision trees and random forests), permutation importance, and SHAP (SHapley Additive ExPlanations) might help determine which attributes contribute the most significantly to predicting outcomes. These strategies make feature selection easier, increase model efficiency, and improve overall transparency and dependability in machine learning applications by prioritising critical characteristics.

4.2.1. Feature Importance Ranking Method

- Use a model that provides feature importance scores, such as Random Forest, GradientBoosting, or XGBoost. (Proposed work – used Random Forest)
- Train the model using dataset.
- Extract feature importance scores for all features.
- Rank the features based on their importance scores.
- Select the top features based on the top N features. (Consider Top 4 Results in our Proposed work)

4.3 Satcking method to prepare hybrid classifier:

The stacking method is an ensemble learning strategy that combines several base models to produce a more powerful and resilient model. The key idea is to use the base models' predictions as input features for a higherlevel model known as the metamodel and it's consider as a hubrid classifier. This meta-model learns how to best integrate the base models' predictions to produce the final result.

Steps to Use the Stacking Method

- Base Model Training & Prediction
- Stacked Feature Creation
- Meta-model Training and Final Prediction

5. EXPERIMENTAL RESULTS

The results obtained can be seen by running the dataset through all the processes outlined in the proposed flow.

Table 2. Results- Applying time and frequency domain features

Sr. No	Classification Algorithm	Accuracy in Time Domain (%)	Acuracy in Frequency Domain (%)
1	Random Forest	90.83	93.33
2	Linear Regression	61.37	47.79
3	SVM	82.5	97.5
4	Naïve Bayes	94.44	91.66
5	Decision Tree	94.44	91.66

Table 3. Results- After applying hybrid features dataset

Sr. No	Classification Algorithm	Accuracy Time Domain (%)	Acuracy Frequency Domain (%)	Hybrid Features Dataset Approach (%)
1	Random Forest	90.83	93.33	95
2	Linear Regression	61.37	47.79	68.61
3	SVM	82.5	97.5	98.33
4	Naïve Bayes	94.44	91.66	94.44
5	Decision Tree	94.44	91.66	94.44
6	XGBoost	66.66	66.66	95.83
7	Ensemble SVM	76.66	88.33	91.66

Table 4. Results- Applying hybrid classifier approach

Sr. No	Meta Model	Base Learner-1	Base Learner- 2	Hybrid Classifier Method (%)
1	Ensemble SVM	XGBoost	RF	98.33
2	SVM	XGBoost	RF	98.61
3	XGBoost	SVM	RF	97.91
4	XGBoost+Ensemble SVM	SVM	RF	97.22

5.1 Classification Performance comparision for Table-2 and Table-3.

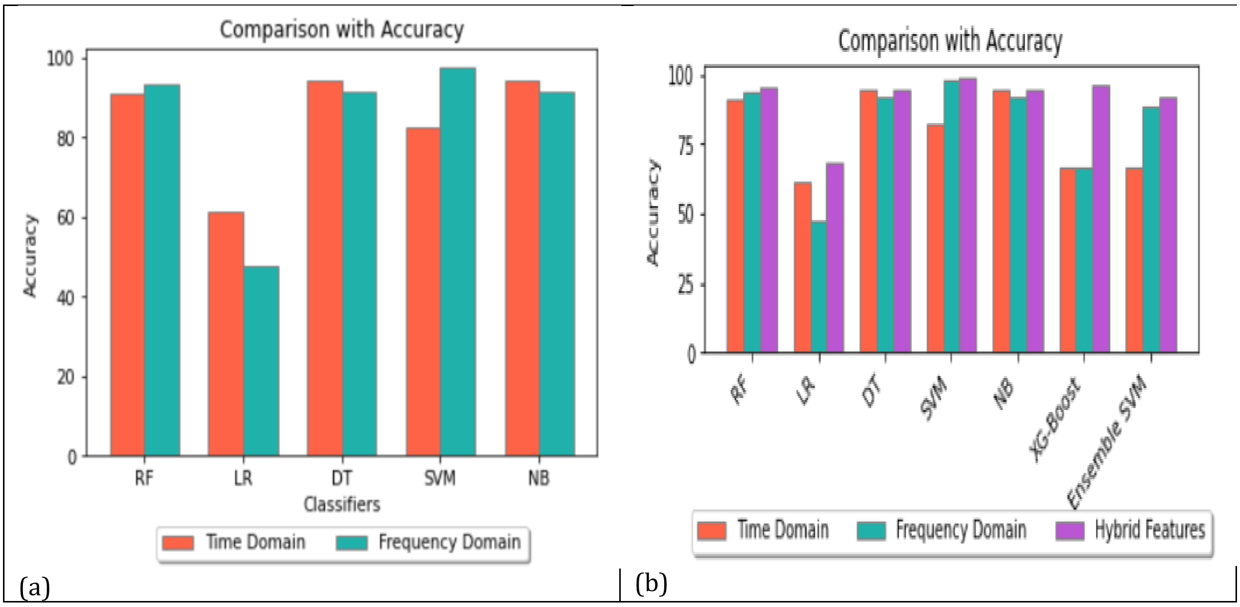

Figure 6. Comarision Results: (a) Table-2&(b) Table-3

5.2 Proposed Results and Discussion

In this section, we compare the EEG dataset used in this research work with those utilized in previous studies. The comparison is presented in the table below.

Table 5. Comparison of Proposed work results with existing work

Sr. No	Classification Algorithm	Result Accuracy (%)
1	Support Vector Machine	98.2
2	Random Forest	98.2
3	CNN-LSTM	96.7
4	WOA-SVM	94.01
5	K- Nearest Neighbour	90.74
6	Cubic SVM	82
7	LSTM	93.58
8	**Hybrid Classifier (Proposed Work)**	**98.61**

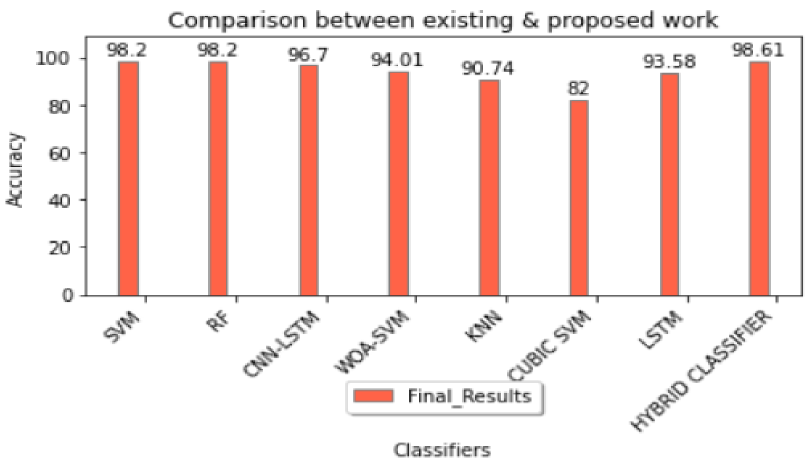

Figure 7. Comarision Results: existing classifier & proposed – hybrid classifier

In this research work – the frequency domain features demonstrated high accuracy with Random Forest (93.33%) and SVM (97.5%). By introducing a hybrid feature dataset—combining features from both the time and frequency domains along with selected channels—we achieved improved accuracy in machine learning models. Specifically, the Random Forest and SVM-ML models achieved accuracies of 95% and 98.33%, respectively, using this hybrid dataset. Further enhancements were achieved by incorporating hybrid techniques with a meta-model. Notably, the base learner classifiers (Random Forest and XGBoost) with a meta-model (SVM) achieved a remarkable accuracy of 98.61%.

6. CONCLUSION

Our research work demonstrates that combining features from both time and frequency domains by using EEG physiological signal significantly enhances the performance of machine learning models in stress detection. The introduction of a hybrid feature dataset led to noticeable improvements in accuracy for both Random Forest and SVM models. Moreover, by applying advanced hybrid techniques on classifier with a meta-model approach, we achieved further enhancements, culminating in an impressive accuracy of 98.61% with the Random Forest and XGBoost base learners combined with an SVM meta-model. These findings highlight the potential of hybrid feature and advanced ensemble techniques in achieving high-performance stress detection models.

7. Future Scope

Future research could explore additional feature combinations and meta-models to further optimize the accuracy and robustness of the system. Our results provide a strong foundation for developing reliable and efficient stress detection systems that can be applied in various real-world scenarios and also check the proposed accuracy comparision by using other Stress dataset.

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