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MACHINE LEARNING BASED FEATURE EXTRACTION METHODS FOR STRESS IDENTIFICATION WITH EEG

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Abstract

In the era of artificial intelligence (AI), the field of biomedicine which aims to improve human health with chemical and medical methods is also using AI solutions to solve medical problems. Machine Learning (ML) has become an important tool in biomedical research and healthcare to completely automate the complex tasks done by humans. This paper explores the use of ML for studding the electroencephalogram (EEG) to solve critical health problems while addressing the brain-computer interface (BCI) systems. EEG measures brain electrical activity and may contain impression of many of psychological and physiological conditions of human mind and body. To establish a direct communication from brain's electrical activity to a machine, Brain-Machine Interface (BMI) technology is used and more precisely if the machine is a computational device the technology is named as BCI. Among all the psychological footprints, stress is gaining increasing attention in research across neuroscience, medicine, psychology, and related fields like affective computing. ML can be utilized in various ways to analyse stress using EEG data. Starting with data acquisition phase, ML Techniques for EEG signal based BCI system needs, data pre-processing, signal analysis for feature extraction, and classification phase for stress level detection problem. Among these, feature extraction, the most difficult phase shows the underlying data embedded in the signal. In this paper we are analysing many temporal and spectral feature extraction methods which are useful in EEG-BCI systems for better accuracy. This paper also includes the EEG Data Analysis using MNE-Python package and then comprehensive analysis of various techniques to train/test the ML model with Python 3.0, which highly motivate the selection of algorithm for subjectively detecting the stress level.

Keywords: Classification, Electroencephalography, Feature extraction, Machine learning models, Python, Stress detection, Signal analysis.

1. Introduction

Artificial Intelligence (AI) the term, coined by John McCarthy in 1956, is no newer but now has many more applications. AI is not only proven in self-driving cars, AI chat bots, artificially created video and images but also have the potential to transform the delivery of health care more fundamentally [1]. Specifically, the use of AI in personalized medicine, drug discovery, word processing of medical data, patient predictive analytics, and virtual medical assistance fuels the use of one inevitable tool of AI called Machine Learning (ML). Biomedical AI uses simple methods to analyse biological data, develop diagnostics, optimize treatments and discover new drugs [2]. AI in media imaging demonstrated exceptional accuracy and speed in analysing a variety of medical images, including X-rays, MRIs, CT scans, and mammograms [1, 2]. AI algorithms can analyse large amounts of data to identify potential drugs, predict their effectiveness, and adjust drug formulations. Personalized medication and treatment plans are the areas where AI plays a key role by analysing genomic data and patient data to identify genes and biomarkers associated with specific diseases. Natural language processing (NLP) using AI can effectively analyse medical data and provide relevant information, saving time while reducing errors.

As stress is an impact of disturbance in mental or physical equilibrium in human body which can lead to negative emotions and physical changes, it is greatly contributing to anxiety, depression, heart dieses, diabetes, high/low blood pressure and obesity as shown in Fig. 1. Recently, cognitive tests have been incorporated into the understanding of stress processes to explain differences in how individuals interpret and respond to anxious stress. According to this view, there is no one-size-fits-all relationship between stress levels and environmental factors. Recent research highlights gender and age differences in stress adaptation and the impact of certain personality traits, such as empathy, social engagement, emotional stability, autonomy, work ethic, and cognitive abilities, which are seen as more vulnerable to stress [3, 4]. With all these challenges stress is receiving increasing attention in research to develop a solution to measure as well classify its level.

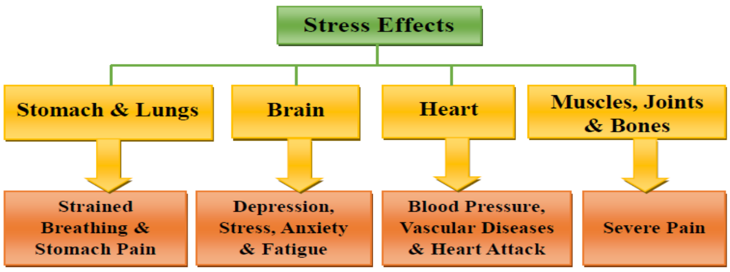


Fig. 1. Psychological and physiological impacts of stress.

To measure the stress level, questionnaire based like Stress Response Inventory (SRI), Hamilton Depression Rating Scale (HDRS) and physiological signals-based methods like Galvanic Skin Response (GSR), Electroencephalogram (EEG), and Electrocardiography (ECG) are available. In this paper we are addressing the EEG signal processing and further classifying the stress level as stress can alter EEG patterns, reflecting changes in brain function. As ML is a dedicated field of research for the development and analysis of statistical methods that extract information from data to perform tasks without explicit instructions, we are using the tool of ML to train the model to classify the EEG signal to detect over anxiety and depression level. Here we are focusing mainly on methods of feature extraction and various ML algorithms while describing the data acquisition phase briefly.

In this paper, after visualizing the EEG data set in section II using MNE-Python package, different feature extraction methods for EEG signal processing are discussed in section III and ML models for stress classification in section IV. After this a comprehensive analysis of these methods is conducted in section V depending on their accuracy in results with plotting multiple Bar charts with Python 3.0. Section VI concludes the paper and also opens the route for a contiguous journey ahead.

2. EEG Data Set and Methodology

Stress identification methods through EEG signal, mainly involving two foremost components: feature extraction and stress classification, are prefixed with EEG signal acquisition and pre-processing. A huge collection of EEG data set is available in literature for systematic review and process. SAM -40 [5] is also a collection of EEG data which is recorder over 40 persons including 14 females and 26 males with mean age of 21.5 years. The signals were recorded in four different conditions and for each condition three trials of signal were recorded. The four different conditions were : 1. Performing Stroop colour-word test, 2. Solving arithmetic questions 3. Identification of symmetric mirror images and 4. State of relaxation. The individual tasks durations were 25 seconds and a 32-channel Emotiv Epoc Flex gel kit with 128Hz sampling frequency was used for recordings . Figure 2 shows the placement of electrodes for 32 channels recording where CMS and DRL are two reference electrodes.

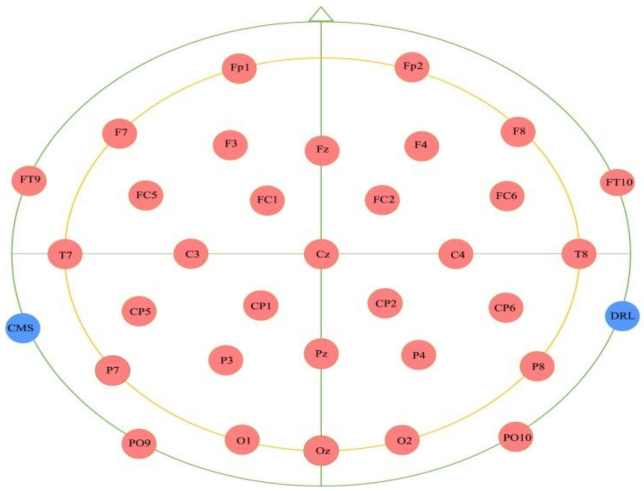
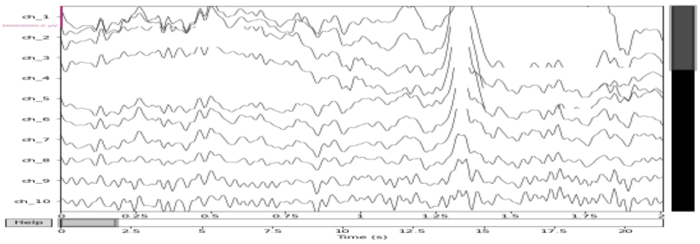
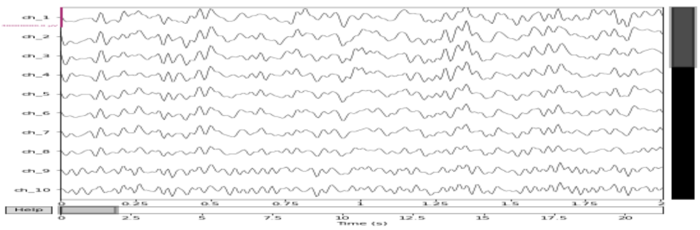


Fig. 2. Locations of electrodes for 32 channel EEG signal recording [5].

To deduce meaningful insights about psychological and physiological conditions EEG data is pre-processed to remove noise, artifacts, and other unwanted interferences from recorded EEG signals to ensure data quality. Here noise may involve random noise, and environmental noise, and physiological artifacts are physiological artifacts like eye nictates and head motions. Here band pass filtering is used for noise removal and artifacts are removed using a combination of Savitzky-Golay filter and wavelet thresholding. Figure 3 shows a comparison between raw EEG data signal and cleaned EEG Data signal for first trial of first person while Performing Stroop colour-word test while using MNE-Python tool.



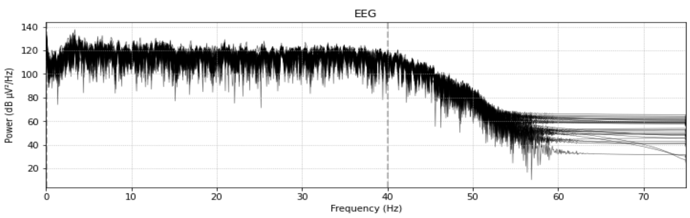
(a)



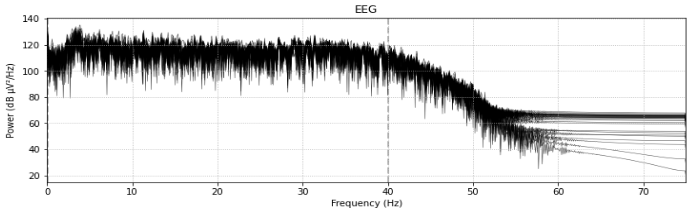
(b)

Fig. 3. Comparison over (a) raw EEG signal and (b) cleaned EEG signal.

Further for understanding of various cognitive and neurological processes the power spectral analysis of EEG data is performed. The Power Spectral Density (PSD) of the EEG signal is the main and basic feature of EEG data which represents the distribution of power for time-domain EEG signals across different frequency bands. Figure 4 presents the PSD's comparison of the cleaned EEG signal for the first trial of first person for all the four conditions.



(a)



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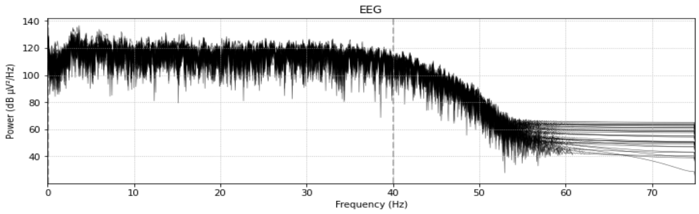
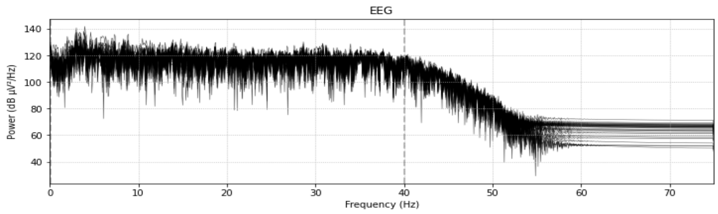


(c)



(d)

Fig. 4. PSD for cleaned EEG Signals for (a) Performing stroop colour-word test (b) Solving arithmetic questions (c) Identification of symmetric mirror images and (d) State of relaxation.

With this pre-processed data set characteristics of the brain's activity are identified by using various feature extraction methods for further classifying the stress level.

3. Feature Extraction with EEG Signal Analysis

Delving in the complex problem solutions through ML, necessitates the study of intricacies of features to elevate the signal processing for further analysing the EEG signal in BCI system for stress detection [6]. Time, frequency, time –frequency domain features, non-linear features, entropy features and spatiotemporal features are the most attended features out of which spatiotemporal is getting a great attention of researchers as it describes the relation between different regions of brain in particular events. In this section we are exploring various feature extraction method to be used for classification further. Autoregressive (AR) modelling analyses time-based data by modelling the current value as a combination of past values and error. Selection of the AR model's order is crucial and can be determined using criteria like Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC) [7]. AR coefficients from EEG signals are used as features for classification tasks, alongside entropy-based techniques to measure EEG signal complexity. Independent Component Analysis (ICA) is a computational technique used to separate mixed signals into independent components. It relies on the assumption that observed data is a blend of signals from different, independent sources [8]. By exploiting this assumption, ICA algorithms can isolate independent components within the data. While powerful, ICA has limitations, including the need for accurate assumptions about signal independence and challenges in resolving uncertainty or mixed noise. Nonetheless, it finds applications in diverse fields such as neuroscience, speech processing, and telecommunications. Popular algorithm like FastICA and Infomax [9] are being used, with ongoing research in the fields of neuroscience for improvements in EEG signals with blind signal separation.

Wavelet Packet Transform (WPT) enhances Discrete Wavelet Transform (DWT) by including wavelet coefficients alongside measurement coefficients [7, 10]. This yields a rich binary tree structure representation, crucial for tasks like compression and noise removal. WPT's optimal basis algorithm tailors selection to specific signal processing needs. In EEG analysis, WPT facilitates disentangling brain activity frequencies, separating artefacts, classifying EEG signals, analysing event-related potentials (ERPs), and exploring brain connectivity. Principal Component Analysis (PCA) is extensively used in EEG studies by reducing data dimensionality while retaining variation [8]. PCA analyses EEG data by identifying spectral coherence factors. When combined with other methods, such as pragmatic component analysis or Multi-Layer Perceptron neural networks, PCA enhances classification accuracy.

Particularly in diagnosing autism spectrum disorder (ASD), PCA aids in diagnosis by facilitating pattern recognition. Empirical Mode Decomposition (EMD) is a method for decomposing non- stationary signals into the Intrinsic Mode Functions (IMFs). In EEG signal analysis, EMD breaks down the signal into IMFs to capture oscillations at different frequencies [11, 12]. Each IMF represents a frequency band, and their analysis can reveal stress related patterns in brain activity. Features extracted from IMFs like statistical measures and dominant frequencies are used to characterize EEG signals for stress detection. Short time Fourier transform (STFT) is a method in BCI systems to dissect EEG signals to reveal frequency changes over time, aiding stress detection. By dividing signals into time blocks and applying Fourier transforms, it generates spectrograms showing frequency evolution [13]. By analysing the alpha, beta, and theta bands, it extracts features like energy and spectral entropy for stress characterization. STFT offers detailed brain behaviour insights, enhancing stress detection accuracy over traditional methods.

The Hilbert- Huang Transform (HHT) is a signal processing technique for analysing nonstationary and nonlinear signals. It employs Empirical Mode Decomposition (EMD) and Hilbert Transform (HT) to break down signals into intrinsic mode functions (IMFs) and generate the Hilbert spectrum [11]. HHT offers superior time resolution compared to traditional methods like wavelet transform (WT) and short-time Fourier transforms (STFT) [11, 13]. In EEG analysis, HHT's adaptive decomposition via EMD effectively captures local oscillations, aid in gin feature extraction and event-related potential (ERP) analysis. It enables the study of brain network dynamics by examining phase synchronization between IMFs from different electrodes [11, 13]. Discrete Fourier Transform (DFT) is a powerful tool in digital signal processing, used to analyse EEG signals for stress detection. EEG signals are pre-processed, then broken down into frequency components using DFT. Features like power spectral density are extracted from frequency bands (alpha, beta, theta, delta) to characterize stress levels. Applying the FFT algorithm for DFT calculation further reduces the computational complexity of method [14]. This method aids in understanding stress-related EEG signals, facilitating stress detection systems.

4. Classification Models for Stress Detection

Once the EEG signal is analysed and the feature extraction phase is over the features are then supplied to classification model to detect the stress level. The data files having extracted features are provided to classifier model for training and then the extracted features of test data are fed to this trained classifier model to determine the stress level and further its accuracy. The EEG-BCI system performance is then validated through methods like cross-validation. In this section we are discussing various classifier models to prove their competence in EEG-BCI system for stress detection solution. Artificial Neural Networks (ANN) models, including deep learning architectures like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), can be employed for feature learning and classification tasks in EEG-based stress detection [15]. Pooling operation reduces dimensionality, while fully connected layers facilitate decision making in CNN. Recent developments in CNNs have shown their prowess in handling non-linear dependencies and effectively decomposing them into their characteristic frequency components [16]. As a result, many developed architectures can operate on raw EEG data without the need for any additional processing. Optimization algorithm like stochastic gradient descent (SGD) refines the parameters during training which further enhances performance on EEG datasets. CNNs can extract spatial features from EEG data, while RNNs can capture temporal dependencies.

Support Vector Machines (SVMs) are often used for classification tasks in EEG analysis to differentiate between different mental states, including stress. SVMs can effectively handle high-dimensional data, making them suitable for EEG data analysis [10-12]. SVM initiates necessary hyper planes among the features of the different classes during its training session to maximize the margins among the classes Random Forest is an ensemble learning method that can be used for classification tasks in EEG analysis. It can handle high-dimensional data and is robust to over fitting. This classifier generates forests with random number of trees. Normal decision tree algorithms are rule based and are solely based on some set of rules for prediction on data [17]. The K-Nearest Neighbours (k-NN) classifier is one of the most popular classification schemes due to its simplicity and computational efficiency [10, 13]. K-NN is an intuitive classification algorithm that can be applied to EEG data for stress detection [18]. It works by identifying the k-nearest data points in the feature space and assigning the most common class label among them. Long Short-Term Memory (LSTM) is a type of RNN that is well-suited for sequence data, such as time-series EEG data. It can capture long term dependencies in the data, making it suitable for modelling temporal aspects of stress [19].

5. Results and Discussion

As explained in sections II and III, the Classification accuracy of the stress level identification is highly dependent on the applied feature extraction method and machine learning algorithm, in this section we are describing various accuracy results with the help of Bar Chart plotted in Python 3.0. The comprehensive analysis is subject to Levels, Bands and Channels and here the level defines number of classes in which the EEG data is finally classified, band means the power used for alpha, beta, and theta bands and channels states the number of channels to record the EEG data. A comparison of accuracy over mapping of feature extraction methods: ICA, WPT, and AR are presented in Table 1 for respective ML algorithms on the results among the proposed methods by respective researchers. According to Table 1 and Fig. 5, the computed accuracy for three feature extraction methods: ICA, AR and WPT for different ML models such as k-NN, SVM, ANN, CNN, RF and LSTM. K-NN does the classification while considering the target classes where it compares the extracted features with the nearest k learning data. To further reduce the bias and variance, k-fold validation is used to separate test data from training data [7, 10]. Here the performance was measured with accuracy, sensitivity, specificity, precision, and F1 score (F1)) for the binary case.

Table 1. Accuracy comparison of different ML algorithms mapped with feature extraction method ICA, WPT and AR.

Signal Analysis	ML Model	Accuracy %	Researchers
ICA	k-NN	71.76	Shon et al. [20]
	SVM	82.5	Pathak, et al. [8]
	ANN	90	Rakhmatulin et al. [16]
	CNN	93.75	Rakhmatulin et al. [16]
	LSTM	78	Rakhmatulin et al. [16]
	RF	74	Edla et al. [17]
WPT	k-NN	99.53	Arı [10]
	SVM	94	Arı [10]
	ANN	63.8	Sbargoud et al. [21]
	CNN	83.8	Sbargoud et al. [21]
	LSTM	79	Sbargoud et al .[21]
	RF	75	Edla et al. [17]
AR	k-NN	99.42	Zhang et al. [7]
	SVM	75.33	Zhang et al. [7]
	ANN	85	Nazneen et al. [11]
	CNN	82.7	Mardiansyah et al. [22]
	LSTM	75.535	Rakhmatulin et al. [16]
	RF	89	Singh et al. [23]

Shon et al. [20] explored the multiclass target while taking the accuracy as performance measure and for that metric calculation was done according to ten-fold cross-validation. Using SVM, stress and pressure were detected by using EEG signals, and with that ICA was used to produce less generalization errors [8]. ANN optimization was done with preprocessing the EEG signals while utilizing the low-pass filter with different cutoffs for improving accuracy. The two types of bio-signals were preprocessed through WPT and classified by the ANN [10]. With the use of belief theory, model uncertainty and imprecision were treated further, which adapts to the ambiguities and conflicts between sources [21]. With the combination of continuous wavelet transforms (CWT) and simplified convolution neural network (SCNN) performance improvement was shown by improving the recognition rate of MI (Motor Imagery)-EEG signals is in [11]. Using the CWT, the MI-EEG signals are mapped to time-frequency image signals. To improvise in EEG classification, 2-layer LSTM and 4-layer improved deep NN learning algorithms are proposed in [16].

RF classification of [17, 23] utilizes multiple decision trees for training and then takes the average of individual trees for output prediction. The AR model's ability to capture temporal dependencies, coupled with the simplicity and effectiveness of the KNN classifier [7], can lead to accurate and reliable classification results in various domains. Combining AR with SVM allows leveraging the temporal dependencies captured by AR models while benefiting from SVM's ability to manage high-dimensional feature spaces and nonlinear decision boundaries [7]. When AR is paired with an ANN classifier, which is known for its ability to learn complex patterns and relationships in data, the combination can lead to accurate and efficient classification results [11]. AR models are effective in capturing temporal dependencies in time series data, while CNNs excel at learning spatial features and patterns from data [22]. The integration of autoregressive feature extraction with LSTM models provides a robust framework for time series prediction tasks, allowing for the capture of complex dynamics in the data and improved forecasting accuracy through the utilization of temporal dependencies and learned representations [16].

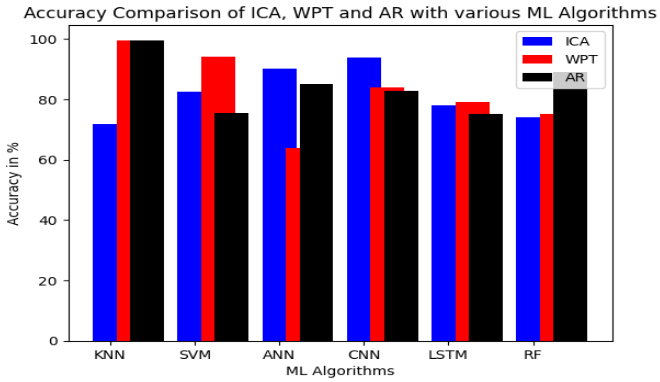


Fig. 5. Accuracy comparison of different ML algorithms mapped with feature extraction method ICA, WPT, and AR.

A comparison of accuracy over mapping of feature extraction methods: STFT, PCA, and HHT are presented in Table 2 for respective ML algorithms on the results among the proposed methods by respective researchers. Accuracy of feature Extraction method of STFT, PCA and HHT is shown in Fig. 6 according to Table 2 and is compared for ML models such as k-NN, SVM, ANN, CNN and LSTM. The combination of STFT feature extraction and KNN classification can leverage the strengths of both approaches. STFT provides a time-frequency representation of the input signal, capturing both temporal and spectral characteristics [18], while SVM is known for its ability to handle the feature spaces with high-dimensional and also can perform better where decision boundaries are non-linear [4]. Time-frequency representation of the STFT can improve over learning complex patterns and relationships in data with ANN [18]. EEG signals may have data redundancy which affects the computational time load and accuracy. This necessitates the reduction in dimensions of the EEG signal data.

The researchers in [24] investigated the performance by dimensionality reduction with PCA on those channels which passed the wavelet feature extraction. While using the criteria of highest eigenvalue the numbers of vectors were determined for representations of the most significant dataset variants and then SVM and k-NN for classification was applied for stress detection [19-20]. ANN for classification is optimized by reducing complexity of input data and then further analysing its time-frequency structure with different cut off low-pass filters [15]. Large amount of repeated information and data are merged in to overcome over fitting with the use of PCA which works with features based on different data variants. Classification with one dimension CNN results in higher accuracy [22].

Table 2. Accuracy comparison of different ML algorithms mapped with feature extraction method STFT, PCA and HHT.

Signal Analysis	ML Model	Accuracy %	Researchers
STFT	k-NN	81.98	Rahman et al. [18]
	SVM	76.82	Hag et al. [13]
	ANN	91.41	Rahman et al. [18]
	CNN	84.06	Kang et al. [19]
	LSTM	53.3	Kang et al. [19]
PCA	k-NN	73.24	Shon et al. [20]
	SVM	85.85	Pathak and Haneef [8]
	ANN	86.57	Maksimenko et al. [15]
	CNN	93.32	Mardiansyah et al. [22]
	LSTM	90.12	Soni et al. [25]
	RF	98.66	Acharya et al. [26]
HHT	k-NN	93.3	Chen et al. [27]
	SVM	99.125	Fu et al. [24]
	ANN	83.25	Nazneen et al. [11]
	RF	98.66	Eraldemir et al. [28]

As HHT reveals the both both dimension of the signal as time and frequency domain it is utilized in analysing both nonstationary and nonlinear signals. Decomposing signals in posteriori enables a great advantage in EEG signal processing for further classifying it in stress level detection [24-25]. HHT based on EMD shows better performance in accuracy as compared to above mentioned method of time and frequency domain. Extracted Features are classified with ANN and RF algorithms [11, 28].

Many researchers in recent years have proved that the feature selection process is highly influenced by the band of EEG signal which led the path of frequency domain processing and power spectral density calculation. DFT and its computationally efficient version: FFT facilitates this requirement with optimum performance in accuracy by applying different classifiers model while using many techniques of FFT such as hamming, hanning, and rectangular window with specific length and overlapping percentage. The Accuracy percentage with the use of power features of theta, alpha and beta bands are compared subjectively with stress detection level of two three and four [29]. Performance of FFT feature extraction method is also evaluated with different channel possibilities at the time of data acquisition and channel Fp1 (forehead area)-alpha band outperforms than any other combination [14].

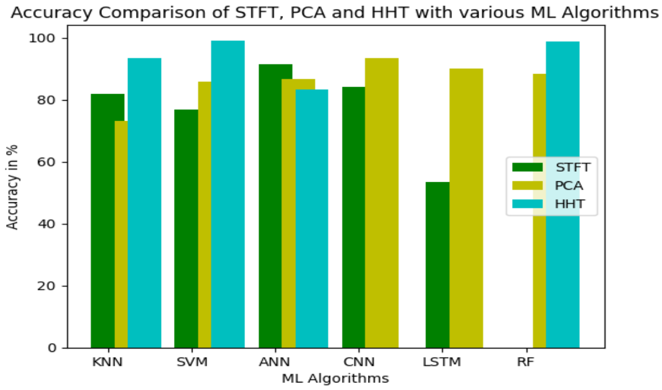


Fig. 6. Accuracy comparisons of different ML algorithms mapped with feature extraction method STFT, PCA and HHT.

Table 3 lists the computed accuracy in stress detection for FFT feature extraction method with two ML algorithms: k-NN and SVM for Level 2, 3, and 4 and according to that Fig. 7 demonstrate the comparison with multiple bar charts plotted in Python 3.0. For time frequency analysis of non-stationary EEG signals using EMD produces the decomposition of the signal in numbers of frequency components known as IMFs. Then the selected features with temporal moment of third order is fed to k-NN and SVM models of ML for training /test phase for which the accuracies are measured for different cases where case denotes the discrimination in EEG signal with its levels[12]. Resultant accuracy is included in Table 3 and Fig. 7.

Table 3. Accuracy comparison of k-NN and SVM ML algorithms with Feature Extraction Method FFT and EMD.

Signal Analysis	Level/ Channel	ML Model	Accuracy %	Researchers
FFT	L2	k-NN	76.72	Hou et al. [29]
		SVM	85.11	
	L3	k-NN	63.24	
		SVM	75.22	
	L4	k-NN	54.31	
		SVM	67.06	
	Fp1	k-NN	99.42	Priya et al. [14]
		SVM	98.72	
EMD	NA	k-NN	92.7	Riaz et al. [12]
		SVM	97.5	

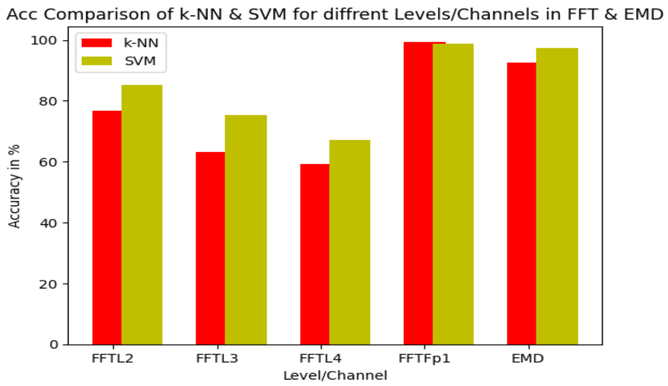


Fig. 7. Accuracy comparison of k-NN and SVM ML algorithms with Feature Extraction Method FFT and EMD.

6. Conclusions

An extensive research and exploration of various methods for analysing the EEG signal and then feeding the extracted features for further classifying the stress level with aid of ML algorithms is done in this paper. EEG is emerging as a valuable signal for studying the functional brain in BCI system. Moreover, with the emerging technology of AI, aid of the ML tool shows a steep leap in the accuracy of stress level detection which further determines many psychological and physiological disorders. In alignment with the given system many researchers have identified the stress level and concluded the result with accuracy given over used ML algorithm and feature extraction method. This research paper intended to distribute the focus on comprehensive analysis of these feature extraction methods and ML algorithms for their relative mapping in calculation of accuracy which also subjects with the use of band, channel and levels. Bar plots of this subjective analysis prove the potential of the explored methods for analysing brain signals as an optimal choice for brain computing applications. However, many limitations like inconsistency in labelling, challenges of real scenarios for stress identification, methodological variations and many more suggest for fusion of traditional machine learning models and usage of multi modal foundation model for feature extraction to significantly enhance the stress identification accuracy.

Abbreviations

AI	Artificial Intelligence
AIC	Akaike Information Criterion
ANN	Artificial Neural Network
AR	Autoregressive Model
ASD	Autism Spectrum Disorder
BCI	Brain-Computer Interface
BIC	Bayesian Information Criterion
CNN	Convolutional Neural Network
CWT	Continuous Wavelet Transforms
DFT	Discrete Fourier Transform
ECG	Electroencephalogram

EEG	Electroencephalogram
EMD	Empirical Mode Decomposition
FFT	Fast Fourier Transform
GSR	Galvanic Skin Response
HDRS	Hamilton Depression Rating Scale
HHT	Hilbert-Huang Transform
ICA	Independent Component Analysis
KNN	K Nearest Neighbour
LSTM	Long Short-Term Memory
ML	Machine Learning
NLP	Natural Language Processing
PCA	Principal Component Analysis
RF	Random Forest
RNN	Recurrent Neural Network
SCNN	Simplified Convolution Neural Network
SRI	Stress Response Inventory
STFT	Discrete Fourier Transform
SVM	Support Vector Machine
WPT	Wavelet Packet Transform

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