International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 8s
DOI: https://doi.org/10.17762/ijritcc.v11i8s.7175
***Article Received**: 18 April 2023 **Revised:** 05 June 2023 **Accepted:** 26 June 2023*

A Comparative Analysis of EEG-based Stress Detection Utilizing Machine Learning and Deep Learning Classifiers with a Critical Literature Review

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Abstract— Background: Mental stress is considered to be a major contributor to different psychological and physical diseases. Different socio-economic issues, competition in the workplace and amongst the students, and a high level of expectations are the major causes of stress. This in turn transforms into several diseases and may extend to dangerous stages if not treated properly and timely, causing the situations such as depression, heart attack, and suicide. This stress is considered to be a very serious health abnormality. Stress is to be recognized and managed before it ruins the health of a person. This has motivated the researchers to explore the techniques for stress detection. Advanced machine learning and deep learning techniques are to be investigated for stress detection.

Methodology: A survey of different techniques used for stress detection is done here. Different stages of detection including pre-processing, feature extraction, and classification are explored and critically reviewed. Electroencephalogram (EEG) is the main parameter considered in this study for stress detection. After reviewing the state-of-the-art methods for stress detection, a typical methodology is implemented, where feature extraction is done by using principal component analysis (PCA), ICA, and discrete cosine transform. After the feature extraction, some state-of-art machine learning classifiers are employed for classification including support vector machine (SVM), K-nearest neighbor (KNN), NB, and CT. In addition to these classifiers, a typical deep-learning classifier is also utilized for detection purposes. The dataset used for the study is the Database for Emotion Analysis using Physiological Signals (DEAP) dataset.

Results: Different performance measures are considered including precision, recall, F1-score, and accuracy. PCA with KNN, CT, SVM and NB have given accuracies of 65.7534%, 58.9041%, 61.6438%, and 57.5342% respectively. With ICA as feature extractor accuracies obtained are 58.9041%, 61.64384%, 57.5342%, and 54.79452% for the classifiers KNN, CT, SVM, and NB respectively. DCT is also considered a feature extractor with classical machine learning algorithms giving the accuracies of 56.16438%, 50.6849%, 54.7945%, and 45.2055% for the classifiers KNN, CT, SVM, and NB respectively. A conventional DCNN classification is performed given an accuracy of 76% and precision, recall, and F1-score of 0.66, 0.77, and 0.64 respectively.

Conclusion: For EEG-based stress detection, different state-of-the-art machine learning and deep learning methods are used along with different feature extractors such as PCA, ICA, and DCT. Results show that the deep learning classifier gives an overall accuracy of 76%, which is a significant improvement over classical machine learning techniques with the accuracies as PCA+ KNN (65.75%), DCT+KNN (56.16%), and ICA+CT (61.64%).

Keywords- Classification, Deep Learning, Electroencephalogram, Feature extraction, Machine Learning, Stress detection.

I. INTRODUCTION

People experience a great deal of stress in their daily life. Stress arises from lots of medical problems like depression, heart attack, suicide, etc. As a result, it is now necessary to recognize and manage stress before it leads to serious health problems. Stress detection is crucial in various fields of research in biomedicine, psychology, neuroscience, automotive, etc. Stress can be caused due to external or internal causes that bring negative emotions (fear and worry) and psychological changes in human behavior. Stress can be caused due to physical, environmental, mental, psychological, social, chronic, and traumatic conditions [1][2].

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1.1 Background

A signal in living things that are measured and monitored continuously is called a biosignal. A biosignal is also called a bioelectric signal. Physiological signals play a vital role in acquiring signals for the detection of anxiety. Various Biao signals are used for stress detection. The physical bio-signals can be obtained from EEG, eye movement, pupil size, electromyography (EMG), voice signal, electrocardiogram (ECG), respiratory signals, Photoplethysmography (PPG), skin temperature, blood volume pressure, and Electro-dermal activity (EDA) [3].

1.2 EEG Signal

EEG is the non-invasive method of capturing the activity signals from the cerebral cortex. EEG signals are recorded using cup electrodes and subdermal needle electrodes. The bioelectric potentials generated by the brain's neuronal activity are known as EEG. In the medical field, the EEG is a vital tool for observing normal and abnormal brainwave activity. The EEG signals are divided into five frequency bands such as delta, theta, alpha, beta, and gamma. The amplitude and frequencies of the EEG signal can help in the diagnosing and monitoring of stress or anxiety disorders.

1.3 Generalized process of Stress Detection

The stress phenomenon is generated in the brain and three types of hormones such as the Hypothalamus, Pituitary gland, and Adrenal cortex instantiate the stress activity. Depending upon personal perception, stress is categorized into two categories such as good stress (eu-stress) and bad stress (distress) [5]. Stress is a natural phenomenon in daily life, the stress is induced in the subjects in a controlled environment or laboratory using clinical stressor techniques. The various clinical stressor includes International Affective Picture System (IAPS) [6], the Stroop Colour-Word Test (SCWT) [7], Mental Arithmetic (MA) tests [8], the Paced Auditory Serial Addition Test (PASAT) [9], the Montreal Imaging Stress Task (MIST) [10], the Berg Card Sorting Task (BCST) [11], simulated Lane Change Test (LCT) [12], Trier Social Stress Test (TSST) [13], the cold pressor test (CPT) [14] and Mannheim Multi-component Stress Test [15].

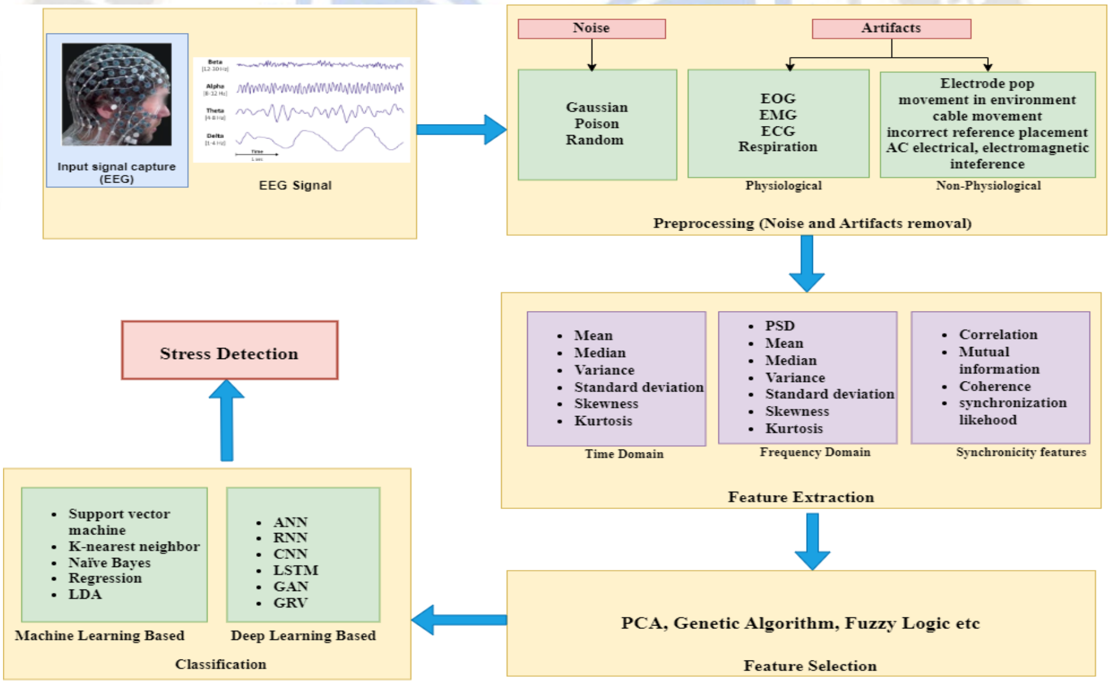

Figure 4: Generalized flow diagram of stress detection

The generalized process of stress detection consists of the stages such as signal acquisition, preprocessing, feature extraction, and a classification stage shown in Figure 4.

EEG signal loading: EEG signal is obtained from electrodes connected around the head. These signals are captured via cup electrodes and sub-thermal needle electrodes. These signals are having different amplitudes such as alpha, beta, gamma, delta, and theta. These signal levels are related to different brain activities such as problem-solving, sleeping, meditation, relaxation, etc. For experimentations, researchers have utilized publicly available databases including DEAP, PhysioNet, SEED, etc.

Pre-Processing: During the capturing of signals, there are noises and artifacts which affect the signal quality. To process the signal further, it needs to be pre-processed. It involves the minimization of the noise and artifacts present in the captured

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raw bio-signal induced due by external factors, body movement, or any other activity.

Feature Extraction Technique: Feature extraction helps to capture the specific attributes of the signal which can describe the signal's uniqueness.

Feature Selection: Feature selection is often employed to choose the salient attributes and reduce the unwanted attributes.

Classification: Finally, The classification step is crucial for classifying the signal into various stress levels. The recital of

the technics will be evaluated based on parameters like accuracy, sensitivity, specificity, etc.

1.4 Organization of paper

The remaining paper is structured as follows: section 1 provides a review of various techniques utilized for the preprocessing of EEG signals, feature extraction, and classification algorithms employed for EEG-based stress detection. Section 3 depicts describes the results of previous methods for stress detection on the DEAP dataset. Afterward, section 4 provides the finding from the review of the various techniques. Lastly, section 5 gives the conclusion and paves the way for the future scope for further improvement.

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II. REVIEW OF LITERATURE

Stress causes many complications in human life and it needs to be detected early to be treated perfectly. EEG signaling is prominently utilized for detection of the stress. Detection involves capturing EEG signals and analyzing the same. Researchers are motivated to analyze these signals via sophisticated and automated computer-aided diagnostic methods. Machine learning and deep learning algorithms are utilized by researchers for this problem. Moreover, major research is done by considering publicly available datasets such as DEAP, SEED, PhysioNet, etc, which are created exclusively for this problem. These are explored in the preceding sub-section.

2.1 EEG Signal Database

Stress detection is more accurate when we utilize EEG brain data since individuals can conceal their emotions through verbal and facial expressions. There are different types of databases available for the analysis of EEG signals. These databases are publicly available and boost scholars to use them for testing their effective state estimation methods. There are different types of EEG databases available such as A Database for Emotion Analysis using Physiological Signals (DEAP), PhysioNet, SJTU Emotion EEG Dataset (SEED), etc.

A. DEAP: Database for Emotion Analysis using Physiological Signals is called DEAP. EEG signals were recorded from 40 channel EEG samples from the DEAP dataset, having a Sampling frequency of 128 Hz. Also Duration segment 63 sec, Samples 8064[16].

B. SEED: SEED stands for SJTU Emotion EEG Dataset. Prof. Bao-Liang Lu's BCMI laboratory provided the SJTU Emotion EEG Dataset (SEED).SEED EEG includes EEG data from 15 different people. SEED Multimodal comprises 12 participants' EEG and eye movement data. EEG and eye movement data from 12 persons, as well as EEG data from three additional patients, are included in the SEED dataset. Data were collected while watching video samples. The video clips were deliberately selected to induce a variety of emotions, including happy, negative, and neutral. The 62-channel ESI NeuroScan System and SMI eye-tracking glasses were used to capture EEG data and eye movements [17].

C. PhysioNet: In the PhysioNet database EEG recordings of subjects before and during mental arithmetic tasks are included in the database having an EEG 23-channel system and 30Hz is the cutoff frequency. In EEG Motor Movement/Imagery Dataset Over 1500 one- and two-minute EEG recordings from 109 volunteers make up this data set. EEG data were recorded from 11 healthy volunteers who were shown images at speeds of 5, 6, and 10 Hz using the Rapid Serial Visual Presentation (RSVP) methodology [18].

A measurement, transformation, or structural element that is distinguishing or characteristic and is taken out of a pattern segment is called a feature **[68]**. The typical feature extraction methods may be divided into two main categories: statistical features and grammatical descriptions **[69]**. The purpose of a feature extraction strategy is to select the characteristics or data that are most crucial for the classification operation **[70]**.

2.2 Preprocessing Techniques

Artifacts or noise are unwanted signals that corrupt brain waves during EEG signal assessment. These artifacts are roughly classified into two types. There are two types of artifacts physiological and Non-physiological [27]. In physiological types artifacts occur due to Eye- Blinks and eyeballs movement producing electrical signals as well as Clenching of jaw muscles, Forehead, and eyelid muscle movements, neck and shoulder muscles tension, etc. Also, Electrical activities of the heart and Body Movement of respiration mechanically affect the impedance of one electrode, Inhalation, or Exhalation and involve those electrodes on which the patient is lying. In non-physiological types artifacts occur due to Spontaneous changes in electrode-skin contact, Movements of other persons around the patient, Movement of the cables connecting the electrodes and the

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amplification system, incorrect reference placement, and AC electrical lines and devices[28].These different types of noises and artifacts are to be removed before the signals are to be processed further for detection and classification purposes. Various strategies for EEG signal noise reduction and artifact removal were implemented in the preceding year. The most often used EEG enhancement techniques are wavelet transform, blind source separation (BSS), regression, empirical mode decomposition, and adaptive filtering [19]. In the presence of many artifacts, the majority of these approaches perform poorly. Several discrete wavelet transform-based methods have been working for EEG signal enhancement and one-dimensional signal enhancement, however, Loss of information, inappropriate thresholding strategies for noise removal, and worse performance for high-level noise all affect the performance of these techniques. [20].

2.3 Feature Extraction Techniques

This is a useful technique for extracting information from a signal such that the attributes can be explained clearly. The data taken out represents the physiology and architecture of brain function. It carries many variables in huge amounts of data, which require a strong algorithm to analyze the data.

2.4 Classification Techniques

In this section, various vital classifiers were used for the classification of the signal-processing activity. In classification, need to predict the correct class label for testing samples of data.

2.4.1 Support Vector Machine (SVM)

For the analysis of classification and regression SVM is used [71]. In Machine learning, a support vector machine is categorized under a supervised learning algorithm. A decision plane is used here; it is a plane that differentiates the two classes of data points. The SVM algorithm is taking data input and generates a line separating those classes if possible. In the SVM algorithm, the points located nearby to the line from both classes are called support vectors **[72]**. Many academics believe the SVM to be a superior classifier for classification. Linear and nonlinear kernel functions are used in SVM. The input EEG signal data are fed into the SVM classifier, and the hyperplane formed identifies the stress. Vanita and Krishnan [29] have presented real-time stress detection using EEG signals based on the Hilbert-Huang Transform (HHT) technique for the extraction of features and classification. They have used a Finite Impulse Response (FIR) filter for the power line noise removal. They have achieved the highest accuracy for alpha waves (94.32%) and average accuracy of 89.07%. Further, Guo Jun et al. [30] investigated mental stress detection with the help of two stressors such as the mental arithmetic test and the Stroop colour-word test. They have used power band features of alpha and beta waves and SVM classifiers for the two-stage and three-stage stress recognition. It has given the accuracy of 88%, 96%, and 75% for the Stroop color-word test, mental arithmetic test, and three-level stress test respectively. Sharma and Chopra [31] have explored early stress detection using Hilbert Huang Transform (HHT) which is a time-frequency domain feature extraction technique and SVM classifier. Their method achieved higher accuracy for the alpha waves [32].

2.4.2 Classification Tree (CT) or Decision Tree (DT)

Classification is a method from an input data set to create classification models. A decision Tree or Classification Tree Classifier is a comprehensive and easily used technique **[73]**. It organized a sequence of test questions and rules in a tree structure. Every time it collects answers, processes go on till the conclusion is reached. Each node of a Classification tree is given a test condition (yes or no). From the root node, the test process begins. Apply test conditions to input records. Follow the suitable branch based on the test result. However, to acquire more accurate and better classification results, more efficient methods may be utilized in this decision tree classifier. The Classification tree classifier is given EEG signal values as input, and the decision tree is built to categorize the EEG values and offer outcomes as different sorts of emotions[33].

2.4.3 Naive Bayes (NB)

The NB algorithm is a supervised learning method for resolving Bayes theorem-based classification issues **[74].** Since it is a probabilistic classifier, predictions made by it are based on the likelihood of an item. The benefit of the naive Bayes technique is that it can tolerate missing values by disregarding feature dependence while calculating opportunity estimates. Furthermore, it can only utilize a few training sample data that are appropriate for our data when it comes to the training sample data [34] having an accuracy is 87.5%.

2.4.4 Logistic regression(LR)

Regression is the task of predicting a continuous quantity such as a continuous variable. The method of logistic regression is employed in both classical statistics and machine learning. LR is helpful to solve the problem of binary classification. Logistic regression used a logistic function at the core of the method. In this method, LR has an S-shaped curve that can convert any real-valued number to a number between 0 and 1. In the [35] to assess human stress levels, the authors utilized 27 subjects' EEG data with Logistics regression having an Accuracy of 98.76% (2 –stress levels) and Accuracy of 95.06% (3- stress levels).

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2.4.5 Sequential Minimal Optimization

It works on two variables at a time. The sequential Minimal Optimization algorithm is used for solving a problem that arises in the support vector machine algorithm. This method solves the quadratic programming optimization problem by reducing the entire problem to the smallest quadratic programming problem possible. It does not require extra matrix storage [36]

2.4.6 K-nearest neighbors

K-is one of the important classification method. It is a supervised type machine learning algorithm. KNN simply stores the dataset during training and classifies newly received data into a group that is relatively similar to the training data. The most considerable value of k is 5. Considering large values for K is good but it creates some difficulty. The advantage of the KNN algorithm is that it is very easy to use. It is also more effective for large training data. In the [31] author used Genetic algorithm(GA), Principle Component Analysis (PCA), and KNN with a Database for Emotion Analysis using Physiological Signals (DEAP)database having an Accuracy of 71.76% (GA) Accuracy of 65.30% (PCA) [37][38].

2.4.7 Artificial Neural Networks (ANN)

A biological network of artificial neurons built to conduct classification, grouping, and pattern recognition inspired an artificial neural network. A neural network is a group of algorithms that certify the underlying relationship in a set of data similar to the human brain **[75].** Biological neurons serve as the motivation for an ANN. Artificial neural works with four parts synapses, axons, cell body, and dendrons. In an Artificial neural network, dendrons received signals from different neurons. The cell body improved the received signals. That enhanced signal is transmitted to the synapse through the axon. When step and signum functions are applied to the processed signal of the "cell body", generate an output signal from the synapse. In the [39] author used Power Spectral Density (PSD), Wavelet coefficient (WT), Fourier Transform (FT), Kalman Filter (KF), Hjorth Complexity (HC), and Hjorth Mobility (HM)+ ANN classifier 30 subjects (Mathematical Questionnaire) having Accuracy 91.00%.

2.4.8 Deep Neural Network (DNN)

DNN is a method that is used to learn attributes and execute classification. DNN can work with a lot of data **[76]**. A neural network with more than three layers, including input and output layers, is known as a deep neural network. Each hidden layer might have a different number of hidden layers and neurons. The ability to detect strong features from data is present in DNN, which is why it has been chosen to find stress in this research. Afterward, Liao et al. [40] investigated a deep neural network with 7 hidden layers for emotional stress detection using EEG signals acquired using Neurosky Mindwave mobile device. They have used the FFT of raw EEG signals as an input to the neural network. It has given an accuracy of 80%.

2.4.9 Deep Convolutional Neural Networks (DCNN)

CNN is a deep learning method that uses convolutional neural networks. The design of a convolutional network generally consists of four layers: convolution, pooling, activation, and fully linked. Convolutional and pooling layers are two types of layers that make up a CNN's structure. Around each window of the input signal, convolutional layers extract the patterns of separate blocks of data. Then there are pooling layers, which are designed to lower the danger of model overfitting as well as the computational cost and time. After the convolutional and pooling layers, a softmax layer was added to identify the learned patterns. Using retrieved features from convolutional and pooling layers, the fully connected neural network seeks to identify the best classifier. In the [41] paper to assess human stress levels, the authors utilized a CNN-BLSTM (Convolution Neural Network and Bidirectional Long Short-Term Memory) is a DWT-based hybrid deep learning model. The level of stress for mental arithmetic activities is determined using the Physionet EEG database (19 channels) having the classification accuracy is 98.10%.

III. EXPERIMENTATION METHODOLOGY

As per the survey, different methods are being considered for experimentation in this work. Some popular feature extraction techniques are utilized including principal component analysis (PCA)**[77]**, independent component analysis (ICA) **[78]**, and discrete cosine transform (DCT) **[79]**. After selecting these features, state-of-the-art machine learning algorithms are employed for classification including NB, CT, SVM, and KNN. The performance of these algorithms is further compared with a conventional DCNN. The following sub-section enlightens the same.

3.1 Dataset Loading

A popular and publicly available dataset DEAP is used in this work for experimentations. DEAP is Database for Emotion Analysis using Physiological Signals. In this database EEG signals were recorded from 40 channel EEG samples, having a Sampling frequency of 128 Hz. Also Duration segment 63 sec, Samples 8064.

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3.2 Feature Extraction

After the loading of the dataset, different features are extracted and are further given to the classifier for classification purposes to detect the stress. Three feature extractors are employed in this study, namely principal component analysis, independent component analysis and discrete cosine transform. These are explored in the preceding sub-sections.

3.2.1 Principal Component Analysis: Principal Component Analysis (PCA) identifies a low-dimensional depiction of a dataset that contains as much variation in the dataset as possible.

3.2.2 Independent Component Analysis: Independent Component Analysis (ICA) is a machine learning technique that decomposes a multivariate signal into distinct non-Gaussian signals. It focuses on unbiased sources. Because the mixing process is unknown, ICA is frequently used as a black box.

3.2.3 Discrete Cosine Transform

The discrete cosine transform (DCT) aids in the separation of an image into parts (or spectral sub-bands) of varying importance (in terms of visual quality). The discrete Fourier transform (DCT) is similar to the discrete Fourier transform in that it transforms a signal or image from the spatial domain to the frequency domain.

3.3 Classification: Classification is performed by using different state-of-the-art machine learning classifiers such as KNN, SVM, DT, and Naïve Bays. In addition, a conventional DCNN is also utilized for classification purposes. These classifiers are explored in the preceding sub-sections.

3.3.1 KNN: The k-nearest neighbors algorithm, also known as KNN or k-NN, is a non-parametric, supervised learning classifier that uses proximity to classify or predict the grouping of a single data point **[80]**. While it can be used for either regression or classification problems, it is most commonly used as a classification algorithm, based on the assumption that similar points can be found nearby. Its goal is to find all of the nearest neighbors to a new unknown data point to determine what class it belongs to. It's a method based on distance. In the k-NN algorithm, the k value specifies how many neighbors will be checked to determine the classification of a specific query point. If k=1, for example, the instance is assigned to the same class as its single nearest neighbor. Different values of k can lead to overfitting or underfitting, so defining it can be a balancing act. Lower k values can have high variance but low bias, while higher k values can have high bias but low variance. The value of k will be determined largely by the input data, as data with more outliers or noise will most likely perform better with higher values of k. Overall, an odd number for k is recommended to avoid ties in classification and cross-validation techniques can help you choose the best k value.

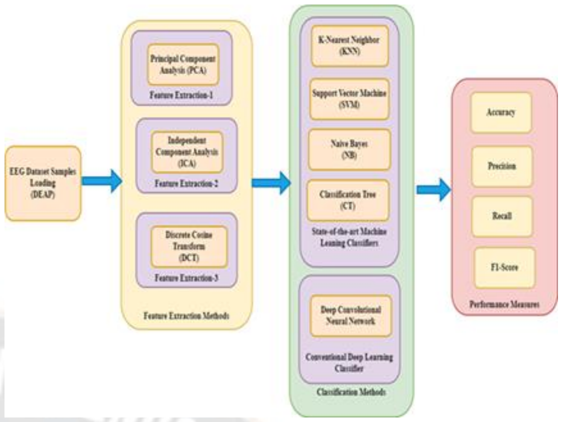

Figure 7: Detailed Experimentation Methodology

3.3.2 Support Vector Machine: Support vector machines (SVMs) are supervised machine learning algorithms that are both powerful and flexible. They are used for classification and regression. However, they are most commonly used in classification problems. SVMs were first introduced in the 1960s, but they were refined in 1990 **[81]**. When compared to other machine learning algorithms, SVMs have a distinct implementation method. They have recently become extremely popular due to their ability to handle multiple continuous and categorical variables.

An SVM model is essentially a representation of various classes in a multidimensional hyperplane. The hyperplane will be generated iteratively by SVM to minimize error. SVM's goal is to divide datasets into classes to find the maximum marginal hyperplane (MMH).

Support vectors are data points that are closest to the hyperplane. These data points will be used to define a separating line.A hyperplane is a decision plane or space that divides a set of objects of different classes.

Margin is defined as the difference between two lines on the closest data points of different classes. It is computed as the perpendicular distance between the line and the support vectors. A large margin is regarded as a good margin, while a small margin is regarded as a bad margin. The primary goal of SVM is to divide datasets into classes to find the maximum marginal hyperplane (MMH). First, SVM will iteratively generate hyperplanes that best separate the classes. Then it will select the hyperplane that correctly separates the classes.

3.3.3. Decision Tree: A tree has many real-world analogies, and it turns out that it has influenced a broad area of machine learning, including classification and regression. A decision tree can be used in decision analysis to visually and explicitly represent decisions and decision-making **[82]**. It employs a decision-tree-like model, as the name implies.

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The algorithm begins at the root node of the tree to predict the class of the given dataset. This algorithm compares the values of the root attribute with the values of the record (real dataset) attribute and then follows the branch and jumps to the next node based on the comparison. The algorithm compares the attribute value with the other sub-nodes and moves on to the next node. It repeats the process until it reaches the tree's leaf node.

3.3.4: Naïve Bayes: The probability of an event is described by Bayes' Theorem based on prior knowledge of the conditions that may be associated with the event.

Naïve The training dataset is assumed to be conditionally independent by Bayes. According to the Bayes' Theorem, the classifier divides data into different classes. However, it is assumed that all input features in a class have an independent relationship. As a result, the model is known as naive.

3.3.5: DCNN: Deep Learning is a subset of Machine Learning that includes algorithms inspired by the operation of the human brain or neural networks. Deep learning models include Artificial Neural Networks (ANN), Autoencoders, Recurrent Neural Networks (RNN), and Reinforcement Learning. However, one model, in particular, has made significant contributions to the field of computer vision and image analysis, and that is the Convolutional Neural Networks (CNN) or ConvNets. CNN is extremely useful because it reduces human effort by automatically detecting features. A typical DCNN architecture can be explained below.

a) Convolution Layer

This is the first layer used to extract the different features from the input images. This layer performs the mathematical operation of convolution between the input image and a filter of size MxM. The dot product between the filter and the parts of the input image to the size of the filter is calculated by sliding the filter over the input image (MxM). When the convolution operation is applied to the input, the convolution layer in CNN passes the result to the next layer.

b) Pooling Layer

A Pooling Layer follows a Convolutional Layer. This layer's primary goal is to reduce the size of the convolved feature map to reduce computational costs. This is accomplished by reducing the connections between layers and operating independently on each feature map. There are various types of Pooling operations depending on the method used. It essentially sums up the features produced by a convolution layer. The largest element from the feature map is used in Max Pooling. Average Pooling computes the average of the elements in a predefined image section size. Sum Pooling computes the total sum of the elements in the predefined section. The Pooling Layer is typically used to connect the Convolutional Layer and the FC Layer.

c) Fully Connected Layer

The Fully Connected (FC) layer, which includes weights and biases as well as neurons, is used to connect neurons from different layers. These layers are typically placed before the output layer and constitute the final few layers of a CNN Architecture.

d) Dropout

Overfitting in the training dataset is common when all features are connected to the FC layer. Overfitting occurs when a model performs so well on training data that it has a negative impact on the model's performance when applied to new data. To address this issue, a dropout layer is used, in which a few neurons are removed from the neural network during the training process, resulting in a smaller model. When a dropout of 0.3 is reached, 30% of the nodes in the neural network are randomly removed.

e) Activation Functions

Finally, the activation function is a critical parameter in the CNN model. They are used to learn and approximate any type of continuous and complex relationship between network variables. In other words, it determines which model information should be fired forward and which should not at the network's end.

IV. EXPERIMENTAL RESULTS

Here, for experimentation DEAP database is used. PCA and ICA methods are used for feature extraction and KNN, CT, SVM linear, NB, and DCNN classifiers are used for the classification of EEG signals for the detection of stress. In this study, EEG-based stress detection has been carried out. Here Statistical features are extracted from the EEG signal. Also performed a quantitative analysis by comparing the feature extraction methods like PCA, ICA, and DCT using three different machine learning classifiers SVM, KNN, NB, and CT as well as deep learning classifier DCNN.

Table 1 Comparative result between PCA KNN (k=7), PCA SVM Linear, PCA CT, PCA NB

Techniques	Accuracy	Precision	Recall	F1 Score
PCA KNN(k=7)	65.7534	0.6207	0.375	0.4675
PCA SVM Linear	61.6438	0.0345	0.0222	0.027
PCA CT	58.9041	0.6786	0.4419	0.5352
PCA NB	57.5342	0.7419	0.5476	0.6301

Comparative results of PCA KNN(k=7), PCA SVM Linear, PCA CT, and PCA NB have displayed in Table 1. also it was observed that Out of feature extraction method and with classification algorithms PCA KNN k=7 has good accuracy.

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Table 2 Comparative result between ICA+KNN (k=3), ICA SVM Linear, ICA CT, ICA NB

Techniques	Accuracy (%)	Precision	Recall	F1 Score
ICA KNN (k=3)	58.9041	0.5714	0.3721	0.4507
ICA SVM Linear	57.5342	0.428571	0.285714	0.342857
ICA CT	61.64384	0.636364	0.466667	0.538462
ICA NB	54.79452	0.333333	0.275	0.30137

Table 2 Comparative result between ICA+KNN (k=3), ICA SVM Linear, ICA CT, and ICA NB also observed that Out of feature extraction method and with classification algorithms ICA CT has good accuracy.

Table 3: Comparative result between DCT KNN, DCT SVM Linear, DCT CT, DCT NB

Techniques	Accuracy	Precision	Recall	F1 Score
DCT KNN	56.16438	0.275862	0.195122	0.228571
DCT SVM Linear	54.7945	0	0	NaN
DCT CT	50.6849	0.4375	0.3784	0.4058
DCT NB	45.2055	0.8621	0.7576	0.8065

Table 3 Comparative result between DCT KNN, DCT SVM Linear, DCT CT, and DCT NB. Also, it was observed that DCT KNN has good accuracy.

Table 4: Comparative result between DCT, PCA, ICA, and DCNN with Accuracy

Techniques	Accuracy	Precision	Recall	F1 Score
DCT KNN	56.16438	0.275862	0.195122	0.228571
PCA KNN(k=7)	65.7534	0.6207	0.375	0.4675
ICA CT	61.64384	0.636364	0.466667	0.538462
DCNN	76.1250	0.6679	0.7756	0.6459

Table 4 shows Comparative result between DCT, PCA, ICA, and DCNN with Accuracy. Also, it was observed that This methodology shows an overall accuracy of 76% for the DCNN deep learning Classifier which has significant improvement over PCA+ KNN (65.75%), DCT+KNN (56.16%), ICA+CT (61.64%).

V. DISCUSSION

Stress detection is done via EEG signal analysis prominently and this method proves fair as the diagnosis is concerned. Due to the adverse effects of stress on human life such as heart problems, anxiety, etc, it is necessary to develop a trusted technique for its diagnosis. This has motivated the researchers the development of sophisticated algorithms and an automated computer-aided diagnosis system. Machine learning and deep learning algorithms are utilized by researchers for stress detection. Moreover, major research is done by using publicly available databases. These datasets are prepared by capturing the EEG signals from the brain of a human being, after playing video clips of different moods in front of the subjects.

As far as machine learning is concerned, there have been several drawbacks, such as higher intra-class variability and reduced inter-class variability of the characteristics. Lower correlation and connectivity in the raw characteristics retrieved from EEG data. In Machine learning, the performance of the classifier is completely dependent upon the types of features. Also, researchers used deep learning algorithms to minimize the drawbacks of occurred in Machine learning.

On reviewing the literature critically following research gaps are identified.

5.1. Research Gaps

- The bio-signals are often subjected to noise and artifacts because of body movement and activity.
- Environmental effects such as temperature and humidity may affect bio-signals and body functions.
- Poor preprocessing has affected performance.
- Most of the raw features are having lower temporal and spectral dependencies
- Larger intra-class variability and lower inter-class variability of the features
- Lower correlation and connectivity in the raw features extracted from the EEG signals.
- Larger recognition time due to larger feature vector
- Less focus has been given to the detection of levels of stress
- The classifier's performance completely depends upon the types of features(ML)

5.2. Discussion on Results

A typical methodology is experimented with in the paper, consisting of different feature extractors and some state-of-the-art machine learning and deep learning classifiers. Feature extractors used are PCA, ICA, and DCT. After this SVM, NB, CT, and KNN machine learning classifiers are applied. In addition, a typical DCNN is also utilized for classification.

Different performance measures are considered for the evaluation of classifiers' performance including accuracy, precision, recall, and F1-score.

With PCA as feature extractor accuracy values obtained for KNN, SVM, CT, and NB are respectively 65.75%, 61.64%, 58.90%, and 57.53%. Precision values for these classifiers with PCA are 0.62, 0.0345, 0.6786, and 0.7419 for KNN, SVM, CT, and NB classifiers respectively. Recall values vary between 0.37 with KNN and 0.547 with the NB classifier. Also, F1-score achieved its maximum value of 0.63 for NB and 0.027 for the SVM classifier. On comparing the accuracies of different machine learning classifiers with PCA feature extractor, KNN was found to have higher accuracy of 65.75%

Features are extracted using ICA preceding with different machine learning classifiers. Accuracy varies from 54.79% for NB to a maximum of 61.64% with the CT classifier. As precision is considered, it has its maximum value of 0.636 with the CT classifier. Recall and F1-score have their maximum value with the CT classifier, taking the values of 0.466, and 0.538 respectively. On comparing the accuracies of different classifiers, CT proved to be giving a fair accuracy of 61.64%

As the next part of experimentation, DCT is applied for feature extraction. The performance measures considered with this combination of DCT- machine learning classifiers also include accuracy, precision, recall and F1-score. Their respective maximum values obtained are 56.16%, 0.8, 0.75, and 0.80 respectively. On comparing the accuracies of different machine learning classifiers, DCT plus KNN provided a fair value of 56.16%

After the utilization of classical machine learning classifiers, a conventional deep learning classifier- DCNN is employed for the classification purpose. The accuracy of classification with DCNN obtained is 76.12% which proved to be better than traditional machine learning models. Other performance measures including precision, recall and F1-score also attain comparable values as 0.66, 0.77, and 0.64 respectively

VI. CONCLUSION AND DIRECTIONS FOR FUTURE WORK

There has been a lot of research in the areas of EEG-based stress detection. Most of the researchers focus on the extraction and selection of features to extend the performance of stress detection. Selecting a classifier is the most difficult assignment in this process. The review concludes that researchers used various classifiers like SVM, ANN, KNN, etc. As per the literature survey, some gaps identified are; that the bio-signals are often subjected to noise and artifacts because of body movement and activity. Environmental effects such as temperature and humidity may affect bio-signals and body functions. The characteristics have greater intra-class variability and lesser inter-class variability. Lower correlation and connectivity in the raw characteristics extracted from the EEG signals. Most of the raw features are having lower temporal and spectral dependencies. The classifier performance completely depends upon the types of features. Thus there is a need to implement an efficient filtering technique to reduce the noise and artifacts in the EEG data. In this study, EEG-based stress detection has been carried out. Here Statistical features are extracted from the EEG signal. Also performed a quantitative analysis by comparing the feature extraction methods like PCA, ICA, and DCT using three different machine learning classifiers SVM, KNN, NB, and CT as well as deep learning classifier DCNN. This methodology shows an overall accuracy of 76% for the DCNN deep learning Classifier which has significant improvement over PCA+ KNN (65.75%), DCT+KNN (56.16%), and ICA+CT (61.64%).

Future work could be extended with the use of different deep learning classifiers for the improvement of different performance measures. This work could also be explored further by using more publicly available datasets.

Conflict of Interest: The authors declare no conflict of interest.

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International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 8s
DOI: https://doi.org/10.17762/ijritcc.v11i8s.7175
***Article Received**: 18 April 2023 **Revised:** 05 June 2023 **Accepted:** 26 June 2023*

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