**CHAPTER 2**

**REVIEW OF RELATED LITERATURE AND STUDIES**

**Related Literature**

Stress detection is a vital aspect of maintaining mental and physical well-being, particularly in our fast-paced modern world. Involving the identification and assessment of physiological, behavioral, and psychological indicators that signify the presence of stress in an individual. Stress detection through Machine Learning (ML) represents a groundbreaking fusion of technology and mental health, changing how we can understand and manage stress. By harnessing vast amounts of data by understanding markers such as heart rate, stimuli, breathing patterns or emotional responses. ML identifies these subtle patterns and signals that indicate stress level, enabling early intervention and personal health support.  
  
 While wearable devices such as EDA sensors enable the unobtrusive detection and sensing of human physiological reactions such as skin conductance response and heart rate in ambulatory settings, the quality of the detected and monitored data from the signals is susceptible to errors and discrepancies when processed and analyzed due to the presence of "noises" or artifacts (Gashi, S. et al., 2020).

In the same investigation, artifacts are described as "changes in the recorded biosignal that do not stem from the signal source in question", which might be created by the recording technique or recognized physiological responses in the system that are not electrodermal signals. These may result in waste of efforts in obtaining electrodermal signals since they give rise to unreliable data because of low quality signals extracted. This work used several methods for an autonomous technique to detect artifacts in the structure of EDA signals and evaluated the signal quality in terms of thermoregulation responses (user movement, and ambient temperature). The model attained a recall of 98%, a remarkable gain of 42 percentage points over the baseline classifier. It is claimed that the technique can replace or minimize the efforts of human specialists to visually analyze the retrieved data, but more extensive future study into additional elements that may appear similar to genuine signals would make a substantial contribution.

Similarly, Llanes-Jurado et al. conducted a study titled "Automatic Artifact Recognition and Correction for Electrodermal Activity in Uncontrolled Environment". al. (2021) discussed the influence of movement artifacts on recorded EDA signals in uncontrolled circumstances, resulting in the obscurity of significant patterns. This study investigated the application of a variety of machine learning and deep learning technologies, including support vector machines, recurrent neural networks (RNNs), and convolutional neural networks (CNN). In the experiment, the model that employed an RNN fed with the raw data recognized 72% of the artifacts and achieved an 87% accuracy rate. The identified artifacts were then automatically corrected using linear interpolation and a high degree polynomial. When assessed, the automatically and manually adjusted signals showed variations from the raw signals. The study produced significant results with regards to the future experiments that may be able to improve and develop artifact detection in EDA signals.

Hossain et. al. (2022), also explored the automatic detection of electrodermal activity data using machine learning. In this study, the researchers worked on an annotated electrodermal database to label data as clean or noisy using a reference signal without motion artifact for a more accurate resolution. In the methodology of the study, a binary classification to detect the EDA segments with motion artifacts was developed. Features from the signals were then extracted, classified, undergone hyperparameter tuning, and evaluated. This experiment resulted in automatic detection of motion artifacts with 94.7% accuracy and the method was compared with other known methods in motion artifact detection. However, there is still room for further studies as this study has limitations and further research would be necessary.

In the study of Sánchez-Reolid et al. (2022), they utilized machine learning techniques for arousal classification from electrodermal activity(EDA), employing various methods to handle the complexities of EDA signal. Using first ML techniques, Support Vector Machines(SVMs) having different kernels, next is Auto-HIdden Markov Models (AHMMs) for temporal modeling and Discriminant Analysis (DA) for dimensionality reduction were key techniques. Decision Trees (DTs), including ensemble methods, and Naive Bayes methods were chosen for their simplicity and robustness. Logistic Regression (LR) was used for binary classification, while K-Nearest Neighbors (KNN) and Artificial Neural Networks (ANNs) tackled EDA signal complexities. The artifact detection process involved signal normalization, artifact removal with filters, noise reduction, feature extraction, and model evaluation using accuracy, precision, recall, specificity, F1-score, AUC, and ROC metrics, ensuring robustness against artifacts and noise .

In other hand, Tronstad et al. (2022) explore various time series data techniques for extracting data in Electrodermal Activity analysis. Time series data plays a pivotal role in modeling and analyzing where the interplay between cognitive processes and electrodermal responses, employing methods such as linear time-invariant (LTI) systems to discern the impact of stimuli on EDA and infer cognitive or neural inputs from the data. Additionally, time series data is integral to deconvolution schemes, aiding in the estimation of sympathetic nervous activity (SNA) time series, peak scoring for identifying physiological or psychological responses, statistical analysis to discern patterns in interpulse intervals, and model inversion for inferring cognitive or neural inputs from observed EDA responses.

Ahuja and Banga (2019) proposed mental stress detection in university student using ML algorithms (Random Forest, Naive Bayes, Support Vector Machine and K-Nearest Neighbour) and calculated their specificity, sensitivity and accuracy of all these and found out that the Support Vector Machine (SVM) is performing well out of the four algorithm used and its giving an accuracy of 85.71%, specificity of 100% and sensitivity of 75%. Random Forest is the next to SVM giving an accuracy of 83.33, specificity of 66.66% and sensitivity of 100 %. Given the percentage of parameters SVM is performing as its a geometric way of classification of data is also less.

Archana and Devaraju (2020) proposed a system of Stress Detection using Machine Learning techniques where the data set was collected from the web considering various attributes. They employed machine learning algorithms to train the dataset and predict stress level based on statistical thresholds. The results showed 100% accuracy across Decision Tree, Naive-Bayes and K-Nearest Neighbor (KNN) algorithms. Sensitivity, specificity, precision and false positive rate were also measured. Predicted that the values were obtained from confusion matrices.

Agrawal et al. (2021) presents a comparative analysis of various machine learning algorithms for early stress detection using Electroencephalography (EEG) signals. Using classic algorithms they tested Naive Bayes, KNN, SVM and Neural Networks on EEG data from multiple studies. The results show that the best performing algorithms were SVM that achieved an accuracy of 96.36% and Fuzzy KNN combined with Discrete Wavelet Transform that achieved an accuracy of 93.25%. They conclude that EGG based stress detection using advanced machine learning techniques can provide an accurate and reliable method for early stress detection which is crucial for preventing long term health complications.

In Comparison, Heyat et al. (2022) proposed a mental stress detection using machine learning models on single lead electrocardiogram signals involving the analysis of Electrocardiography (ECG) signals from researchers who’s under mental stress and normal condition. Employing the classification techniques including Decision Tree (DT), Naive Bayes (NB), Random Forest (RF), and Logistic Regression (LR) classifiers with various models. The results showed that the DT achieved the highest performance with the recall of 93.3%, specificity of 96.7%, precision of 94.4% accuracy of 93.3% and F1 score of 93.5% in the intra-subject classification of mental stress and normal conditions.

Alshorman et al. (2022) focused on establishing a framework for mental stress detection utilizing Support Vector Machine (SVM) and Naive Bayes (NB) classifiers. The experiment involved collecting EEG data from 14 participants, comprising a total of 182 samples. They utilized EGI's Geodesic EEG System with 128 channels to capture brain activities originating from the frontal lobe of the participants. The analysis revealed that the classification based on individual subjects using SVM and NB classifiers exhibited remarkable efficacy, achieving an average accuracy rate of 98.21%, sensitivity of 98.21%, specificity of 97.77%, F1-score of 98.17%, and precision of 98.49%. Furthermore, the classification involving a mixture of conditions (mental stress vs. control) utilizing SVM RBF Kernel, SVM Linear, SVM Polynomial, SVM Sigmoid, and NB classifiers also showcased encouraging outcomes, with the NB classifier attaining the highest accuracy of 90.6% through a 3-fold cross-validation. These results imply that the suggested approach, which integrates EEG data analysis, feature extraction, and machine learning classifiers, can reliably identify mental stress with a high degree of accuracy, thereby establishing itself as a valuable instrument for monitoring and evaluating mental health.

Hemakom et al. (2023) proposing multilevel classification of stress level in distinct gender using machine learnings based of ECG and EEG based detection where utilized a various of machine learning algorithms, such as Naive Bayes (NB), Logistic Regression (LR), AdaBoost (ADAB), k-Nearest Neighbors (kNN), Random Forest (RF), Support Vector Machine (SVM), and Radial Basis Function SVM (RBF-SVM).For stress identification, the kNN classifier attained the highest accuracy of 72.50% for combined genders, 73.50% for females, and 74.17% for males solely utilizing ECG characteristics. Upon incorporating both ECG and EEG features, the RBF-SVM classifier obtained the highest accuracy of 77.50% for mixed genders, 78.00% for females, and 77.50% for males. In terms of multilevel stress classification, the stacking method, that amalgamated the outcomes from all individual classifiers, achieved the peak accuracy of 75.00% for mixed genders, 76.00% for females, and 74.17% for males. These results demonstrate the effectiveness of the proposed machine learning approaches in accurately detecting and classifying stress levels across different genders.

1. **Stress Detection Using Electrodermal Activity’**

Electrodermal Activity (EDA) also known as galvanic skin response is the constant fluctuation in the skin's electrical characteristics, which are dependent on the moisture level of the sweat glands and blood flow in the sympathetic and parasympathetic nervous system. Electrodermal Activity holds significant relevance and importance in various domains due to its ability to provide valuable insights on the body’s autonomic nervous system activity. In stress detection, it serves as a sensitive indicator to enable the real-time monitoring of physiological response to stressors.

Liu and Du (2018) presents a simple method for detecting three levels of stress (low,medium,high) based on Electrodermal Activity (EDA) signals. EDA data sets came from the MIT media lab real driving stress database. The use of Fisher protection and linear discriminant analysis achieved a good recognition rate of 81.82%. The study demonstrates that the single EDA can effectively detect different stress levels with acceptable degree of accuracy.The approach using only EDA signals for stress detection is considered a pragmatic and practical method compared to using multiple physiological signals. The EDA signals for stress detection can provide a more convenient approach in identifying and managing stress levels effectively.

Sanchez-Reolid et al. (2020) presents a method for identifying stress from electrodermal activity signals using Deep Support Vector Machines D-SVMs.The study compares the performance of D-SVMs and SVMs in detecting stress conditions. The study demonstrates that D-SVMs outperform classical methods in terms of F1-score, achieving values between 89.10% to 92.01%. The results indicate that D-SVMs provide robustness at a reasonable computational cost .

Gashi et al. (2020) presents an automatic approach to detect artifacts in electrodermal activity (EDA) signals. The study utilized deep neural networks , ensemble classifiers , linear and non-linear classifiers to detect shape artifacts in electrodermal activity (EDA) signals. The approach involves creating ground-truth labels based on human annotators, extracting features related to the shape of EDA signals and training various classifiers.The results of the study showed that the automatic approach achieved a high recall of 98% using the XGBoost classifier for detecting artifacts. The study implied that the need for human annotators could be eliminated and the approach could be used for automatic artifact detection in electrodermal activity (EDA )signals.

Nardelli et al. (2022) proposed a novel approach called ComEDA for characterizing the complex dynamics of electrodermal activity (EDA) signals. The study conducted experiments involving different stressful tasks to analyze the complexity of electrodermal activity (EDA) using the ComEDA algorithm.In the first two experiments,participants engaged in physical stress task involving submaximal handgrip and forced maximal exhalation protocols the results showed decrease in complexity of EDA dynamics while the other two experiments focused on mental stress tasks such as mental computation and the stroop color and word test, increased the complexity of the EDA dynamics. The results show that the ComEDA is effective in capturing the complexity changes in EDA signals during physical and mental stressors ,highlighting its potential for stress assessment and monitoring autonomic responses.

1. **Challenges in Processing and Analyzing Electrodermal Activity Signals**

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