APPLICATION OF A HYBRIDIZED LSTM-SVM IN THE DETECTION OF ARTIFACTS IN ELECTRODERMAL ACTIVITY SIGNALS FOR STRESS DETECTION

A Thesis Proposal

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**Benolirao, Johana**

**Calubayan, Christaline**

**Cueva, Larry Miguel**

**Quiray, Deseree**

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# CHAPTER 1

**THE PROBLEM AND ITS SETTING**

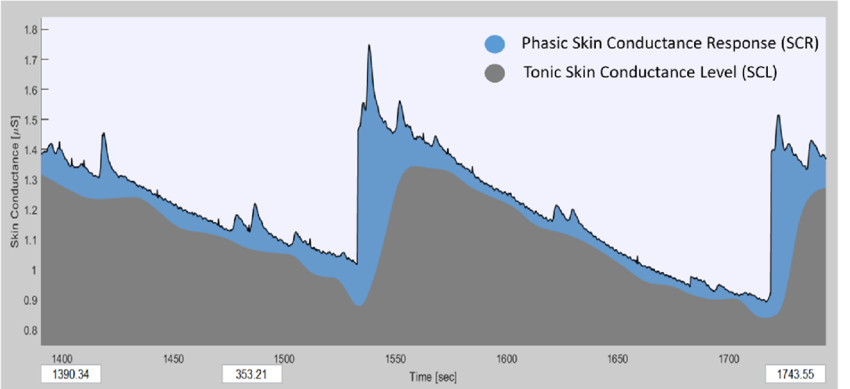
## Introduction

Stress is defined as a condition that involves worry or mental strain generated by a challenging circumstance (World Health Organization, 2022). Stress can be found in different aspects or events. In the country of Jordan during the COVID-19 pandemic, the healthcare workers revealed that they are experiencing high level of stress and found out that 22.5% of participants had severe stress, 16.2% had extremely severe stress and 21.1% had a moderate stress in total of 60% of their healthcare workers experienced this level of stress (Alnazly et al., 2021).This high levels of stress experienced by healthcare workers during the pandemic can have negative impacts on their psychological well-being, job performance, and ability to provide quality patient care. With its negative connotations, numerous studies focused on detecting stress signals that may help in mitigating and managing stress to prevent and handle its effects better.

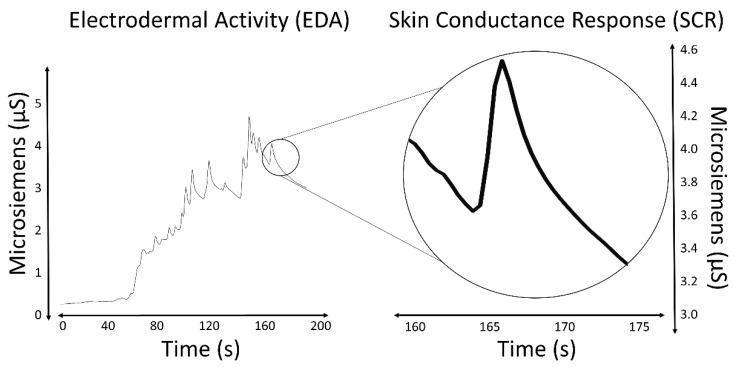
Furthermore, utilization of wearable sensors to detect psychological and physiological responses has been a trend over the course of years. In the investigation of Dzedzickis et. al., (2020), the researchers conducted a review of sensors and models utilized for human emotion identification. In a publication by Semmlow (2004), many physiological processes produce energy that can be detected directly by a device generally known as a transducer which converts energy from one form to another. The energy that is converted by the input transducer may be generated by the physiological processes of the body itself. The measurement of electrical activity in the heart, muscle, or brain, provides other examples of direct measurement of physiological energy. For these measurements, the energy is already electrical and only needs to be converted from ionic to an electric current using an electrode. These includes physiological processes that produces electrical energy, namely: electrocardiogram (ECG), electroencephalogram (EEG), electromyogram (EMG),

Among the techniques used in measuring physiological responses is Galvanic Skin Response (GSR), also known as Electrodermal Activity (EDA) or more specifically, Skin Conductance Response (SCR) measured in microsiemens (μS). It is a method of detecting the electrical attributes of human skin.

*Components of EDA*



*Figure 1. Components of an EDA Signal, Phasic and Tonic*

*Figure 2. Skin conductance response relevant to time*

Emotional fluctuations cause sweating, which is most evident on the palms, fingers, and soles. This process alters the quantity of salt in the skin and changes its electrical resistance. This sensor provides less information about the emotional state compared to EEG and ECG, but it has a few advantages: it requires fewer measuring electrodes, which allows for easier use of wearable devices and definition of emotional states in ambulatory settings; it provides fewer raw data, which allows for faster analysis of obtained data; and it requires less computational power, and compared to other measurements, equipment needed for the measurement is much simple and cheaper.

On the other hand, Jose (2022) has stated that within the domain of statistical computing, time series analysis is a statistical technique that deals with trend analysis and time series data. Time series analysis made its way into medicine when the ﬁrst practical electrocardio-grams (ECGs), which can diagnose cardiac conditions by recording the electrical signals passing through the heart, were invented in 1901. Time series analysis is a speciﬁc way of analyzing a sequence of data points collected over an interval of time. In time series analysis, analysts record data points at consistent intervals over a set period of time rather than just recording the data points intermittently or randomly.

Having established that signals measured from ECGs, EEGs, EMGs, and GSRs/EDAs all have similar characteristics in that they are sequences of data points collected over an interval of time, GSR or EDA data therefore can be categorized as time series specific data. Electrodermal Activity (EDA) is a low-cost and non-intrusive way of monitoring the emotional state of a subject, and a viable gateway\\ to study the Sympathetic Nervous System (SNS), which is responsible for the so-called ﬁght-or-ﬂight responses happening at the unconsciousness level (Boucsein, 2012). EDA is also a frequently used modality in psychophysiology, because of its ability to obtain a distinct Electrodermal Response (EDR) in response to a stimulus. The possible uses of EDA are well documented; the most important examples include research on epilepsy, autism, stress and anxiety (Banganho, et. al., 2022).

Nonetheless, similar to other physiological signals, EDA signals face challenges. With the recent trend of wearable technologies for psychophysiological monitoring in ambulatory settings, the data quality from these sensors can be compromised by "noise" or artifacts in long-term recordings. Artifacts, which are unwanted changes in recorded biosignals not originating from the intended source (Boucsein, 2012), can result from unstable electrode contact, environmental factors like temperature and humidity, or movement (Hossain, 2022). According to Boucsein (2012), detecting these artifacts typically requires visual inspection of the data. While signal processing techniques like low-pass filtering can be used to reduce the need for visual inspection, they risk altering the physiological response, potentially transforming the entire EDA trace and making artifacts appear as genuine responses. Recent studies have focused on developing models to automatically identify and remove artifacts (Gashi et al., 2020).

In the study conducted by Llanes-Jurado et. al. (2023) on automatic recognition and elimination of artifacts in electrodermal activity (EDA) signals using their EDABE dataset, they collected data from 43 participants in a stress-inducing VR study. The researchers developed and trained four models, two of which replicated traditional machine learning methods by Taylor et al. (2015) and Hossain et al. (2022).

Replicating the Taylor et al. (2015) method, they extracted 62 hand-crafted features, selected 40 via backward selection with a Support Vector Classifier, and used three classifiers: Logistic Regression, Support Vector Classifier, and Random Forest. They performed hyperparameter tuning and selected the model with the highest accuracy.

Additionally, they also had reimplemented the same methodology used in the recent paper by Hossain et al. (2022), where instead of 5s segments as it was in the latter paper, they used 0.5s segments of EDA signals. They engineered typical statistical features as with the paper by Taylor et al. (2015). The researchers included the optimized coefficients of an autoregressive model as features, excluding the bias or intercept coefficient. Finally, they used two time frequency transformation methods to extract time frequency features in order to capture non-stationary characteristics from the signals. A total of 50 features were engineered and extracted from the raw EDA signal data, then reduced to 40 using a Random Forest classifier as a feature selection method. The features before being fed as input for Support Vector Machine, Gradient Boosted Tree, Random Forest, and Logistic Regression classifiers were standard scaled and normalized using min-max. In order to select the best model for each classifier, the use of hyperparameter tuning has been repeated for each classifier together with the use of 5-fold cross validation to select the best model out of each classifier. The model that had the highest accuracy out of each classifier category was defined as the best model.

In addition to these, they proposed new models, which includes LSTM with a 1D-CNN and a 2D-CNN for analyzing signal spectrograms. The LSTM-1D CNN model recognized 72% of artifacts with 76% AUC (area under curve), 57% F1-Score, and 88% accuracy on the test set. Future work includes adding expert manual correction, developing movement protocols, and fine-tuning model architectures. This study reaffirmed that SVM, Gradient Boosted Tree, and Random Forest classifiers achieved the best accuracy on the validation set, consistent with previous findings.

In another study of Lee et al. (2020), artifact detection is a crucial aspect addressed in the research. The denoising method proposed in the study focuses on alleviating intrinsic respiration noise and extrinsic noise in Electrodermal Activity (EDA) signals collected by a wearable biosensor. The method involves detecting and attenuating irregular respiration-induced noise in EDA signals. Specifically, irregular respiration is identified and removed as respiration noise using a machine learning model that detects irregular respiration patterns from Photoplethysmography (PPG) signals collected simultaneously. This artifact detection process is essential for improving the accuracy of stress measurement by reducing noise interference in EDA signals, thus enhancing the reliability of stress metrics extracted from the data.

Despite these findings, traditional machine learning methods have limitations in healthcare signal processing. Sun et al. (2018) found that hand-designed EEG feature extraction methods resulted in poor analytical performance. They addressed this by using recurrent autoencoders for feature extraction. Hussein et al. (2018) further supported this by employing LSTM networks to capture high-level patterns in EEG signals. In their approach, a fully connected layer was used to extract robust, epileptic-relevant features, while a softmax layer provided predicted labels. This method maintained high detection performance, particularly in identifying artifacts like eye movements, muscle movements, and background noise. Additionally in a study by Jamshidzadeh et al. (2023) one of these limitations with regards to the use of traditional ML methods was specifically the inability of SVM models to extract significant features from data.

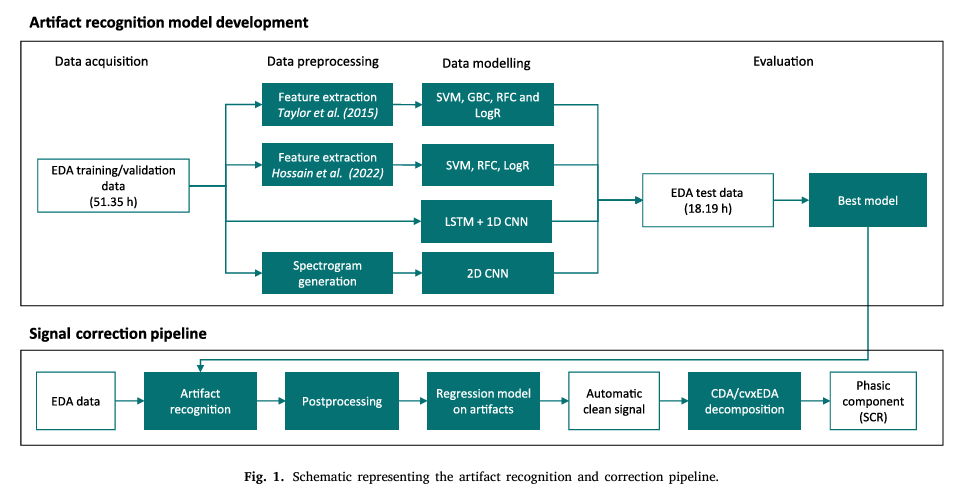
Moreover, while it has been established that convolutional neural networks achieve superior performance on high dimensional data such as images and used in different automated tasks, such as classification, detection, segmentation, data augmentation Szegedy et al. (2016) CNNs however according to Wang et al. (2020), Park & Yang (2019), Li et al. (2022) are still considered as a ‘Black box’ in terms of the underlying mechanism which makes it difficult to interpret the results and have confidence that they provide the optimal solution. A paper by Azam et al. (2023) also states that the ‘black box’ nature of CNNs is a key research interest currently where different research has attempted to provide different insight. There are several research questions related to the ‘black box’, such as the inner mechanism of CNN layers, feature interpretation and decision making schemes and as such CNNs are still poorly understood, not only by non-technical users but also by experts. This lack of knowledge according to Lange et al. (2018) may cause ambiguity and a hesitance in relying on the predictions of CNNs, especially in critical applications like the medical domain. And by opening up the ‘black box’ it can increase the confidence of users such as medical specialists in the results of neural networks as per studies conducted by [Ferdinand & Mercier, (n.d.](https://www.sciencedirect.com/science/article/pii/S2667305323000583?fbclid=IwZXh0bgNhZW0CMTAAAR237Nav-d71WwmVzTLNLOBqE1XXAkd6BSOqSv_C7nxX_ucXZ_Q7_5pZ-3o_aem_AQigPAAWF8bKS27hMiDqyvmg_qlmIqHGDdt3kI_JnosTqgs_apWmIkyg3SSq1gQ4LIR6basuDJs93-vtpaEE7NA7#bib0012)), [Brahimi et al. (2018](https://www.sciencedirect.com/science/article/pii/S2667305323000583?fbclid=IwZXh0bgNhZW0CMTAAAR237Nav-d71WwmVzTLNLOBqE1XXAkd6BSOqSv_C7nxX_ucXZ_Q7_5pZ-3o_aem_AQigPAAWF8bKS27hMiDqyvmg_qlmIqHGDdt3kI_JnosTqgs_apWmIkyg3SSq1gQ4LIR6basuDJs93-vtpaEE7NA7#bib0004)), and [Dependent et al. (2021](https://www.sciencedirect.com/science/article/pii/S2667305323000583?fbclid=IwZXh0bgNhZW0CMTAAAR237Nav-d71WwmVzTLNLOBqE1XXAkd6BSOqSv_C7nxX_ucXZ_Q7_5pZ-3o_aem_AQigPAAWF8bKS27hMiDqyvmg_qlmIqHGDdt3kI_JnosTqgs_apWmIkyg3SSq1gQ4LIR6basuDJs93-vtpaEE7NA7#bib0008)).

Finally, to address these challenges present in the aforementioned studies, the researchers propose a hybridized LSTM-SVM model, where the LSTM aims to address the shortcomings of traditional ML methods on feature extraction from time series data, specifically those involving EDA signals, and the integrated mechanism of traditional ML-based methods to the LSTM namely the Support Vector Machine (SVM) aims to address the shortcomings of the use of difficult to interpret architectures of CNNs.

## Statement of the Problem

1. What would be the performance of the hybridized LSTM-SVM model in comparison to other existing models that automatically detect artifacts in EDA signals in terms of its:
2. AUC
3. Precision
4. Recall
5. F1-Score
6. Accuracy
7. What would be the optimal Gamma and C hyperparameters for the SVM mechanism of the model to achieve higher validation metrics as opposed to the other state-of-the-art automatic artifact detection methods such as SVM, Random Forest, Gradient Boosted Tree, and LSTM-CNN?

## Theoretical Framework

The purpose of this study is to improve the detection of anomalies in electrodermal activity (EDA) signals by utilizing advanced machine learning methodologies, specifically through a hybridized Long Short Term Memory (LSTM) infused with Support Vector Machine (SVM). This strategy will be contrasted with conventional machine learning approaches like Support Vector Machines, Linear Regression, Random Forests, and Naive Bayes, which have been previously utilized in stress recognition research.

*Figure 3. Schematic representing artifact detection and correction pipeline*

*(Llanes-Jurado et.al., 2023)*

1. **Machine Learning and Deep Learning Theories**

**1.1. LSTM & SVM:** Long Short Term Memory (LSTM) networks and Support Vector Machines (SVM) are both prominent techniques in the realm of machine learning, each offering distinct advantages in handling sequential and non-linear data, respectively. The hybridization of LSTM with SVM offers a promising approach to utilize the strengths of both models for improved anomaly detection in electrodermal activity (EDA) signals, particularly in the context of stress detection.

1. **Signal Processing Theory**

**2.1. Electrodermal Activity (EDA):** The measurement of Electrodermal Activity (EDA) involves assessing the skin's electrical conductance, which fluctuates in response to sweat gland activity and is modulated by the sympathetic nervous system. This method is frequently utilized in the identification of stress and in psychophysiological investigations. For a precise analysis of EDA signals, it is imperative to conduct efficient artifact removal procedures to ensure that the collected data accurately represents genuine physiological responses, rather than being distorted by noise or artifacts stemming from motion or environmental factors.

**2.2. Artifact Detection in EDA Signals:** The presence of artifacts within EDA signals can have a notable impact on the precision of stress detection models. Traditional techniques for identifying artifacts typically entail manual scrutiny or the application of heuristic algorithms, which can be labor-intensive and may yield suboptimal results.

1. **Stress Detection Framework**

**3.1. Machine Learning in Stress Detection**: Conventional machine learning techniques such as Support Vector Machine, Linear Regression, Random Forests, and Naive Bayes have been extensively utilized for stress identification utilizing physiological signals. These approaches usually necessitate thorough feature manipulation and may not entirely capture the temporal dynamics of EDA signals. In contrast, Sequence-to-Sequence models can acquire knowledge directly from unprocessed data, potentially resulting in enhanced performance in identifying and rectifying anomalies.

**3.2. Comparative Analysis:** This analysis will evaluate the efficiency of Sequence-to-Sequence models in comparison to conventional machine learning methods. Essential criteria for evaluation will encompass precision, recall, and computational efficiency. The claim argues that the hybridized LSTM-SVM model will excel over conventional techniques in anomaly detection within EDA signals by effectively utilizing contextual information from both preceding and subsequent data points.

Through analyzing these models with conventional artificial intelligence methodologies, this investigation seeks to enrich the domain of tension identification by enhancing the precision and dependability of EDA signal analysis. This framework will guide the research design, data collection, analysis, and interpretation, ensuring a comprehensive evaluation of the proposed methods.

## Conceptual Framework

*Figure 4. Conceptual Framework of the Study*

The conceptual framework illustrates the process of the application of hybridized Long Short Term Memory (LSTM) with Support Vector Machine (SVM). The framework is divided in three stages: input,process,and output. Input stage involves the preprocessing of raw EDA data. The process stage involves the preprocessing of raw data, training baseline classifiers, and training the hybrid LSTM-SVM. Output stage involves evaluating the performance of the classifiers in terms of its Area Under Curve (AUC), accuracy, precision, recall, and F1-score.

## Hypotheses of the Study

**Null Hypothesis (H0)**

There is no difference between the performance of the hybridized LSTM-SVM model compared to the existing automatic detection and removal models in terms of AUC, F1-score, accuracy, precision, recall.

**Alternative Hypothesis (H1)**

There is a difference between the performance of the hybridized LSTM-SVM model compared to the existing automatic detection and removal models in terms of AUC, F1-score, accuracy, precision, recall.

## Scope and Delimitations

This study focuses on the application of hybridized Long Short Term Memory (LSTM) with Support Vector Machine (SVM) in the detection of artifacts in Electrodermal Activity signals for stress detection. The study will utilize the use of pre-existing datasets, specifically the Electrodermal Activity artifact correction BEnchmark or the EDABE datasets which contain electrodermal activity (EDA) recordings of hand and body motion artifacts. This study is limited only in detection of artifacts and the removal or the correction of artifacts as with the benchmark study of Llanes-Jurado (2023) will be omitted. The process of this study includes the collection of preprocessing electrodermal activity (EDA) data, identifying artifacts, and training the hybridized LSTM-SVM using the processed data to differentiate between authentic physiological signals and artifacts.

## Significance of the Study

This study holds significance in the improvement in Electrodermal Activity (EDA) for stress detection.This study will be beneficial for the following:

**Caretakers.** This study will allow caretakers to potentially be able to identify and distinguish what is noise from what is a real stress response.

**Healthcare Professionals.** This study may help healthcare professionals under the pressure of time in ambulatory situations to easily interpret and distinguish what is noise/artifacts from the stress response of a patient.

**Healthcare Technology Companies.** This study may grasp this advancement to develop more precise, non-surgical stress detection devices, leading to better stress management solutions and ultimately to improve patient outcomes and quality of life.

**Future Researchers**. This study will help future researchers to build on this hybrid approach to enhance the accuracy of data that leads to more reliable result and to overall performance of EDA-based stress detection, potentially leading to more advanced and practical applications in health monitoring, psychological assessment, and stress monitoring devices

## Definition of Terms

**Ambulatory Settings** - it refers to medical services performed on an outpatient basis, without admission to hospital or other facility. Ambulatory setting is also defined as any environment where patients receive healthcare services without being admitted to hospital. This includes clinics, doctor’s offices and home-base care environments where EDA signals might be collected.

**Artifact/Artefact** - refers to unwanted disturbances or noise in EDA data that can compromise the accuracy of the measurements. It can arise due to various factors including motion, quantization errors, sudden changes in EDA associated with movement, or other sources of interference. As any anomalies in the EDA signal data that do not originate from the physiological responses but from external or technical sources. These need to be detected and filtered out to ensure the accuracy of the stress detection.

**Electrodermal Activity** - pertains to the skin’s electrical properties that shift in response to sweat secretion. These changes are frequently associated with mental and physical arousal. EDA is measured as the variation in the electrical conductance of the skin over time, reflecting the physiological arousal related to stress. The signals are collected using sensors and analyzed to detect stress levels.

**Gated Recurrent Unit** - is a type of recurrent neural network (RNN) that was introduced by Cho et al. in 2014 as a simpler alternative to Long Short-Term Memory (LSTM) networks. GRU is used as component of the hybridized model for processing time series EDA data, offering a simpler yet efficient way to capture dependencies in the sequential data.

**Long-Short Term Memory** - is a type of deep neural network that is designed to capture historical information of time series data and is suitable for predicting long-term nonlinear series. LSTM are employed to analyze and predict patterns in EDA signals by retaining information over longer periods, which helps in identifying stress related changes in the data.

**Microsiemens (μS) -** It is the unit of measurement for skin conductance, which is a key component for EDA. This study’s goal is to use a machine learning approach to filter out noise and improve the reliability of stress detection from EDA signals.

**Non-Stationary** - refers to a process of time series of statistical properties, such as mean, variance, and autocorrelation that change over time.It can also arise due to trends, cycles, abrupt changes, or other time-varying behavior in the data. This involves identifying and addressing the time-varying nature of these EDA signals when detecting artifacts.

**Psychophysiological Signals -** refers to physiological responses of the human body that are influenced by psychological factors. These signals include EDA, heart rate, respiration rate and blood pressure but it is not limited. It specifically focuses on EDA signals, which are measurements of the skin’s electrical conductance caused by sweat gland activity. EDA is closely related to the sympathetic nervous system’s activity and is often used as an indicator of emotional arousal or stress detection.

**Recurrent Neural Network** - is a deep learning model that is trained to process and convert a sequential data input into a specific sequential data output. RNNs including their variants like LSTM and GRU, are utilized to handle the sequential nature of the EDA data, enabling the detection of stress over time.

**Sequential Models** - a class of machine learning models designed for tasks that involve sequential data, where the order of elements in the input is important. Sequential data includes textual data, time series data, audio signals, video streams or any other ordered data. Sequential models the one that processes the EDA signal data to detect artifacts and subsequently stress patterns.

**Stationary** - It is the contrast of nonstationary processes, where the statistical properties such as mean, variance and autocorrelation, do not change over time. By identifying the segments of the signal that deviated, this can pinpoint the artifacts. Also, by analyzing its properties of the signals this can differentiate between normal variations and stress-induced changes.

# CHAPTER 2

# REVIEW OF RELATED LITERATURE AND STUDIES

## Related Literature

## Electrodermal Activity Artifacts Detection using Machine Learning Techniques

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.

Include here other metrics they used

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.

A study by Llanes-Jurado et.al. (2023) utilized a dataset called Electrodermal Activity Artifact Correction Benchmark (EDABE) dataset comprising raw EDA signals and manually corrected signals as ground truth, collected from 43 participants in a VR study inducing stress. Four models were then developed and trained, two of which were approached in a manner that used traditional machine learning methods by Taylor et al. (2015) and Hossain et al. (2022). Llanes-Jurado et al. (2023) had essentially replicated the same methods used in the paper by Taylor et al. (2015) which employed the extraction of 62 hand crafted features in total (40 of which was chosen using a backward selection feature based on a Support Vector Classifier), then fed to three different classifiers: Logistic Regression, Support Vector Classifier, and a Random Forest Classifier. Subsequently, in order to select the best model for each classifier, Llanes-Jurado et al. (2023) used hyperparameter tuning for each category to select the best model out of each classifier. The model with highest accuracy was selected among other fitted/trained models of each of the three kinds of classifiers.

**Synthesis of the Study**

Despite these findings, traditional machine learning methods have limitations in healthcare signal processing. Sun et al. (2018) found that hand-designed EEG feature extraction methods resulted in poor analytical performance. They addressed this by using recurrent autoencoders for feature extraction. Hussein et al. (2018) further supported this by employing LSTM networks to capture high-level patterns in EEG signals. In their approach, a fully connected layer was used to extract robust, epileptic-relevant features, while a softmax layer provided predicted labels. This method maintained high detection performance, particularly in identifying artifacts like eye movements, muscle movements, and background noise. Additionally in a study by Jamshidzadeh et al. (2024) one of these limitations with regards to the use of traditional ML methods was specifically the inability of SVM models to extract significant features from data. They also added that there is always a dependency of the accuracy of the model on the choice of input combinations, which requires the use of robust input selection methods i.e. feature selection which can be prone to bias due to it being manually done by humans and so feature selection methods like SVC and Random Forest have been used as with studies by Taylor et al. (2015) and Hossain et al. (2022) in order to select appropriate features from the data. This is further reinforced in the studies by Koklu et al. (2022) and Agarwal et al. (2023) regarding water quality prediction as they state that predicting water quality, it was indeed essential to develop SVM models with thorough feature engineering and extraction methods for accurate water quality prediction due to their limitations in extracting important features from time series data, since they may not accurately handle complex data and may not perform optimally.

Moreover, while it has been established that convolutional neural networks achieve superior performance on high dimensional data such as images and used in different automated tasks, such as classification, detection, segmentation, data augmentation Szegedy et al. (2016) CNNs however according to Wang et al. (2020), Park & Yang (2019), Li et al. (2022) are still considered as a ‘Black box’ in terms of the underlying mechanism which makes it difficult to interpret the results and have confidence that they provide the optimal solution. A paper by Azam et al. (2023) also states that the ‘black box’ nature of CNNs is a key research interest currently where different research has attempted to provide different insight. There are several research questions related to the ‘black box’, such as the inner mechanism of CNN layers, feature interpretation and decision making schemes and as such CNNs are still poorly understood, not only by non-technical users but also by experts. This lack of knowledge according to Lange et al. (2018) may cause ambiguity and a hesitance in relying on the predictions of CNNs, especially in critical applications like the medical domain. And by opening up the ‘black box’ it can increase the confidence of users such as medical specialists in the results of neural networks as per studies conducted by [Ferdinand & Mercier, (n.d.](https://www.sciencedirect.com/science/article/pii/S2667305323000583?fbclid=IwZXh0bgNhZW0CMTAAAR237Nav-d71WwmVzTLNLOBqE1XXAkd6BSOqSv_C7nxX_ucXZ_Q7_5pZ-3o_aem_AQigPAAWF8bKS27hMiDqyvmg_qlmIqHGDdt3kI_JnosTqgs_apWmIkyg3SSq1gQ4LIR6basuDJs93-vtpaEE7NA7#bib0012)), [Brahimi et al. (2018](https://www.sciencedirect.com/science/article/pii/S2667305323000583?fbclid=IwZXh0bgNhZW0CMTAAAR237Nav-d71WwmVzTLNLOBqE1XXAkd6BSOqSv_C7nxX_ucXZ_Q7_5pZ-3o_aem_AQigPAAWF8bKS27hMiDqyvmg_qlmIqHGDdt3kI_JnosTqgs_apWmIkyg3SSq1gQ4LIR6basuDJs93-vtpaEE7NA7#bib0004)), and [Dependent et al. (2021](https://www.sciencedirect.com/science/article/pii/S2667305323000583?fbclid=IwZXh0bgNhZW0CMTAAAR237Nav-d71WwmVzTLNLOBqE1XXAkd6BSOqSv_C7nxX_ucXZ_Q7_5pZ-3o_aem_AQigPAAWF8bKS27hMiDqyvmg_qlmIqHGDdt3kI_JnosTqgs_apWmIkyg3SSq1gQ4LIR6basuDJs93-vtpaEE7NA7#bib0008)).

**Present why use LSTM to address ml methods and feature extraction gap**

In relation to CNNs since it is after all a subset of deep learning, deep learning is a more complex subset of machine learning. Deep learning models, albeit require more training time, often have provided higher accuracy as detailed by a paper by Kamath et al. (2018) because they can perform automated feature extraction and classification concurrently, whereas a feature selection process is required prior to training a machine learning algorithm.

According to Jamshidzadeh et al. (2024) Recurrent Neural Networks (RNNs) represent a specialized class of Artificial Neural Network (ANN) models meticulously designed for the analysis of sequential data. RNNs also incorporate cyclical connections within their architecture, which equip them with the unique capacity to manage and process sequences of variable lengths, as detailed by Wu et al. (2020). Fundamental to the RNN’s operation is an internal hidden state, serving as a form of memory. This hidden state undergoes continual updates at each time step and is under the influence of both the incoming input data and the hidden state from the previous time step. Conceptually, the architecture of an RNN can be envisioned as an interlinked chain of repeating modules or cells. These recurrent connections within the RNN structure facilitate the preservation of information from previous time steps. At any given time t the hidden state t-1 is computed as a function of the current input x\_t at time t and the preceding hidden state h\_(t-1) at time t-1 employing a set of learned weights and an activation function. This sequential data processing mechanism culminates in the RNN’s ability to systematically process input data as it unfolds in a temporal sequence as detailed also in a paper by Weerakody et al. (2021). Specifically, the input x\_t is fused with the hidden state from the previous time step h\_(t-1) to compute the new hidden state h\_t, a process underpinned by a set of adaptively learned weights and an activation function. Following the update of h\_t, the RNN is poised to generate an output corresponding to the current time step t. This description according to Jamshidzadeh et al. (2024) encapsulates the essence of how RNNs operate in the context of sequential data analysis.

More studies such as the one by Mohsen et al. (2023) which involved the classification of EEG signals using an LSTM and a traditional ML method the SVM classifier, shows that the LSTM provided the best performance, with a testing accuracy of 99.00%. Moreover the weighted average precision, recall, and F1-score for the LSTM are 99.00%. The results of the SVM classifier in terms of accuracy, sensitivity, and specificity reached 91%, 93.52%, and 91.3%. Given such results they have shown that the LSTM classifier provides better performance than SVM in the classification of EEG signals. Reinforcing the idea that when it comes to feature extraction the LSTM itself gives superior results as opposed to traditional machine learning methods that require manual feature extraction and engineering.

And going back to Jamshidzadeh et al. (2024) their study has shown that when it came to predicting water quality parameters their proposed models which consists of a BILSTM-SVM, LSTM-SVM, BILSTM, and both a standalone LSTM, and SVM had an accuracy index of 0.97, 0.92, 0.89, 0.85, and 0.82, respectively, at the training level. Where they concluded that the BILSTM-SVM model performed better than the LSTM-SVM model because it considered both past and future observations, secondly that the hybrid model (BILSTM-SVM and LISTM-SVM) performed better than the LSTM, BILSTM, and SVM models, and thirdly that the SVM model had lower Accuracy Index (AI) and R2 values compared to other models, and all other models outperformed the SVM model. Similarly at the testing level, the AI values of the BILSTM-SVM, LSTM-SVM, BILSTM, LSTM, and SVM models were 0.94, 0.86, 0.83, 0.81, and 0.78, respectively, showing again evidence that SVM models paled in comparison to LSTM models in terms of extracting features from time series data such as water quality parameters.

In another study by Juneau et al. (2021) which sought to

Detect foot strikes in lower Extremity Amputee Populations

The best performing decision tree model had a maximum tree depth of 10 and class weighting of 1:20 (label 0: label 1). The decision tree classification accuracy was 98.7%, sensitivity was 82.8%, specificity was 99.2%, and precision was 78.6%. The LSTM model with the best performance had a batch size of 64, dropout of 0.4, one LSTM layer with 100 hidden LSTM nodes, one dense layer with 50 hidden dense nodes, and a class weighting of 1:2 (label 0: label 1). The LSTM classification accuracy was 99.0%, sensitivity was 86.4%, specificity was 99.4%, and precision was 83.7%.

**Present why svm?**

Indicate studies that address computational simplicity of svm

**Present the use of LSTM-SVM**

moreover the svm mechanism addresses the concern of interpretability of cnns as with llanes jurados paper

why combine?

it has been shown that standalone lstm is

**Hybridization of Long Short Term Memory and Support Vector Machine for Time Series Data**

* **LSTM by itself**
* **SVM by itself**
* **LSTM-SVM**

# 

# CHAPTER 3

# METHODOLOGY

## Research Design

In this study, the researchers will adopt an experimental and quantitative method to achieve the objective of automatically detecting artifacts from electrodermal activity (EDA) signals used for stress detection. The study will employ hybridized Long Short-Term Memory (LSTM) and Support Vector Machine (SVM) model and compare their performance to existing models, including binary classifiers such as SVM, k-Nearest Neighbors (KNN), Logistic Regression, Random Forest, and Naive Bayes. The goal is to determine the efficacy of the hybrid LSTM-SVM model in improving the overall performance in terms of AUC, accuracy, precision, recall, and F1-score, also including the reliability of stress detection from EDA signals by effectively handling artifacts. To attain this objective, the researchers propose the application of hybridized LSTM-SVM to address the concern with the non-stationary characteristic of EDA data, meaning it could change through the course of time, which is deemed unfitted for the existing traditional models. The study consists of independent variables which are the EDABE dataset, the existing models by Taylor et. al. (2015), Hossain et. al. (2022), and Llanes-Jurado et. al. (2023), and the proposed model, which is the hybridization of LSTM and SVM. Dependent variables comprise the performance of the baseline models and the proposed model in terms of AUC, accuracy, precision, recall, and F1-score. The researchers expect that results from the proposed model will either match, excel, or underperform over the performance of the existing models.

## Sources Of Data

This study will utilize the Electrodermal Activity artifact correction BEnchmark (EDABE) dataset as its primary source of data. The EDABE dataset consists of electrodermal activity (EDA) recordings of hand and body motion artifacts. EDABE includes 74.46 hours of EDA recordings, which are influenced by hand and body movement artifacts, from 43 subjects. The dataset is split into a training set with 33 subjects (56.27 hours) and a test set with 10 subjects (18.19 hours). The recordings were obtained using a Shimmer3 GSR+ Unit at a sampling rate of 128 Hz. Each file's name contains the user ID and the expert who corrected the signal. Additionally, the file includes the signal with the following variables.

| **time** | Timestamp of the signal |
| --- | --- |
| **rawdata** | Raw data obtained by Shimmer3 GSR+ Unint |
| **cleandata** | Reconstructed clean signal performed by a human expert |
| **binarytarget** | Label of each sample as artefact or no artifact |
| **signal\_automatic** | Automatic cleaning of the signal performed by the automatic pipeline |
| **predArtifacts** | Label predicted by the automatic cleaning pipeline |
| **postProcessedPredArtifacts** | Label predicted by the automatic cleaning pipeline after post processing |

*Table 1. Signal components in EDABE dataset*

## Research Instrument

This study will be implemented using Python as the programming language. Python is a highly versatile and widely utilized programming language in data science and machine learning research for its readability, simplicity, and extensive library support. Its comprehensive environment of libraries and frameworks makes it ideal for implementing complex models, performing data analysis, and visualizing results.

It will also utilize the dataset, EDABE (ElectroDermal Activity and Body motion Artifact Dataset), which comprises 74.46 hours of EDA recordings impacted by hand and body motion artifacts from 43 subjects. It is split into a training set with 33 subjects (56.27 hours) and a test set with 10 subjects (18.19 hours). The data was recorded using a Shimmer3 GSR+ Unit at a sampling rate of 128 Hz.

For the tools and technologies, the study will be utilizing TensorFlow, scikit-learn, and Google Colab. TensorFlow, an open-source machine learning framework developed by Google, is extensively used for building and deploying machine learning models, particularly deep learning models. In this study, TensorFlow can be utilized to implement and train a Long Short-Term Memory (LSTM) network, which is well-suited for analyzing time series data such as EDA signals. On the other hand, scikit-learn is a robust machine learning library in Python that offers simple and efficient tools for data mining, analysis, and model evaluation. In this study, scikit-learn will be employed to implement the Support Vector Machine (SVM) model, which will be combined with the LSTM network to detect artifacts. Lastly, Google Colab is a cloud-based Jupyter notebook environment that allows you to write and execute Python code directly in your browser. It provides free access to GPUs and TPUs, making it a valuable resource for computationally intensive tasks like training deep learning models.

## Procedures

**Replicating Taylor et al. (2015) baseline models**

Data Collection: (reference)

* Will use publicly available dataset (EDABE)

Preprocessing:

* Load data into software (e.g., EEGLAB, jupyter notebook).
* Segment EDA signals into 0.5s

Feature Extraction & Engineering

* extraction features from signal: minimum, maximum, mean, median, standard, deviation, and range
* Compute aforementioned statistical features over the first and second derivative of the segment.
* Transform raw signal of 0.5s segments to a low pass filtered version of 16hz then extract min, max, mean, median, standard deviation, and range
* Differentiate the 16hz version of the signal over first and second once again amd compute aforementioned statistical features
* Extract time frequency related features using wavelet decomposition with haar window of level 3 (three levels).
* In each level compute mean, median, max, standard deviation and number of coefficients above zero
* Apply SVC as a feature selection method from the 0.5s segment of signals

Model Training & Evaluation

* feed selected features to three different classifiers: Logistic Regression, Support Vector Classifier, and a Random Forest Classifier.
* Use grid search for finding optimal hyperparameters for each classifier category:
* 0.01, 0.1, 1, 10 and 100 for the C hyperparameter in the Logistic Regression classifier
* 200, 400, and 600 & 10, 30 and 50 for the Estimators and Max Depth hyperparameters respectively for the Random Forest classifier
* 1, 10, 100 and, 1000 & 0.001, 0.01, 0.1, and 1 for the C and Gamma hyperparameters respectively in the SVM model.
* The model with highest validation AUC, was selected among other fitted/trained models of each of the three kinds of classifiers
* The model among each classifier category with the highest validation AUC is selected

**Replicating Hossain et al. (2022) baseline models**

Data Collection: (reference)

* Will use publicly available dataset (EDABE)

Preprocessing

* Load data into software (e.g., EEGLAB, jupyter notebook).
* Segment EDA signals into 0.5s

Feature Extraction & Engineering

* extraction features from raw signal: mean, median, standard deviation, minimum, maximum, range, and the Shannon entropy
* Compute aforementioned statistical features over the first and second derivative of the segment
* Train an autoregressive model and extract its optimized coefficients as features excluding bias/intercept coefficient
* Extract time frequency related features using wavelet decomposition with Haar window of level 3 (three levels)
* In each level compute mean, standard deviation, median, and range
* Extract time frequency related features using variable frequency complex demodulation (VFCDM) from 0.5s segment signals using 64hz, 48hz, 32hz, and 16hz frequencies (transform raw signal by low pass filtering).
* In each frequency compute the standard deviation and mean
* Apply Random Forest classifier as a feature selection method to remove redundant features.

Preprocessing

* Final extracted features are scaled and normalized using min-max

Model Training & Evaluation

* The features before being fed as input for Support Vector Machine, Gradient Boosted Tree, Random Forest, and Logistic Regression classifiers
* Use grid search to find optimal hyperparameters for each classifier category together with the use of 5-fold cross validation
* 0.01, 0.1, 1, 10 and 100 for the C hyperparameter in the Logistic Regression classifier
* 200, 400, and 600, 0.01 and 0.1 & 3, 5 and 10 for the Estimators, the Learning Rate, and the Max Depth hyperparameters respectively for the Gradient Boosted classifier
* 200, 400, and 600 & 10, 30 and 50 for the Estimators and the Max Depth hyperparameters respectively for the Random Forest classifier
* 1, 10, 100 and, 1000 & 0.001, 0.01, 0.1, and 1 for the C and Gamma hyperparameters respectively in the SVM model.
* The model with highest validation AUC, was selected among other fitted/trained models of each of the three kinds of classifiers
* The model among each classifier category with the highest validation AUC is selected

**Replicating Llanes-Jurado et al. (2023) baseline model**

Data Collection: (reference)

* Will use publicly available dataset (EDABE)

Preprocessing:

* Load data into software (e.g., EEGLAB, jupyter notebook).
* Segment EDA signals into 0.5s
* Expand dimensionality of EDA signals for LSTM

Model Training

details the model architecture. Its first two layers were LSTM layers of 16 neurons that returned the hidden state output for each input time step. Subsequently, the network included four convolutional

levels, each of which featured three convolutional layers with a batch normalization operation performed after each convolution. Finally, each level included a dropout value of 0.05 and a max-pooling operation of size 2. The numbers of filters in each level were 32, 64, 128, and 256; kernel size was 5. Finally, the model featured two fully connected layers of 256 and 16 neurons and a final fully connected layer comprising a single perceptron with a sigmoid activation function.

The model was trained with the rmsprop optimizer at a learning rate of 5 × 10−5 and a batch size of 16. Due to the imbalance, the cost function used to train the model was the Dice-Sørensen coefficient (DSC). The model had an early stopping threshold of 30 epochs. The percentage of artifacts in the training set was 12.60%. No filter was applied to the raw signal. For each 5 s segment, min–max scaling was applied.

**Proposed approach**

Data Collection

Data preprocessing

LSTM mechanism

2 LSTM layers 16 neurons

Return hidden state of last time step

SVM mechanism

Use hidden state as features to SVM mechanism model with different Gamma and C parameters e.g. 1, 10, 100 and, 1000 & 0.001, 0.01, 0.1, and 1

## 

## 

## System Architecture

* Include the sub-architecture

## Ethical Considerations

In conducting this research on developing a hybridized LSTM-SVM model for artifact detection, we will ensure data privacy by using anonymized, consented datasets and adhering to all licensing agreements for data usage. The model's accuracy and limitations will be transparently reported, with considerations for minimizing false positives and negatives to mitigate adverse impacts on downstream applications. We will acknowledge the dual-use nature of the technology and propose safeguards against misuse. Performance comparisons with existing models will be conducted under identical conditions using standardized metrics to ensure fairness.

## Data Analysis (Procedure and Treatment)

Llanes-Jurado et al. (2023) had essentially replicated the same methods used in the paper by Taylor et al. (2015) which employed the extraction of 62 hand crafted features in total

minimum, maximum, mean, median, standard

deviation and range.

These statistical features were also computed over

the first and second derivative of the segment.

A low pass filtered version of the 0.5s segments of signals of 16hz (hertz) were then again used to compute the min, max, mean, median, std, and then differentiated once to again compute these statistical features and then finally differentiated for the second time to again compute these statistical features to achieve 18 features for this low pass filtered 16hz version of the 0.5s segments of the EDA signals

(40 of which was chosen using a backward selection feature based on a Support Vector Classifier) from a 0.5s segment of signals rather than 5s as it was in the latter paper, then fed to three different classifiers: Logistic Regression, Support Vector Classifier, and a Random Forest Classifier. Subsequently in order to select the best model for each classifier Llanes-Jurado et al. (2023) used hyperparameter tuning for each classifier to select the best model out of each classifier; 0.01, 0.1, 1, 10 and 100 for the C hyperparameter in the Logistic Regression classifier; 200, 400, and 600 & 10, 30 and 50 for the Estimators and Max Depth hyperparameters respectively for the Random Forest classifier; 1, 10, 100 and, 1000 & 0.001, 0.01, 0.1, and 1 for the C and Gamma hyperparameters respectively in the SVM model. The model with highest accuracy was selected among other fitted/trained models of each of the three kinds of classifiers, and finally

Moreover they also had reimplemented the same methodology used in the recent paper by Hossain et al. (2022) where instead of 5s segments as it was in the latter paper they used 0.5s segments of EDA signals. They engineered typical statistical features as with the paper by Taylor et al. (2015) such as mean, median, standard deviation, minimum, maximum, range, and the Shannon entropy from the raw signal itself, as well as the signals first and second order derivatives. Moreover they included as features the optimized coefficients of an autoregressive model (excluding however the bias/intercept coefficient). Finally they used two time frequency transformation methods to extract time frequency features in order to capture non-stationary characteristics (or variables of the data that do not change over time) from the signals. Namely these were wavelet transformation and variable frequency complex demodulation (VFCDM). The mean, standard deviation, median, and range were then computed from each level from the result of a three level wavelet decomposition using a Haar window, and finally VFCDM was applied to the 0.5s segment signals using 64hz, 48hz, 32hz, and 16hz frequencies to extract from these decompositions the last needed features: the standard deviation and mean. A total of 50 features were engineered and extracted from the raw EDA signal data, then reduced to 40 using a Random Forest classifier as a feature selection method to remove redundant features. The features before being fed as input for Support Vector Machine, Gradient Boosted Tree, Random Forest, and Logistic Regression classifiers were standard scaled and normalized using min-max.

In order to select also the best model for each classifier Llanes-Jurado et al. (2023) again used hyperparameter tuning for each classifier together with the use of 5-fold cross validation to select the best model out of each classifier; 0.01, 0.1, 1, 10 and 100 for the C hyperparameter in the Logistic Regression classifier; 200, 400, and 600, 0.01 and 0.1 & 3, 5 and 10 for the Estimators, the Learning Rate, and the Max Depth hyperparameters respectively for the Gradient Boosted classifier; 200, 400, and 600 & 10, 30 and 50 for the Estimators and the Max Depth hyperparameters respectively for the Random Forest classifier; 1, 10, 100 and, 1000 & 0.001, 0.01, 0.1, and 1 for the C and Gamma hyperparameters respectively in the SVM model. The model that had the highest accuracy out of each classifier category was defined as the best model.

This section proposes the use of a hybridized LSTM-SVM and BI-LSTM-SVM in the detection in the last 0.5 s of a 5 s signal segment. This model’s main purpose is to learn from the signal’s temporal evolution. The architecture of this model was inspired by the work of Antczak (2018) and Bento, Belo, and Gamboa (2020), who both used CNN and LSTM to extract features from a raw ECG signal.

We then use the extracted features by the LSTM/BI-LSTM as input to the SVM classifier

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