**APPLICATION OF SEQUENCE-TO-SEQUENCE MODELS IN THE DETECTION OF ARTEFACTS IN ELECTRODERMAL ACTIVITY SIGNALS FOR STRESS DETECTION**

**BiRGEAR: Bidirectional Recurrent Gradient Boosted Network for Electrodermal Artifact Recognition in the Domain of Stress Detection**

A Thesis Proposal

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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). 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.

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. Frequently used techniques include electroencephalography, skin resistance measures, blood pressure, heart rate, eye activity, and motion analysis. Among the techniques described, Galvanic Skin Response, also known as Electrodermal Activity or Skin Conductance, is a method of detecting the electrical attributes of human skin. 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.

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 responses, there have been issues with the use of EDA signals. As new wearable technologies for the detection of psychophysiological signals are utilized in ambulatory settings, allowing for unobtrusive and continuous monitoring of the response, the quality of data acquired from the sensors may be influenced by "noises" or artifacts in terms of long-term data. Artifacts are defined as changes discovered in recorded biosignals that did not originate from the signal source under test (Boucsein, 2012). These artifacts might be generated by unstable electrode contact, environmental temperature and humidity, or movement (Hossain, 2022). To detect artifacts, according to Boucsein (2012), a widely cited textbook in regards to electrodermal activity, it requires a visual inspection of the data gathered. Signal processing techniques such as low-filter processing may also be utilized to avoid the need to do a visual inspection, but doing so may alter the physiological response. Recent studies concentrated on the development of models that automatically identify and remove the artifacts. (Gashi et. al., 2020)

There have been several studies that focused on the automatic recognition and elimination of the artifacts. 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 are already existing state-of-the-art models by Taylor et al. (2015) and Hossain et al. (2022), along with the newly proposed models which are LSTM with a 1D CNN and 2D CNN analyzing the signal’s spectrogram. Previous models detected whether segments of signals include artifacts, however, it did not provide a final clean signal enabling the computation of the phasic component. The LSTM-1D CNN model recognizes 72% of artifacts with 88% accuracy in the test set. Future works comprise of developments such as additional expert for manual correction to reduce bias, generation of protocols for movement, and considerations for researching the development of fine-tuned architectures for different models.

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.

In this study, the researchers propose the use of encoder-decoder architecture, specifically the implementation of Sequence-to-Sequence (Seq2Seq) models in the detection of artifacts in electrodermal activity signal data, in contrast to the previously developed approaches to applying machine learning methods, such as the deployment of algorithms namely Support Vector Machine, Linear Regression, Random Forests, Naive Bayes, and others adapted from previous studies, in the field of stress detection. In this method, we will be investigating the performance of the use of encoder-decoder architecture using Bidirectional LSTM (Long Short Term Memory and Bidirectional Gated Recurrent Unit).

**Statement of the Problem**

1. What is the optimal learning rate for training the encoder-decoder to achieve higher performance metrics than other state of the art models
2. What is the optimal number of layers for training the encoder-decoder to achieve higher performance metrics than other state of the art models

**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 an encoder-decoder framework that incorporates Sequence-to-Sequence (Seq2Seq) models with Bidirectional Long Short-Term Memory (LSTM) and Bidirectional Gated Recurrent Unit (GRU). 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.

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

**1.1 Sequence-to-Sequence (Seq2Seq) Models**: Seq2Seq architectures are a category of neural network structure crafted for converting sequences from one domain to another. Originally devised for language interpretation, these architectures are currently widely utilized in various fields, such as temporal data analysis and signal processing. The fundamental elements of Seq2Seq architectures include the encoder and decoder neural networks. In the context of this research, the encoder analyzes the input EDA signals to generate a context array, while the decoder utilizes this context array to forecast the output sequence, which, in this instance, would constitute the purified EDA signals free from anomalies.

**1.2. Bidirectional LSTM and GRU**: LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit) represent variations of recurrent neural networks (RNNs) renowned for their ability to grasp prolonged dependencies. Bidirectional adaptations of these networks handle data in both forward and reverse directions, furnishing a more thorough comprehension of the sequence context. This bidirectional handling proves particularly beneficial for identifying patterns in time-series data like EDA signals, where historical and forthcoming contexts hold significance.

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. The proposed utilization of Seq2Seq models incorporating Bidirectional LSTM and GRU is aimed at streamlining and enhancing the accuracy of artifact detection through the exploitation of deep learning's capacity to capture intricate, non-linear patterns within the data.

1. **Stress Detection Framework**

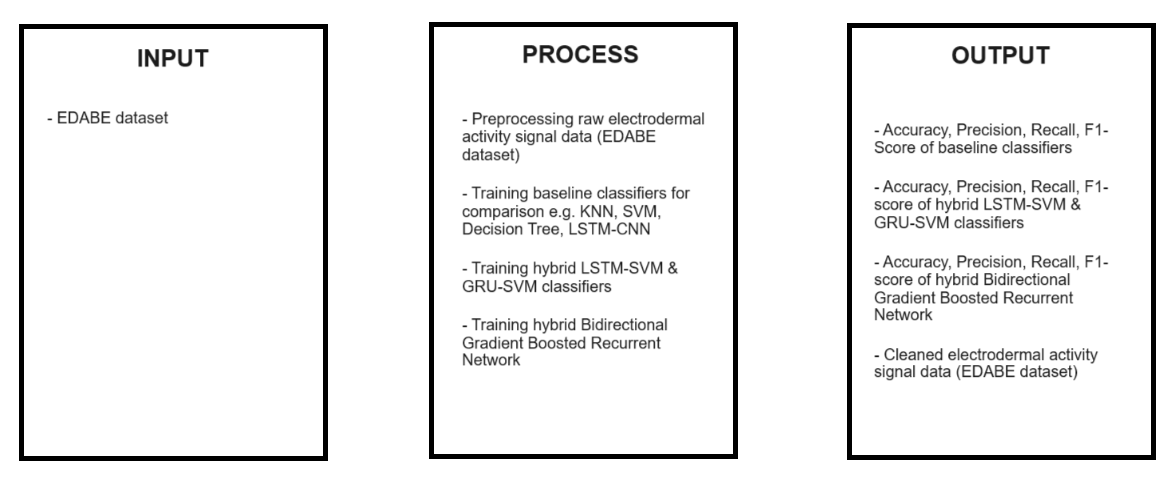
**3.1. Machine Learning in Stress Detection**: Conventional machine learning techniques such as Support Vector Machine, Linear Regression, Random Forests, and Naive Bayes have been extensively utilized for stress identification utilizing physiological signals. These approaches usually necessitate thorough 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 Sequence-to-Sequence models, particularly those employing Bidirectional Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), will excel over conventional techniques in anomaly detection within EDA signals by effectively utilizing contextual information from both preceding and subsequent data points.

The theoretical framework for this investigation integrates principles from artificial intelligence, data processing, and tension identification to evaluate the efficacy of Seq2Seq models with Bidirectional LSTM and GRU in anomaly detection for EDA signals. Through analyzing these s 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**

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*Figure 1. Conceptual Framework*

In this framework, we present the variables of the study and their relationships. We have the proposed a Sequence-to-Sequence model that uses both a Bidirectional LSTM and Bidirectional GRU, the traditional models to be compared with, and the raw EDA signals to be used as the independent variables. On the other hand, detection accuracy, precision, recall, and the final cleaned data falls under the dependent variable. We can see that there is a direct relationship between the variables that are included in the study. The proposed Seq2Seq model with the Bidirectional LSTM/GRU used in the raw EDA signal data from a dataset and Traditional ML Models that will be compared with it directly affects the performance accuracy, precision, and result of the cleaned data.

**Hypotheses of the Study**

**Null Hypothesis (H0)** - There is no significant difference between the performance of existing artifact-detecting methods and techniques and the proposed tool for the detection of artifacts in electrodermal activity signals.

**Alternative Hypothesis (H1)** - There is a significant difference between the performance of existing artifact-detecting methods and techniques and the proposed tool for the detection of artifacts in electrodermal activity signals.

**Scope and Delimitations**

This study focuses on the application of sequence to sequence models using in the detection of artifacts in Electrodermal Activity signals for stress detection.The study will be delimited only to the use of lower level architectures, the encoder-decoder. The study will employ pre-existing datasets instead of getting new data from wearable sensors. This includes the collection of preprocessing electrodermal activity (EDA) data, identifying artifacts, and training the encoder-decoder model to differentiate between authentic physiological signals and artifacts. This study aims to provide a clear and specific analysis of its efficacy in artifact detection.

**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.

**Future Researchers**. This study will help future researchers to gain additional knowledge for future advancement about the application of sequence to sequence model in Electrodermal Activity (EDA).

**Definition of Terms**

**Ambulatory Settings** - it refers to medical services performed on an outpatient basis, without admission to hospital or other facility. These settings include offices of physicians and other healthcare professionals.

**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.

**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.

**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.

**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.

**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.

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**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.

**Below are backups in case encoder decoder does not get approved or has holes panelists can point out. So idea of main proposal would be to use lstm combined with decision tree or svm that will be compared to baseline models such as lstm-cnn, svm, knn, decision tree in artefact detection/recognition/identificationeeclassification**

**Tasks to do:**

Describing EDABE

EDABE dataset: "Electrodermal Activity artifact correction BEnchmark" (EDABE) is a dataset for training and testing artifact recognition and correction models to automatically remove major artifacts in electrodermal activity (EDA) signals. It is the first public benchmark to compare methods.

EDABE contains a total of 74.46 hours of EDA recording affected by hand and body motion artifacts from 43 subjects. It is divided into a training set with 33 subjects (56.27 h), and test set with 10 subjects (18.19 h). The data was collected using a Shimmer3 GSR+ Unit at 128 Hz.

The dataset is used to develop a fully automatic pipeline that emulates the manual correction done by the expert, providing a final clean signal. The paper that describe the pipeline is currently in a peer-review process.

Features of the public dataset

time: timestamp of the signal.

rawdata: raw data obtained by Shimmer3 GSR+ Unit.

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 postprocessing.

Supporting the claim that electrodermal data is time series data

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.

HEART RATE Time series analysis is also used in the medical ﬁeld to monitor the heart rate of patients who may be on certain medications to make sure that heart rate doesn’t ﬂuctuate too wildly during any given time of the day.

Jose, Jonath. (2022). INTRODUCTION TO TIME SERIES ANALYSIS AND ITS APPLICATIONS.

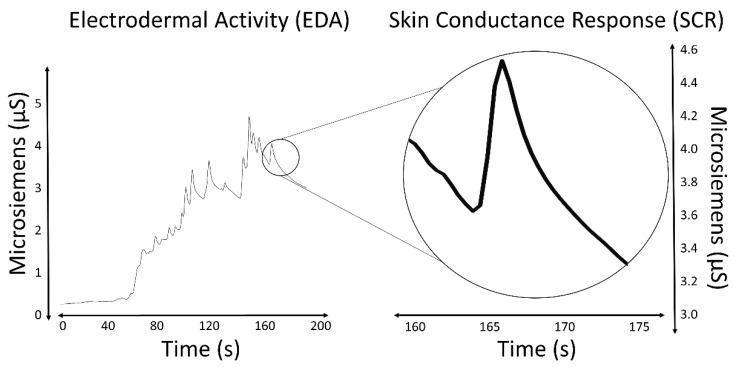
The most salient characteristic of an EDA signal is the occurrence of skin conductance responses (SCRs) resulting from an underlying sympathetic reaction to a stimulus. The SCRs are the rapid and smooth transient events noticeable in the EDA signal (Figure 1). At least three pathways lead to the production of SCRs: hypothalamic control, contralateral and basal ganglion influences (involves one pathway of excitatory control by the premotor cortex and another pathway of exhibitory and excitatory influences in the frontal cortex), and the reticular formation in the brainstem [13,15,16].

Posada-Quintero H. Ph.D. Thesis. University of Connecticut; Storrs, CT, USA: 2016. Electrodermal Activity: What It Can Contribute to the Assessment of the Autonomic Nervous System. [Google Scholar] [Ref list]

Sequeira H., Roy J.-C. Cortical and Hypothalamo-Limbic Control of Electrodermal Responses. In: Roy J.-C., Boucsein W., Fowles D.C., Gruzelier J.H., editors. Progress in Electrodermal Research. Springer; New York, NY, USA: 1993. pp. 93–114. (NATO ASI Series). [Google Scholar] [Ref list]

Roy J.-C., Sequeira H., Delerm B. Neural Control of Electrodermal Activity: Spinal and Reticular Mechanisms. In: Roy J.-C., Boucsein W., Fowles D.C., Gruzelier J.H., editors. Progress in Electrodermal Research. Springer; Boston, MA, USA: 1993. pp. 73–92. (NATO ASI Series). [Google Scholar] [Ref list]

These pathways imply different functional roles associated with the central mechanisms: activation of the reticular formation is associated with gross movements and increased muscle tone, hypothalamic activity controls thermoregulatory sweating, amygdala activation reflects affective processes, premotor cortex activity occurs in situations requiring fine motor control, and prefrontal cortical activity is associated with orienting and attention [11,17,18]. All these processes influence the EDA signal.



Edelberg R. Electrodermal Mechanisms: A Critique of the Two-Effector Hypothesis and a Proposed Replacement. In: Roy J.-C., Boucsein W., Fowles D.C., Gruzelier J.H., editors. Progress in Electrodermal Research. Springer; New York, NY, USA: 1993. pp. 7–29. (NATO ASI Series). [Google Scholar] [Ref list]

Boucsein W. Electrodermal Activity. Springer; Boston, MA, USA: 2012. [Google Scholar] [Ref list]

Davidson R.J. In: Psychophysiology: The Mind–Body Perspective. Hugdahl K., editor. Harvard University Press; Cambridge, MA, USA: 1995. [Google Scholar] [Ref list]

Measures of the SCRs are used to evaluate a subject’s response to event-related experiments (“startle-like” stimuli) or tonic stimuli tests (like a change in condition, workload, cognitive stress, and so forth). In event-related experiments, the occurrence of an SCR is expected after the stimulus is applied. In such experiments, the SCRs are usually called the event-related SCRs (ERSCRs) [13]. Quantitative measures are obtained from SCRs by computing their amplitude, rise time (also referred to as onset-to-peak time), and other metrics. Figure 2 illustrates some of the quantitative measures available from an individual SCR. In the figure, time is relative to the stimulus and amplitude values are relative to the SCR onset level.

Posada-Quintero H. Ph.D. Thesis. University of Connecticut; Storrs, CT, USA: 2016. Electrodermal Activity: What It Can Contribute to the Assessment of the Autonomic Nervous System. [Google Scholar] [Ref list]

Finding papers that use KNN, SVM, Decision Tree, and other ML methods for time series data more importantly electrodermal activity signals or signal based data like eeg, ecg

In the present work, the field of machine learning is regarded as a subset of the field of artificial intelligence, and a superset of the field of deep learning methods. In that scope, we present the SVM and Decision Tree-based approaches to the problem of time series forecasting for the machine learning family of methods and the basic deep learning models that are used by the publications presented in the rest of the study. The models we selected to present do not form an exhaustive list of machine learning techniques; rather, they represent some of the main algorithmic categories used in the recent scientific literature for benchmarking the ARIMA models against machine learning techniques.

Kontopoulou VI, Panagopoulos AD, Kakkos I, Matsopoulos GK. A Review of ARIMA vs. Machine Learning Approaches for Time Series Forecasting in Data Driven Networks. Future Internet. 2023; 15(8):255. <https://doi.org/10.3390/fi15080255>

<https://www.mdpi.com/1999-5903/15/8/255#B3-futureinternet-15-00255>

A stationary time series can be thought of as a combination of signal and noise. The ARIMA model handles the time signal, after first separating it from the noise, and outputs its prediction for a subsequent time point.

Rundo, F.; Trenta, F.; di Stallo, A.L.; Battiato, S. Machine learning for quantitative finance applications: A survey. Appl. Sci. 2019, 9, 5574. [Google Scholar] [CrossRef] [Green Version]

The ARIMA model is a generalization of the ARMA model (AutoRegressive Moving Average model), suitable for handling non-stationary time series. As the classical ARMA model takes for granted the stationarity of the time series it is asked to analyze, the management of inherently non-stationary time series requires their transformation into a static data series by eliminating seasonality and trends, through a finite-point differentiation.

Box, G.E.; Jenkins, G.M.; Reinsel, G.C.; Ljung, G.M. Time Series Analysis: Forecasting and Control; John Wiley & Sons: Hoboken, NJ, USA, 2015. [Google Scholar]

The highest classifier accuracy was obtained as MLP with an accuracy of 78.94%. The lowest classifier accuracy was obtained from SVM classifier with 63.15%. When evaluated in terms of all other performance metrics in classification of physical stress stages with first relaxation, MLP showed the highest score in all performance metrics. In the classification of cognitive stress stages with first relaxation, the highest classifier accuracy was classified as MLP with 97.36% accuracy. The lowest classifier accuracy was classified as KNN classifier with 81.57%. When evaluated in terms of all other performance metrics in the classification of first relaxation and cognitive stress stages, MLP showed the highest score in all performance metrics. In the classification of emotional stress stages with first relaxation, the highest classifier accuracy was classified as KNN with an accuracy of 63.15%. The lowest classifier accuracy was classified as KNN classifier with 52.63%

Ileri, Ramis & Latifoglu, Fatma. (2020). Analysis of The Electrodermal Activity Signals for Different Stressors Using Empirical Mode Decomposition. 8. 407-414. 10.21541/apjes.601235. <https://www.researchgate.net/publication/341526295_Analysis_of_The_Electrodermal_Activity_Signals_for_Different_Stressors_Using_Empirical_Mode_Decomposition>

Physical models may be combined with Machine Learning models to form hybrid models as proposed in [17], the hybrid model combines Deep Belief Network (DBN) and Empirical Mode Decomposition (EMD). Generally, hybrid models have proved to achieve excellent prediction performance specifically for short term forecasts between an hour [18] to a week [19]. However, few approaches in the literature that were proposed to address medium to long term forecasts with previous studies achieved high error in excess of 40 to 50% [13].

Fu, G., Deep belief network based ensemble approach for cooling load forecasting of air-conditioning system.

Energy, 2018. 148: p. 269-282.

Qing, X. and Y. Niu, Hourly day-ahead solar irradiance prediction using weather forecasts by LSTM. Energy,

2018. 148: p. 461-468.

Iwafune, Y., et al. Short-term forecasting of residential building load for distributed energy management. in

2014 IEEE International Energy Conference (ENERGYCON). 2014. IEEE

Yun, K., et al., Building hourly thermal load prediction using an indexed ARX model. Energy and Buildings, 2012. 54: p. 225-233.

[Time Series Forecasting with XGBoost - Use python and machine learning to predict energy consumption](https://www.youtube.com/watch?v=vV12dGe_Fho&t=576s&pp=ygUieGdib29zdCB0aW1lIHNlcmllcyBjbGFzc2lmaWNhdGlvbg%3D%3D): <https://www.youtube.com/watch?v=vV12dGe_Fho&t=576s&pp=ygUieGdib29zdCB0aW1lIHNlcmllcyBjbGFzc2lmaWNhdGlvbg%3D%3D>

Finding papers that prove ML-based methods pale in comparison to RNNs for sequential data or time series data

Comparison of Decision Tree and Long Short-Term Memory Approaches for Automated Foot Strike Detection in Lower Extremity Amputee Populations: <https://www.mdpi.com/1424-8220/21/21/6974>

Performance Comparison of LSTM‑based Deep Learning Model versus Conventional Machine Learning Algorithms for Streamflow Forecasting: <https://www.researchgate.net/publication/353945024_Performance_Comparison_of_an_LSTM-based_Deep_Learning_Model_versus_Conventional_Machine_Learning_Algorithms_for_Streamflow_Forecasting>

But it would be better if the data used was close if not electrodermal activity signal data itself, however some closely resembling data that the paper we are searching could use as much as possible (in hierarchical order) EEG data, ECG data, financial market, stock market, water quality prediction, time series healthcare data, etc.

There are already papers which use EEG data for classifying signals which are located in the RRL we just did

Finding papers on how to pre process signals or extracting feature inputs in electrodermal activity signal data for machine learning models since deep learning models already does this feature extraction part automatically

Finding existing sequence models that detect/classify artefacts:

Automatic artifact recognition and correction for electrodermal activity based on LSTM-CNN models: <https://www.sciencedirect.com/science/article/pii/S0957417423010837>

the architecture is defined in a tensorflow manner which I will need to draw out to understand how it works. <https://github.com/ASAPLableni/EDABE_LSTM_1DCNN.git>

Md-Billal Hossain, Hugo F. Posada-Quintero, Youngsun Kong, Riley McNaboe, Ki H. Chon, Automatic motion artifact detection in electrodermal activity data using machine learning, Biomedical Signal Processing and Control, Volume 74, 2022, 103483, ISSN 1746-8094, https://doi.org/10.1016/j.bspc.2022.103483.

Taylor S, Jaques N, Chen W, Fedor S, Sano A, Picard R. Automatic identification of artifacts in electrodermal activity data. Annu Int Conf IEEE Eng Med Biol Soc. 2015;2015:1934-7. doi: 10.1109/EMBC.2015.7318762. PMID: 26736662; PMCID: PMC5413200.

Finding hybridized models that use ML and RNNs in classification for sequential data to serve as proposal against current models

A hybrid model using LSTM and decision tree for mortality prediction and its application in provider performance evaluation:

P. Shi, A. Gangopadhyay, C. Owens, B. Blunt and C. Grogan, "A hybrid model using LSTM and decision tree for mortality prediction and its application in provider performance evaluation," 2019 IEEE International Conference on Big Data (Big Data), Los Angeles, CA, USA, 2019, pp. 2773-2781, doi: 10.1109/BigData47090.2019.9005958. keywords: {Data models;Logistics;Regression tree analysis;Predictive models;Machine learning;Diseases;Mortality prediction;LSTM;decision tree;ESRD},

<https://sci-hub.se/https://doi.org/10.1109/BigData47090.2019.9005958>

hybrid lstm with decision tree showed a higher AUC performance metric when compared to other baselines such as logistic regression, vanilla lstm classifier, and decision tree classifier

Tandem LSTM-SVM Approach for Sentiment Analysis: <https://ceur-ws.org/Vol-1749/paper_030.pdf>

so essentially the concept of hybridizing lstms and traditional ml based methods is that when the hidden state and cell state is produced by the lstm this can essentially serve as a vector representation of the whole given sequence or input sequence which we can use as features to feed into our decision tree, svm, jnn, logistic regression, or as we traditionally do our softmax classifier to classify this input sequence.

and akin to images we can essentially use this 1D "image" vector of hidden states produced by the LSTM as our features for a CNN model to use as an image, we can then learn higher vector representations of these hidden states and therefore make our classifier even powerful

Dynamic Light Weight Recommendation System for Social Networking Analysis Using a Hybrid LSTM-SVM Classifier Algorithm: <https://link.springer.com/article/10.3103/S1060992X2201009X>

Bidirectional Long Short-Term Memory (BILSTM) - Support Vector Machine: A new machine learning model for predicting water quality parameters: <https://www.sciencedirect.com/science/article/pii/S2090447923003994>

ways to combine lstm and cnn: <https://medium.com/@mijanr/different-ways-to-combine-cnn-and-lstm-networks-for-time-series-classification-tasks-b03fc37e91b6#:~:text=Main%20ways%20to%20combine%20a,the%20input%20to%20the%20CNN>.

combining tensorflow with decision trere: <https://stackoverflow.com/questions/55900608/keras-how-to-connect-a-cnn-model-with-a-decision-tree>

Finding papers indicating the use of LSTM hidden state as feature vector in other algorithms such as SVM, KNN, Trees, Forests, aside from what is typically which is feed the hidden state/s to a dense/fully connecyed layer (basically a neural network)

LSTM hidden state as feature vector for CNN and vice versa in classification tasks: <https://arxiv.org/pdf/1602.05875>

Bale ang methodology in a nutshell is to

Recreate ftaylor et al. feature engineering steps for the raw eda signal data

recreate

**References**

Banganho, António & Santos, Marcelino & Plácido da Silva, Hugo. (2022).

Electrodermal Activity: Fundamental Principles, Measurement and Application. IEEE Potentials. 41. 35-43. 10.1109/MPOT.2020.2983381.

Dzedzickis, A., Kaklauskas, A., & Bucinskas, V. (2020, January 21). *Human Emotion*

*Recognition: Review of Sensors and Methods*. Sensors. <https://doi.org/10.3390/s20030592>

Gashi, S., Di Lascio, E., Stancu, B., Swain, V. D., Mishra, V., Gjoreski, M., & Santini,

S. (2020). *Detection of Artifacts in Ambulatory Electrodermal Activity Data. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 4(2), 1–31.* doi:10.1145/3397316

Hossain, M. B., Posada-Quintero, H. F., Kong, Y., McNaboe, R., & Chon, K. H. (2022, April 1). *Automatic motion artifact detection in electrodermal activity data using machine learning*. Biomedical Signal Processing and Control. https://doi.org/10.1016/j.bspc.2022.103483

Lee, G., Choi, B., Jebelli, H., Ahn, C. R., & Lee, S. (2020). Noise reference Signal–Based denoising method for EDA collected by multimodal biosensor wearable in the field. *Journal of Computing in Civil Engineering*, *34*(6). https://doi.org/10.1061/(asce)cp.1943-5487.0000927

Llanes-Jurado, J., Carrasco-Ribelles, L. A., Alcañiz, M., Soria-Olivas, E., & Marín-Morales, J. (2023, November 1). *Automatic artifact recognition and correction for electrodermal activity based on LSTM-CNN models*. Expert Systems With Applications. https://doi.org/10.1016/j.eswa.2023.120581

*Stress*. (2022, June 17).

<https://www.who.int/news-room/questions-and-answers/item/stress#:~:text=Stress%20can%20be%20defined%20as,experiences%20stress%20to%20some%20degree>.

W. Boucsein, Electrodermal activity, 2nd ed. Springer US, 2012.