Application of a Hybridized LSTM-SVM in the Detection of Artifacts in Electrodermal Activity Signals for Stress Detection

Larry Miguel R. Cueva
College of Computer and Information Sciences
Polytechnic University of the Philippines
Sta. Mesa, Manila
+63 970 745 1021
michaelaveuc571@gmail.com

Johana G. Benolirao
College of Computer and Information Sciences
Polytechnic University of the Philippines
Sta. Mesa, Manila
+63 908 143 3123
johanabenolirao@gmail.com

Christaline B. Calubayan
College of Computer and Information Sciences
Polytechnic University of the Philippines
Sta. Mesa, Manila
+63 926 133 0031
calubayanchristaline@gmail.com

Deseree O. Quiray
College of Computer and Information Sciences
Polytechnic University of the Philippines
Sta. Mesa, Manila
+63 948 722 8844
desereequiray01@gmail.com

ABSTRACT

Stress is a condition that can cause a severe influence on individuals, which may affect their physical and psychological health. In order to address this, utilization of wearable sensors to measure stress levels has been a trend, one example is the usage of electrodermal activity (EDA) signals to identify psychophysiological reactions of the body. However, artifacts or "noises", usually obtained along with genuine reaction during data gathering, frequently interfere in proper stress detection. This work introduces hybridized Long Short Term Memory (LSTM) and Support Vector Machine (SVM) in order to detect artifacts and properly treat it before using the signal for detecting stress levels. The researchers used a hybridized LSTM-SVM model to overcome limitations in traditional machine learning techniques for time series data, particularly EDA signals. By integrating both LSTM (for high-level features) and SVM (for traditional lower-level features), the model is expected to outperform both deep learning models, which typically use only high-level features, and conventional ML models, which rely solely on low-level features. The study replicated previous studies' models to be compared to the LSTM-SVM models, which are Logistic Regression, Random Forest, Gradient Boosted Tree, Support Vector Machine, and LSMT-CNN based on significant performance measures such as accuracy, ROC-AUC, precision, recall, and F1-Score. The model has an accuracy of 0.8953, ROC-AUC of 0.7836, precision of 0.8867, recall of 0.8953, and F1-score of 0.8840. While competitive, it has room for development compared to modern techniques such as LSTM-CNN. Optimization of hyperparameters, testing on various datasets, enabling real-time applications, and investigating adaptive learning are among the recommendations. The model shows promise for stress detection and artifact removal in wearable devices, potentially leading to advances in biological signal processing.

Keywords

Electrodermal activity signals, artifact detection, machine learning, LSTM-SVM, signal processing, stress detection

1. INTRODUCTION

Stress is defined as a condition that involves worry or mental strain generated by a challenging circumstance [1]. 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 a 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 moderate stress in a total of 60% of their healthcare workers experienced this level of stress [2].

The utilization of wearable sensors to detect psychological and physiological responses has been a trend over the years, where a review of sensor and models was conducted to utilized a human emotion identification [3]. Physiological processes generate energy detected by a transducer, converting it into another form. Some processes, like heart, muscle, or brain activity, produce electrical energy, requiring only conversion from ionic to electric current via electrodes. Examples include ECG, EEG, EMG, EOG, and EDA [4]. Galvanic Skin Response (GSR), also known as Electrodermal Activity (EDA) or Skin Conductance Response (SCR), is measured in microsiemens (μS) and provides a low-cost, non-intrusive way to monitor emotional states. It is widely used in psychophysiology to study the Sympathetic Nervous System (SNS) and its fight-or-flight responses [5]. EDA is particularly useful in research on epilepsy, autism, stress, and anxiety [6]. Sweating, triggered by emotional fluctuations, affects skin conductivity, especially in the palms, fingers, and soles. While EDA provides less emotional data than EEG or ECG, it offers advantages such as fewer electrodes, easier wearable integration, faster data analysis, and lower computational power. EDA consists of short-term phasic changes (SCR) and longer-lasting tonic changes (SCL). Phasic changes are rapid electrical shifts within seconds, while tonic changes reflect prolonged skin conductance levels [5]. Due to its link to SNS activation, EDA signals are widely used to detect stress.

However, EDA signals, like other physiological signals, face challenges, especially with wearable technologies in ambulatory settings. Data quality can be compromised by noise or artifacts from unstable electrode contact, environmental factors, or movement)[5]. Noisy and referenced EDA channels appear similar in shape but differ in amplitude [7]. Detecting artifacts often relies on visual inspection, which is unreliable for large-scale studies [5]. While low-pass filtering helps, it risks altering the physiological response. Persistent noise may distort results, potentially mimicking skin conductance responses (SCR) linked to stress [8]. Recent studies aim to develop models for automatic artifact removal [9].

To address the challenges in previous studies, the researchers propose a hybrid LSTM-SVM model. LSTM extracts higher-order features from EDA signals while incorporating lower-order, manually constructed features used in earlier studies. Integrating SVM enhances this approach by combining deep learning's complex feature extraction with traditional ML's handcrafted features. This hybrid method is expected to outperform deep learning models that rely solely on higher-order features and ML models that use only lower-order features, leading to improved overall performance.

2. REVIEW OF LITERATURE AND STUDIES

In the paper by Hossain et al. [7] they validated their motion artifact detection algorithm, by systematically adjudicating the dataset as artifacts and clean signal albeit manually. Taylor et al. [8] their process involved obtaining three experts/observers to manually annotate the signals using specific criteria. No fixed window was defined for the annotation, as the observers were able to mark the start and end of artifact segments. Firstly, a signal was annotated as a motion artifact if the EDA signal ranged outside 10 seconds to 40 seconds inclusively, secondly if the EDA signal changed quickly i.e. faster than ± 10, thirdly if the EDA peak decays i.e. (EDA is considered noisy if EDA peak does not follow an exponential decay except when there are two peaks within a short period), and finally if there was correlation of reference and noisy EDA channels (however sometimes a signal is considered clean and without artifacts if and only if the correlation coefficient was greater than or equal 0.95). In addition, in the study by Llanes-Jurado et al. [10] although the use of experts to manually annotate the raw EDA signals according to a set of criteria was again conducted, explicit criteria such as those used in the two previous studies were not shown.

Table 1. Guidelines for Annotation of EDA Signals

Index	Criteria
1	EDA out of range (*EDA range -10s to 40s*)
2	Quick change in EDA (*if EDA changes faster than* $\pm 10s$)
3	EDA peak decays (*EDA is considered noisy if EDA peak does not follow an exponential decay except when there are two peaks within a short period of time*)
4	Correlation of reference and noisy EDA channels (*considered clean only if the correlation coefficient is* $\geq$ 0.95)

Llanes-Jurado et al. conducted a study titled "Automatic Artifact Recognition and Correction for Electrodermal Activity in Uncontrolled Environment"[10], wherein the researcher 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 future experiments that may be able to improve and develop artifact detection in EDA signals

Sánchez-Reolid et al. [11] study applied machine learning algorithms to classify arousal levels from electrodermal activity signals while implementing different strategies to deal with EDA signal complexity. The study employed Support Vector Machine (SVMs) with different kernels then employed Auto-Hidden Markov Models (AHMMs) for temporal modeling together with Discriminant Analysis (DA) for dimensionality reduction as its main techniques. The experimental design selected Decision Trees (DTs) in combination with ensemble methods together with Naive Bayes method because of their simple structure and reliable performance. Logistic Regression (LR) served as the designated binary classifier, yet K-Nearest Neighbors (KNN) and Artificial Neural Networks (ANNs) performed analyses on the EDA signal complexity. The artifact detection procedure involved signal normalization techniques with filtering methods to remove artifacts and applied noise reduction followed by feature extraction, and lastly model evaluation using accuracy, precision, recall, specificity, F1-score, AUC, and ROC metrics.

In another study by Sánchez-Reolid et al. [12] they demonstrate yet again the simplicity of ML methods in the domain of stress detection from EDA signal data, as they've shown that the simplicity of the classification model they proposed, namely the SVM allows the system to work in the long term, as the SVM across 3 different sets of cross validation given 20 second segments of EDA signal features managed to produce at most 70.8%, 75%, and 75% accuracy, for 5, 7, and 10 folds of cross validation. Similarly, 4 second segments of EDA signal features given to the SVM managed to produce at most 87.7% accuracy in the 5, 7, and 10 folds of cross validation.

In the more recent literature in the domain of sequential data processing such as NLP and signal processing, the recent study by Llanes-Jurado et al. [10] where they proposed a hybridized LSTM-CNN model for automatic artifact detection in EDA signal data, it has fairly become common practice to adopt approaches of hybridizing Machine Learning and Deep Learning methods to making more accurate predictions from sequential data.

A study by Cimino & Dell'Orletta [13] demonstrates this by hybridizing an LSTM and SVM in the domain of sentiment analysis i.e. subject classification, polarity detection, and irony detection. With this proposed model they sought to compare it with other baseline models, these being a standalone LSTM and an SVM model. They consider an SVM since it is an extremely efficient learning algorithm and hardly to outperform, unfortunately these type of algorithms capture "sparse" and "discrete" features in document classification tasks, making hard the detection of relations in sentences, which is often the key factor in detecting the overall sentiment polarity in documents details [14].

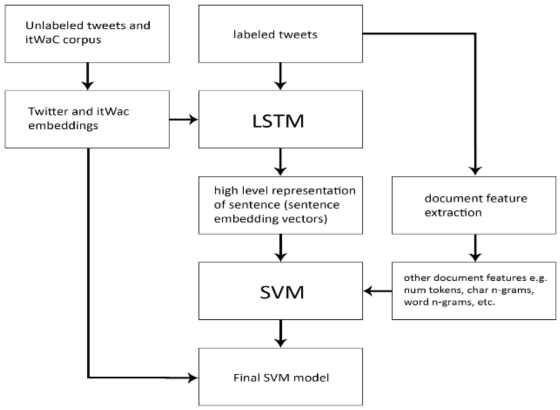

Figure 1. Cimino & Dell'Orletta hybridized LSTM-SVM architecture

3. METHODOLOGY

3.1 Research Design

The researchers employed an experimental and quantitative approach to achieve their goal of automatically identifying artifacts from electrodermal activity (EDA) data used in stress detection. The study used hybridized Long Short-Term Memory (LSTM) and Support Vector Machine (SVM) model and compared their performance to existing models by previous study of [6],[7],[9].

3.2 Sources of Data

This study utilized 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. input was also incorporated to refine the data and ensure its relevance to the research objectives.

3.3 Research Instrument

1. *Programming Language:* The study was implemented using Python, an interpreted, object-oriented, high-level programming language. Python's simple syntax promotes code readability, reducing program maintenance. It provides modules and packages that enhance program modularity and code reuse.
2. *Dataset:* The study utilized the EDABE (Electrodermal Activity Artifact Correction Benchmark) dataset, which comprises 74.46 hours of EDA recordings affected by hand and body motion artifacts from 43 subjects. The dataset is divided 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.
3. *Machine Learning Frameworks:*
   a. *TensorFlow:* An open-source platform designed for developing advanced machine learning applications. It was initially developed by the Google Brain Team for machine learning and deep neural network (DNN) research.
   b. *Scikit-learn:* An open-source machine learning library for Python that includes classification, regression, and clustering algorithms. It integrates well with NumPy and SciPy for data modeling and machine learning implementations.
4. *High-Performance Computing (HPC) Service*: The study utilized the Department of Science and Technology – Advanced Science and Technology Institute's (DOST-ASTI) Computing and Archiving Research Environment (COARE). COARE provides an HPC service that facilitates efficient storage, analysis, and exchange of scientific data. The HPC service was used for training the models, allowing for faster and more resource-efficient data processing compared to traditional computing environments.
5. *Development and Collaboration Tools:*
   a. *Figma*: Used for designing the user interface of the system.
   b. *GitHub*: Employed for version control, collaboration, and storage of project files.
   c. *ReactJS*: Utilized in the development of the system's front-end interface, ensuring a dynamic and responsive user experience.

3.4 System Architecture

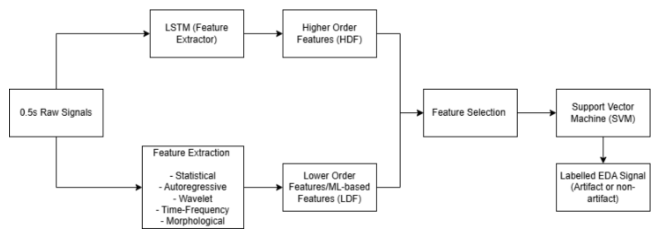

Figure 2. System Architecture

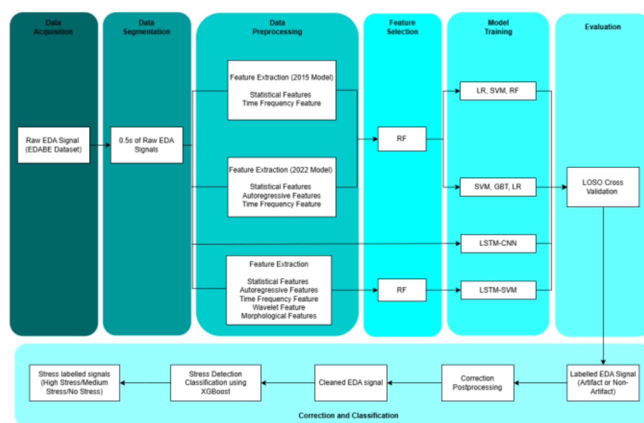

Figure 3. System Workflow

The system architecture for analyzing Electrodermal Activity (EDA) signals, typically used in stress detection, is divided into several stages. It starts with data acquisition from the EDABE dataset, which contains EDA signals from 42 subjects. The raw signals are segmented into 0.5-second windows for further processing. Two feature extraction techniques, based on prior research by [6], [7] are applied to extract statistical, autoregressive, and time-frequency features. Relevant features are then selected using Recursive Feature Elimination (RFE) based on a Random Forest (RF) model. Multiple machine learning models, including Support Vector Machine (SVM), Logistic Regression (LR), Random Forest (RF) and Gradient Boosted Trees (GBT), are trained using the selected features. Additionally, hybrid models such as LSTM-CNN and LSTM-SVM are trained. The models undergo Leave-One-Subject-Out cross validation technique to search for the best hyper parameter configuration and then classify the electrodermal activity signal into artifacts and non-artifacts. Thereafter, the labeled signals will be subjected to correction, which will result in clean EDA signals. These now clean signals will be further classified into 3 levels of stress, namely baseline or no perceived stress, medium stress, and high stress.

3.5 Data Procedure

The research examines an LSTM-SVM model's performance against established baseline methods presented in previous studies. The research utilizes three baseline models from [5],[6],[7] using the EDABE dataset that was segmented into 0.5-second intervals for processing signals. Recursion-based Random Forest classifier performs feature elimination to eliminate redundancy from statistical, time frequency and wavelet features. Each baseline model makes use of different classifiers including Logistic Regression and SVM together with Random Forest and Gradient Boosted Trees. The model parameters were optimized by running grid search combined with Leave-One-Subject-Out (LOSO) cross validation approaches. The study [5] introduces their deep learning-based LSTM-CNN model as part of multiple baseline models. The proposed LSTM-SVM model combines LSTM produced high-level features with traditionally derived low-level features which were originally presented in earlier work. The proposed model implements an SVM classifier as it uses hyperparameter optimization to achieve optimal performance. This research uses LOSO cross-validation with 43 subjects to evaluate the data without any shared information between training and testing phases for enhanced generalization capabilities. The model selected from cross-validation testing possesses superior results that are checked against baseline approaches for the final assessment.

3.6 Data Analysis

To measure and to evaluate the performance of the proposed hybridized LSTM-SVM to automatically detect the artifacts found in an EDA signal, the researchers utilized the following performance metrics:

ROC-AUC.

This metric provides a more reliable measure for future comparisons utilizing the dataset to address the concern regarding the unbalanced classes in the dataset. It refers to the measure of the total area covered by a curve on a graph, which allows quantification of the extent region beneath the curve between points.

$$Area = \int_a^b y.\,dx$$

$$\Rightarrow Area = \int_a^b f(x).\,dx$$

$$\Rightarrow Area = [\,g\,(x)]_a^b$$

$$\Rightarrow Area = g(b) - g(a)$$

Figure 4. Formula for ROC-AUC

Accuracy

It refers to how close a measurement is to the true or accepted values. In this study, it is used to evaluate the performance of the models in terms of the quotient of correctly predicted instances to the total number of instances.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Figure 5. Formula for Accuracy

Precision

Precision is the ratio of true positive predictions to the total number of positive predictions, including both true positives and false positives. Researchers use it to assess the relevance of positive predictions, especially in imbalanced datasets.

$$Precision = \frac{TP}{TP + FP}$$

Figure 6. Formula for Precision

F1-Score

It is a metric used to evaluate automatic artifact detection models' performance. It measures a model's accuracy by combining precision and recall scores, providing a single metric for easy comparison of different models.

$$F1 - Score = 2\,x\,\frac{Precision * Recall}{Precision + Recall}$$

Figure 7. Formula for *F*1-Score

Recall

Also known as sensitivity or True Positive Rate, this parameter is utilized to calculate the percentage of results that are positive findings among all actual positive samples.

$$Recall = \frac{TP}{TP + FN}$$

Figure 8. Formula for Recall

4. RESULTS AND DISCUSSION

The researcher used the EDABE dataset, divided into a training set of 33 subjects and a testing set of 10 subjects. The High-Performance Computing (HPC) service from DOST- ASTI's COARE was used to train the models. The artifact detection models were evaluated using performance metrics like accuracy, precision, F1-score, recall, and ROC-AUC. The findings aim to address the research questions defined in the Statement of the Problem and are presented in a tabular format for clarity and coherence.

Table 2. Performance of C and Gamma Hyperparameter Tuning for LSTM-SVM

Hyperparameter (*C*, *Gamma*)	Accuracy	F1-Score	ROC-AUC	Precision	Recall
1, 0.1	0.8953	0.8840	0.7836	0.8867	0.8953
1, 0.5	0.8721	0.8354	0.7995	0.8471	0.8721
1, 1	0.8720	0.8178	0.7818	0.8161	0.8720
10, 0.1	0.8876	0.8814	0.7847	0.8813	0.8876
10, 0.5	0.8903	0.8814	0.7445	0.8800	0.8903
10, 1	0.8686	0.8174	0.7664	0.8038	0.8686
100, 0.1	0.8759	0.8734	0.7680	0.8749	0.8759
100, 0.5	0.8607	0.8328	0.7782	0.8286	0.8607

Table 2 shows the experiment of different combinations of C and Gamma values in hyperparameter tuning. The ideal configuration was identified as C = 1 and Gamma = 0.1, It achieved accuracy of 0.8953, F1-Score 0f 0.8840, ROC-AUC of 0.7836, Precision of 0.8867, Recall of 0.8953, which outperformed other tested configurations. This configuration was then compared to existing models like SVM, RF, LR, GBT, and LSTM- This comparative analysis evaluates the performance of LSTM-SVM with different hyperparameter tuning using C and Gamma values and how it affects results in detecting artifacts in electrodermal activity signals.

Table 3. Performance of the models during testing phase in accordance to ROC-AUC, Recall, Precision, F1-Score and Accuracy

Artifact Detection Models	Accuracy	F1-Score	ROC-AUC	Precision	Recall
LSTM-SVM (1, 0.1)	**0.8953**	**0.8840**	**0.7836**	**0.8867**	**0.8953**
Taylor RF (600, 30)	0.9092	0.9000	0.8432	0.9017	0.9092
Taylor SVM (1000, 0.1)	0.9076	0.8894	0.8195	0.9007	0.9076
Taylor LR (100)	0.8977	**0.8717**	**0.7719**	0.8955	0.8977
Hossain LR (10)	0.9072	0.8913	0.8201	0.8996	0.9072
Hossain GBT (600, 0.01, 10)	0.9105	0.9011	0.8434	0.9039	0.9105
Hossain SVM (100, 0.01)	0.9111	0.8981	0.7926	0.9034	0.9111
Llanes-Jurado LSTM-CNN	**0.8832**	0.8845	0.8838	0.9054	**0.8832**

The study evaluated the automatic detection of artifacts in EDA signals using various metrics. The proposed LSTM- SVM model achieved a ROC-AUC of 0.7836, precision of 0.8867, F1-score of 0.8840, accuracy of 0.8953, and recall of 0.8953. However, it slightly outperformed other models in certain metrics. The SVM model by [6] achieved higher accuracy and recall of 0.9111, indicating its ability to detect positive labels in the signal. The GBT model by [6] was recorded as the superior model in terms of F1-Score of 0.9011, indicating its ability to classify between artifacts and non-artifacts, especially in imbalanced datasets. The LSTM- CNN model by [5] exhibited the highest ROC-AUC of 0.8838 and precision of 0.9054, but its F1-Score was 0.8845 and accuracy was 0.8832. Compared to traditional methods like Logistic Regression and Support Vector Machines, the LSTM-SVM model consistently demonstrated better ROC- AUC and precision. Despite having competitive precision and accuracy, models like Random Forest and Gradient Boost outperform the LSTM-SVM in terms of F1-Score and accuracy.

5. SUMMARY FINDINGS

This study evaluated the performance of the LSTM-SVM model for detecting artifacts in electrodermal activity (EDA) signals, focusing on optimizing hyperparameters C and Gamma. The best configuration (C = 1, Gamma = 0.1) achieved an accuracy of 0.8953, an F1-score of 0.8840, and a ROC-AUC of 0.7836. While models like Random Forest (RF), Gradient Boosted Trees (GBT), and LSTM-CNN slightly outperformed LSTM-SVM in certain metrics, the hybrid approach demonstrated a balanced performance across various evaluation criteria.

The results highlight the effectiveness of hybrid models in bridging gaps between traditional machine learning and deep learning approaches. Despite minor performance differences, LSTM-SVM remains a competitive option for artifact detection in EDA signals, offering a viable alternative for handling sequential data in time-series analysis.

6. CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

By combining LSTM and SVM techniques the study aimed to address the gap of detecting noises in electrodermal activity signals. To create an efficient and effective classification system the researchers used machine learning and deep learning. They focused on the best C and Gamma values and compared existing detection models to the LSTM-SVM. The researchers found that hyperparameter optimization or tuning helped the model achieve optimal results. The SVM component of the hybridized LSTM-SVM performed well in detecting artifacts in electrodermal activity signals, with higher accuracy and recall compared to the baseline LSTMCNN model and higher F1-score and ROC-AUC from Logistic Regression. Despite underperforming in terms of ROC-AUC and F1- Score, the LSTM-SVM still provided good results in classifying EDA signals into artifacts and non-artifacts, providing a clean signal for stress detection. However, there is room for improvement in the system for classification and correction. The study highlights the potential of using hybridized machine learning and deep learning models to address the limitations and challenges of detecting noises in electrodermal activity signals.

6.2 Recommendations

Based on the findings of this study, several recommendations are proposed to further enhance the hybrid LSTM-SVM model and its application in detecting artifacts in Electrodermal Activity (EDA) signals:

1. SVM component of the LSTM-SVM can be further improved by providing a larger pool of hyperparameter configuration values to use in tuning other than the utilized values in this study (e.g. 1, 10, 100, and 1000 & 0.001, 0.01, 0.1, and 1 for C and gamma hyperparameters as opposed to 1, 10, and 100 & 0.001, 0.01, 0.1, and 1). This could aid in allowing more evaluation and representation, and could help produce the best results from the model.
2. It is also recommended to test the model on larger, more diverse, and more balanced dataset to ensure its reliability and applicability, while examining its adaptability across different scenarios.
3. Other recommendations in the domain of model optimization would include using a much powerful machine for these computationally intensive tasks of training, as SVM based models for instance can entail long and intensive training time i.e. 3 days for using one hyperparameter configuration or permutation.
4. Physical and real-time implementation of the model, specifically in using wearable devices to gather electrodermal activity signals is another area for development. Physically-gathered signals could provide data significantly different from datasets, and it could further develop the model in its detecting and classifying tasks.

By addressing these recommendations, future research can advance the field of biomedical signal analysis and contribute to the development of more accurate, reliable, and practical stress detection systems.

7. ACKNOWLEDGEMENTS

The researcher would like to express deepest gratitude to the success of this research work.

To Almighty God thank you for the blessings, wisdom, and strength that guided us throughout this journey.

To the Department of Science and Technology-Computing and Archiving Research Environment (DOST-COARE) for providing the necessary computing resources, which greatly contributed to the data processing and analysis of this research.

Special thanks to our professors and panelists for their knowledge,

encouragement, and assistance.

To our families and friends, thank you for unwavering support, love, and encouragement. Your motivation and belief in us have been a great source of strength.

8. REFERENCES

[1] World Health Organization, “Stress,” World Health Organization, Feb. 21, 2023. https://www.who.int/news-room/questions-andanswers/item/stress

[2] Alnazly, E., Khraisat, O. M., Al-Bashaireh, A. M., & Bryant, C. L.(2021).Anxiety,depression, stress, fear and social support during COVID-19 pandemic among Jordanian healthcare workers. PloS One, 16(3), e0247679. https://doi.org/10.1371/journal.pone.0247679

[3] Dzedzickis, A., Kaklauskas, A., & Bucinskas, V. (2020, January 21). Human Emotion Recognition: Review of Sensors and Methods. Sensors. https://doi.org/10.3390/s20030592

[4] Semmlow, J. L. (2004). Biosignal and medical image processing. CRC Press.

[5] Boucsein, W. (2012). Electrodermal activity. In Springer eBooks. https://doi.org/10.1007/978-1-4614-1126-0

[6] Banganho, A., Santos, M., & Da Silva, H. P. (2022). Electrodermal activity:Fundamental principles, measurement, and application. IEEE Potentials, 41(5), 35–43. https://doi.org/10.1109/mpot.2020.2983381

[7] 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

[8] Taylor, S., Jaques, N., Chen, W., Fedor, S., Sano, A., Picard, R. (2015). 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.

[9] 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

[10] 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-CNNmodels. Expert Systems With Applications. https://doi.org/10.1016/j.eswa.2023.120581

[11] Sánchez-Reolid, R., De La Rosa, F. L., Sánchez-Reolid, D., López, M. T., & Fernández-Caballero, A. (2022). Machine Learning Techniques for Arousal Classification from Electrodermal Activity: A Systematic Review. Sensors, 22(22), 8886. https://doi.org/10.3390/s22228886

[12] Sánchez-Reolid, R., Martínez-Rodrigo, A., & Fernández-Caballero, A. (2019). Stress Identification from Electrodermal Activity by Support Vector Machines. In Lecture notes in computer science (pp. 202–211). https://doi.org/10.1007/978-3-030-19591-5_21

[13] Cimino, A., & Dell’Orletta, F. (2016). Tandem LSTM-SVM approach for Sentiment Analysis. In *Accademia University Press eBooks* (pp. 172–177). https://doi.org/10.4000/books.aaccademia.2003

[14] Tang, Y. (2013). Deep Learning using Linear Support Vector Machines. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.1306.0239

AUTHORS

Johana Benolirao is a fourth-year undergraduate student at the Polytechnic University of the Philippines, pursuing a Bachelor of Science in Computer Science. With a strong technical foundation, she possesses intermediate skills in web development and is proficient in programming languages such as Java, C, and Python. Additionally, she is well-versed in workspace applications and design tools, including Canva and Figma.

Christaline Calubayan is a fourth-year undergraduate student at the Polytechnic University of the Philippines, pursuing a Bachelor of Science in Computer Science. Her skill set includes programming in Python, Java, and C, along with skill in front-end web development using HTML, TailwindCSS, and Javascript. She has experience in graphic design and a background in database management.

Larry Miguel Cueva is a fourth-year undergraduate student at the Polytechnic University of the Philippines, pursuing a Bachelor of Science in Computer Science. His expertise spans multiple programming languages and frameworks, including Python, JavaScript, Flask, React, and Svelte. He is also proficient in machine learning libraries such as TensorFlow, Keras, and Scikit-Learn. With a strong passion for artificial intelligence, his interests lie in machine learning and deep learning, data loading and preprocessing, as well as data analysis and visualization.

Deseree Quiray is a fourth-year Computer Science undergraduate at the Polytechnic University of the Philippines. She is skilled in database management using SQL and web application development with HTML, CSS, and JavaScript. Additionally, she is proficient in Microsoft Office applications and design tools like Figma and Canva. She also has experience working with programming languages such as C, Java, and Pytho