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

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***Abstract*— The study addresses to solve Electrodermal Activity Signals (EDA) artifact detection issues which are used by wearable sensors to measure stress. The stress monitoring assessments based on EDA signals encounter problems due to noise that may distort their measurement accuracy. The research solves traditional method limitations through the implementation of a Long-Short Term Memory (LSTM)-Support Vector Machines (SVM) hybrid model. This methodology utilizes LSTM for extracting temporal features from EDA signals while implementing the SVM model to include standard handcrafted features at the lower level. The framework has been designed to provide better outcomes than independent deep learning and traditional machine learning methods. The hybridized model processed data reached 0.8953 accuracy with 0.7836 ROC-AUC together with 0.8867 precision and 0.8953 recall and 0.8840 F1-Score. The obtained results demonstrate competency but suggest further improvements since more sophisticated techniques exist. Wearable device stress detection and artifact removal may experience substantial progress through the promising outcomes of this study.**

***Keywords*— Electrodermal activity signals, artifact detection, machine learning, Long-Short Term Memory (LSTM)-Support Vector Machine (SVM), signal processing, stress detection**

I. INTRODUCTION

Stress is a condition characterized by worry or mental strain caused by challenging circumstances [1]. During the COVID-19 pandemic, healthcare workers in Jordan experienced high levels of stress, with 22.5% experiencing severe stress, 16.2% experiencing extremely severe stress, and 21.1% experiencing moderate stress [2]. This high stress can negatively impact their psychological well-being, job performance, and ability to provide quality patient care. To mitigate and manage stress, numerous studies have focused on detecting stress signals using wearable sensors. Electrodermal activity (EDA) is a low-cost and non-intrusive way of monitoring emotional states and a gateway to studying the Sympathetic Nervous System (SNS). EDA is commonly used in psychophysiology for research on epilepsy, autism, stress, and anxiety. The phasic component of EDA signal, obtained from decomposing an EDA signal, is closely associated with SNS activation when stimuli such as external stressors are present [3]. Time series analysis is a statistical technique that deals with trend analysis and time series data. It has been used in medicine since the invention of practical electrocardiograms (ECGs) in 1901. However, EDA signals face challenges, such as "noise" or artifacts in long-term recordings. These artifacts can result from unstable electrode contact, environmental factors like temperature and humidity, or movement. Detecting these artifacts typically requires visual inspection of the data, but this is unreliable in large-scale EDA studies and long-term monitoring outside clinical settings [4]. A study on automatic recognition and elimination of artifacts in electrodermal activity (EDA) signals using their EDABE dataset [5] They developed and trained four models, two replicating traditional machine learning methods by [6],[7]. They also proposed new models, including 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, 57% F1-Score, and 88% accuracy on the test set [5]. Artifact detection is crucial in healthcare signal processing, as it helps improve the accuracy of stress measurement by reducing noise interference in EDA signals. Traditional machine learning methods have limitations in healthcare signal processing, such as hand-designed EEG feature extraction methods and the inability of SVM models to extract significant features from data [8].

To address these difficulties, the researchers propose a hybridized LSTM-SVM model that integrates both higher and lower-order features, resulting in better performance than deep learning models and typical machine learning models. This arrangement is expected to enhance overall model performance by capturing complicated, high-level features and combining them with lower order, manually constructed ones.

II. METHODOLOGY

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 [5],[6],[7].

A. 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.

B. System Architecture

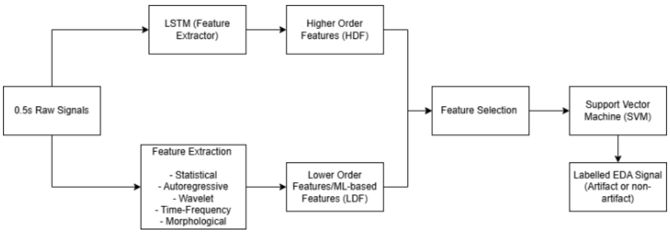

Fig. 1 System Architecture

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.

C. Data Generation 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 is checked against baseline approaches for the final assessment.

D. 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.

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

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

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

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

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.

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

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.

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

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.

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

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.

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

III. 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.

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

Researchers experimented with 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.

B. Comparison of the Proposed Model and the Existing Model

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.

IV. CONCLUSIONS

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 thebaseline LSTM-CNN 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.

The study suggests several improvements to the hybrid LSTM-SVM model for detecting artifacts in Electrodermal Activity (EDA) signals. The SVM component could be improved by providing a larger pool of hyperparameter configuration values, such as 1, 10, 100, and 1000 & 0.001, 0.01, 0.1, and 1 for C and gamma hyperparameters. This would allow for more evaluation and representation, resulting in better results. The model should also be tested on a larger, more diverse, and balanced dataset to ensure reliability and applicability. Additionally, using a powerful machine for computationally intensive tasks of training is recommended, as SVM-based models can require long training times. Physical and real-time implementation of the model, particularly using wearable devices to gather electrodermal activity signals, is another area for development. These recommendations could advance biomedical signal analysis and contribute to the development of more accurate, reliable, and practical stress detection systems.

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