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A Novel Deep Learning-Based Classification Model For ECG-Derived Stress Recognition

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Abstract
Stress recognition using electrocardiogram (ECG) signals is a promising approach for real-time health monitoring, offering a non-invasive, efficient, and cost-effective solution for detecting stress in individuals. Since stress can have detrimental effects on both physical and mental health, early detection is critical for preventive healthcare. Hence, the proposed model intends to improve a robust model for stress recognition by analyzing ECG signals collected under different stress-inducing conditions. This research utilizes a Kaggle dataset, which includes features from the Stress and Workload Evaluation of Lifelong Learning (SWELL) and Wearable Stress and Affect Detection (WESAD) datasets. To enhance signal quality and ensure accurate analysis, preprocessing techniques using StandardScaler are applied to standardize feature distributions. The significant features were extracted using a novel framework called Weighted Adaptive Hybrid Independent Discriminant Linear Extraction (WAHIDLE), integrating Weighted Independent Component Analysis (WICA) and Adaptive Linear Discriminant Analysis (ALDA). For classification, a novel Ensemble Randomized Support Vector Convolutional Neuro Net (ERSV-ConvNet) is employed to categorize signals into stress and non-stress categories. A range of Python-based tools and libraries, combined with comprehensive comparative analyses, are utilized to demonstrate the effectiveness and robustness of the proposed method. The results indicate that the approach outperforms existing stress recognition models, delivering improved accuracy (99.98%), and efficiency. The findings contribute to the development of personalized health applications and wearable devices capable of real-time stress detection, empowering individuals to manage stress more effectively and mitigate its negative health impacts.

Keywords: Electrocardiogram (ECG), Wearable Devices, Healthcare, Stress recognition, Ensemble Randomized Support Vector Convolutional Neuro Net (ERSV-ConvNet).

I. INTRODUCTION

Electrocardiogram (ECG) is a crucial medical test utilized to record the electrical activity of the heart. The heart produces electrical impulses that trigger its contraction and blood circulation, and these impulses are detected through small sensors, referred to as electrodes that are placed on the skin of the chest, arms and legs [1-3]. The ECG measures these electrical impulses and presents them in the form of a graph of different waves. Each wave in the heartbeat cycle corresponds to a distinct phase of cardiac activity: the P-wave reflects the electrical impulses that trigger atrial contraction; the QRS complex, comprising the Q, R, and S waves. This signifies the initiation of ventricular contraction; and the T-wave signifies the lessening or recovery phase of the ventricles [4]. ECG is widely used to diagnose multiple types of heart diseases, including arrhythmias, myocardial infarction (heart attacks), and electrical conduction disturbances. It is a painless and important evaluation of heart health [5]. In addition to cardiac evaluation, ECG analysis is also used to evaluate stress levels. Stress activates the autonomic nervous system, which results in changes in Heart Rate (HR), rhythm, and variability components that can be seen in an ECG recording [6,7]. The ECG gives important psychological insights by analyzing HR Variability (HRV) and characteristic waveform patterns, and it is a non-invasive approach for tracking the influence of stress on cardiac function.

A stress classification technique called Multi-Dimensional Feature Fusion-Based ECG [8], fuses multi-dimensional features using long short-term memory (LSTM) and Xception, which focused on removing outliers from the ECG signals to develop the classification accuracy. The model achieves the optimal stress classification accuracy because of the use of the multi-dimensional feature fusion; however, the complexity of the ECG data is difficult to manage. Nevertheless, analysing multi-dimensional features has complex data preprocessing and computational requirements which may not be viable in real world situations. An ensemble multi-classifier (EMC) is investigated to understand driver stress detection (DSD) and to help prevent accidents. It examine fiducial and non-fiducial characteristics in order to have the compromise of detection accuracy and implementation feasibility. The neural network with backpropagation (NNBP) is responsible for identifying the ECG signals, which are derived from the fiducial outputs. The transformed ECG signals are then used to make non-fiducial features, which are analyzed with a 1-D Convolutional Neural Network (1-DCNN). This network is integrated with a composite decision-making layer, enabling the estimation of stress levels based on the extracted features. These results demonstrate optimal model fitness and detection accuracy (95.9%). This research heavily relies on the availability and quality of ECG signals that cannot be consistent in real-world driving scenarios. The integration of NNBP and 1-DCNN increases computational complexity, potentially hindering real-time implementation and scalability. Supervised learning algorithms involved in examining the stress and relaxation states using HRV measurements [10]. Machine learning (ML) techniques are employed to address the challenges associated with small datasets, including limitations in feature selection, data segmentation, and model evaluation. The experimental results indicate that the Random Forest (RF) method achieves optimal presentation in individual stress states from non-stress conditions with accuracy (86.3%) and F1-score (65.8%). Although it concentrates only on improving validity, hence developing more explainable and interpretable ML models relies on real-world applications, especially when dealing with limited detests.
To address the issues of conventional methods, an intelligent stress recognition model is developed by analyzing ECG signals collected under various stress-inducing conditions. The data is collected from Kaggle, which includes HRV and electrodermal activity features from Smart Reasoning Systems. It is divided into three categories, such as interim, intermediate, and final. Initially, the raw data is preprocesses using StandardScaler and used to standardize feature distributions, to enhance signal quality and ensure accurate analysis. Further, the Weighted Adaptive Hybrid Independent Discriminant Linear Extraction (WAHIDLE) is utilized, to extract features such as time-domain and frequency-domain analysis. The research proposes a novel Ensemble Randomized Support Vector Convolutional Neuro Net (ERSV-ConvNet), used to classify signals as stress or non-stress. Python software is used, and the results are analysed to predict the model efficiency. The findings exhibit the improvements of personalized health applications and wearable devices capable of real-time stress detection, empowering individuals to manage stress more effectively and moderate its negative health impacts.

Key contribution of this research

- The ECG and electrodermal activity data are sourced from Kaggle, incorporating the SWELL and WESAD datasets.
- Furthermore, Label Encoding is used to convert categorical variables into numerical labels, while StandardScaler normalizes the features for uniform variance, ensuring class balance and improved ML model compatibility. After preprocessing the raw data, the WAHIDLE technique is applied to extract significant features.
- The proposed ERSV-ConvNet model is evaluated for their effectiveness in classifying ECG signals into stress levels.
- The model is evaluated against existing methods using key metrics like precision, recall, accuracy, and F1-score to validate its efficiency in accurately detecting and categorizing stress levels from ECG signals.

The organization of this research is followed by this structure: Section I introduces the importance of ECG-based stress recognition and outlines the research objectives. Section II reviews related literature, highlighting recent advancements and limitations in stress detection techniques. Section III deliberates the methodology, including data collection and data preparation. Section IV displays the experimental results, while Section V concludes the investigation with significant findings and recommendations for further research.

II. LITERATURE REVIEW

Xception pre-trained neural networks for improved deep transfer learning (DTL) models were developed [11], to predict stress with faster computations. These models classified the stress levels of drivers, based on ECG, respiration (RESP) signals, electromyogram (EMG), HR, and Galvanic Skin Response (GSR). The Xception model obtained optimal results with validation accuracies for ECG (97.2%), RESP (86.4%), HR (82.7%), GSR (71.9%), and EMG signals (68.9%). It possessed some drawbacks in performing stress demonstrating by directly using signals to Deep Neural Networks (DNNs) for classification. A multimodal stress dataset [12] was introduced, where stress was elicited through a simulated digital job interview. This dataset comprised data from 40 participants, capturing audio, video, and physiological signals to comprehensively assess stress responses. It also incorporated time-continuous annotations, providing detailed tracking of stress levels and emotional states as it unfolded over time. Various ML techniques were used to train and estimate the data for binary stress classification tasks. The suggested model performed well, and LSTM attained the optimal classification accuracy of (91.7%) and F1-score (90.2%). The data lacked continuous valence and arousal annotations, which restricted continuous valence and stimulation observations by transformer models.

The Major Depressive Disorder (MDD) BranchNet model [13] employed a parallel-branch DL structure for binary classification of MDD based on single-channel ECG inputs, enriched with supplementary ECG-derived signals. The model suggested that MDD was likely uniform throughout the recording, and assessed predictions using localized segments of the ECG signal, which typically exhibits minimal variation. The accuracy of the model increased by about 7% with the use of derived branches. Using overlapping 20-second segments of ECG data, the model demonstrated increased effectiveness for MDD detection when 70% prediction threshold was applied. The model concentrated on ECG-derived signals, which missed other physiological indicators relevant to MDD detection. Performance varied with noisy or low-quality ECG recordings, limiting robustness in uncontrolled real-world settings.

The relationship between fall risk and HR incontinence during regular activities was investigated [14] among individuals over 40 years old. The purpose of the research was to explore the potential of HRV as a metric of stress and loss of balance. The data was analyzed using ML techniques, which were divided into two stages: supervised and unsupervised clustering classification. In addition, it was found that Gradient Boosting performed optimally, attaining precision (93.10%), accuracy (95.45%), and recall (85.71%). The research involved a small sample size, limiting generalizability to broader populations. Additionally, reliance on HRV features ignored other critical factors influencing fall risk and stress levels. Arrhythmia detection was performed [15] that leveraged ECG data and incorporated explainable Artificial Intelligence (AI) through three key approaches. Initially, an improved R peak detection technique was developed, which incorporated specialized data into the ECG, increasing the precision of peak recognition for the distinctive characteristics of R peaks. A modified CNN structure was used to classify arrhythmias by processing a trio of cardio cycles, including present, previous, and following cycles, to cover sequential requirements and hidden features. An interpretation method was implemented, explaining CNN's results with medically related indicators, which assisted in making the results accessible to clinicians. The technique attained improved accuracy, and F1-scores for major arrhythmia classes. The model exhibited high computational costs and limited robustness to noise and artifacts. It also struggled with class imbalance and restricted classification coverage for diverse arrhythmias.

III. MODEL FRAMEWORK

The aim of the proposed model is to develop a robust system for stress recognition by analyzing ECG signals. These signals are collected from individuals, and recognized under various stress-inducing conditions to ensure a comprehensive dataset. Figure 1 denotes the pictorial representation of the research outline, which presents the overall architecture of the proposed ECG-based stress recognition framework. Initially, the method begins with dataset acquisition, followed by preprocessing using Label Encoding and Standard Scaler to prepare the data. Feature extraction is performed using the WAHIDLE method, combining Weighted Independent Component Analysis (WICA) and Adaptive Linear Discriminant Analysis (ALDA), and the data is split for training and testing. The ERSV-ConvNet classifier is then applied, and experimental results are analyzed using feature importance, accuracy, F1-score, precision, recall, and confusion matrix visualizations.

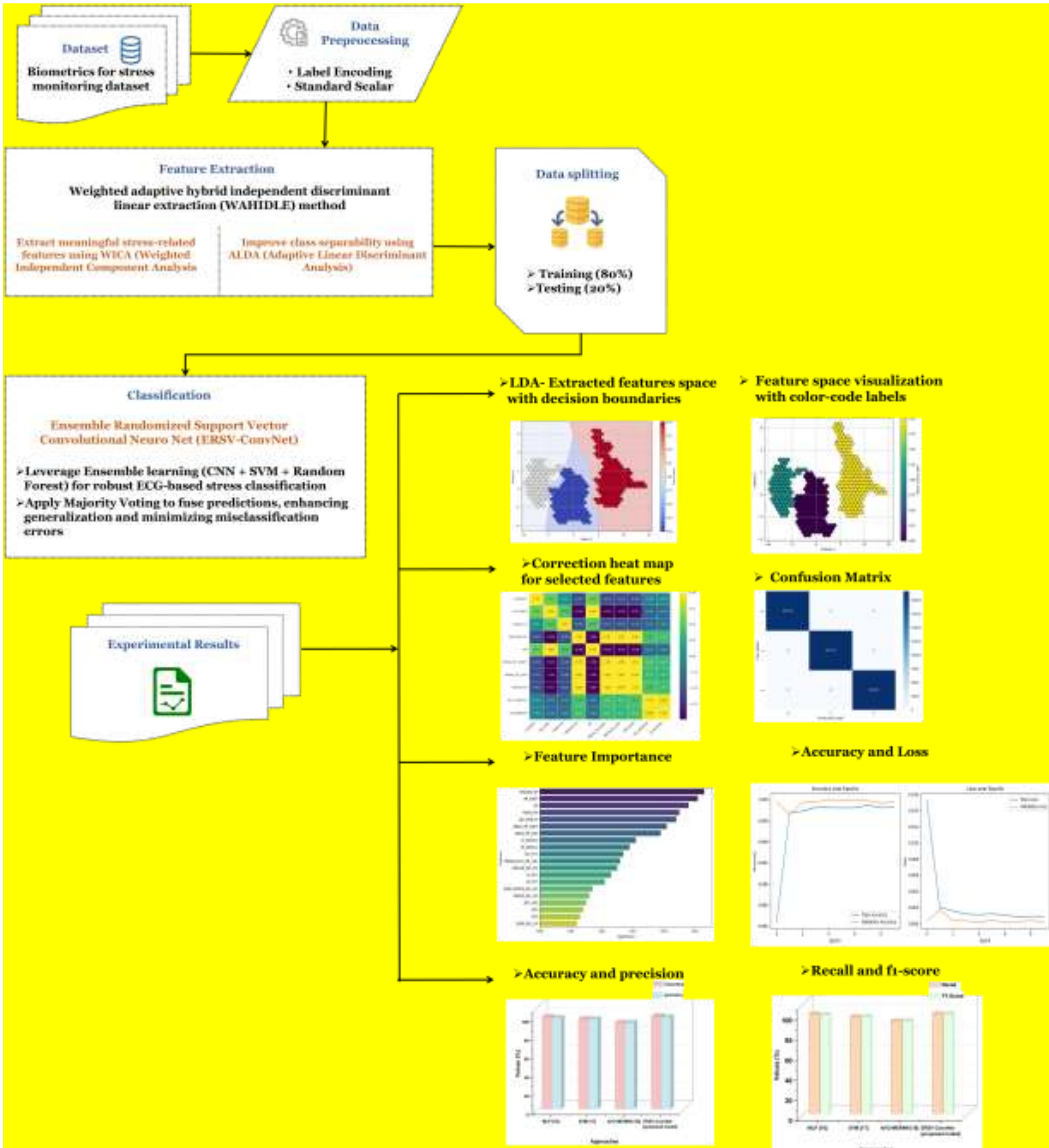


Figure 1: Schematic representation of the proposed flow

3.1 Data acquisition

Biometrics for the stress monitoring dataset (https://www.kaggle.com/datasets/qiriro/stress) is collected from Kaggle. The stress monitoring dataset consists of HRV and Electrodermal Activity (EDA) characteristics from the SWELL and WESAD datasets. The data also comprises 3 directories and sub-directories, such as interim, raw EDA, and final. The intermediate directory covers the data experiments, raw EDA signals, and the inter-beat interval, which are extracted from the ECG signal. The raw EDA signals are obtained from the included papers. The processed directory covers files established from the middle directory, facilitating further analysis. The final directory covers the files that are used for generating the model, with 2 sub-directories. **Table 1** offers the sample for ECG-derived HRV and EDA features used in the research.

Table 1: Sample Data Description

Features	01	02	03	04	05
MEAN_RR	660.7566	762.0045	978.5871	690.3339	724.2703
MEDIAN_RR	657.2423	769.0288	973.0284	669.5485	721.5978
SDRR	34.8571	106.0359	80.3231	79.6778	71.6631
RMSSD	7.4083	13.5918	20.3180	15.1737	13.5804
SDSD	7.4081	13.5802	20.3165	15.1731	13.5804
SDRR_RMSSD	4.7051	7.8015	3.9533	5.2511	5.2770
HR	91.0501	80.2677	61.7208	87.9963	83.6371
pNN25	1.75	6	20.5	8.75	5
pNN50	0	1	1.5	1.5	0.75
SD1	5.2449	9.6147	14.3839	10.7425	9.6148
SD2	49.0155	149.6489	112.6797	112.1682	100.8898
KURT	2.1875	-0.8358	0.3025	-0.1943	-0.0387
SKEW	0.7731	0.2520	0.3811	0.8254	0.4419
subject id	13	9	4	8	4
condition	baseline	baseline	amusement	stress	stress
SSSQ class	medium	low	medium	low	medium
SSSQ Label	1	0	1	0	1
condition label	0	0	1	2	2

3.2 Data Preprocessing

After gathering the stress monitoring dataset, the raw data is cleaned up using the label encoder and the typical scaler technique, which assures compatibility with ML methods. In this research, Label Encoding is utilized to convert the categorical variables into numeric format, and the Standard Scaler normalizes the numerical features. This process is intended to improve data consistency and support accurate model training.

- **Label Encoding for Numeric Representation of Categories**

In this stage, Label Encoding converts categorical variables into numerical form. The preprocessing module was used to transform the categorical columns condition and Short Stress State Questionnaire (SSSQ) class in the DataFrame (df) into numerical labels. The encoder.fit_transform() was used for each column, in which both labels identify the unique values and convert them into integer codes. The data set consisted of 67 columns of ECG-derived physiological features representing HRV and stress responses. Along with the physiological features were categorical labels (the experimental condition and SSSQ classification). These labels were encoded to SSSQ labels and condition labels in a way that they are compatible with ML models. Specifically, in the SSSQ labels, low level is signified by a value of 1, whereas, high level is characterized by a value of 2. This structured preprocessing enables ML models to detect patterns related to stress from both physiological and psychological perspectives. Figure 2 illustrates the encoded distributions of the two variables (a) condition distribution and (b) SSSQ class distribution.

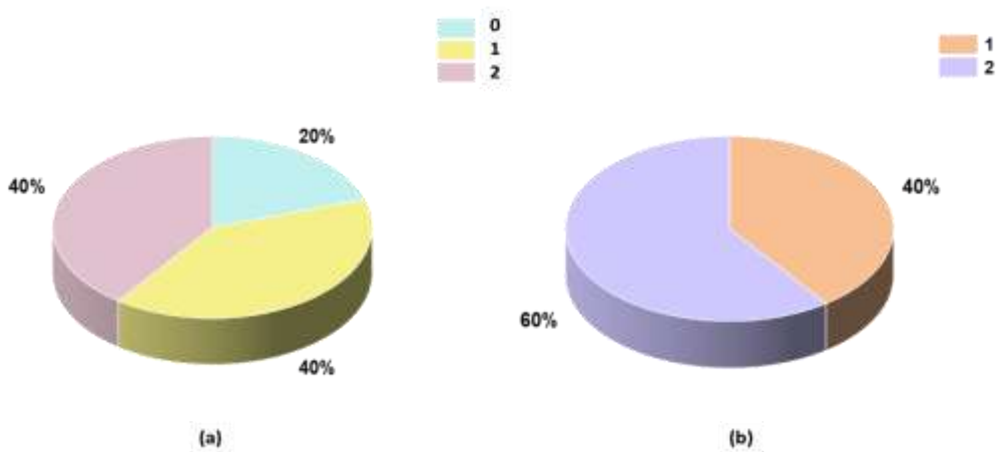


Figure 2: Graphical representation of (a) Encoded condition distribution and (b) Encoded SSSQ class distribution

For the 'condition' variable, the values 0, 1, and 2 are distributed as 20%, 40%, and 40%, respectively, while the 'SSSQ class's variable shows values 1 and 2 at 40% and 60%, respectively. The distribution percentage was considered by counting occurrences of individually unique values, separating the total of each value by the entire quantity of entries, and multiplying by 100. For example, in the list [1, 1, 0, 2, 2], value 0 occurs 1/5 = 20%, value 1 arises 2/5 = 40%, and value 2 arises 2/5 = 40%.

- **StandardScaler for data standardizing and transformation**

After encoding the data, the research uses StandardScaler method, to standardize the feature distributions, enhance the signal quality and ensure accurate analysis. The StandardScaler standardizes features and has a mean of 0 and Standard Deviation (SD) of 1, assuming that data is usually adopted inside each component. After calculating the element's mean and SD, the component is scaled based on equation (1).

$$Z_{Scaled} = \left(\frac{x-\mu}{\sigma}\right) \quad (1)$$

In equation (1), μ denotes mean, and σ represents the SD. The ECG dataset comprising 214,920 samples with 66 features was standardized using StandardScaler, ensuring zero-centered mean and unit variance across all variables. Its comprehensive preprocessing ensures feature uniformity and class balance, thereby optimizing the dataset for effective and accurate stress classification modeling. At last, after applying StandardScaler, the data has been balanced across the three categories of stress classes (0, 1, and 2) to represent equally.

3.3 Weighted adaptive hybrid independent discriminant linear extraction (WAHIDLE) method

Following data processing, the study employed an advanced feature extraction method known as WAHIDLE, which facilitated the analysis of both time and frequency-domain features. It incorporates adaptive Linear Discriminant Analysis (ALDA) and weighted Independent Component Analysis (WICA), to enhance ECG signal analysis by maximizing class separability and ensuring feature independence.

- **Weighted independent component analysis (WICA)**

WICA is a more sophisticated version of Independent Component Analysis (ICA) that can be used for separating sources with nonlinear dependency. The underlying concept of WICA, F-correlation, computes optimal correlation between random variables defined in a reproducing kernel Hilbert space (RKHS). F-correlation operates in an RKHS, allowing correlation computations in a high-dimensional feature space using inner product operations. It improves the WICA contrast function through correlation estimation in function space. Mapping data into a higher-dimensional space with kernel functions allows for a division of elements with nonlinear dependencies, resulting in the extraction of independent components from data and providing a robust solution to issues with complicated nonlinear relationships. Enhancing source separation robustness in data with complex nonlinear structures involves mapping the data into a higher-dimensional feature space. This method promotes separation of sources and increases robustness, especially in more complex datasets, by separating two types of random variables. Equation (2) defines the E-correlation as the maximum correlation between the transformed versions of the random variables w_1 and w_2 and let E be an $R-R$ functions' vector space. E denotes the E −correlation as the maximum correlation between the random variables $e_1(w_1)$ and $e_2(w_2)$. The E-correlation is mathematically expressed:

$$\rho E == \max_{e_1, e_2 \epsilon E} \frac{cov(e_1(w_1), e_2(w_2))}{(var\ e_1(w_1))^{1/2}(var\ e_2(w_2))^{1/2}} \quad (2)$$

If (w_1) and (w_2) are independent, then $\rho E = 0$, indicating no statistical dependence in the transformed space. Here, ρE denotes the E-correlation, which is the maximum possible correlation between transformed versions of w_1 and w_2 in the Hilbert space E. If w_1 and w_2 variables are independent, then the E-correlation is equal to zero. Let L_1 and L_2 be Mercer kernels with feature maps (Φ_1, Φ_2) and feature spaces $(E_1, E_2 \subset Q^w)$. Mercer kernels are positive semi-definite functions that enable mapping data into higher-dimensional feature spaces through kernel tricks. To address numerical stability and improve generalization, a regularization term d is incorporated into the model, enhancing its robustness and reducing the risk of overfitting in complex data scenarios. Equation (3) introduces a regularized canonical correlation optimization, improving numerical stability and generalization in high-dimensional data. To improve numerical stability and generalization, especially in high-dimensional data, WICA introduces a regularization parameter d, as expressed in the following equation (3).

$$\hat{\rho}_E^d(L_1, L_2) = \max_{\alpha_1, \alpha_2 \epsilon Q^M} \frac{\alpha_1^S L_1 L_2 \alpha_2}{\left(\alpha_1^S\left(L_1 + \left(\frac{Md}{2}\right)J\right)^2 \alpha_1\right)^{1/2} \left(\alpha_2^S\left(L_2 + \left(\frac{Md}{2}\right)J\right)^2 \alpha_2\right)^{1/2}} \quad (3)$$

The minimal eigenvalue of this problem is denoted in equation (4) as $\hat{\lambda}_E^d(L_1,\ldots,L_m)$. Here, J denotes the centering matrix and M is the number of samples.

$$\hat{J}_{\lambda_E}(L_1,\ldots,L_n) = -\frac{1}{2}\log\hat{\lambda}_E^d(L_1,\ \ldots,L_n) \tag{4}$$

If the contrast function, $J_{\lambda_E} = 0$, then the variables $w^1, w^2, \ldots, w^n$ are pairwise independent. Given a kernel function $L(w,z)$ and data vectors $z^1, z^2, \ldots, z^n$, WICA evaluates contrast functions to estimate independence through generalized eigenvalue decomposition. WICA enhances ECG signal analysis by improving source separation and ensuring robust extraction of independent features through higher-dimensional feature mapping. To ensure the reliability of the WICA-derived components, quality control procedures such as kurtosis analysis, F-correlation thresholding, and component stability testing were employed to validate independence and relevance.

- **Adaptive linear discriminant analysis (ALDA)**

For comparative analysis, the within-class and between-class scatter measures are redefined so that data pairs from different classes are mapped farther apart, while the local structure of samples within the same class is conserved in the reduced subspace. An innovative feature extraction method called ALDA is presented, based on $\acute{T}_A$ and $\grave{T}_{RW}$. Equation (5) represents the matrix with columns that maximize the ratio of the determinant of $\acute{T}_A$ and $\grave{T}_{RW}$, which is the optimal projection X_{opt} that ALDA achieves.

$$X_{opt} = \underset{X}{arg\,max}\ \frac{|X^S\acute{T}_A X|}{|X^S\grave{T}_{RW}X|} = [\omega_1\ \omega_2\ \ldots.\omega_n] \tag{5}$$

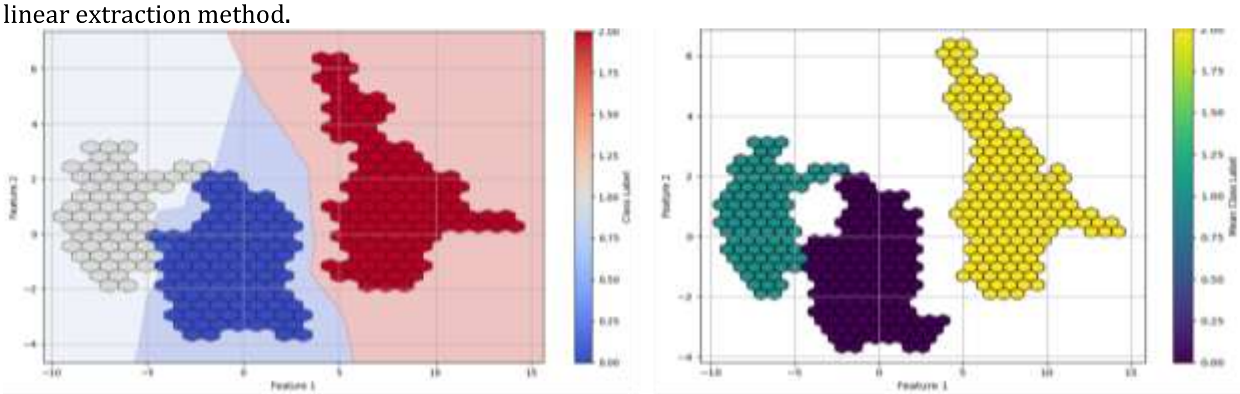
The set of general eigenvectors of $\acute{T}_A$ and $\grave{T}_{RW}$ that is parallel to the n largest generalized eigenvalues $\{\omega_j | j = 1,2,\ldots,n\}$ is represented by $\{\lambda_j | j = 1,2,\ldots,n\}$ in equation (6).

$$\acute{T}_A\omega_j = \lambda_j\grave{T}_{RW}\omega_j, j = 1,2,\ldots,n \tag{6}$$

However, dimensions that capture significant discriminative information are eliminated during this step. ALDA approach avoids the small size issue and the complexity of a singular $\grave{T}_{RW}$ is avoided. The maximum margin criterion (MMC) suggests maximizing and achieving the most discriminant feature vector in equation (7).

$$X_{MMC} = \underset{W}{arg\,max}(X^S(\acute{T}_A - \acute{T}_{RW})X) \tag{7}$$

Where, the first M largest orthonormal eigenvectors of $\acute{T}_A - \grave{T}_{RW}$ are $X = (\omega_1\ \omega_2\ \ldots.\omega_n)$. ALDA improves stress classification accuracy by projecting ECG features into a lower-dimensional space, preserving local structure. It addresses small sample size problems without losing discriminative information, creating a feature space for better classification, with linear decision boundaries. Figure 3(a) demonstrates the ALDA-Extracted Features, in which the plot shows three clusters with centers at approximately (-6, 0) for white, (0, -1) for blue, and (8, 1) for red. Clear decision boundaries are formed, indicating strong class separability and effective feature extraction. Figure 3(b) illustrates the results of distributed features, using the weighted hybrid independent linear extraction method.



(a) (b)

Figure 3: (a) ALDA-Extracted Feature Space with Decision Boundaries and (b) Feature space visualization with color-coded class labels

The WAHIDLE technique integrates WICA and ALDA, obtaining string feature independence and maximum class separability for ECG stress signals. Therefore, the stress recognition model intends to improve personalized health applications and wearable devices capable of real-time stress detection. The results exhibit empowering individuals to manage stress more effectively and moderate its negative health impacts. The data was categorized into training (80%) and testing (20%) sets to assess model performance.

3.4 Classification based on Ensemble Randomized Support Vector Convolutional Neuro Net (ERSV-ConvNet)

The ERSV-ConvNet is a hybrid classification framework that integrates Support Vector Machine (SVM), Convolutional Neural Network (CNN), and RF within an ensemble architecture. This model leverages CNN's feature abstraction, SVM's precise boundary classification, and RF's robustness to variability for accurate ECG-based stress detection and classification. Majority voting is used to combine predictions, enhancing generalization and reducing overfitting. The model effectively classifies ECG signals into stress and non-stress categories with high accuracy and interpretability.

- **Support Vector Machine (SVM)**

SVM ensures high classification precision by finding the optimal hyperplane that separates stress and non-stress classes in the transformed feature space. It effectively handles non-linear decision boundaries using a radial basis function (RBF) kernel. The architecture of SVM is illustrated in Figure 4. This model contributes strong boundary-based decision-making to the ensemble framework, improving sensitivity to subtle feature differences. The SVM model utilizes an RBF kernel with hyperparameters C, gamma, and probability=True, applied on StandardScaler-normalized features for optimal classification.

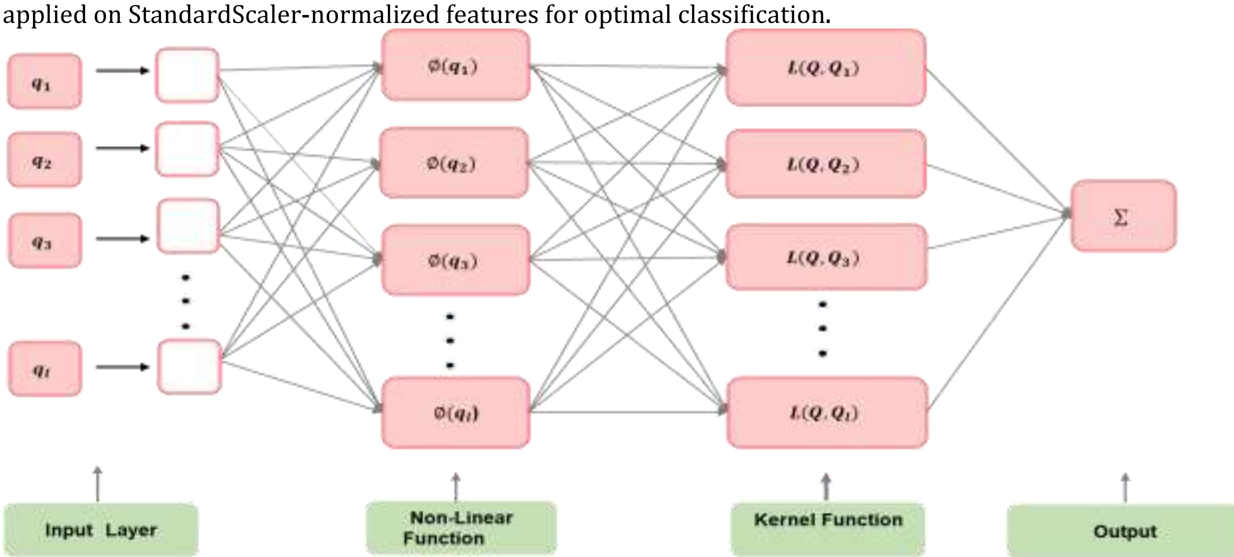


Figure 4: Workflow Representation of the SVM Classification Process

Consider input vector data as $W = \{q_l\} \in q^c$ and output vector data as $Z = \{t_l\} \in Q$. These are combined to create the training data as $\{(q_1, s_1), (q_2, t_2), \ldots, (q_M, T_M)\}$ with $T_l \in \{-1, +1\}$. This data is separated into two components, as explained in equation (8).

$$\begin{cases} x^S q_l + a \geq +1, \ if \ t_{l=} + 1 \\ x^S q_l + a \geq +1, \ if \ t_{l=} + 1 \end{cases} \quad (8)$$

It is written as shown in equation (9):

$$Z[x^s W + a] \geq 1 \quad (9)$$

The SVM model utilizes convex optimization and classical optimality characteristics, to identify restricted optimization issues, utilizing Lagrange multipliers in the dual space and is denoted in equation (10).

$$t(q) = sign[\textstyle\sum_{l=1}^{M} \propto_l t_l q_l^S q + a] \quad (10)$$

This approach defines the current problem and the revised set of inequalities given below in equation (11) using an extra variable.

$$Z[x^S W + a] \geq 1 - \xi, where \ \xi = \{\xi_1, \xi_2, \ldots, \xi_N\} \quad (11)$$

The equation is used to evaluate linear and nonlinear functions. In the SVM framework, a least squares variant of SVM is utilized to handle equality constraints effectively. In addition, the SVM reformulation approach is applied to reduce the computational time needed for solving complex problems efficiently. The primary space is defined as shown in equation (12):.

$T(q) = sign[x^S q + a]$ (12)

Here, a is a real constant, and the dual space of the non-linear classification has the form in equation (13),

$t(q) = sign[\sum_{l=1}^{M} \propto_l t_l L(q, q_l) + a]$ (13)

a is a real constant, and $\alpha 1, \alpha 2, \ldots, \alpha N$ are positive real constants. In general, $L(q, q_l) = \langle \varphi(q_l), \varphi(q) \rangle$. The innermost design is represented as $\langle \cdot, \cdot \rangle$. While $\varphi(q)$ is a nonlinear mapping from higher dimensions to the initial space. Equation (14) represents the shape of the SVM model for functional estimation.

$t(q) = \sum_{l=1}^{M} \propto_l t_l L(q, q_l) + a$ (14)

$L(q, q_l)$ denotes a kernel function that meets the Mercer requirement that is defined as in equation (15).

$L(q, q_l) = \Phi(q)^S \Phi(q_l)$ (15)

The RBF comprises two parameters: regularization constant (γ) *and width* (α). The SVM model enhances classification precision by constructing optimal hyperplanes for stress separation. Its output strengthens the ensemble's ability to distinguish subtle class boundaries. The SVM outputs discrete class labels based on the optimal hyperplane that separates stress and non-stress states. It can also provide class probabilities when probability=True is enabled, enhancing decision confidence in the ensemble.

- **Random Forest (RF)**

The RF method provides robust and generalized classification by aggregating decisions from multiple decision trees trained on randomized subsets. The RF in ERSV-ConvNet used n_estimators, random_state, criterion, and max_features as key hyperparameters, to ensure robust and generalized classification. It handles feature variability and noise effectively, offering high interpretability and resilience. Its role in the ensemble model boosts diversity and reduces overfitting through bagging and majority voting. Tree-structured classifiers make up the RF used to execute the RF algorithm, and each tree casts a vote for the most popular class at input W. Figure 5 denotes the schematic representation of RF.

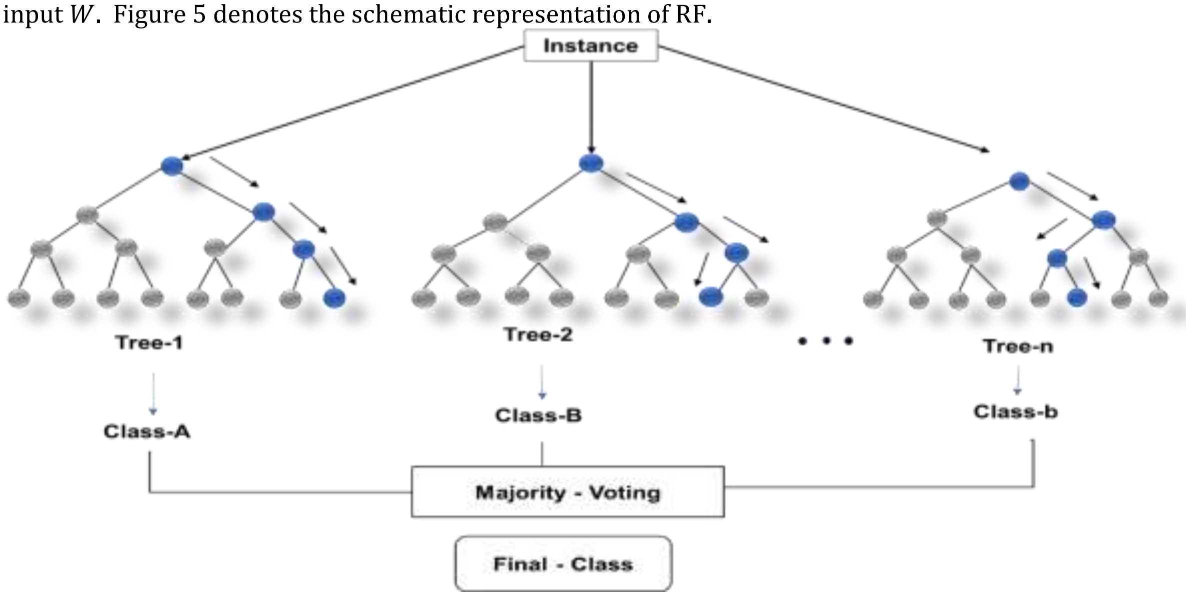


Figure 5: Structural Overview of RF-Based Classification Model

The margin function is defined using a collaborative of classifiers, with the training set drawn randomly from the random vector distribution, as shown in equation (16).

$nh(W, Z) = bu_l J(g_l(W) = Z) - max_{i \neq z\, bu_l} J(g_l(w) = i)$ (16)

For practically all sequences, OF^* converges to equations (17) and (18) as the number of trees rises.

$O_{W,Z} (O_\Theta(g(W, \Theta) = Z) - max_{i \neq Z} O_\Theta(h(W, \Theta) = i) < 0)$ (17)

$OF^* = O_{W,Z}(nh(W, Z) < 0)$ (18)

According to equation (19), the margin function for an RF is $nq(W, Z)$.

$nq(W, Z) = O_\Theta(g(W, \Theta) = Z) - max_{i \neq Z}\, o_\Theta(g(W, \Theta) = i)$ (19)

Equation (20) shows the strength of the collection of classifiers $g(W, \Theta)$.

T= $F_{W,Z}\, nq(W, Z)$ (20)

The variance of mr may be expressed in a more illuminating way using equation (21).

$\hat{\imath}(W, Z) = arg\, max_{i \neq Z} O_\Theta(g(W, \Theta) = i)$ (21)

As a result, equation (22) displays the margin function for an RF.

$$nq(W,Z) = O_\Theta(g(W,\Theta) = Z) - O_\Theta(g(W,\Theta) = \hat{\imath}(W,Z) = F_\Theta[J(g(W,\Theta) = Z) - J(g(W,\Theta) = \hat{\imath}(W,Z)] \quad (22)$$

The function for raw margin is provided in equation (23).

$$qnh(\Theta, W, Z) = 1(g(W,\Theta) = Z) - J\big(g(W,\Theta) = \hat{\imath}(W,Z)\big) \quad (23)$$

Equation (24), provides an upper bound on the generalization error.

$$OF^* \leq \frac{\bar{O}\,(1-T^2)}{T^2} \quad (24)$$

RF contributes robustness through ensemble decision trees, effectively handling noisy and diverse inputs. Its aggregated predictions improves generalization and reduce overfitting. The RF outputs class predictions by combining the votes from multiple decision trees. It also provides class probabilities based on the proportion of trees predicting each class, ensuring robust and interpretable outputs. The outputs from SVM and RF are leveraged as auxiliary inputs to the CNN to enrich its learning process. This integration enhances classification accuracy by combining boundary-based precision and ensemble robustness.

- **Convolutional Neural Network (CNN)**

CNN captures complex, hierarchical feature patterns from ECG-derived inputs, enabling deep learning (DL)-based discrimination of stress states. In the suggested ensemble, the CNN uses the predictions of SVM and RF as auxiliary inputs allowing the CNN to learn better feature representations that are informed by the decisions of the boundaries and the ensemble. The CNN, automatically extracts features via the dense layers, which increases the model's probability of generalizing over different distributions of inputs. In the ensemble, CNN adds deep representation power and temporal learning capacity, critical for physiological data. Figure 6 illustrates the Structured CNN-Based Learning Model for stress category prediction. The CNN model requires preprocessed ECG features as input and extracts deep temporal patterns through multiple Conv1D and dense layers. Dropout layers are used to reduce excessive fitting and increase generalization under varying stress situations. Finally, the final output layer produces three class probabilities (0, 1, or 2), and the class with the highest probability is selected as the prediction. Table 2 displays the architectural breakdown of the CNN utilized in the proposed ensemble model.

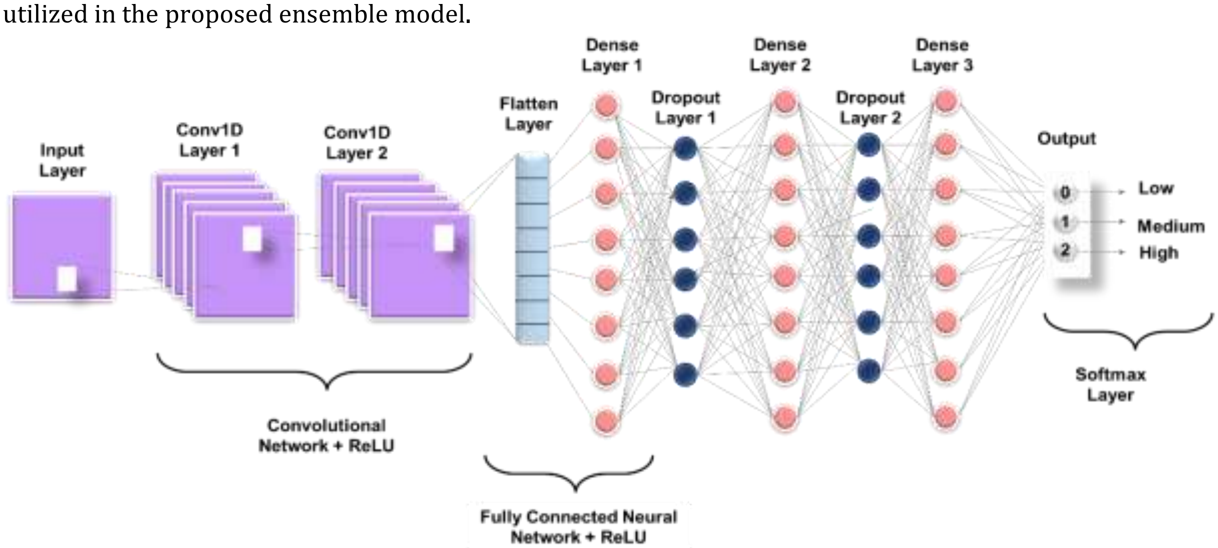


Figure 6: Architecture for Stress Recognition and Classification

Table 2: Comprehensive CNN Architecture for ECG-Based Stress Detection

Layer Type	Output Shape	Number of Units / Filters / Kernels	Activation Function	Dropout Rate
Input Layer	(None, N, 1)	N = X_final.shape[1]	-	-
Conv1D Layer 1	(None, N, 64)	64 filters, kernel_size=3	ReLU	-
Conv1D Layer 2	(None, N, 32)	32 filters, kernel_size=3	ReLU	-
Flatten Layer	(None, N * 32)	-	-	-
Dense Layer 1	(None, 128)	128 neurons	ReLU	-

Dropout Layer 1	(None, 128)	-	-	0.5
Dense Layer 2	(None, 64)	64 neurons	ReLU	-
Dropout Layer 2	(None, 64)	-	-	0.3
Dense Layer 3	(None, 32)	32 neurons	ReLU	-
Output Layer	(None, num_classes)	num_classes = len(set(y_resampled))	Softmax	-

- **Input Layer:** It reshapes flat input from (None, N) to (None, N, 1) to ensure compatibility with Conv1D operations in the CNN. This ensures that the input data is appropriately structured and arranged for deep neural processing without applying any activation functions. This layer serves a basic function in matching the input physiological data structure with the input structure expected by the network. It provides a seamless link between the raw feature space and original processing layers.
- **Conv1D Layer 1:** This layer is designed to extract meaningful local patterns from the ECG-derived feature sequences using sliding window filters. It captures short-term dependencies and variations that are crucial for identifying stress indicators. By applying multiple filters across the input, it generates feature maps that highlight significant temporal changes. This enhances the model's ability to detect subtle stress-related patterns in physiological data.
- **Conv1D Layer 2:** This layer improves on the feature maps from the previous layer, honing in on more abstract, higher level patterns from the ECG signal. Further, it deepens the understanding of the network itself by capturing higher temporal dependencies. This layer helps distinguish subtle differences between stress and non-stress states. The refined features contribute to improved classification accuracy in later layers.
- **Flatten Layer:** This converts the multi-dimensional convolutional feature maps into a one-dimensional vector. This conversion prepares the data to be processed by fully connected dense layers. It serves as a link between convolutional layers and classification layers. Flattening preserves learned features for effective stress prediction.
- **Dense Layer 1:** It learns high-level global feature interactions from the flattened input. It captures complex relationships that are important for accurate classification of stress. It's an initial fully connected layer in the architecture, and has 128 neurons and produces an output shape. It employs the Rectified Linear Unit (ReLU) Activation function enables discontinuity, allowing the model to learn complicated mapping between ECG signals and stress states. The layer takes standardized inputs and starts the process of transforming them into meaningful latent representations. It serves as the first step to developing high-level patterns of importance for the classification of stress.
- **Dropout Layer 1:** Following the first dense layer, it randomly deactivates 50% of neurons during training to prevent overfitting. This improves the model's generalization and robustness on unseen data. It maintains the output shape of (None, 128) but with a dropout rate of 0.5, which helps prevent overfitting to the training data. This stochastic reduction of connections enables the architecture to form new more robust and more generalized representations. This process can be very helpful in dealing with variability and noise, often seen in physiological ECG data.
- **Dense Layer 2:** It further refines the learned feature representations from the previous layer. This improves the model's capacity to distinguish among subtle stress patterns. It aggregates more refined abstract patterns from the previous representation modes of the cluster that are designed to improve the model's ability to discriminate between categories of stress states. This enables the framework to remember only the most significant data and to de-emphasize lesser useful variations. The decreased dimensions allow for more effective calculation, and increased the accuracy for the classification task compared to models trained on all available variations.
- **Dropout Layer 2:** This randomly removes 30% of the neurons during training to improve generalization. This minimizes overfitting and improves the model's performance on unseen data. It continually learns refined and abstracted patterns from previous results, focusing on improving the model's ability to differentiate among different levels of stress. It allows the model to retain only the most useful information and discard less useful variations. Less dimensions results in efficient compute and improved classification accuracy.
- **Dense Layer 3:** The 32 neurons and an output shape of (None, 32), this third dense layer further compresses the learned feature representations. It continues to utilize the ReLU activation function to

retain non-linear transformations, essential for modeling complex physiological relationships. This layer acts as a final refinement stage before classification, distilling abstract features into a compact, decision-relevant form. It connects the deep feature extraction process and the final output layer for processing, making sure that you are absolutely in the best position to predict stress.

- **Output Layer:** A SoftMax activation function is utilized in the output layer, which creates probabilities among the classes as it is multi-class classification it just selects the most probable stress category. The softmax activation function will take the dense output and convert it into normalized probabilities for each class.. This allows the model to perform multi-class stress classification with confidence scores for each predicted label. The layer delivers interpretable results that are suitable for real-time integration in wearable health monitoring systems. CNN predictions are converted into class labels using the Softmax activation in the output layer, which transforms logits into probabilities for each stress class. The class with the highest probability is selected and mapped back to the original labels using reverse label encoding for interpretation. The pseudocode 1 illustrates the design framework of proposed ERSV-ConvNet for classification.

Pseudo code 1: Ensemble Randomized Support Vector Convolutional Neuro Net (ERSV-ConvNet) for Classification

1. $Start\ Program$
2. $Data\ Preparation$
   2.1. $Load\ dataset\ \rightarrow\ X\_final\ (features), y\_resampled\ (labels)$
   2.2. $Split\ the\ dataset\ into\ training\ and\ test\ sets$
      $-\ X\_train, X\_test, y\_train, y\_test\ =\ train\_test\_split(X\_final, y\_resampled, test\_size = 0.2)$
3. $Train\ SVM\ Model$
   3.1. $Initialize\ StandardScaler\ and\ SVM\ with\ RBF\ kernel$
   3.2. $Create\ SVM\ pipeline: [StandardScaler\ \rightarrow\ SVM]$
   3.3. $Fit\ the\ pipeline\ on\ training\ data\ (X\_train, y\_train)$
   3.4. $Predict\ class\ labels\ on\ test\ data\ \rightarrow\ y\_pred\_svm$
4. $Train\ Random\ Forest\ Model$
   4.1. $Initialize\ RandomForestClassifier\ with\ 100\ estimators$
   4.2. $Fit\ Random\ Forest\ on\ training\ data\ (X\_train, y\_train)$
   4.3. $Predict\ class\ labels\ on\ test\ data\ \rightarrow\ y\_pred\_rf$
5. $Train\ CNN\ Model$
   5.1. $Define\ CNN\ Architecture:$
      $-\ Dense\ Layer: 128\ neurons, ReLU\ activation, input\_shape = (number\ of\ features)$
      $-\ Dropout\ Layer: rate\ 0.5$
      $-\ Dense\ Layer: 64\ neurons, ReLU\ activation$
      $-\ Dropout\ Layer: rate\ 0.3$
      $-\ Dense\ Layer: 32\ neurons, ReLU\ activation$
      $-\ Output\ Dense\ Layer: softmax\ activation\ with\ number\ of\ neurons\ =\ number\ of\ unique\ labels$
   5.2. $Compile\ CNN\ using\ Adam\ optimizer\ and\ sparse\ categorical\ cross-entropy\ loss$
   5.3. $Train\ CNN\ on\ (X\_train, y\_train), for\ 10\ epochs, batch\_size\ =\ 32$
   5.4. $Predict\ class\ probabilities\ on\ X\_test\ \rightarrow\ cnn\_probabilities$
   5.5. $Convert\ probabilities\ to\ class\ labels: cnn\_preds\ =\ argmax(cnn\_probabilities)$
6. $Ensemble\ Voting$
   6.1. $For\ each\ sample\ i\ in\ the\ test\ set:$
      $-\ Collect\ predictions: [y\_pred\_svm[i], y\_pred\_rf[i], cnn\_preds[i]]$
      $-\ Count\ the\ occurrences\ of\ each\ predicted\ class$
      $-\ Select\ the\ class\ label\ with\ the\ highest\ count$
      $-\ Store\ it\ as\ final\_preds[i]$
7. $Evaluate\ Ensemble\ Model$
   7.1. $Calculate\ accuracy: compare\ final\_preds\ with\ y\_test$
   7.2. $Display\ accuracy\ score$
   7.3. $Optionally: display\ classification\ report\ and\ confusion\ matrix$
8. $End\ Program$

IV. PERFORMANCE ANALYSIS AND DISCUSSION

The goal of the research is to analyze ECG signals obtained under various stress-inducing conditions to create a robust model for stress recognition. Table 3 displays the experimental setup for implementing ECG-Based Stress Recognition, developed using MATLAB and hardware configuration, accompanied by additional tools for auxiliary processing and analysis.

Table 3 Experimental Setup

Parameter	Specification
Programming Language	Python 3.11.2, MATLAB R2023a
RAM	16 GB DDR4 @ 3200 MHz
Processor (CPU)	Intel® Core™ i7-12700H @ 2.30GHz
GPU	NVIDIA GeForce RTX 3060 (6 GB GDDR6)
Storage	1 TB NVMe SSD
Operating System	Windows 11 Pro (64-bit)
Software Tools	MATLAB

4.1 Analysis of feature importance

The feature are analyzed and the relative significance of various heart rate variability (HRV) features are determined in predicting a physiological or analytical outcome. It comprehends feature significance and helps to identify the most influential biomarkers, develop model interpretability, and control feature selection in clinical decision-making systems. Figure 7 demonstrates the graphical findings of feature significance.

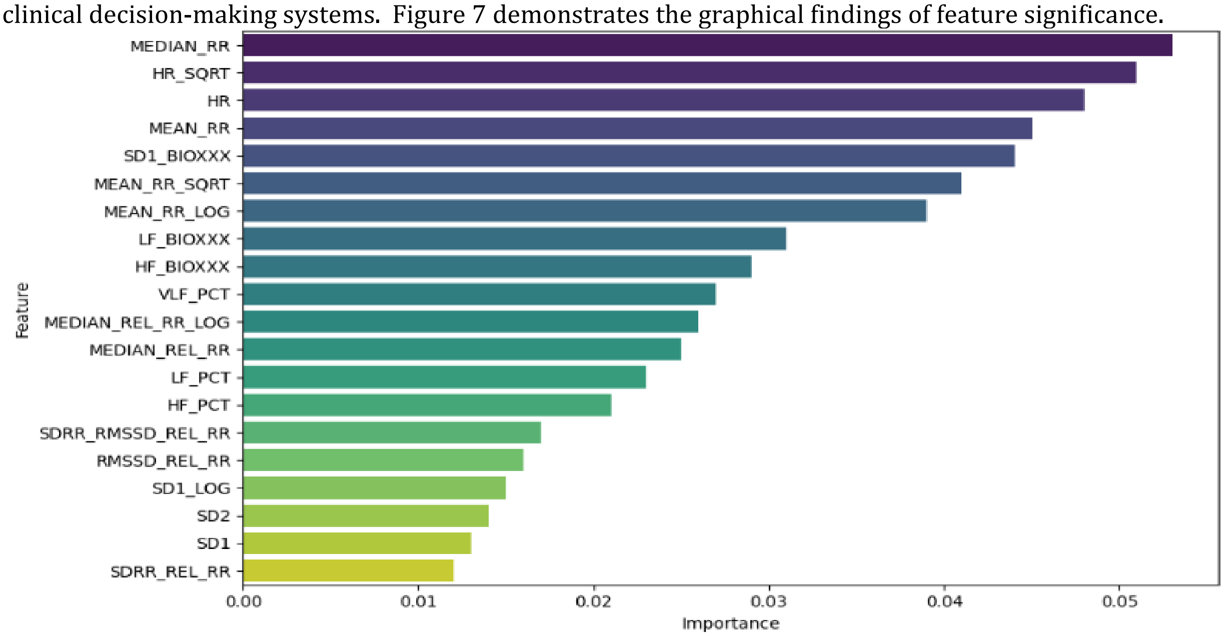


Figure 7: Graphical depiction of feature importance results

The most significant feature is MEDIAN_RR with an importance score of 0.054, indicating its strong predictive value. It is followed by HR_SQRT (0.051) and hr (0.047), both closely influencing the model.

4.2 Confusion Matrix Insights for Selected Features

Confusion matrix is used to estimate the efficiency of input data features by associating predicted and true labels. It demonstrates how the method distinguishes patterns in the features and maps them to the correct output labels. Figure 8 defines the graphical findings of the Confusion Matrix for data features.

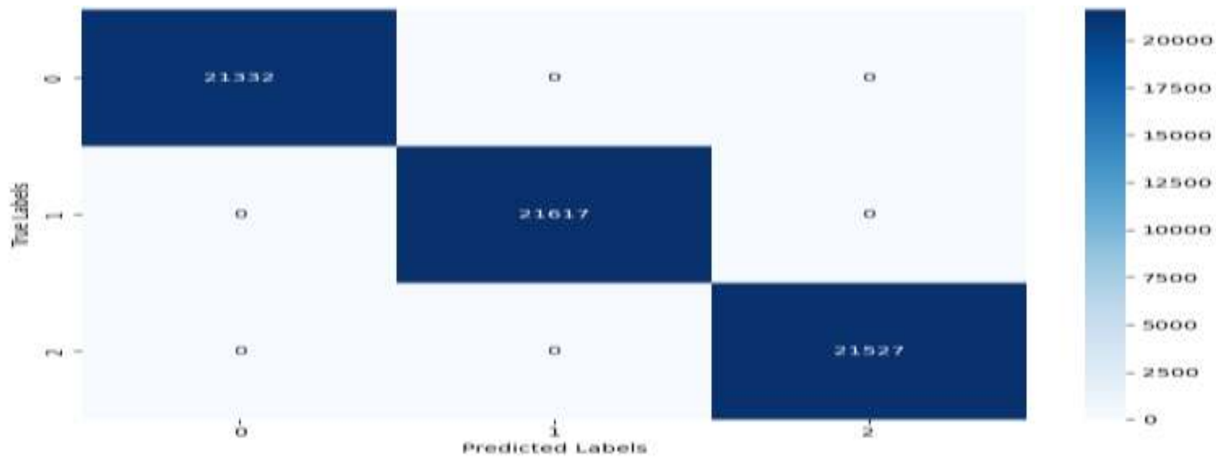


Figure 8: Graphical representation of Confusion Matrix based on selected features

In Figure 8, it is interpreted that the model was able to predict the true positives (21332, 21617, and 21527) with null negatives. This demonstrates that the proposed recognition model exhibits enhanced detection of actual positive cases.

4.3 Heatmap analysis for identifying inter-feature correlations

The correlation matrix visualizes the connected relationships between physiological data features using correlation coefficients. Figure 9 displays the feature correlations heat map findings, with values ranging from -1 to 1, indicating perfect positive, negative, or no correlation.

Figure 9: Correlation heatmap for selected data features

The correlation matrix reveals strong negative correlations between HR features and RR intervals (HR is negatively correlated with MEDIAN_RR (r = -0.85) and strong positive correlations among RR-derived metrics (e.g., MEAN_RR related to MEAN_RR_LOG = 0.96).

4.4 Evaluation of Accuracy and Loss

The overall accuracy of the ERSV-ConvNet model in distinguishing between stress and non-stress states from ECG signals is measured by accuracy. It shows the proportion of overall accurate predictions. The research demonstrates the model's dependability in detecting stress in its entirety. Loss is a quantitative number that indicates the distance between a method's forecasts and the actual goal values. It quantifies the error made during training or testing. Lower loss indicates better model performance. Figure 10 denotes the findings of the (a) testing accuracy and (b) testing loss performance showing lower quality performance compared to training efficiency.

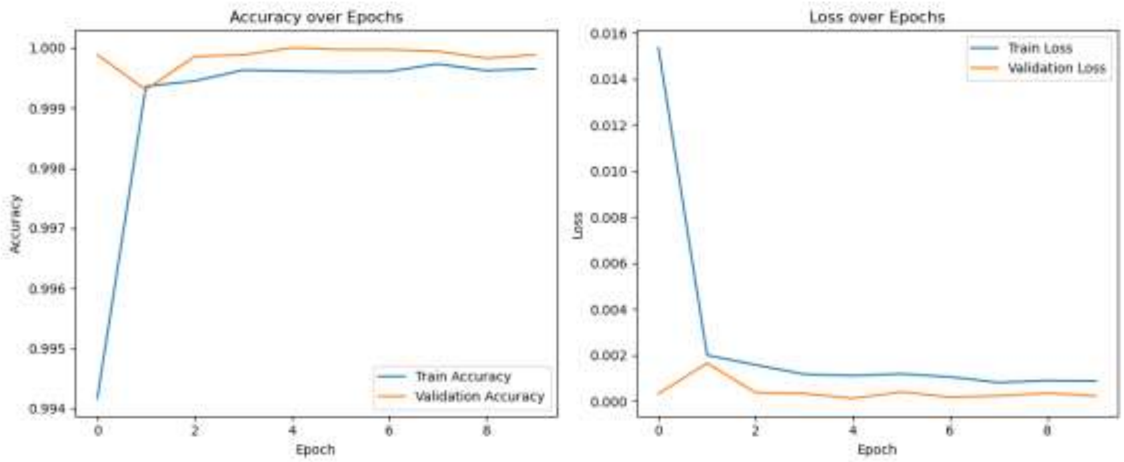


Figure 10: Graphical representation of (a) Accuracy and (b) Loss

4.5 Comparative analysis

To develop a robust model for stress recognition using ECG signals under various stress-inducing conditions. Existing methods like SVM [16], and African vulture optimization (AVO)-based modified Elman recurrent neural network (MERNN) [17] were used for comparison. The proposed and existing models have been validated for their enhanced capability in accurate and reliable stress classification. Table 4 demonstrates the findings of proposed and existing models.

Table 4: Numerical outcomes of compared metrics

Parameters	MLP [16]	SVM [17]	AVO-MERNN [18]	ERSV-ConvNet [proposed model]
Precision	98.29	97	93.0	99
F1-Score	99.03	97	92.9	99.95
Recall	99.85	97	92.82	99.95
Accuracy	99.04	97	93	99.98

Accuracy: Accuracy determines how accurate the overall correctness of the ERSV-ConvNet model is in recognizing stress and non-stress states from ECG signals (equation 25). It reflects how many total predictions are correct. In the research, it demonstrates the model's dependability in complete stress detection. The ERSV-ConvNet obtained the maximum accuracy (99.98%), outperforming MLP (99.04%), SVM (97%), and AVO-MERNN (93%), indicating the superior classification of ECG signals.

$$Accuracy = \frac{T_P+T_N}{T_P+T_N+F_P+F_N} \quad (25)$$

Precision: It evaluates how many of the ECG signals predicted as "stress" are truly stress cases (equation 26). It is crucial for minimizing false alarms in real-time stress monitoring. High precision in the proposed model ensures fewer misclassifications of relaxed individuals as stressed. With a precision of 99%, higher than MLP (98.29%), SVM (97%), and AVO-MERNN (93%), the model effectively reduces false positive stress predictions. Figure 11 denotes the graphical findings of accuracy and precision.

$$Precision = \frac{TP}{TP+FP} \quad (26)$$

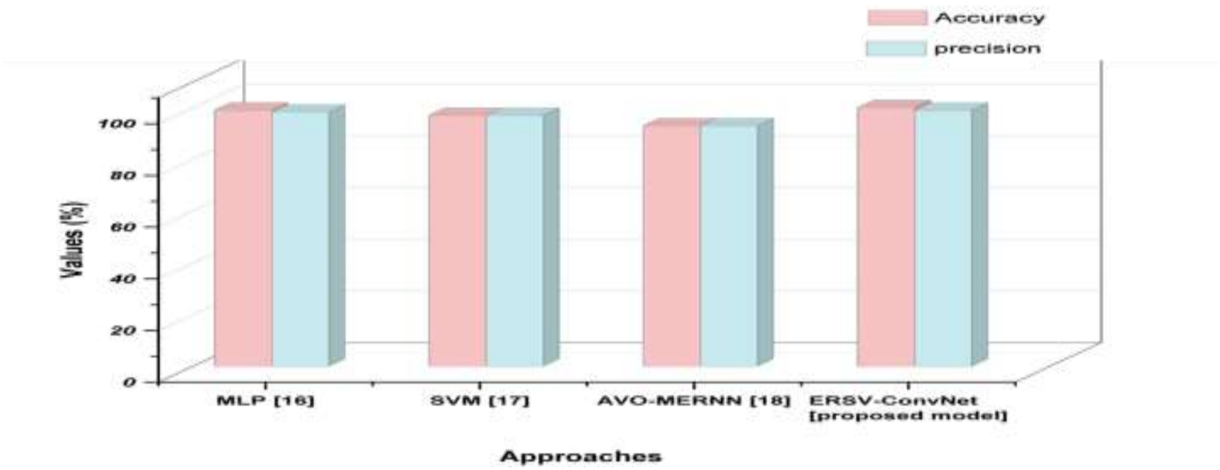


Figure 11: Comprehensive evaluation of Accuracy and Precision

Recall: This metric indicates how well the model detects all actual stress cases from the ECG signals (equation 27). It reflects the sensitivity of the system in identifying stressed individuals. A high recall in the proposed model ensures fewer missed stress events, which is vital for preventive health interventions. ERSV-ConvNet attained a recall of 99.95%, exceeding MLP (99.85%), SVM (97%), and AVO-MERNN (92.82%), showing its strong sensitivity to actual stress cases.

$$Recall = \frac{TP}{TP+FN} \tag{27}$$

F1-Score: It is the harmonious average of accuracy and recall, balancing the two metrics in one number. It is particularly important when the dataset has imbalanced stress and non-stress cases (equation 28). The proposed model's high F1-score confirms it performs well in both correctly detecting and avoiding misclassification of stress conditions. Achieving the top F1-score of 99.95%, compared to MLP (99.03%), SVM (97%), and AVO-MERNN (92.9%), the model demonstrates an excellent balance between precision and recall. Figure 12 represents the outcomes of recall and f1-score.

$$F1\ Score = 2.\frac{Precision \cdot Recall}{Precision + Recall} \tag{28}$$

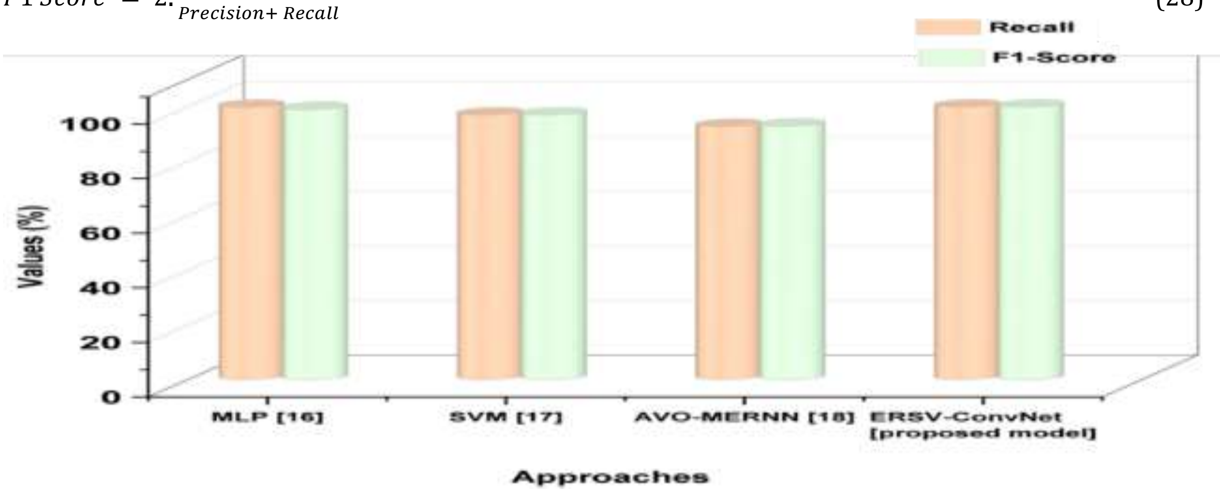


Figure 12: Performance analysis based on Recall and F1-score

4.6 Confusion matrix

A confusion matrix is a method for evaluating performance in classification tasks by comparing anticipated labels to actual labels. It is typically structured as a square table that shows the counts of true positives, true negatives, false positives, and false negatives, helping assess how well the model distinguishes between classes. In the ECG-based stress recognition model, the confusion matrix revealed high counts of true positives across all classes, indicating strong accuracy and effective class separation. Figure 13 demonstrates the findings of the confusion matrix.

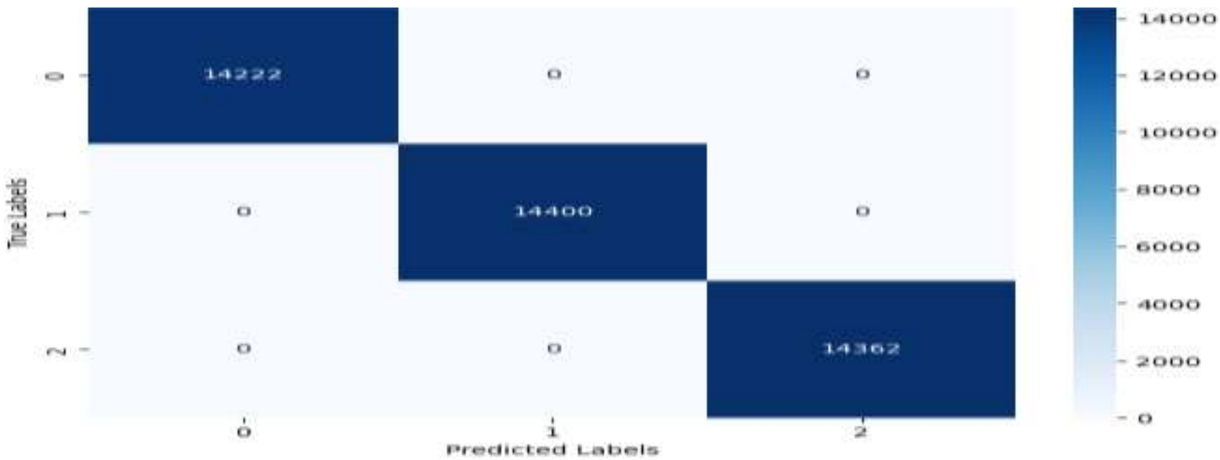


Figure 13: Graphical Outcomes of the Confusion Matrix

This visualization aids in identifying model strengths and weaknesses by revealing class-specific prediction errors. The confusion matrix showed high true positive values: 14222 for class 0, 14400 for class 1, and 14362 for class 2, with no false negatives. This indicates the model effectively distinguished stress levels with near-perfect classification. The results confirm the model's greater accuracy and reliability in recognizing actual stress cases.

4.7 Discussion

ECG signals obtained under various stress-inducing circumstances will be analyzed to create a reliable model for stress recognition. Although MLP [16] was used to classify stress using heart rate data, it lacked robustness across varying stress-inducing conditions. The model performed inconsistently when tested on new subjects, limiting its real-world applicability. Its weak transfer learning capability failed to handle inter-subject ECG variations effectively. This restricts its suitability for generalized stress recognition systems. The SVM model [17] struggled to maintain consistent accuracy across different psychological stress states. It relied on manually extracted features, which may not generalize across varied ECG patterns. The approach had limited ability to adapt under non-linear and subtle stress responses. Such reliance on handcrafted inputs reduces its robustness in dynamic contexts. While AVO-MERNN [18] suffered from computational complexity, making it unsuitable for real-time stress recognition. The model's sensitivity to ECG noise undermines reliability under practical stress-inducing conditions. It also demands extensive parameter tuning, which reduces deployment efficiency. These factors limit its robustness for generalized stress detection. The ERSV-ConvNet is a highly effective hybrid model for ECG-based stress recognition that leverages the strengths of CNN, SVM, and RF, in its ensemble architecture. It utilizes the deep feature abstraction of CNN, the defined margins of decision-making of SVM, and the approach of RF that accounts for variability to provide reliable and accurate classification of stress. The use of majority voting improves generalization while reducing overfitting, making it ideal for real-time, personalized health monitoring applications.

V. CONCLUSION

A robust stress recognition model using ECG signals collected under varied stress-inducing conditions was developed to predict the stress level. Initially, the dataset was preprocessed using Label Encoding and StandardScaler, to normalize feature distributions. Feature extraction was performed using a novel WAHIDLE method combining ICA and LDA. For classification, an ERSV-ConvNet was proposed, ensembling CNN, SVM, and RF and generates outcomes based on majority voting. The proposed ERSV-ConvNet achieved outstanding results such as precision (99%), recall (99.95%), accuracy (99.98%), and F1-score (99.95%). Additionally, the model was evaluated against existing techniques including MLP, SVM, and AVO-MERNN showing that the proposed model outperformed the other state-of-art methods. These findings showed the capacity of the model to recognize stress with superior accuracy and predictability. Also, it contributes to the field of wearable healthcare applications aimed at real-time detection of stress, and improvement of decision support accuracy. However, the model relied on high-quality, clean ECG signals and was tested on pre-segmented datasets, limiting its robustness to noisy real-world data. Future work should explore real-time implementation on wearable devices, adaptive learning for inter-subject variability, and multimodal stress indicators for broader applicability.

Declaration Statement;

Data availability

Not applicable.

Code availability

Not applicable.

Declarations

Ethics approval

Not applicable.

Consent to participate

Not applicable.

Consent for publication

Not applicable.

Conflict of interest

The authors declare no competing interests

Funding

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