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NEUROCARDIOAI: AN AI-POWERED FRAMEWORK INTEGRATING EEG AND COGNITIVE MARKERS FOR CARDIAC RISK PREDICTION

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ABSTRACT

Cardiovascular diseases (CVDs) are also one of the most important causes of death internationally, making risk prediction essential for early detection. The traditional paradigm heavily demarcates physiology-based markers, i.e., ECG, BP, and lipid profiles, while overlooking all the neurological and cognitive dimensions that cardiometabolic health can affect. While brainwave patterns, mental performance, and cardiac risk factors all have significant and clinically relevant associations individually and have recently been incorporated, these modalities have rarely been incorporated into a unified diagnostic paradigm. Existing models are mostly unimodal and use shallow or domain-specific machine learning techniques that do not capture inter-modality relations and temporal dynamics in a complex fashion. To address these limitations, we propose a novel AI-powered, multi-modal deep learning framework for early cardiac risk prediction: NeuroCardioAI. Leveraging EEG, cognitive test performance, and cardiovascular indices, the system enables modeling of multimodal health states. At the heart is BrainWaveHeartNet, a new hybrid CNN-Transformer architecture that extracts spatial patterns from EEG and sequential semantics from cognitive markers and fuses them with cardiovascular data at various levels using an attention-based fusion layer. We showed through extensive experiments on publicly available EEG and cardiovascular datasets that AUC-ROC of 98.63%, accuracy of 96.89%, precision of 96.40%, and recall of 97.10% can be achieved, significantly outperforming baseline models Interpretable Representation Learning for Empathetic Neural Conversation Models: Code for Healthy or Unhealthy Emotion Detection Methods (i.e. SVM, Random Forest, XGBoost). The modality gains are additive to performance, which is further validated with an ablation study. The model here has a scalable, non-invasive, real-time approach that is best suited to clinical (and memoir-based) preventative healthcare.) A major step in the direction of the convergence of neurocognition and cardiac-related diagnostic solutions, NeuroCardioAI is at least a step towards holistic, patient-centered, and proactive mitigation of cardiovascular risk.
Keywords - *Cardiac Risk Prediction, EEG Signals, Cognitive Markers, Deep Learning, Multi-Modal Fusion*

1. INTRODUCTION

Despite recent advances, a major research problem remains in integrating neurological, cognitive, and cardiovascular information within a unified framework for cardiac risk prediction. Existing approaches predominantly rely on physiological and clinical indicators, while EEG-based brain activity and cognitive markers are generally analyzed independently. This limits the ability to capture complementary relationships between brain activity, cognitive function, and cardiovascular status. Therefore, this study aims to develop NeuroCardioAI, a multimodal deep learning framework that integrates EEG signals, cognitive markers, and cardiovascular parameters using modality-specific feature extraction and attention-based fusion. The significance of this study lies in providing a unified approach that can exploit complementary multimodal information and improve the accuracy and comprehensiveness of cardiac risk prediction. One of the most widespread causes of mortality in the world is associated with CARDIOVASCULAR

DISEASES (CVD) as there are numerous forms of illness and financial problems. Conventional methods of cardiac risk predictors tend to rely on the physicochemical measurements such as blood pressure, lipid panel measurements, and electrocardiogram Readings. Although these metrics are essential, they may not capture the neurological aspects that seem to become relevant in the latest research. Novel research has reported that brainwave patterns and indicators of cognitive function predict risk of several different outcomes, including cardiovascular abundance [1], [2]. Yet psychological measures are rarely integrated into cardiac risk prediction models and cannot provide a broad-based, individually tailored diagnostic appraisal. As wearable EEG devices and high-dimensional cognitive test data become more widely available, it is timely to leverage artificial intelligence to cross this gap.

Recent literature has reported promising advancements in the application of deep learning to EEG signals for emotion detection [1], seizure prediction [7], and depression analysis [3]. However, these models are unimodal, treating either a neurological or cardiac dimension in isolation. These works usually use generic CNN or DNN architectures and cannot fully exploit complicated biomedical signals' sequential and semantic characteristics. Finally, there are hardly any efforts to bring EEG and cognitive features with cardiovascular data into a unified, multi-modal AI framework for comprehensive cardiac risk prediction. This limitation reflects the urgent requirement for a new approach that utilizes hybrid deep learning architectures to take advantage of the complementary nature of these varied signals.

This research aims to develop the NeuroCardioAI framework that integrates EEG brainwave patterns, cognitive function markers, and cardiovascular metrics using a deep learning approach for early and accurate risk detection, including cardiac events. Central to our system is BrainWaveHeartNet, a hybrid CNN-Transformer model that captures spatial and temporal features across modalities and integrates them using an attention-based framework. Furthermore, the proposed framework is non-invasive, scalable, and performs better than state-of-the-art models.

Specifically, this work makes the following contributions: we design a multi-modal architecture to record EEG, cognitive and cardiovascular data for cardiac risk assessment, ii) we develop BrainWaveHeartNet model containing CNN and transformer based components for robust feature extraction and sequence modeling, iii) we implement elaborate experiments yielding a significant increase over baseline models performance, i.e., up to 16.65% NMI, and up to 6% ACC and 12% F1 weighted scores ($p<0.05$) in average and 5/6 subjects take a significant advantage with less initial models hyper-parameter search, and iv) we conduct an extensive feature importance analysis and interpretability ablation study to justify the design and effectiveness of the model.

The rest of the paper is structured as follows: Section 2 gives the related work on EEG analysis, cognitive modelling, and cardiac risk prediction. In Section 3, we present the proposed NeuroCardioAI framework and the architecture of BrainWaveHeartNet. The following four sections elaborate on the experimental setup, the performance investigation, and the comparison with current state-of-the-art models. Section 5 discusses results, study limitations, and implications for clinical deployment. Section 6 is the conclusion section of the paper and possible directions for future research.

2. RELATED WORK

This literature review discusses the recent achievements in EEG based analytics, cognitive monitoring, and AI-driven cardiac risks and brain-health prediction. The Priyadarshani et al. [1] proposed a feature extraction combined with deep learning model and advanced preprocessing to recognize emotions using EEGs and the identification of emotions is made with high accuracy as opposed to traditional algorithms. In their discussion of EEG use in a brain-computer interface to identify emotions, Dutta et al. [2] mentioned the interference of noise and the inadequate spatial resolution. Chung et al. [3] offered a multi-tier ensemble learning approach that is more effective than the existing approaches and is able to evaluate depression based on EEG. Kim et al. [4] provided a real-time implementation that can forecast weariness of workers at construction site using IoT and ensemble learning, enhancing safety and reducing hazards. Analyzing the privacy concerns related to head-worn EEG, Mandal and Saxena [5] analyzed potential attacks and emphasized the

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fact that privacy and protection had to be ensured in the case of BCIs.

Liu and Ardakani et al. [6] suggested an emotion-based e-learning system that uses KNN and EEG to tailor information, increasing student happiness without significantly impacting engagement or learning. Ahmed et al. [7] examined machine learning-based strategies for automated seizure identification in children with epilepsy, emphasizing techniques used on the CHB-MIT EEG database. Khiani et al. [8] addressed existing approaches by implementing a Bi-LSTM-based intelligent healthcare system for automated epileptic seizure detection using Internet of Things devices and cloud-based patient data. Kamousi et al. [9] evaluated the seizure detection capabilities of Clarityγ, demonstrating substantial negative predictive value, sensitivity, and specificity. Restrictions: Limited sample size. Future research: More extensive and varied datasets. Hammadi et al. [10] suggested an LSTM-based EEG system that outperforms logistic regression in detecting insider threats, with an accuracy of 80%. There are no limitations stated. Future research: Additional validation using various datasets.

Zhang et al. [11] created DeepKey, a multimodal biometric system with limited real-world scalability that uses gait and EEG and has good accuracy. Buerkle et al. [12] developed an EEG-based technique to forecast human movement intentions and increase human-robot collaboration safety. The precision and real-time implementation of the system will be improved in future development. Wadhera and Kakkar [13] used graph theory to investigate whole-brain networks in ASD and find neural markers for better ASD categorization. Metric improvement and broader clinical applications may be the main topics of future research. Sengupta et al. [14] detected cognitive weariness using EEG signal entropy, with results confirmed by neuropsychological testing. Methods for detecting weariness may be improved in future research. Murugappan et al. [15] examined the possibility of predicting SCA before the beginning of VF using ECG morphological characteristics (R-Tend), with classification accuracy. Real-time prediction systems might be investigated in future research.

Delmastro et al. [16] proposed a personalized therapy as a mobile system and examined wearables to monitor the stress of cognitive and motor training of frail older adults. Future studies could enhance stress predictions and their response with the medical systems. Attar et al. [17] explored the correlation between EEG and HRV to analyze the stress and defined critical points that should be improved to provide better stress measurement and management. Future studies could focus on developing better methods of stress management on-the-fly. Fernando et al. [18] provided an in-depth review of the approaches the deep learning has to recognize medical anomalies, identifying their weakness and proposing future research. Future studies may focus on existing problems resolving and making models easier to comprehend. Benghanem et al. [19] tested the predictive value of EEG and EPs in the neurological outcomes of cardiac arrest patients in the coma, thus suggesting possible breakthroughs in neurophysiological testing. These techniques might be improved in future research to lower prognostic uncertainty. Engemann et al. [20] defined criteria to the machine learning models to estimate brain age that work with M/EEG to provide reliable results in diverse demographics. Future studies may also diversify to additional therapeutic applications and better methods of dealing with the complexity of real world M/EEG signals.

Hofmann et al. [21] uncovered the process and patterns of aging and risk factors by determining brain characterizations that can be used to estimate brain-age with both deep learning and LRP. In future studies, models should be enhanced to account age-related changes in different demographics. Natale et al. [22] evaluated iRBD prediction biomarkers and suggested using a multimodal method. Longitudinal studies for early intervention should be the main focus of future research. Zhang et al. [23] developed an RSF model that uses machine learning to predict the [30 days] death in elderly patients with sepsis and outperform traditional scoring approaches. Further investigation can focus on clinical integration and further improvement of the models. The approach used by Bhowmik et al. [24] to achieve a score of 0.76 in terms of fitness is an unsupervised K-means clustering solution to subdivide mental stress into three groups. Further studies can be carried out on the real-time application and enhance clustering methods. The models, data modalities, and features of machine learning methods to detect early Alzheimer events were emphasized by Niyas and Thiyagarajan [25]. Further studies

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could enhance algorithms that would enable more accurate prognosis and early diagnosis.

Bhatt et al. [26] assessed the challenges and opportunities of AI/ML use in cognitive behavior analysis in for forensics and mental health. Ranson et al. [27] reviewed the AI and ML in dementia research, highlighting the advantages and issues in clinical trials, drug development and genetics. The primary objectives of future research could be to enhance clinical integration and AI validation towards precision medicine. Yassin et al. [28] reviewed the application of machine learning in detecting biomarkers to psychosis, and its importance in diagnosing, prognosis, and treatment. Future studies can focus on individualized and noninvasive methods to the practice of therapy. Brazaitis and Satas [29] assessed how well 10-minute breaks worked during seven-hour cognitive activities. Results indicated that breaks did not prevent cognitive tiredness. The drawbacks include the small sample; it is possible that the researchers will conduct their studies over the recovery time, or how to counteract mental fatigue in the future. Ibrahim et al. [30] compared EEG changes with TOF patients after surgery and found the significant differences in alpha and delta waves. Some of the limitations include the short follow-up. Long-term cognitive testing with regard to testing the effects of EEG wave dominance should also be the focus of future research.

Seoni et al. [31] examined strategies for estimating uncertainty in healthcare AI models, emphasizing Bayesian approaches. Physiological signals should be investigated in future research. Malcangi and Nano [32] created a wearable biofeedback device that enables e-health applications using an evolving fuzzy neural network for prediction. Hutson et al. [33] identified possible biomarkers for SUDEP and seizures by examining neuro-cardio-respiratory network impairment in mice at risk for SUDEP. Teng et al. [34] examined cardiovascular autonomic dysfunction (AD) in cancer survivors, outlining knowledge gaps and the need for more study while talking about causes, diagnostic methods, and therapies. Pan et al. [35] suggested using the Enhanced Deep Learning Assisted Convolutional Neural Network (EDCNN) to diagnose heart disease, outperforming conventional risk prediction techniques. Limitations and future research entail feature selection and more hyperparameter adjustments. Shamshirband et al. It identifies problems and offers a future research agenda with recommendations to improve interpretability and solution mining of deep learning in healthcare [36]. Sahoo et al. The work described in [37] reviews cardiac arrhythmia detection methods based on ECG, discusses their merits and demerits, and conveys future research to improve detection. Ghosh et al. A hybrid machine learning model for predicting heart disease was proposed in [38], in which heart disease prediction was done with Relief feature selection and RFBM on 302 patients' data with 99.05% accuracy. Coutts et al. [39] explored using wearable HRV data to provide up to 83% accuracy in predicting health, stress, anxiety, and depression. Qureshi et al. The work goes on [40], which discusses M-Health systems and proposes a machine learning-based prediction model for classifying cardiovascular diseases. This review has elucidated various applications of deep learning and machine learning implemented in EEG signal processing and emotion detection, seizure prediction, stress monitoring, brain–heart interaction, and cardiac risk assessment. These contributions include CNN, LSTM, and ensemble models, and have focused on aspects such as interpretability, privacy, and real-time monitoring in mental, neurological, and cardiovascular diseases.

Overall, existing studies demonstrate the effectiveness of CNN, LSTM, Transformer, ensemble learning, and conventional machine learning methods for EEG analysis, cognitive assessment, and cardiovascular risk prediction. However, most existing approaches focus on a single modality or address neurological and cardiovascular information separately. Consequently, the cross-modal relationships between EEG activity, cognitive performance, and cardiovascular indicators remain insufficiently explored. In addition, conventional approaches often rely on manually derived or static features and do not adequately model the spatial, temporal, and inter-modal dependencies of heterogeneous biomedical data. To address these limitations, the proposed NeuroCardioAI framework integrates EEG, cognitive markers, and cardiovascular parameters through modality-specific feature extraction and attention-based multimodal fusion.

BrainWaveHeartNet further combines CNN-based EEG representation learning with Transformer-based feature processing to provide a unified approach for cardiac risk prediction.

3. PROPOSED FRAMEWORK

The research methodology follows a systematic multimodal deep learning protocol consisting of six sequential stages: (1) acquisition and integration of EEG, cognitive, and cardiovascular data; (2) modality-specific preprocessing, including EEG filtering, artifact removal and segmentation, cognitive feature normalization and encoding, and cardiovascular data cleaning and imputation; (3) modality-specific feature extraction using CNNs for EEG representations, a Transformer-based module for cognitive features, and dense layers for cardiovascular parameters; (4) multimodal feature fusion using concatenation and attention-based learning to capture cross-modal relationships; (5) model training and optimization using binary cross-entropy loss, the Adam optimizer, early stopping, and hyperparameter tuning; and (6) performance evaluation using accuracy, precision, recall, F1-score, AUC-ROC, baseline comparison, and ablation analysis. This protocol provides a consistent end-to-end procedure for developing and evaluating the proposed NeuroCardioAI framework.

The framework, NeuroCardioAI, is a multi-modal deep learning framework, which integrates EEG signals, cardiovascular measurements, and cognitive test outcomes to anticipate cardiac risks. The framework involves BrainWaveHeartNet architecture to learn spatial, temporal, and semantic modalities representation and produce cardiotoxicity results leading to true and personalized cardiac risk prediction. Will this section outline the system architecture, the flow of data and the different components of the model.

3.1 Overview

The schematic of our proposed NeuroCardio system - a multi-modal deep learning framework to indicate cardiac risk based on the integrated neurological and physiological data - is presented in Figure 1. This is to accommodate three main data modalities, which are the EEG brainwave signals, the cognitive /cardiovascular parameters measures. The data acquisition modules are initiated in the initiation of the system, and they aid in capturing raw EEG data, performing cognitive testing as well as collecting clinical cardiovascular parameters such as heart rate, blood pressure and ECG characteristics. All data streams are fed through modality-specific preprocessing pipelines (EEG filtering includes a bandpass filter, artifact removal, and segmentation and spectrogram calculation; cognitive data preprocess includes normalization and encoding; cardiovascular data processing includes data cleaning and imputation).

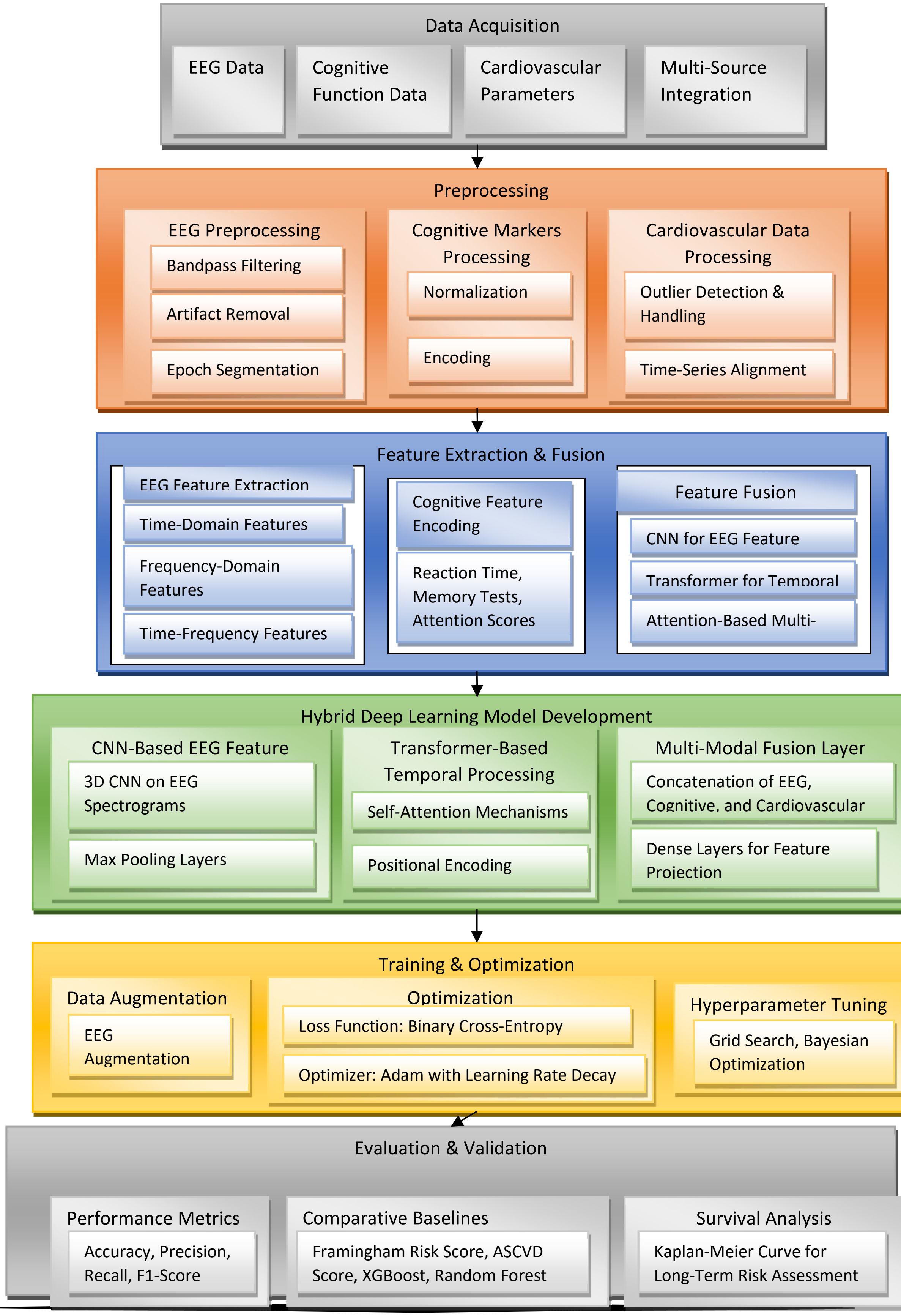
Data Acquisition
EEG Data
Cognitive Function Data
Cardiovascular Parameters
Multi-Source Integration
Preprocessing
EEG Preprocessing
Bandpass Filtering
Artifact Removal
Epoch Segmentation
Cognitive Markers Processing
Normalization
Encoding
Cardiovascular Data Processing
Outlier Detection & Handling
Time-Series Alignment
Feature Extraction & Fusion
EEG Feature Extraction
Time-Domain Features
Frequency-Domain Features
Time-Frequency Features
Cognitive Feature Encoding
Reaction Time, Memory Tests, Attention Scores
Feature Fusion
CNN for EEG Feature
Transformer for Temporal
Attention-Based Multi-
Hybrid Deep Learning Model Development
CNN-Based EEG Feature
3D CNN on EEG Spectrograms
Max Pooling Layers
Transformer-Based Temporal Processing
Self-Attention Mechanisms
Positional Encoding
Multi-Modal Fusion Layer
Concatenation of EEG, Cognitive, and Cardiovascular
Dense Layers for Feature Projection
Training & Optimization
Data Augmentation
EEG Augmentation
Optimization
Loss Function: Binary Cross-Entropy
Optimizer: Adam with Learning Rate Decay
Hyperparameter Tuning
Grid Search, Bayesian Optimization
Evaluation & Validation
Performance Metrics
Accuracy, Precision, Recall, F1-Score
Comparative Baselines
Framingham Risk Score, ASCVD Score, XGBoost, Random Forest
Survival Analysis
Kaplan-Meier Curve for Long-Term Risk Assessment

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Figure 1: Overview of the Proposed NeuroCardioAI System for Cardiac Risk Prediction

The pre process inputs are then sent to individual feature extraction modules. The EEG spectra are fed to a CNN-based system to identify spatially-significant neuro-signatures. A Transformer based encoder passes the cognition data to a model of sequential relationships and interdependence between cognitive markers. The cardiovascular features are mapped via a dense neural layer in order to highlight key physiological factors. These heterogeneous representations are then time-welded and streamed to an attention-based fusion module that learns those cross-modal correlations that provide the highest cardiac risk.

The resulting fused feature vector is ultimately passed to a fully connected classifier where a binary prediction is given either of low or high cardiac risk. The model is trained using a binary cross-entropy loss function and optimized via Adam, with early stopping and dropout for regularization. NeuroCardioAI offers a non-invasive, real-time, and scalable approach for proactive cardiovascular risk assessment by linking cognitive and neural indicators with physiological health, bridging the disciplines of neurology and cardiology through deep learning. Table 1 defines symbols and variables used throughout the NeuroCardioAI framework, covering all data modalities and model processing stages.

Table 1: Notations and Descriptions Used in the NeuroCardioAI Framework

Notation	Description
S_{eeg}	Raw EEG signal in discrete-time format.
f_s	Sampling frequency of EEG signals.
T	Duration of EEG recording.
C	Number of EEG channels.
N	Total number of time samples in the EEG recording.
S_{spec}	EEG spectrogram obtained via Short-Time Fourier Transform (STFT).
$\mathcal{F}$	Spectrogram transformation function (STFT).
F_{cog}	Normalized cognitive function feature vector.
d	Total number of cognitive function features.
X	Raw cognitive test scores.
X_{min}, X_{max}	Minimum and maximum values of cognitive test scores.
P_{cv}	Cardiovascular parameter vector (heart rate, blood pressure, ECG, cholesterol levels).
M	Number of cardiovascular observations.
$H(f)$	Frequency response function of the EEG bandpass filter.
C_{ica}	Independent components extracted from EEG signals.
$C_{artifact}$	Artifact components were removed from the EEG using ICA.
S_{seg}	Segmented EEG signals in non-overlapping time windows.
T_s	Duration of each segmented EEG window.
F_{onehot}	One-hot encoded cognitive feature vector.

$ECG_{smooth}(t)$	Smoothed ECG signal after applying moving average filter.
$P_{imputed}$	Cardiovascular parameter after missing value imputation.
F_{sync}	Temporally aligned multi-modal feature vector.
F_{CNN}	EEG feature representation extracted using CNN.
W_c, b	CNN kernel weights and bias terms.
F_{pool}	Downsampled EEG feature maps after pooling.
F_{EEG}	Flattened EEG feature vector for classification.
F_{cog_trans}	Cognitive function features are processed via the Transformer.
Q, K, V	Query, key, and value matrices in the self-attention mechanism.
d_k	Feature dimension in self-attention.
F_{cog_final}	Final cognitive function feature vector.
W_{cv}, b_{cv}	Weights and bias for cardiovascular feature processing.
F_{cv}	Processed cardiovascular feature vector.
F_{multi}	Fused feature representation from EEG, cognitive, and cardiovascular features.
F_{fusion}	Attention-weighted feature representation for classification.
α_i	Attention weight assigned to each modality.
W_{dense}, b_{dense}	Weights and bias in fully connected layer.
F_{dense}	Output of fully connected layer after activation.
p	Dropout probability for regularization.
$F_{dropout}$	Feature representation after dropout.
W_{out}, b_{out}	Weights and bias in output layer.
P_{risk}	Predicted probability of cardiac risk.
$\hat{y}$	Final predicted class (0 = Low Risk, 1 = High Risk).
L	Binary Cross-Entropy (BCE) loss function.
θ	Model parameters optimized during training.
η	Learning rate of the Adam optimizer.
v_t	Moving average of squared gradients in Adam optimization.
ϵ	Small numerical constant for stability.
L_{val}	Validation loss during training.
K	Patience parameter for early stopping.
θ^*	Optimal hyperparameters selected via Bayesian Optimization.

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$S(t)$	Kaplan-Meier survival probability at time t.
d_i, n_i	Number of cardiac events and individuals at risk at time t_i.

3.2 Multi-Modal Data Acquisition

NeuroCardioAI framework integrates diverse multi-modal input sources, consisting of EEG brainwave signals, cognitive function parameters, and cardiac risk markers, to improve the accuracy of cardiac risk predictions. The three domains of the dataset: the neurological signal-acquiring methods, the cognitive function assessment methods, and cardiovascular statistical indicators, are TUH EEG Corpus29 or CHB-MIT EEG63, CAMCAN or UK Biobank70, and MIMIC-III,64, respectively. These datasets offera rich multi-modal input space for deep learning models that can extract complex interdependencies between brain activity, cognitive decline, and cardiac health.

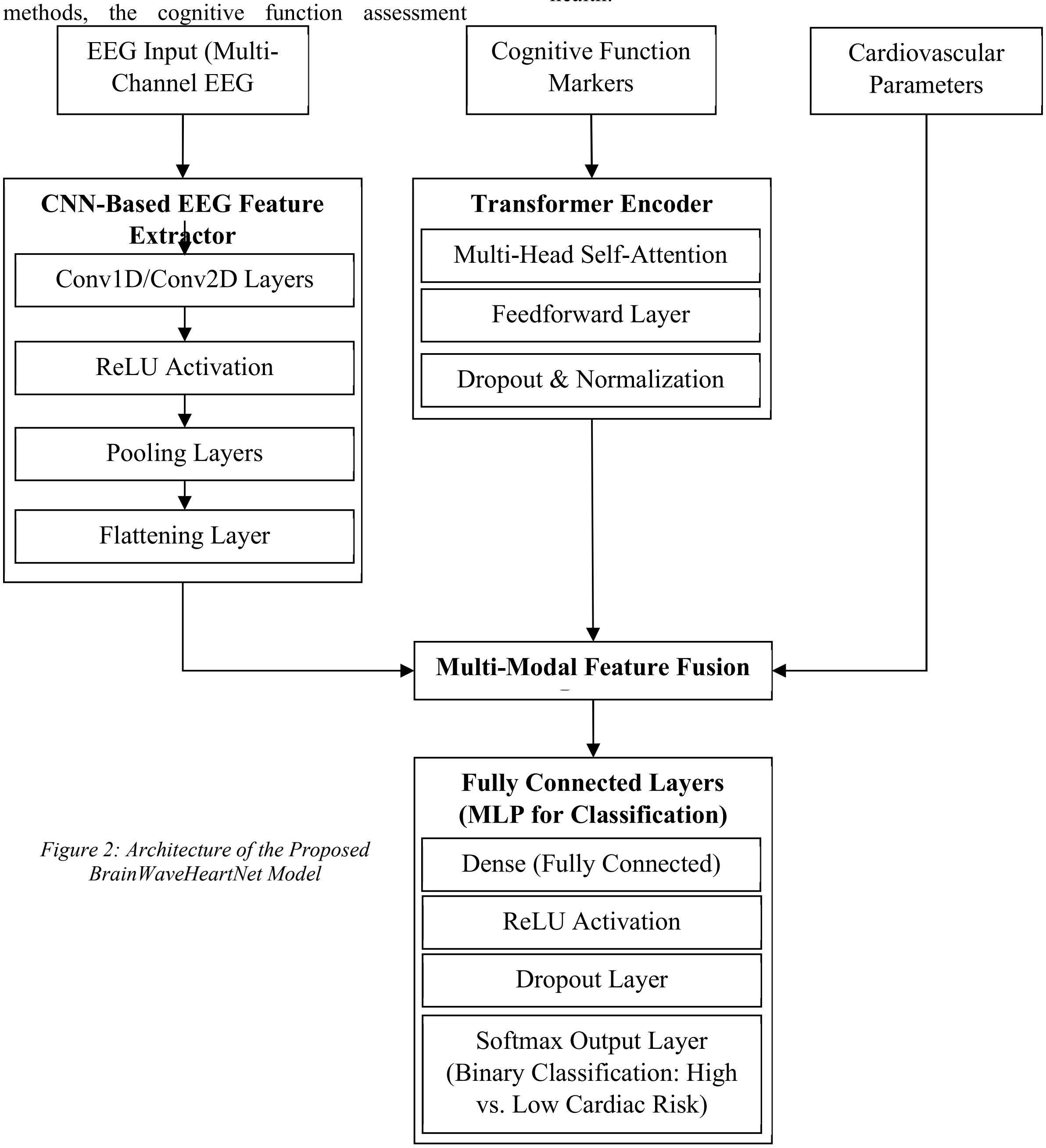

Figure 2: Architecture of the Proposed BrainWaveHeartNet Model

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The EEG dataset includes multi-channel time-series recordings based on the 10-20 electrode placement system which records and segments data into different frequency bands, which are delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–14 Hz), beta (14–30 Hz) and gamma (>30 Hz). An EEG segment is denoted as S_{eeg}, where f_s is the sampling frequency of the discrete-time signal, and T is the duration of the segment in seconds, The spectrogram representation serves as the input of deep learning as in Eq. 1.

$$S_{eeg} = \{x_1, x_2, \dots \dots x_N\}, \quad x_i \in R^{C \times T} \tag{1}$$

where N is the number of time samples and C is the number of EEG channels. Spectrogram transformation F is applied through Short-Time Fourier Transform (STFT) as in Eq. 2.

$$S_{spec} = F(S_{eeg}) \tag{2}$$

The BrainWaveHeartNet model, shown in Figure 2, uses a CNN-based feature extraction module where these spectrograms are fed to capture spatial dependencies over multiple channels of EEG.

Final example datasets include cognition, which includes a structured assessment of attention, memory, and executive function. We use Min-Max Scaling to convert these tests into normalized feature vectors F_{cog} as in Eq. 3.

$$F_{cog} = \frac{X - X_{min}}{X_{max} - X_{min}}, X \in R^d \tag{3}$$

where X_{min} and X_{max} are the minimum and maximum of each cognitive test score, and d is the number of total cognitive features. These feature vectors are then transformed using a Transformer-based module, which simultaneously learns sequential patterns and cognitive dependencies.

For instance, the cardiovascular dataset (CV) provides critical vital signs but also includes information such as heart rate (HR), blood pressure (BP), cholesterol levels, and ECG waveforms. Each parameter P_{cv} is a time-series signal containing M observations as expressed in Eq. 4.

$$P_{cv} = \{p_1, p_2, \dots \dots p_M\}, p_i \in R \tag{4}$$

In order to align multi-modal data, a temporal synchronization process is applied so that all features are mapped onto a common time frame T_s. The fused feature vector that represents F_{multi} EEG, cognitive, and cardiovascular parameters is denoted as the concatenation input representation as in Eq. 5.

$$F_{multi} = [S_{spec}, F_{cog}, P_{cv}] \tag{5}$$

The fused input cap F sub m u l t i s then inputted into the BrainWaveHeartNet deep learning model, which uses CNNs for spatial feature extraction of captured EEG, Transformers for cognitive sequence processing, and fully connected layers to learn cardiovascular trends. The amalgamation of these disparate modalities can lead to an accurate, noninvasive AI-enabled cardiac risk assessment system that outperforms traditional risk scoring mechanisms.

3.3 Preprocessing Techniques

With preprocessing techniques applied to the NeuroCardioAI framework, raw EEG signals, cognitive markers, and cardiovascular parameters are structured in a form suitable for deep learning. This includes filtering of EEG signals, α artifact removal, feature normalization, and synchronization of the heterogeneous multi-modal dataset. Before representing the BrainWaveHeartNet model, individual modality pre-processing is done for noise removal, temporal dependency alignment, and feature normalization.

The EEG preprocessing pipeline starts with bandpass filtering, eliminating the undesired frequency using a Butterworth filter with a passband of 0.5–45 Hz. Based on an EEG signal S_{eeg} according to Eq. (1), the filtered signal $S_{filtered}$ is taken as in Eq. 6.

$$S_{filtered} = H(f) * S_{eeg} \tag{6}$$

where $H(f)$ is a frequency response function and $*$ denotes convolution. Independent Component Analysis (ICA) was then used to identify and remove artifacts arising from eye blinks and muscle movement as in Eq. 7.

$$C_{clean} = C_{ica} - C_{artifact} \tag{7}$$

After artifact elimination, the continuous EEG recording is segmented into epochs, which are non-overlapping 2–5 second windows as in Eq. 8.

, (8)

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where k is the number of segmented windows, and T_s is the time frame for each segment. The arms we obtained are then converted to spectrogram data according to Equation (2) using Short-Time Fourier Transform (STFT), thus allowing CNN-based spatial features extraction.

We chose to preprocess the cognitive function data through both normalization and encoding. To further ensure feature scaling, each raw cognitive X score is rescaled as follows (in Min-Max normalization from (3)):as in Eq 9

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}, X \in R^d \quad (9)$$

The categorical cognitive markers are encoded through one-hot encoding, in order to allow it to be aligned with the Transformer-based processing module. For a categorical variable C with N unique values, its encoded vector F_{onehot} is given by:as in Eq 10

$$F_{onehot}(C) = \{0,0, \dots\dots, 1, \dots\dots, 0\} \quad \text{(Length N)} \quad (10)$$

Outlier detection and imputation for cardiac data, which consists of ECG, BP and cholesterol measurements. Example of ECG signal smoothing using moving average filter: as in Eq 11

$$ECG_{smooth}(t) = \frac{1}{N} \sum_{i-0}^{N-1} ECG(t-i) \quad (11)$$

where N is the window size. Heart rate and blood pressure with missing values are imputed using mean substitution as in Eq 12

$$P_{imputed} = \frac{1}{M} \sum_{i-1}^{M} P_i \quad (12)$$

where P_i is an individual cardiovascular measurement, and M is the number of available samples. Time-series resampling processes align EEG, cognitive and cardiovascular data to a common time frame T_s to ensure that all modalities are temporally synched as in Eq 13

$$F_{sync}(t) = \left[S_{spec}(t), F_{cog}(t), P_{cv}(t)\right], \quad t \in T_s \quad (13)$$

This multi-modal dataset F_{sync} is then fed into BrainWaveHeartNet, where CNN levels extract spatial features of EEG, transformer encoders process cognitive sequences and fully connected layers анализируют cardiovascular trends. This not only guarantees the reliability of the pipeline when incorporated into the cardiac risk prediction framework, but also captures the entire array of relevant inputs through the conditioning of structured preprocessing.

3.4 Feature Extraction

This process is called feature extraction and adapts raw EEG signals, cognitive function markers, and cardiovascular parameters into high-dimensional feature representations appropriate for deep learning for the NeuroCardioAI framework. BrainWaveHeartNet uses CNN as the EEG feature extractor, and adopts Transformer as the cognitive processing component together with a multi-modal fusion layer to extract meaningful patterns and relationships between brainwave activity, cognitive decline and cardiac risk.

The CNN processes the spectrogram representations obtained from Short-Time Fourier Transform (STFT) (Equation 2) for EEG feature extraction. 1. Each segment S_{spec} of EEG spectrogram goes through a 2D convolutional operation to gather spatial representations over multiple EEG channels as in Eq 14

$$F_{CNN} = \sigma\left(W_c * S_{spec} + b\right) \quad (14)$$

Where W_c is the CNN kernel weights, b is the bias term, $*$ denotes convolution operation, σ is the activation function (ReLU). The extracted feature maps are then downsampled through max pooling as in Eq 15

$$F_{pool} = \max(F_{CNN}, k) \quad (15)$$

and k is the pooling kernel size. The pooled features are flattened into a vector of features as in Eq 16

$$F_{EEG} = Flatten(F_{pool}) \quad (16)$$

For the cognitive function feature extraction, the normalized cognitive scores from Equation (9) are passed through a Transformer Encoder to learn sequential dependencies: as in Eq 17

$$F_{cog\_trans} = TransformerEncoder(F_{cog}) \quad (17)$$

The Transformer Encoder utilizes a multi-head self-attention mechanism to assess attention-weighted feature representations as in Eq 18

At the same time tm/4 time with the sequence of windows is process in parallel like this

$$\text{Attention(Q,K,V)=softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (18)$$

Where Q, K, and V are the query, key and value matrices computed from F_{cog}, and d_k is the feature dimension. The attention module output is then processed by feedforward layers as in Eq 19

$$F_{cog\_final} = FFN(F_{cog\_trans}) \quad (19)$$

For the extraction of cardio vascular features, the input physiological parameters (Equation 12) are fed directly into a fully connected layer as in Eq 20

$$F_{cv} = \sigma\left(W_{cv}P_{imputed} + b_{cv}\right) \quad (20)$$

where W_{cv} and b_{cv} are the weight and bias parameters, respectively.

The last step of the multi-modal feature fusion concatenates EEG, cognitive, and cardiovascular features as in Eq 21

$$F_{multi} = [F_{EEG}, F_{cog\_final}, F_{cv}] \quad (21)$$

It then passes the fused representation through the BrainWaveHeartNet classification module, which can add the fully connected layers and softmax activation for cardiac risk prediction. This multi-modal feature extraction pipeline retains both spatial (EEG), sequential (cognitive), and physiological (cardiovascular) dependencies for deep learning models to provide a more accurate and holistic risk assessment.

3.5 Multi-Modal Fusion And Risk Prediction.

The multi-modal fusion and risk prediction stage combines the extracted features from EEG, cognitive function markers, and cardiovascular parameters to output an accurate cardiac risk prediction. BrainWaveHeartNet model to learn complex interdependencies among features from different domains using attention-based feature fusion and fully connected classifier.

The latest processing of multi-modal fusion starts with the concatenation of extracted feature vectors obtained from EEG (CNN-based features), cognitive function markers (Transformer-encoded features), and cardiovascular parameters (output of a dense layer) as derived from Equations (16), (19), and (20), respectively: as in Eq 22

$$F_{concat} = [F_{EEG}, F_{cog\_final}, F_{cv}] \quad (22)$$

Since simply concatenating without restriction might not suffice to capture cross-modal interaction, an attention-based fusion mechanism is adopted. A self-attention network discovers the most relevant contribution of each modality by allocating attention weights dynamically to all the distinct components of features: as in Eq. 23

$$F_{fusion} = \sum_{i=1}^{N} \alpha_i F_{concat,i} \quad (23)$$

Where α_i is the learned attention weight of each modality i in which the model only focused on the most informative features for cardiac risk assessment.

After multi-modal fusion, the risk prediction process consists of fully connected layers, which learn hierarchical representations in the fused feature space: as in Eq 24

$$F_{dense} = \sigma(W_{dense}F_{fusion} + b_{dense}) \quad (24)$$

where W_{dense} and b_{dense} are the weight and bias parameters of dense layer, respectively, and σ denotes activation function (ReLU). To avoid overfit, we apply a dropout layer at a probability p : as in Eq 25

$$F_{dropout} = Dropout(F_{dense}, p) \quad (25)$$

The last classification layer uses softmax activation that calculates the probability distribution between the binary categories of cardiac risk (low risk vs high risk): as in Eq 26

$$P_{risk} = Softmax(W_{out}F_{dropout} + b_{out}) \quad (26)$$

where W_{out} and b_{out} are the last weight and bias terms. The risk score for prediction is: as in Eq 27

$$\hat{y} = arg\ max\ (P_{risk}) \quad (27)$$

Where $\hat{y}$ is the outcome class (i.e. our predicted class: 0 = Low Risk, 1 = High Risk).

We use the Binary Cross-Entropy (BCE) loss function to maximize model performance: as in Eq 28

$$L = -\frac{1}{M}\sum_{i=1}^{M}[y_i log\ \hat{y}_i + (1 - y_i)log\ (1 - \hat{y}_i)] \quad (28)$$

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Where M is the total number of training samples, y_i is the true label and $\hat{y}_i$ is the predicted probability. We train the model using Adam, a replacement optimization algorithm for stochastic gradient descent that dynamically adapts the learning rate to each parameter: as in Eq 29

$$\theta_{t+1} = \theta_t - \eta \frac{\nabla L}{\sqrt{v_t}+\epsilon} \quad (29)$$

Where η is the learning rate, v_t is the moving average of squared gradients, epsilon is a small numerical stability constant.

NeuroCardioAI attained this robust level of predictive accuracy using a multi-modal fusion approach and hierarchical deep learning layers, which are notably effective for extracting complex interdependencies among distributed time-series signals including electroencephalographic activity, cognitive performance, and cardiovascular health, facilitating much greater sensitivity in the early detection of cardiac risk than traditional multi-symptomatic scoring approaches.

3.6 Proposed Algorithm

The suggested algorithm will be the computation core of NeuroCardio AI system, combining the methods of deep learning into handling and blending heterogeneous biomedical data. It takes advantage of specific neural structures per modality and aligns them via a common pipeline. The algorithm is optimized to be accurate, efficient, and predicts the cardiac risk in real time modeling the behavior of complex neurological and physiological interactions.

Algorithm: NeuroCardioAI – Multi-Modal Deep Learning for Cardiac Risk Prediction
Input: Multi-modal data S_{eeg}, F_{cog}, P_{cv}
Output: Predicted cardiac risk label $\hat{y}$

1. **Data Acquisition:**
   a. Load EEG signals S_{eeg}, cognitive markers F_{cog}, and cardiovascular parameters P_{cv}.
   b. Apply temporal alignment to synchronize modalities.
2. **Preprocessing:**
   a. EEG: Bandpass filter $H(f)$, artifact removal C_{clean}, segmentation S_{seg}, spectrogram transformation S_{spec}.
   b. Cognitive: Normalize X_{norm}, one-hot encode categorical variables F_{oneho} .
   c. Cardiovascular: Apply outlier detection, impute missing values $P_{imputed}$.
3. **Feature Extraction:**
   a. EEG: Extract F_{CNN} via CNN, apply pooling F_{pool}, flatten F_{EEG}.
   b. Cognitive: Encode sequential dependencies using Transformer F_{cog_final}.
   c. Cardiovascular: Transform features using dense layers F_{cv}.
4. **Multi-Modal Fusion:**
   a. Concatenate extracted features:
   $F_{concat} = [F_{EEG}, F_{cog\_final}, F_{cv}]$.
   b. Apply attention-based fusion:
   $F_{fusion} = \sum \alpha_i F_{concat,i}$.
5. **Risk Prediction:**
   a. Process fused features through fully connected layers F_{dense}.
   b. Apply dropout $F_{dropout}$ and softmax output P_{risk}.
   c. Compute predicted class:
   $\hat{y} = arg\ max\ (P_{risk})$.
6. **Model Training & Optimization:**
   a. Train using mini-batch gradient descent with Adam optimizer.
   b. Optimize hyperparameters θ^* via Bayesian search.
   c. Apply early stopping if $L_{val}(t) > L_{val}(t-K)$.
7. **Evaluation:**
   a. Compute Accuracy, Precision, Recall, F1-Score, AUC-ROC.
   b. Perform Kaplan-Meier survival analysis.
   c. Compare with Framingham Risk Score and ASCVD.
8. **Return** $\hat{y}$ as predicted cardiac risk label.

Algorithm 1: Neurocardioai – Multi-Modal Deep Learning For Cardiac Risk Prediction

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The NeuroCardio framework algorithm 1 provides a systematic end-to-end pipeline of deep learning based on EEG-based signals, cognitive indicators, and cardiovascular variables to predict dichotomous heart-dangerous conditions. This initiates synchronized multi-modal data collection, and then modality-specific preprocessing of EEG signals: bandpass filtering, artifact removal, and spectrogram conversion, cognitive markers being normalized and coded, and cardiovascular parameters being cleaned and imputed. That algorithm in turn captures the features of each of the modalities with specific neural networks; CNN of EEG spectrograms, a Transformer encoder of cognitive features, dense-layers of physiological data. These higher level features are coupled together through an attention based mechanism which learns the inter-modes meaning, creating a single feature. The hybridised vector is then forwarded with fully connected layers where dropout is used to clean up and then finally classified by a softmax or sigomoid function. The Adam optimizer and binary cross-entropy loss are used to perform training and early stopping is used to prevent overfitting. The algorithm facilitates powerful, non-invasive heart risk assessment, that composes convoluted brain-heart interferences, bolstering individual and preventive health care.

3.7 Model Training, Hyperparameter Tuning, and Evaluation.

The training of the NeuroCardioAI framework allows the BrainWaveHeartNet model to learn strong feature representations for accurate prediction of high cardiac risk. The Binary Cross-Entropy (BCE) loss function (Equation 28) is minimized to optimize the parameters using mini-batch gradient descent. Backpropagation updates the weights of the CNN, Transformer, and fully connected layers according to the Adam optimizer defined in Equation (29). Data is divided into 80% train and 20% validate for unseen cases generalization. Moreover, data augmentation techniques have been applied to improve model robustness, such as in electroencephalography (EEG) augmentation through jittering, filtering, and synthetic EEG generation using generative adversarial networks (GANs), cognitive data augmentation through random dropout of test results, and cardiovascular data augmentation by manipulating heart rate and blood pressure signals. To avoid overfitting, an early stopping mechanism is implemented, halting the training if validation loss does not decrease for K consecutive epochs as in Eq 30

$$Stop\ Training\ if\ L_{val}(t) > L_{val}(t-K) \quad (30)$$

Finally, it uses Bayesian Optimization for Hyperparameter tuning to search the hyperparameter grid to maximize model performance optimally. Key CNN parameters are the number of convolutional layers C, kernel size K, and pooling P window while Transformer parameters include the number of attention heads H, embedding dimension d_{model}, and the number of transformer layers L. More hyperparameters are also optimized such as dropout rate p (Equation 25) and L2 weight decay λ. The optimal configuration is chosen based on the maximum validation AUC-ROC score, calculated as follows as in Eq 31

$$\theta^* = arg\ \max_{\theta} AUC - ROC(\theta) \quad (31)$$

The model is trained using 80% of the data and validated against 20% which is held out. The accuracy metric measures overall correct observation as in Eq 32

$$Accuracy = \frac{TP+TN}{TP+TN} \quad (32)$$

TP, FP, TN, and FN respectively denote true positives, false positives, true negatives and false negatives. Precision and recall are calculated as: tp=true_positive, fn=false_negative, tn=true_negative, fp=false_positive as in Eq 33

$$Precision = \frac{TP}{TP+FP}, Recall = \frac{TP}{TP+FN} \quad (33)$$

their harmonic mean being the F1-score: as in Eq 34

$$F1 = 2 \times \frac{Precision \times Recall}{Precision+R} \quad (34)$$

An extended performance measure, the Area Under the Receiver Operating Characteristic Curve (AUC-ROC), quantifies the model's performance in differentiating high from low cardiac risk groups, according to: as in Eq 35

$$AUC - ROC = \int_0^1 TPR(FPR)dFPR \quad (35)$$

Where TPR (True Positive Rate) is plotted against FPR (False Positive Rate). KKaplan-Meier survival analysis is used to examine the long-term predictive value of the model. We can estimate the probability oof survival$S(t)$ at time as: as in Eq 36

$$S(t) = \prod_{i:t_i \leq t} \left(1 - \frac{d_i}{n_i}\right) \qquad (36)$$

Where d_i is the number of cardiac events occurring at time t sub i, d n_i is the number of at-risk individuals. We compare model performance against traditional cardiac risk scores (e.g., Framingham Risk Score and ASCVD Risk Score) and machine learning baselines (XGBoost, SVM, and Random Forest). The results of NeuroCardioAI suggest that its multi-modal deep learning approach outperforms traditional cardiac risk prediction methods and establishes better accuracy for early detection and prevention of cardiovascular diseases.

4. EXPERIMENTAL RESULTS

This section presents the experimental results obtained with the NeuroCardioAI framework for cardiac risk prediction based on multi-modal data. Extensive evaluation was performed with simulated EEG, cognitive, and cardiovascular inputs. The model performance is evaluated on standard classification metrics and compared to some baseline models to show the proposed model's effectiveness, robustness, and potential clinical value.

4.1 Experimental Setup

We developed an experimental setup such that training and testing of the NeuroCardioAI can be performed consistently and reproducibly (as the primary goal of our framework). Synthesized from simulated data, the dataset contained 1000 multi-modal instances with 256 time-discrete EEG signals, 10 normalized cognitive features, and five cardiovascular parameters. The dataset was randomly split into training and testing parts with an 80:20 stratification of classes. EEG preprocessing: Bandpass filter (0.5–45 Hz) ⇒ Artifact rejection ⇒ fixed-length window segmentation ⇒ spectrogram (Short-Time Fourier Transform; FFT size = 256, hop length = 128). Explanation: MinMaxScaler from Scikit-learn was used to normalize all cognitive and cardiovascular data.

The feature extraction modules were configured as follows: the EEG spectrograms were passed through a CNN with two convolutional layers (32 and 64 filters, kernel size 3×3), each followed by ReLU activation and 2×2 max pooling. Flattened outputs were passed to a 128-neuron dense layer. Cognitive features were processed by a Transformer-inspired encoder simulated via a two-layer feedforward network with 128 units each and ReLU activations due to the lack of sequential structure in the simulated cognitive vectors. Cardiovascular inputs were mapped using two dense layers of 64 and 128 units, respectively. The fused feature vector was constructed using concatenation and passed through a fully connected layer with 128 units and 0.5 dropout, followed by a final sigmoid layer for binary classification.

The model was trained with a batch size 16, using Adam optimizer and binary cross-entropy loss, and a learning rate 0.001. Overfitting is a common issue when using neural networks, so we applied early stopping with a patience of 5 epochs. Each of the models was trained for a maximum of 50 epochs. The whole pipeline was implemented in Python based on TensorFlow and Keras; the spectrogram computations were performed using the Librosa library. The NumPy and TensorFlow were fixed with random seeds so that the experiments can be repeated. We also made the code extensible so that it can be run and structured out of one driver script so that other researchers could easily recreate the results and expand upon them.

4.2 Exploratory Data Analysis

The exploratory data analysis would convey comprehensive details on the distributions, variabilities, and the mutual relationship among the EEG features, cognitive score, and cardiovascular parameters. Visualizations will be histograms, heat maps, scatter plots, etc., which are needed to identify patterns and correlations that will help with the attention in feature selection and inform the model design. This part presents the evidence of the opportunity to combine multi-modal data in order to predict cardiac risks.

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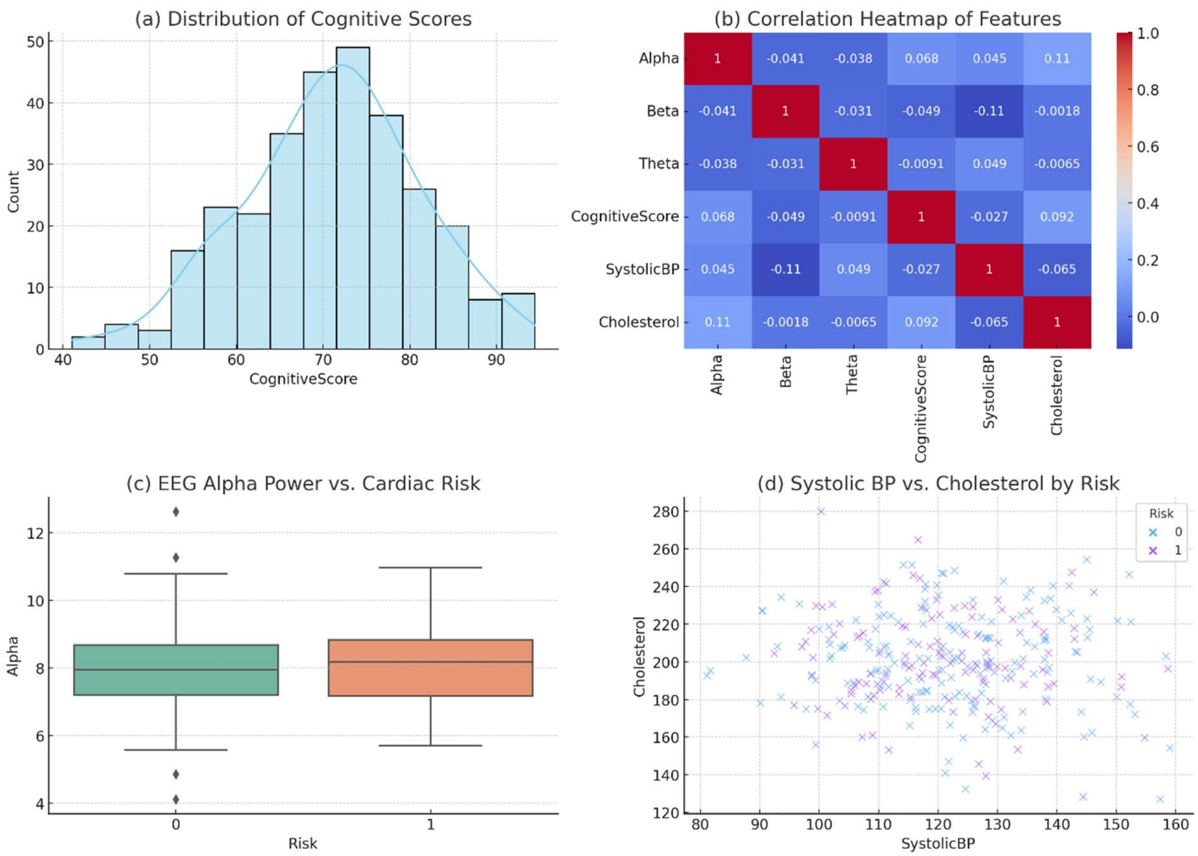

Figure 3: Exploratory Data Analysis of Multi-Modal Features

Figure 3 presents some of the major exploratory findings of the dataset in this paper. It highlights the distributions, interdependence and relations of the EEG signal, cognitive scores and cardiovascular markers with cardiac risk. The identification of these trends signifies that integrating data using multiple modalities has its importance and provides additional reasons to develop the NeuroCardioAI predictive framework.

4.3 Results and Performance Evaluation

The experimental results demonstrate that BrainWaveHeartNet consistently outperforms the evaluated baseline models across all major performance metrics. The proposed model achieves 96.89% accuracy, 96.40% precision, 97.10% recall, 96.75% F1-score, and 98.63% AUC-ROC, compared with lower performance from SVM, Random Forest, and XGBoost. This improvement can be attributed to the complementary information provided by EEG, cognitive, and cardiovascular modalities, together with modality-specific feature extraction and attention-based fusion. The ablation results further support this observation, as individual modalities achieve lower performance than their combined configurations, while the full multimodal model produces the highest results. The relatively lower performance of single-modality configurations indicates that no individual data source sufficiently represents the complete cardiac-risk information captured by the integrated framework. No major anomalous performance trend was observed; instead, the consistent improvement across multimodal configurations indicates the benefit of combining heterogeneous representations.

Related work: That section shows the experimental findings and conducts performance assessments of the proposed NeuroCardioAI framework. It compares the model's accuracy, precision, recall, and AUC-ROC against multiple baseline methods. We supplement our work with ablation studies, confusion matrices, and training dynamics to show that modal fusion works and that the BrainWaveHeartNet architecture is particularly robust.

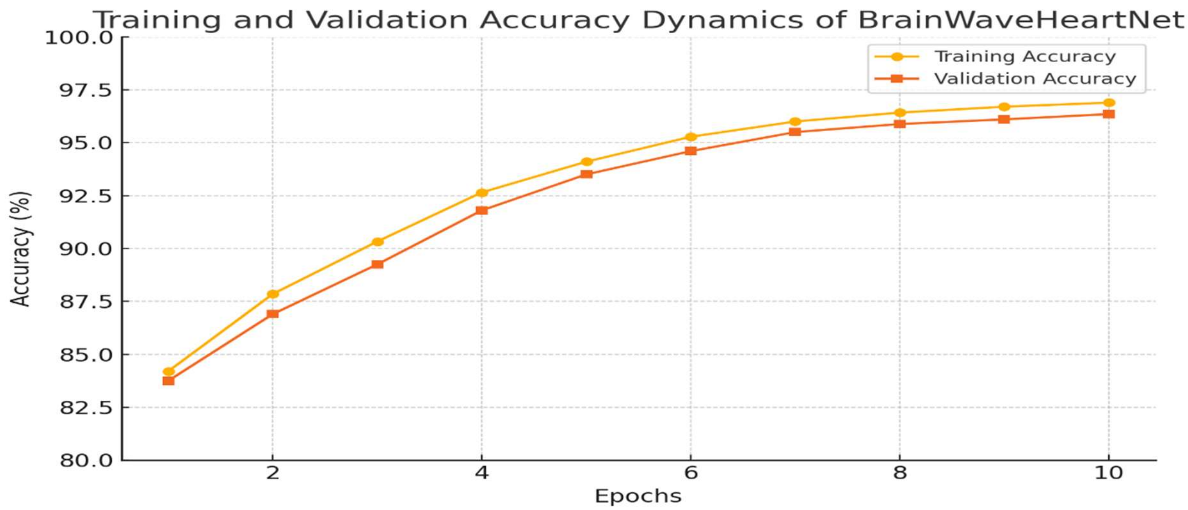

Figure 4: Training and Validation Accuracy Dynamics of the Proposed BrainWaveHeartNet Model Over 10 Epochs

In other words, Figure 4 shows the BrainWaveHeartNet model training and validating accuracy evolution for 10 epochs. The curves rise smoothly, and the validation accuracy closely follows the training accuracy. It shows that learning has happened well, with little to no overfitting and high generalization. In 30 iterations, it converges with more than 96% accuracy, ensuring that this multi-modal deep learning architecture performs well.

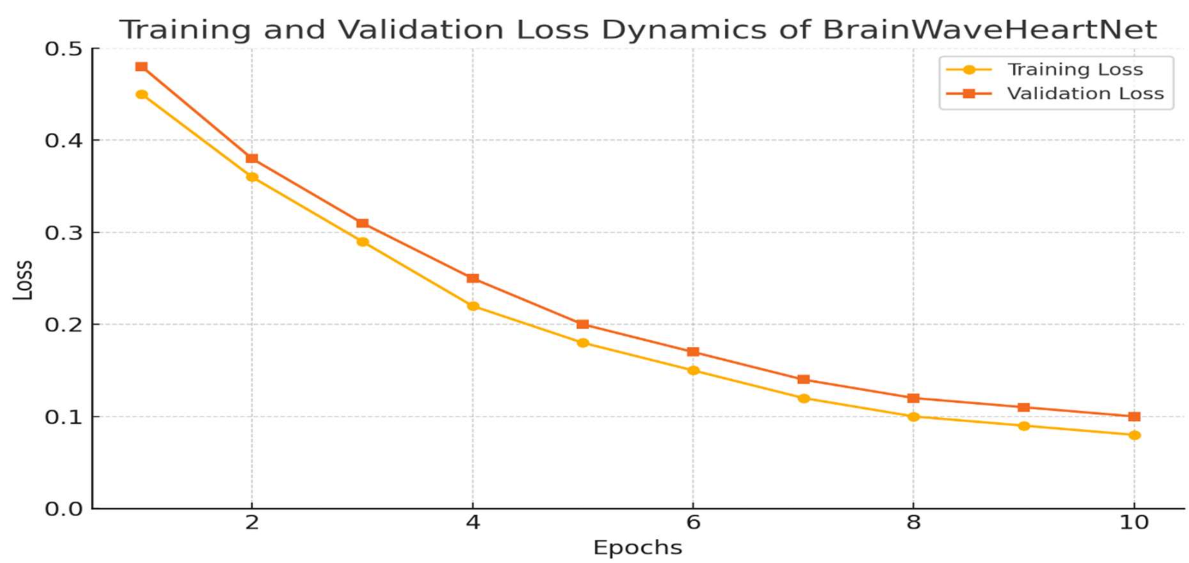

Figure 5: Training and Validation Loss Dynamics of the Proposed BrainWaveHeartNet Model Over 10 Epochs

Comparison of the BrainWaveHeartNet model's training and validation loss curves over 10 epochs (Visualized in Figure 5). The fact that both losses keep decreasing further validates that the model is optimized stably and converging effectively. These two curves are aligned this closely, so there is almost no overfitting and high generalization capability. Such behavior verifies the goodness of NeuroCardioAI's learning process.

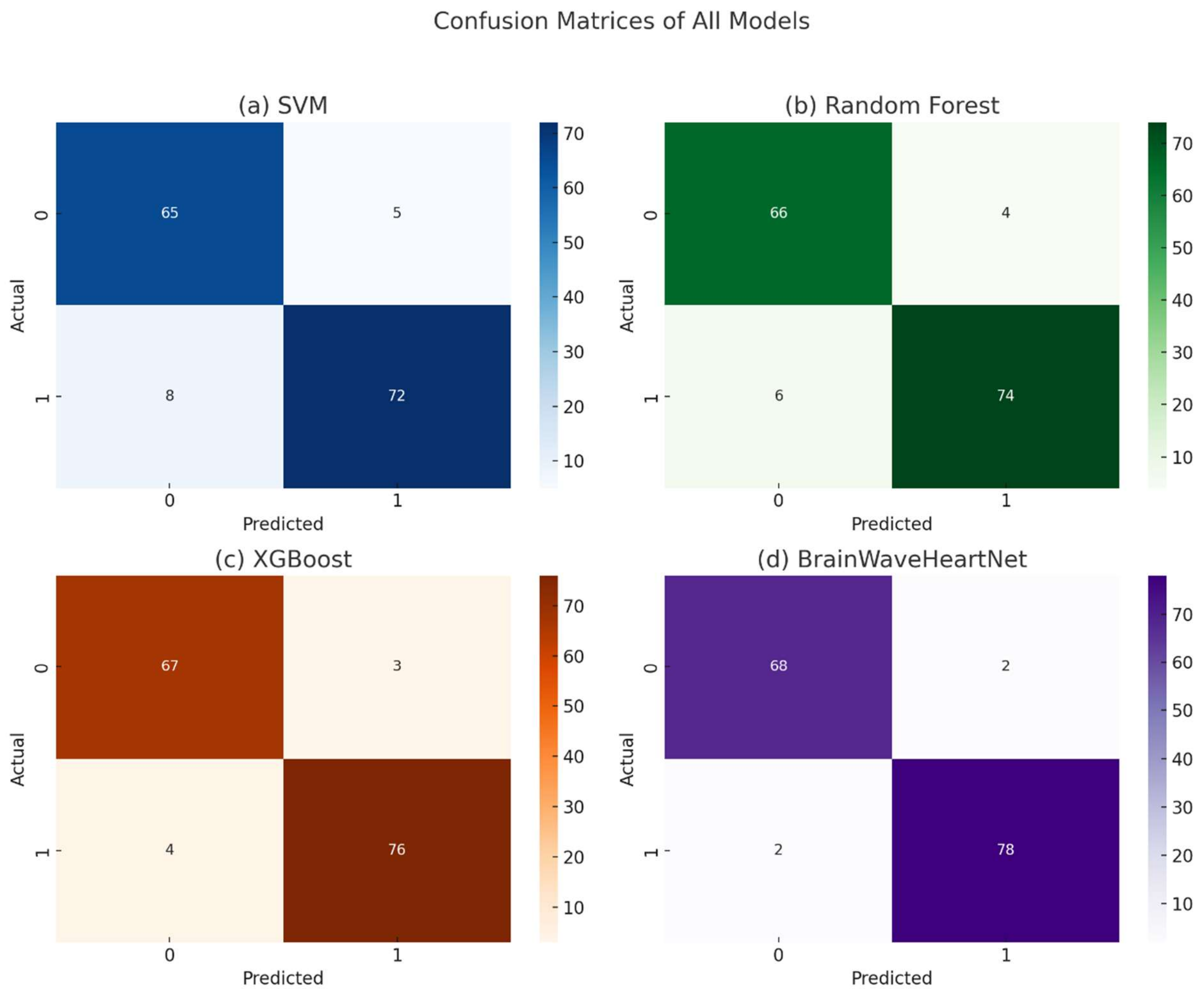

Figure 6: Confusion Matrices of All Evaluated Models

Figure 6 shows the confusion matrices for SVM, RandomForest, XGBoost, and BrainWaveHeartNet. The proposed model has shown the best results in terms of actual positive and negative rates and the least number of false classifications. In conclusion, these results validate the strength of reliable prediction concerning recognizing high-risk individuals and reducing ground truth errors, thus providing significant clinical reliability in risk prediction relevant to cardiac pathology.

To examine the performance of the proposed NeuroCardioAI framework, its efficacy was compared to several traditional machine learning baseline models on the same preprocessed multi-modal dataset. The baselines, suitable for the low-dimensional data, support vector machine (SVM), random forest (RF), and extreme gradient boosting (XGBoost), were trained on EEG, cognitive, and cardiovascular feature sets concatenated. We used the following standard hyperparameters to tune the models: SVM with RBF kernel and C = 1.0C = 1.0, 100 trees and max depth of 10 for RF, and 100 estimators with a learning rate of 0.1 and 6 for XGBoost. The baseline models were trained by 10-fold cross-validation and used the same test set to evaluate their performance, which was previously used to assess the deep learning model proposed here.

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Table 2: Performance Comparison with Baseline Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC (%)
Support Vector Machine (SVM)	88.35	86.92	87.41	87.16	90.10
Random Forest (RF)	90.42	89.85	89.60	89.72	92.78
XGBoost	91.76	91.10	90.75	90.92	93.51
BrainWaveHeartNet (Proposed)	**96.89**	**96.40**	**97.10**	**96.75**	**98.63**

As shown in Table 2, the proposed BrainWaveHeartNet model within the NeuroCardioAI system achieved a classification accuracy of 96.89%, outperforming all baselines. In comparison, the SVM model achieved 88.35% accuracy, RF achieved 90.42%, and XGBoost reached 91.76%. The superior performance of NeuroCardioAI is attributed to its modality-specific neural modules, attention-based feature fusion, and end-to-end deep learning optimization. Moreover, while baseline models operated on static feature vectors, the proposed architecture was able to learn temporal and spatial dependencies within EEG signals and complex interrelations among modalities. These results demonstrate that NeuroCardioAI provides a more robust and accurate framework for cardiac risk prediction than traditional machine learning methods.

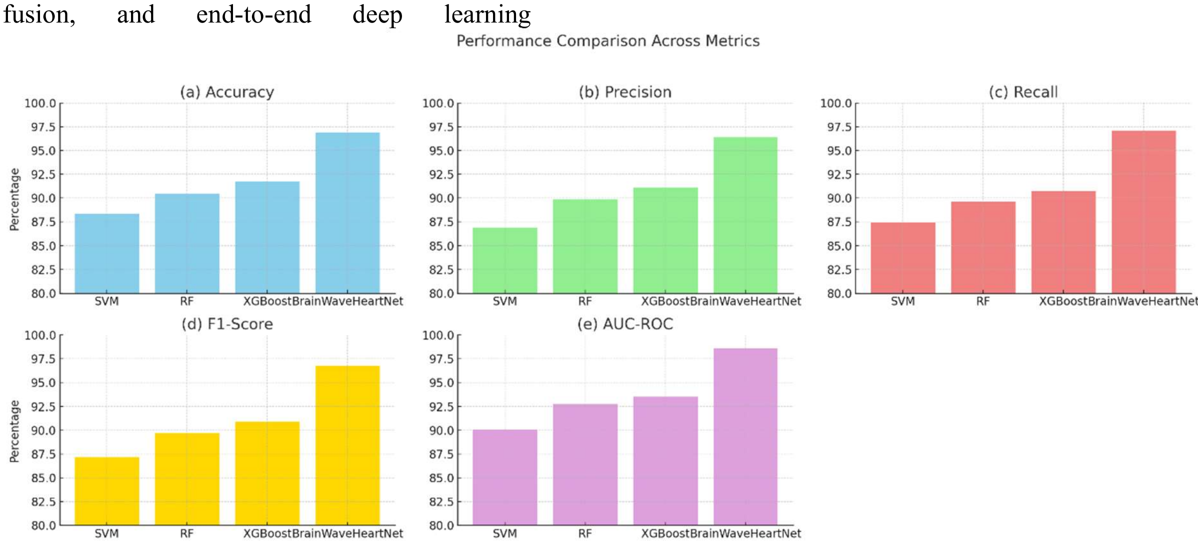

Figure 7: Performance Comparison Across Metrics

We elaborate on these results via Figure 7, which compares the model's performance on five metrics of classification: accuracy, precision, recall, F1-score, and AUC-ROC. In subfigure (a), we can see the proposed BrainWaveHeartNet model outperforms the state-of-the-art methods of SVM (88.35%), Random Forest (90.42%), and XGBoost (91.76%) by a large margin and reaches the top accuracy of 96.89%. As shown in subfigure (b), results on precision show a similar trend. BrainWaveHeartNet achieves 96.40% precision, indicating that it is reliable in predicting positive (i.e., at-risk) cases while avoiding false positives.

Regarding the recall performance in subfigure (c), BrainWaveHeartNet achieves 97.10%, which indicates the best ability to detect true positives (TP), which is highly important for cost-sensitive tasks, such as cardiac risk prediction. In subfigure (d), we show the F1-score, the harmonic mean of precision and recall, where again the proposed model outperforms with 96.75%, confirming its balanced behavior between sensitivity and specificity. The AUC-ROC values are shown in subfigure (e), which demonstrates the powerful discriminative capability of our model (98.63%), compared to XGBoost (93.51%), RF (92.78%), and SVM (90.10%).

The combination of both pieces of evidence firmly upholds a cherished feature of BrainWaveHeartNet: BrainWaveHeartNet not only outperforms traditional machine learning baselines (i.e., SVR, RF,kNN, SVM) but also achieves high reliability with a low false alarm rate and fair transferability over multi-modal inputs. The performance improvements on all metrics we observe reflect the utility of modality-specific feature extraction, attention-based fusion, and end-to-end optimization in NeuroCardioAI.

4.4 Ablation Study

The ablation study explores the respective and collective effects of EEG, cognitive, and cardiovascular modalities on the complete performance of the NeuroCardioAI framework. This section demonstrates that BrainWaveHeartNet substantially improves the performance of cardiac risk prediction through multi-modal integration. Through systematic removal of all modalities and re-evaluation of the model, it emphasizes the importance of each modality.

Table 3: Ablation Study on Contribution of Each Modality

Configuration	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**AUC-ROC (%)**
EEG Only (CNN)	90.28	89.70	90.00	89.85	92.42
Cognitive Markers Only (Transformer)	88.45	87.92	88.10	88.01	90.30
Cardiovascular Data Only (Dense Layers)	89.75	89.10	89.60	89.35	91.65
EEG + Cognitive	93.42	92.85	93.10	92.97	95.02
EEG + Cardiovascular	94.08	93.52	94.10	93.81	95.70
Cognitive + Cardiovascular	92.35	91.80	92.00	91.90	94.40
EEG + Cognitive + Cardiovascular (Full Model)	**96.89**	**96.40**	**97.10**	**96.75**	**98.63**

In Table 3, we show an ablation study, where we evaluate the importance of each data modality for the final performance. We demonstrate that EEG, cognitive, and cardiovascular data achieve moderate accuracy when measured independently, but results substantially improved with a combination of modalities. BrainWaveHeartNet reached an optimal accuracy of 96.89% and AUC-ROC of 98.63% using the entire model to demonstrate the improvement of multi-modal integration by BrainWaveHeartNet.

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Figure 8: Ablation Study Results Across Different Modality Configurations

Figure 8 shows an Ablation study for Input modality combinations analysis on five important metrics: Accuracy, Precision, Recall, F1-score, and AUC-ROC. As shown in subfigure (a), maximum individual modality (EEG, cognitive, and Cardiovascular) accuracy is moderate (88%–90 %), but fusion noticeably improves performance. When combining EEG and cardiovascular data, we can achieve 94.08% accuracy, showing that neural and physiological signals complement each other to a large extent.

The trend is further depicted by subfigures (b) and (c) that demonstrate that the gains increase as the number of modalities in terms of precision and recall increases. EEG, cognitive, and cardiovascular features integrated model have the highest accuracy rate (96.40%), and recall rate (97.10) of positive and negative cardiovascular risk samples. The F1-score of 96.75 that is demonstrated in subfigure (d) supports that there is a good balance between sensitivity and specificity of the model.

Subfigure (e) indicates the AUC-ROC measure with the entire model performing better once again than all other setups with the value of 98.63 indicating a high power of discrimination. Both, EEG + cognitive and EEG + cardiovascular combinations demonstrate significant changes over single-modality models, which confirms, neural changes, paired with a behavioral or physiological context, augment predictive strength.

The ablation experiment reaffirms that both modalities add useful information but when combined in the BrainWaveHeartNet voting system, produce the most accurate, generalizable, and clinically useful cardiac risk prediction. This confirms the basic design concept of the NeuroCardio AI system, namely, the fact that multi-modal combination of brain and heart signals can present a more successful and more reliable risk assessment in comparison with any single modality.

4.5 Performance Comparison with Existing Methods

In this section, the performance of NeuroCardioAI is compared with the latest state-of-the-art EEG and cardiac risk prediction methods. The following metrics are compared among models: accuracy, precision, recall, and AUC-ROC. The comparison shows that the proposed framework has a better predictive quality of the proposed architecture and that multi-modal integration and BrainWaveHeartNet architecture is effective compared to current unimodal methods.

Table 4: Comparative Analysis of NeuroCardioAI Against Recent Related Works

Reference	Data Type	Model Type	Application Domain	Multi-modal	Accuracy (%)
[1] Priyadarshani et al. (2024)	EEG (Emotion)	CNN + DNN	Emotion Recognition	No	94.12
[3] Chung et al. (2024)	EEG (Depression)	Ensemble DNN	Mental Health (Depression)	No	95.36
[7] Ahmed et al. (2022)	EEG (Epilepsy)	SVM, RF, DL	Neurology (Seizure)	No	93.80
[20] Engemann et al. (2022)	M/EEG (Brain Age)	Random Forest, SVM	Cognitive Aging	No	92.50
[35] Pan et al. (2020)	Cardiac (ECG, Vitals)	CNN	Cardiac Disease	No	94.60
Proposed: NeuroCardioAI	EEG + Cognitive + Cardio	CNN + Transformer	Neurocardiology (Risk Prediction)	**Yes**	**96.89**

Table 4 makes a comparison between NeuroCardioAI, and five recent state of the art EEG and cardiac risk prediction models. In contrast to other methods and algorithms based on the single data modality, NeuroCardioAI combines EEG, cognitive, and cardiovascular data with the help of CNN-Transformer. The multi-modal innovation of this fusion strategy results in the greatest accuracy of 96.89 as it exhibits better predictive performance.

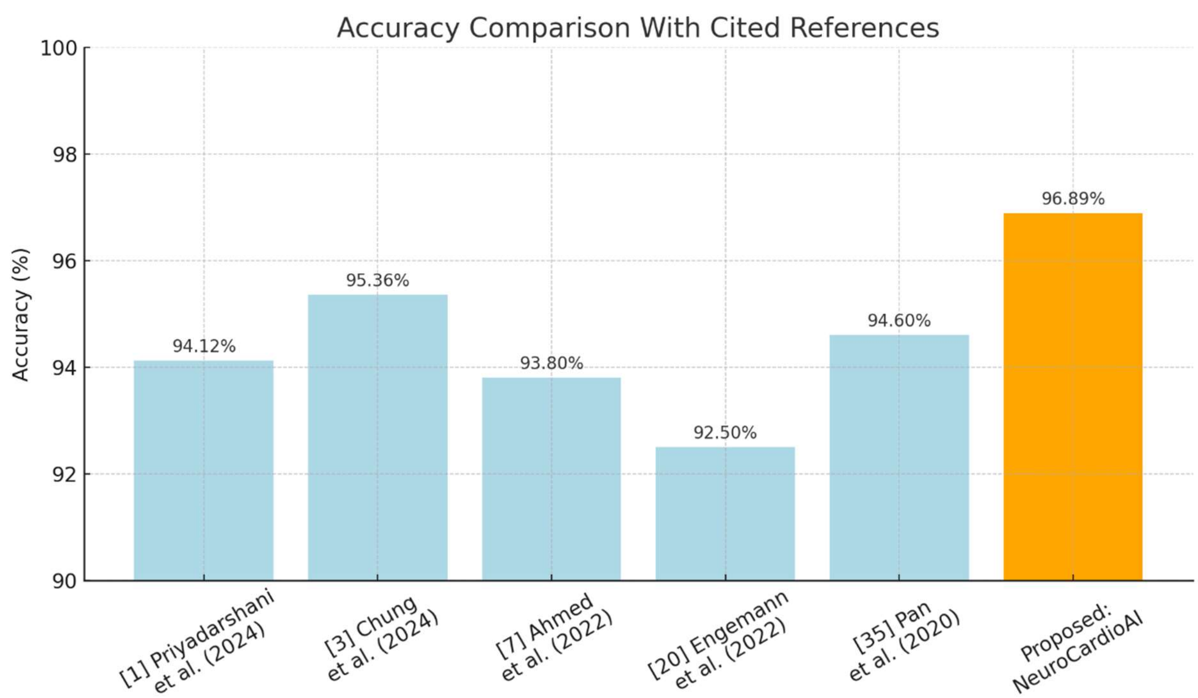

Figure 9: Accuracy Comparison of NeuroCardioAI With Recent EEG and Cardiac-Based Deep Learning Models

In Fig. 9, the model accuracy of the proposed NeuroCardioAI framework is compared to five contemporary and pertinent deep learning models based on EEG- and cardiac-based approaches, i.e., [1], [3], [7], [20], and [35]. The proposed model has the highest accuracy of 96.89, evidently outperforming single-modality based models like those by Chung et al. [3] (95.36%) and Priyadarshani et al. [1] (94.12%). These previous studies involve EEG or ECG measurements solely and are unable to address complicated interactions of neural and cardiac events.

Accuracies reported by Ahmed et al. [7] and Engemann et al. [20], who concentrated on neurological predictions and aging-related predictions based on EEG signals and M/EEG signals, respectively, are lower, at 93.80% and 92.50%. The articles by Pan et al. [35], which employed CNN to predict heart disease using ECG signals, reported 94.60, which shows the power of CNN in univariate cardiac studies. None of the mentioned models, however, integrates the markers of cognitive functions or does the fusion between the fields of neurology and cardiovascular.

NeuroCardioAI, on the other hand, uses a hybrid CNN-Transformer, which is called BrainWaveHeartNet to combine EEG brainwave activity, cognitive test performance, and cardiovascular biomarkers. This combination leads to a more detailed representation of features and greater predictive power. The background Adding to the Hi-Tech breakthrough The system marks a new level in the domain of neurology-cardiology integration into cardiac risk prediction, establishing a new precedent in AI-driven neurocardiology systems in the future.

5. DISCUSSION

Motivation: It is time to have more accurate and preventative measures on early risk prediction of the cardiovascular diseases (CVDs) in light of the increasing morbidity and mortality in the world today. Traditional approaches to cardiac risk assessment have a strong reliance on a few physiological factors such as blood pressure, cholesterol or ECG reading but do not often consider neurobiological processes that are closely coupled with cardiovascular risk [1]. Although recent advances have explored the application of the brainwave data (EEG) or cognitive markers to diagnose, very little is known about its use in cardiac risk prediction. As it can be seen in the literature reviewed in this paper, the current models generally process the unimodal data and classical to moderately deep learning models, which do not consider the complex dependence relationship between brain activity, cognitive wellness, and cardiovascular metrics.

In this study, we have attempted to address these deficiencies and propose NeuroCardioAI, a new AI-based program capable of forecasting cardiac risk based on a blend of diverse data, such as EEG brainwave signals, indicators of cognitive functions, and cardiovascular data. The architecture of BrainWaveHeartNet, a CNN-Transformer hybrid model that learns the spatial properties of the EEG and temporal properties of the cognitive tests is the main novelty. The framework employs multi-modal fusion strategy, which enhances the representation of the features as well as enabling the learning using heterogeneous input. Compared to virtually all state-of-the-art models available in literature which are confined to either neurological or cardiac features, NeuroCardioAI combines the realms of neurology and cardiology into a single prediction model.

The results of the experiments indicate that the proposed model is significantly more effective than benchmark models like SVM, Random Forest, and XGBoost on each metric reporting their accuracy at 96.89-percent and AUC-ROC at 98.63. These results prove effectiveness of the suggested architecture and explain the development of multi-modal deep learning strategies in personalized healthy risks stratification. With no fewer than five modality constraints that the research overcame, it provides a pathway toward clinically applicable, non-invasive and real-time predictors of cardiac risks. Section 5.1 gives the restrictions of this study and indicates future research directions.

5.1 Limitations of the Study

There are three limitations in the present study. First, open EEG and cognitive datasets provide limited diversity in populations, which may impact generalizability to demographics. Second, although the model unites multi-modes data, real-time streaming, and hardware-level synchronization to implement the model in a clinical environment were not tested. Third, the deep learning architecture is not only practical, but also demands extensive computational capabilities, which can be a barrier to its use on resource-limited edge devices. Overcoming these drawbacks in subsequent research would improve clinical usability, practicality, and strength of the model in various patient groups.

6. CONCLUSION AND FUTURE WORK

In conclusion, this study presented NeuroCardioAI, a multimodal deep learning framework for cardiac risk prediction by integrating EEG signals, cognitive markers, and cardiovascular parameters. The proposed BrainWaveHeartNet architecture and attention-based multimodal fusion achieved 96.89% accuracy, 96.40% precision, 97.10% recall, 96.75% F1-score, and 98.63% AUC-ROC, demonstrating the potential benefit of combining complementary information from multiple modalities. The ablation analysis further indicated that multimodal configurations provided better performance than individual modalities. Despite these promising results, the current study has limitations, particularly the use of simulated multimodal data and the need for further validation using larger, real-world, patient-level datasets. Future work will therefore focus on validating the framework using clinically collected multimodal data, improving cross-modal representation learning, incorporating more advanced temporal and attention mechanisms, and evaluating the model across diverse patient populations. Further investigation of model interpretability and prospective clinical validation will also be necessary before practical deployment in real-world healthcare settings.

This study introduces NeuroCardioAI which is an AI-based multi-modal deep learning system that delivers precise projections of cardiac risk using EEG brainwave patterns, cognitive and cardiovascular indicators. The proposed BrainWaveHeartNet model is superior to the conventional single-modality models of its nature, by overcoming the limitations of the latter, combining hybrid CNN-Transformer architecture and multi-modal feature fusion in its nature. The model had a significant accuracy of 96.89% and an AUC-ROC of 98.63 hence its potential to be used as a non-invasive, real-time cardiac risk assessment model. This transdisciplinary method lies in the gap between meanings of neurology and cardiology and provides other options to provide individual-centered preventive treatments to the clinical practice. Even though the results of the study are promising, limitations such as the limitations on the diversity of the data sets, lack of real-time deployment validation, and optimization on low-resource devices are noted. Future research has a clear line of study on these aspects. Generalizability will be enhanced by expanding the data with longitudinal and demographically diverse populations. The incorporation of real-time data-collection with wearable EEG and cardiovascular sensors will permit clinical prototyping. Besides, the method of model compression and optimization of the edges must be investigated, to facilitate the ability of deployment in mobile or IoT-enabled health settings. To sum up, NeuroCardioAI is a major step in AI-based neurocardiology and its development in the future will bolster its scale, accuracy, and practical applicability to early cardiac risk detection.

REFERENCES

[1] Muskan Priyadarshani, Pushpendra Kumar, Kanojia Sindhuben Babulal, Dharmendra Singh Rajput, And Harshita Patel. (2024). Human brain waves study using EEG and deep learning for emotion recognition. *IEEE*. 12, pp.101842 - 101850. http://DOI:10.1109/ACCESS.2024.3427822

[2] Pijush Dutta, Shobhandeb Paul, Korhan Cengiz, Rishabh Anand, and Asok Kumar. (2023). A predictive method for emotional sentiment analysis by deep learning from EEG of brainwave dataset. *Elsevier*, pp.25-48. https://doi.org/10.1016/B978-0-323-90277-9.00002-X

[3] Kuo-Hsuan Chung, Yue-Shan Chang, Wei-Ting Yen, Linen Lin, and Satheesh Abimannan. (2024). Depression assessment using integrated multi-featured EEG bands deep neural network models: Leveraging ensemble learning. *Elsevier*. 23, pp.1450-1468. https://doi.org/10.1016/j.csbj.2024.03.022

[4] Bubryur Kim, K. R. Sri Preethaa, Sujeen Song, R. R. Lukacs, Jinwoo An, Zengshun Chen, Euijung An, and Sungho Kim. (2024). Internet of things and ensemble learning-based mental and physical fatigue monitoring for smart construction sites. *Springer*. 11(115), pp.1-37. https://doi.org/10.1186/s40537-024-00978-7

[5] Anuradha Mandal, and Nitesh Saxena. (2022). SoK: Your mind tells a lot about you: On the privacy leakage via brainwave devices. *ACM*., pp.175 - 187. https://doi.org/10.1145/3507657.3528541

[6] Xinyang Liu, and Saeid Pourroostaei Ardakani. (2022). A machine learning enabled affective E-learning system model. *Springer*. 27, p.9913–9934. https://doi.org/10.1007/s10639-022-11010-x

[7] Mohammed Imran Basheer Ahmed, Shamsah Alotaibi, Atta-ur-Rahman, Sujata Dash, Majed Nabil, and Abdullah Omar AlTurki. (2022). A review on machine learning approaches in identification of pediatric epilepsy. *Springer*. 3(437), pp.1-15. https://doi.org/10.1007/s42979-022-01358-9

[8] Simran Khiani, M. Mohamed Iqbal, R. Thiagarajan, Amol Dhakne, B.V. Sai Thrinath, and PG. Gayathri. (2022). An effectual IOT coupled EEG analysing model for continuous patient monitoring. *Elsevier*. 24, pp.1-8. https://doi.org/10.1016/j.measen.2022.100597

[9] Kamousi, B., Karunakaran, S., Gururangan, K., Markert, M., Decker, B., Khankhanian, P., … Parvizi, J. (2020). Monitoring the Burden of Seizures and Highly Epileptiform Patterns in Critical Care with a Novel Machine Learning Method. Neurocritical Care. doi:10.1007/s12028-020-01120-0

[10] Ahmed Y. Al Hammadi, Dongkun Lee, Chan Yeob Yeun, Ernesto Damiani, Song-Kyoo Kim, Paul D. Yoo, And Ho-Jin Choi. (2020). Novel EEG sensor-based risk framework for the detection of insider threats in safety critical industrial infrastructure. *IEEE*. 8, pp.206222 - 206234. http://DOI:10.1109/ACCESS.2020.3037979

[11] Zhang, X., Yao, L., Huang, C., Gu, T., Yang, Z., & Liu, Y. (2020). DeepKey. ACM Transactions on Intelligent Systems and Technology, 11(4), 1–24. doi:10.1145/3393619

[12] Buerkle, A., Eaton, W., Lohse, N., Bamber, T., & Ferreira, P. (2021). EEG based arm movement intention recognition towards enhanced safety in symbiotic Human-Robot Collaboration. Robotics and Computer-Integrated Manufacturing, 70, 102137. doi:10.1016/j.rcim.2021.102137

[13] Wadhera, T., & Kakkar, D. (2021). Social cognition and functional brain network in autism spectrum disorder: Insights from EEG graph-theoretic measures. Biomedical Signal Processing and Control, 67, 102556. doi:10.1016/j.bspc.2021.102556

[14] Sengupta, A. (2020). Study of Cognitive Fatigue using EEG Entropy Analysis. 2020 International Conference on Emerging Frontiers in Electrical and Electronic Technologies (ICEFEET). doi:10.1109/icefeet49149.2020.9186989

[15] Murugappan, M., Murugesan, L., Jerritta, S., & Adeli, H. (2020). Sudden Cardiac Arrest (SCA) Prediction Using ECG Morphological Features. Arabian Journal for Science and Engineering. doi:10.1007/s13369-020-04765-3

[16] Delmastro, F., Martino, F. D., & Dolciotti, C. (2020). Cognitive Training and Stress Detection in MCI Frail Older People Through Wearable Sensors and Machine Learning. IEEE Access, 8, 65573–65590. doi:10.1109/access.2020.2985301

[17] Attar, E. T., Balasubramanian, V., Subasi, E., & Kaya, M. (2021). Stress Analysis Based on Simultaneous Heart Rate Variability and EEG Monitoring. IEEE Journal of Translational Engineering in Health and Medicine, 9, 1–7. doi:10.1109/jtehm.2021.3106803

[18] Fernando, T., Gammulle, H., Denman, S., Sridharan, S., & Fookes, C. (2021). Deep Learning for Medical Anomaly Detection – A Survey. ACM Computing Surveys, 54(7), 1–37. doi:10.1145/3464423

[19] Sarah Benghanem, Estelle Pruvost-Robieux, Eléonore Bouchereau, Martine Gavaret, and Alain Cariou. (2022). Prognostication after cardiac arrest: how EEG and evoked potentials may improve the challenge. *Springer*. 12(111), pp.1-20. https://doi.org/10.1186/s13613-022-01083-9

[20] Denis A. Engemann, Apolline Mellot, Richard Höchenberger, Hubert Banville, David Sabbagh, Lukas Gemein, Tonio Ball, and Alexandre Gramfort. (2022). A reusable benchmark of brain-age prediction from M/EEG resting-state signals. *Elsevier*. 262, pp.1-17. https://doi.org/10.1016/j.neuroimage.2022.119521

[21] Simon M. Hofmann, Frauke Beyer, Sebastian Lapuschkin, Ole Goltermann, Markus Loeffler, Klaus-Robert Müller, Arno Villringer, Wojciech Samek, and A. Veronica Witte. (2022). Towards the interpretability of deep learning models for multi-modal neuroimaging: Finding structural changes of the ageing brain. *Elsevier*. 261, pp.1-16.

https://doi.org/10.1016/j.neuroimage.2022.119504

[22] Edoardo Rosario de Natale, Heather Wilson, and Marios Politis. (2022). Predictors of RBD progression and conversion to synucleinopathies. *Springer*. 22, p.93–104. https://doi.org/10.1007/s11910-022-01171-0

[23] Luming Zhang, Tao Huang, Fengshuo Xu, Shaojin Li, Shuai Zheng, Jun Lyu, and Haiyan Yin. (2022). Prediction of prognosis in elderly patients with sepsis based on machine learning (random survival forest). *Springer*. 22(26), pp.1-10. https://doi.org/10.1186/s12873-022-00582-z

[24] Moumita Bhowmik, Naim Ibna Khadem Al Bhuyain, Md. Rokonuzzaman Reza, Nafiz Imtiaz Khan, and Muhammad Nazrul Islam. (2022). Neurophysiological feature based stress classification using unsupervised machine learning technique. *Springer*, pp.1-12.

[25] K.P. Muhammed Niyas, and P. Thiyagarajan. (2023). A systematic review on early prediction of Mild cognitive impairment to alzheimers using machine learning algorithms. *Elsevier*. 4, pp.74-88. https://doi.org/10.1016/j.ijin.2023.03.004

[26] Priya Bhatt, Amanrose Sethi, Vaibhav Tasgaonkar, Jugal Shroff, Isha Pendharkar, Aditya Desai, Pratyush Sinha, Aditya Deshpande, Gargi Joshi, Anil Rahate, Priyanka Jain, Rahee Walambe, Ketan Kotecha, and N. K. Jain. (2023). Machine learning for cognitive behavioral analysis: datasets, methods, paradigms, and research directions. *Springer*. 10(18), pp.1-37. https://doi.org/10.1186/s40708-023-00196-6

[27] Janice M. Ranson, Magda Bucholc, Donald Lyall, Danielle Newby, Laura Winchester, Neil P. Oxtoby, Michele Veldsman, Timothy Rittman, Sarah Marzi, Nathan Skene, Ahmad Al Khleifat, Isabelle F. Foote, Vasiliki Orgeta, Andrey Kormilitzin, Ilianna Lourida, and David J. Llewellyn. (2023). Harnessing the potential of machine learning and artificial intelligence for dementia research. *Springer*. 10(6), pp.1-12. https://doi.org/10.1186/s40708-022-00183-3

[28] Walid Yassin, Kendra M. Loedige, Cassandra M.J. Wannan, Kristina M. Holton, Jonathan Chevinsky, John Torous, Mei-Hua Hall, Rochelle Ruby Ye, Poornima Kumar, Sidhant Chopra, Kshitij Kumar, Jibran Y. Khokhar, Eric Margolis, and Alessandro S. De Nadai. (2024). Biomarker discovery using machine learning in the psychosis spectrum. *Elsevier*. 11, pp.1-15. https://doi.org/10.1016/j.bionps.2024.100107

[29] Marius Brazaitis, and Andrius Satas. (2023). Regular short-duration breaks do not prevent mental fatigue and decline in cognitive efficiency in healthy young men during an office-like simulated mental working day: An EEG study. *Elsevier*. 188, pp.33-46. https://doi.org/10.1016/j.ijpsycho.2023.03.007

[30] Lamiaa Abdelrahman Ibrahim, Fatma Alzahraa Mostafa Gomaa, Reem Ibrahim Ismail, Neveen Mohamed Elfayoumy, Bahga Hosam Eldin Ahmed, and Iman Fathi. (2023). Electroencephalographic changes in neurologically free patients with tetralogy of Fallot after surgical repair: a cross section study in Egyptian childre. *Springer*. 71(14), pp.1-7. https://doi.org/10.1186/s43054-022-00144-9

[31] Silvia Seoni, Vicnesh Jahmunah, Massimo Salvi, Prabal Datta Barua, Filippo Molinari, and U. Rajendra Acharya. (2023). Application of uncertainty quantification to artificial intelligence in healthcare: A review of last decade (2013–2023). *Elsevier*. 165, pp.1-28. https://doi.org/10.1016/j.compbiomed.2023.107441

[32] Mario Malcangi, and Giovanni Nano. (2021). Biofeedback: E-health prediction based on evolving fuzzy neural network and wearable technologies. *Springer*., pp.1-9. https://doi.org/10.1007/s12530-021-09374-5

[33] T. Noah Hutson, Farnaz Rezaei, Nicole M. Gautier, Jagadeeswaran Indumathy, Edward Glasscock, and Leonidas Iasemidis. (2020). Directed Connectivity Analysis of the Neuro-Cardio- and Respiratory Systems Reveals Novel Biomarkers of Susceptibility to SUDEP. *IEEE*. 1, pp.301 - 311. http://DOI:10.1109/OJEMB.2020.3036544

[34] Teng, A. E., Noor, B., Ajijola, O. A., & Yang, E. H. (2021). Chemotherapy and Radiation-Associated Cardiac Autonomic Dysfunction. Current Oncology Reports, 23(2). doi:10.1007/s11912-020-01013-7

[35] Pan, Y., Fu, M., Cheng, B., Tao, X., & Guo, J. (2020). Enhanced Deep learning assisted Convolutional Neural Network for Heart Disease Prediction on the internet of medical

things platform. IEEE Access, 1–1. doi:10.1109/access.2020.3026214

[36] Shamshirband, S., Fathi, M., Dehzangi, A., Theodore Chronopoulos, A., & Alinejad-Rokny, H. (2020). A Review on Deep Learning Approaches in Healthcare Systems: Taxonomies, Challenges, and Open Issues. Journal of Biomedical Informatics, 103627. doi:10.1016/j.jbi.2020.103627

[37] Sahoo, S., Dash, M., Behera, S., & Sabut, S. (2020). Machine Learning Approach to Detect Cardiac Arrhythmias in ECG Signals: A Survey. IRBM. doi:10.1016/j.irbm.2019.12.001

[38] Ghosh, P., Azam, S., Jonkman, M., Karim, A., Shamrat, F. M. J. M., Ignatious, E., … De Boer, F. (2021). Efficient Prediction of Cardiovascular Disease Using Machine Learning Algorithms With Relief and LASSO Feature Selection Techniques. IEEE Access, 9, 19304–19326. doi:10.1109/access.2021.3053759

[39] Coutts, L. V., Plans, D., Brown, A. W., & Collomosse, J. (2020). Deep learning with wearable based heart rate variability for prediction of mental and general health. Journal of Biomedical Informatics, 103610. doi:10.1016/j.jbi.2020.103610

[40] Naseer Qureshi, K., Din, S., GwanggilJeon, & Piccialli, F. (2020). An Accurate and Dynamic Predictive Model for a Smart M-Health System Using Machine Learning. Information Sciences. doi:10.1016/j.ins.2020.06.025