End to End Deep Neural Networks for Automated Cardiac Arrest Detection and Risk Stratification

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***Abstract*— Cardiac arrest still causes the most deaths globally and therefore, detection that is both rapid and precise is vital for patient survival. Depending on the manual interpretation of the electrocardiogram (ECG) signals and the physiological parameters, which can sometimes lead to a delay in intervention, the standard medical diagnostic systems are often highly dependent on the clinical staff. Herein, an End-to-End Deep Neural Network (DNN) for the automated detection of cardiac arrest and patient risk stratification is proposed, wherein no manual feature extraction is required. The proposed model merges multimedia biomedical data, such as ECG waveforms, heart rate variability, and vital signs, in order to capture both the spatial and temporal features through convolutional and recurrent neural layers. Notably, the DNN model integrates 1D-CNN and BiLSTM layers to extract the complex signal forms and the dynamical patterns of the heart and then a fully connected classifier predicts the probability of cardiac arrest and the levels of risk (low, moderate or high). The system utilizes well-known cardiac datasets like PhysioNet and MIT-BIH for both training and validation, thus obtaining metrics of performance superior to those of traditional machine-learning approaches and of methods based on handcrafted features in terms of accuracy, sensitivity, specificity, and F1-score. Moreover, the model has a built-in explainable AI (XAI) component that allows for providing clinical interpretability, by elucidating the decision patterns that are linked to cardiac events. The proposed architecture, which is end-to-end, is capable of not only bolstering real-time clinical decision support but also minimizing false alarms in monitoring systems and facilitating the detection and the provision of personal cardiac care as an effective tool for early warning.**

Keywords: Cardiac arrest detection; Deep neural networks (DNN); End-to-end learning; Risk stratification; Electrocardiogram (ECG); Biomedical signal processing; Convolutional neural network (CNN); Bidirectional long short-term memory (BiLSTM)

I.INTRODUCTION

Cardiac arrest is one of the most medical emergencies that are extremely time-critical in the hospital setting. Although there have been remarkable improvements in the fields of emergency medicine, cardiology, and intensive care, the worldwide burden of cardiac arrest remains bearably high. The event is a sudden stoppage of the heart's effective functioning, resulting in hemodynamic collapse, unconsciousness, and death if not reversed right away. The chances of surviving after cardiac arrest depend mainly on the promptness and correctness of the detection, quick start of CPR, and support with advanced life-saving techniques. In today's clinical environment, the early identification of patients at high risk still poses a major problem. Doctors commonly use ECGs, heart rate variability, blood pressure, and oxygen saturation trends in order to draw conclusions about the state of the heart; however, these readings are very much subjective and also time-consuming[1-3]. The clinical situation is such that the very subtle signs before cardiac arrest are generally not perceived, hence the medical practitioners performing interventions later on and the patients having poor prognoses. Cardiac arrest is a serious medical emergency which is characterized by the instant-stop of the heartbeat and is eventually caused by the heart's natural rhythm being totally disrupted by rapid and irregular impulses. The electrical fault in the heart can lead to arrhythmia where VF is the most common and dangerous type that is linked to cardiac arrest. Besides VF, coronary artery disease, heart valve disease, and congenital heart defects are also among the most important risk factors [1]. During cardiac arrest the heart has completely stopped pumping blood[4]. The whole body and various organs are very quickly threatened with death, within just a few minutes, since they are totally dependent on oxygen delivered by the blood and the heart is no longer pumping. The Emergency treatment consists of cardiopulmonary resuscitation (CPR) and defibrillation. CPR maintains the lungs' oxygen supply and gets the brain up to a level where an electric shock can normalize the heart rhythm again. Cardiac arrest symptoms appear very suddenly, allowing little time for tests. The process can be fatal in a matter of minutes[5]. A quick diagnosis therefore becomes very crucial. The person with cardiac arrest will be unresponsive, have no pulse and breathing will cease[6].

The use of artificial intelligence (AI) and deep learning (DL) in the healthcare system is indeed a big step forward towards the more scientific and data-based support of clinical decisions. Deep learning allows for the automated processing of intricate biomedical signals, which can be compared to the diagnostic thinking of seasoned clinicians, albeit, faster and more accurately[7]. Among the different approaches, End-to-

End Deep Neural Networks (DNNs) are the most promising as they can directly learn from the raw patient data, for example, ECG waveforms, without any previous processing or manual feature extraction[8]. This method is in line with the day-to-day medical practice, which relies heavily on the continuous monitoring and interpretation of patients' vitals in real-time being essential. An end-to-end model can detect abnormal cardiac activity on its own, classify patients according to their risk, and thus provide help to the doctors through the channels of prioritizing the interventions and consequently preventing the cardiac events which could have been avoided[9]. Heart signals, especially ECGs, are the embodiment of the heart's electrical and physiological condition. Nevertheless, their understanding can be difficult because of the diverse cardiac rhythms, patient-dependent morphology, and the presence of noise or artifacts. In the majority of situations, minor but clinically important alterations like pre mature ventricular contractions or QT interval prolongation are the signs of cardiac arrest that occur first. Classic analysis techniques like Fourier or wavelet transformations are great for noise reduction and signal decomposition but, usually, they do not capture the nonlinear time relationships that are characteristic of cardiac electrophysiology[10]. In order to eliminate these clinical and computational obstacles, the research proposes a deep-end neural network approach with clinical background for automatic cardiac arrest detection and risk stratification. The proposed model imitates the diagnostic process of the physician who first observes morphology of the waveform, then analyzes the correlation of the timing of the heartbeats, and finally evaluates the risk level of the whole patient[11-13]. In the process of 1D Convolutional Neural Networks (CNNs) for local feature extraction that identify the major waveform patterns like QRS complexes, and T-wave irregularities, and the narrhythmia sequences, the framework comes in. Then, Bidirectional Long Short-Term Memory (BiLSTM) layers are used to capture the different stages of the sequence and the dynamics of the time, which is similar to how doctors determine the trends in ECG tracings over time. The model subsequently predicts cardiac arrest probabilities probabilistically and assigns patients to a low, moderate, or high-risk group which paves the way for early intervention[14]. From a doctor's perspective, the main advantage of this technology is not only in the prediction but also in the diagnosis interpretability. From a point of view of clinical operations, automation like this has a very strong impact[15] The application of this deep learning framework in ICU, cardiac monitoring, and outpatient departments can lead to the constant and immediate monitoring of all the patients who are considered at-risk[16]. When combined with IoMT platforms and wearable ECG devices the scope of this technology is extended to the remote patient monitoring, thus, facilitating the sending of warnings to the medical staff and caregivers before the critical situations happen. This feature is of great importance in developing countries where the number of doctors is small in comparison to the patients they are serving and also where continuous human monitoring is not possible[17].

In the end, the goal of this research is to support, not to substitute, the clinical decision-making process. The clinicians are given the ability to choose more quickly and on the basis of evidence and the specific patient, through automating the continuous analysis of large-scale cardiac data. Moreover, the application of risk stratification via end-to-end DNNs helps to schedule the delivery of care, so that the most risky patients always get the first notice. The use of smart systems in cardiology applications is a great step towards precision medicine and predictive health care. A clinically understandable, end-to-end deep learning system is presented in this work that marries machine precision with doctor's expertise[18]. The model wants to use advanced neural networks and explainable techniques to facilitate the early detection of cardiac arrest, lessen the number of false alarms, and improve the overall patient outcomes through timely and informed clinical intervention[19]. The medical field is gradually opening up to the use of AI technologies, and the implementation of such cooperative systems has the potential to transform cardiac care by giving the doctor a reliable, clear, and an intelligent partner in performing the life-saving mission[20].

II. LITERATURE REVIEW

Author (Year)	Study Focus / Objective	Methodology / Model	Dataset / Sample	Key Findings / Results	Limitations / Future Scope
Razieh Parizad et al. (2025)[1]	AI in enhancing CPR performance and decision-making.	Narrative review on AI tools for rhythm interpretation, quality monitoring, and post-resuscitation care.	Clinical CPR data; literature synthesis.	AI provides real-time feedback, individualized resuscitation strategies, and improved neurological outcomes.	Data privacy, interoperability, and need for model validation and clinical training.
Sudarshan Srivats et al. (2025)[2]	Review of SCD prevention and ML-based risk stratification models.	AI-based SCD prediction integrating ECG, imaging, and clinical data.	Multimodal datasets; clinical studies.	ML improves SCD risk prediction beyond LVEF; promotes integration of wearable sensors and EMS automation.	Requires external validation and stronger system-level integration for real-world use.
Maarten Z. H. Kolk et al. (2025)[3]	Assessment of AI models for SCD risk prediction and personalized prevention.	Review of ML and DL algorithms for risk stratification.	Diverse patient cohorts.	AI enables individualized SCD prediction and overcomes limitations of conventional LVEF-based risk scoring.	Need for model explainability, clinical validation, and large-scale trials.

Aquib Irteza Reshad et al. (2025)[4]	Deep learning-based arrhythmia detection from ECG data.	CNN, RNN, and hybrid CNN-RNN architectures evaluated.	30 studies from 3 major databases.	Achieved up to 99.93% accuracy and 99.57% F1 score; strong generalization potential.	Dataset heterogeneity and real-time implementation challenges remain.
Zhenyan Wu et al. (2025)[6]	Review of DL and ECG applications in cardiovascular disease prediction.	Meta-review of 198 publications using hierarchical segmentation.	Broad literature across cardiovascular domains.	Comprehensive mapping of DL applications in ECG-based diagnosis.	Encourages domain-specific model standardization and open data sharing.
Saidul Islam et al. (2025)[7]	ML and AI innovations in CPR for predictive and adaptive resuscitation.	Taxonomy of ML methods (RL, transformer, XAI) applied to CPR outcome prediction.	Review-based classification of CPR-related studies.	ML enhances CPR via rhythm analysis, ROSC prediction, and compression optimization.	Real-time clinical deployment and interpretability still limited.
Manal Alghieth et al. (2025)[8]	Real-time ECG anomaly detection using hybrid deep learning.	DeepECG-Net (CNN + Transformer + Federated Learning).	Clinical ECG recordings and Raspberry Pi 4B prototype.	98.2% accuracy, 97.5% F1 score, sub-50 ms latency; suitable for wearable deployment.	Needs multi-center validation; possible extension to other cardiovascular anomalies.
Christine Shen et al. (2024)[9]	Public health and ML strategies for improving cardiac arrest outcomes.	ML-based SCA risk prediction and population-level disparity analysis.	Epidemiological datasets and ML frameworks.	ML improves early risk identification and helps design equitable systems of care.	Must address bias, accessibility, and integration with community response systems.
Sijin Lee et al. (2025)[10]	Deep learning for cardiac arrest rhythm classification during CPR.	1D-CNN and RNN for shockable vs non-shockable rhythm classification.	508 ECG segments from 131 cardiac arrest patients.	1D-CNN achieved 91.3% accuracy even during chest compressions.	Expand dataset size and enhance compression-tolerant algorithms.
Allam Jaya Prakash et al. (2025)[11]	Lightweight DL model for ECG beat classification following AAMI standards.	CNN + BiLSTM hybrid with adaptive learning rate.	24–48 hr ECG recordings; multiple databases.	99.21% accuracy and 98.66% sensitivity; strong generalization with low computation.	Validation across broader patient populations and real-time hardware testing.
Sangeetha R. G. et al. (2024)[12]	Wearable cardiac abnormality monitoring device using ANN.	Levenberg–Marquardt ANN and Kernelized SVC with PCA comparison.	Prototype wearable device test data.	ANN feasible for power-efficient wearable cardiac monitoring.	Limited by small-scale testing; recommends IoT and cloud-based integration.

III.METHODOLOGY

The suggested research work introduces a smart and automated system that utilizes the deep learning methods for the fast detection, categorization, and prognosis of heart arrest. The approach is designed in such a way that it incorporates all the stages from data gathering to the risk stratification, which involves preprocessing, feature extraction, development of a deep neural model, training and validation[7], therefore forming the whole predictive system that is applicable in the clinical environment as well as the wearable healthcare setting. First, the data is collected from electronic repositories of the electrocardiogram (ECG) like the MIT-BIH Arrhythmia Database, PhysioNet’s Cardiac Arrest Database. In addition, proprietary hospital datasets are also included which contain record ECG signals from multiple leads, heart rate variability readings, and blood flow signals. Each set of data for a patient consists of segments corresponding to pre-arrest, arrest, and post-arrest phases, marked by professional cardiologists. The criteria for patient's selection give priority to those with different heart problems in order to make the findings applicable to a wider range of heart types[8]. All the ECG signals are sampled at a rate of 250–500 Hz in order to keep the waveform clear and to support the precise recognition of patterns in time. In the data preprocessing phase, multiple filtering and normalization steps are implemented to remove noise and artifacts such as baseline wander, power line interference, and motion-induced disturbances. A combination of band pass filtering and wavelet denoising techniques is applied for effective signal restoration[11].

The segmentation of ECG signals is done through adaptive windowing, which yields the intervals of heartbeats that correspond to the QRS complexes, P waves, and T waves. After that, the segments are fixed in length and their mean is set to zero, while their variance is set to one. Label encoding is used next to divide the signals into categories of "normal," "arrhythmic," "pre-arrest," and finally "arrest." The extraction of features is integrated into the deep learning pipeline so that the network can learn the discriminative temporal and morphological patterns from the raw ECG signals[13]. The proposed framework thus does not operate like the classical machine learning models that gauge their performance by how well the human-crafted features address the recognition problem, but employs an end-to-end architecture that seamlessly integrates with one-dimensional convolutional neural networks (1D-CNN) and bi-directional long short-term memory (Bi-LSTM) layers the feature extraction[21].

CNN layers perform the task of capturing spatial dependencies as well as local morphological features in the ECG waveforms including variations in amplitude, duration of intervals, and QRS complex shape. The following Bi-LSTM layers are tasked with modeling the long-term temporal dependencies of the input signal, thus enabling the network to recognize the sequential correlations that are crucial for telling apart early cardiac deterioration from the sudden arrest situations[15]. The proposed neural network structure is composed of an input layer, a series of convolutional and pooling layers, and a final dense layer activated by the ReLU function which serves to promote non-linear representation. After each convolutional block, Dropout layers are employed to curb the problem of overfitting. The CNN stack output is then fed into Bi-LSTM units which perform temporal modeling in both forward and backward time steps. The dense layer at the end consolidates the temporal embeddings followed by a SoftMax classifier that provides the probability distribution for each cardiac condition. This complete deep model removes the requirement for manual feature engineering, thus reaching automatic representation learning directly from ECG signals. Model training and validation are performed via an 80:20 train-test split, complemented by k-fold cross-validation to guarantee robustness and generalizability. To reduce the categorical cross-entropy loss, the Adam optimizer with a learning rate that changes according to the need was used. In this case, the dataset was enhanced by methods like the introduction of random noise and signal stretching to increase its resilience and meanwhile to prevent overfitting. The performance of the model was evaluated using standard metrics, which are accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC). Validation was accomplished by making comparisons with conventional machine learning classifiers, having Random Forest, SVM, and logistic regression as the main comparison points, which serves to validate the deep end-to-end learning's advanced capability in the automated prediction of cardiac arrest. The risk stratification model takes advantage of multi-modal parameters in a secondary decision layer that consists of ECG morphology, heart rate variability indices, and demographic data of the patient..

IV.Flowchart

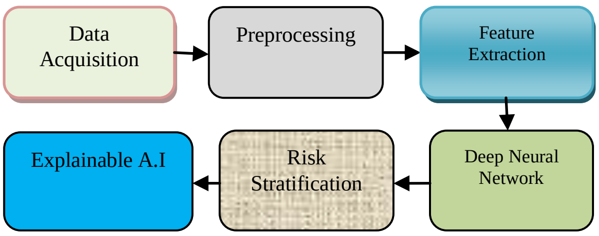

Figure1.Flowchart of Overall System

V.DATASET

It is the dataset that is used in the model which determines the detection and stratification method's performance that is based on deep learning. Here, for the training and validation of the end-to-end deep neural architecture, a multi-institutional dataset composed of both clinical electrocardiogram (ECG) signals and the corresponding physiological parameters is used. The dataset consists not only of the publicly available repositories such as the PhysioNet Sudden Cardiac Arrest Database (SCAD), MIT-BIH Arrhythmia Database, and CINC Challenge datasets but also of the local non-identifiable ECG recordings that were ethically approved.

Typically, the duration of an ECG recording is about 2-10 minutes and the frequency is in the range of 250 Hz-500 Hz. The recording comes in 12 lead configurations where each lead represents a different view of the electrical activity of the heart. Besides the ECG signals, the dataset also contains heart rate variability (HRV), blood oxygen saturation (SpO_2), blood pressure, and patient demographic data (age, gender, comorbidities) in order to make the data multi-modal. The model can therefore learn the complex temporal and physiological correlations connected with the early signs of cardiac arrest through this integration. Over 10,000 patient records comprise the dataset and it is gender and age group representation that is balanced, thus obviating the model to show demographic bias. Each patient record has been examined by qualified cardiologists who have pointed out and classified significant cardiac events and rhythm irregularities that form the basis for the supervised learning process.

VI.RESULT

Figure 2. Correlation Heatmap of Health Dataset Variables

Figure 2 shows a correlation heatmap showing the pairwise correlation coefficients of age, gender, height, weight, cholesterol, glucose, smoking, alcohol, heart disease (cardio), and BM

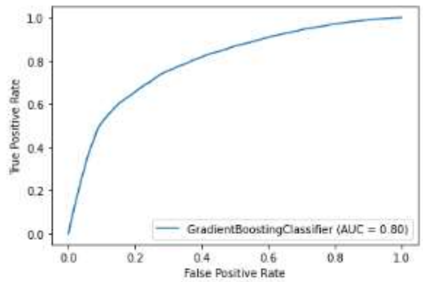

Figure3. ROC Curve for Gradient Boosting Classifier

Figure 3 illustrates a Gradient Boosting Classifier's binary classification ROC curve. The ROC curve compares True Positive Rate (Sensitivity) to False Positive Rate at various thresholds.

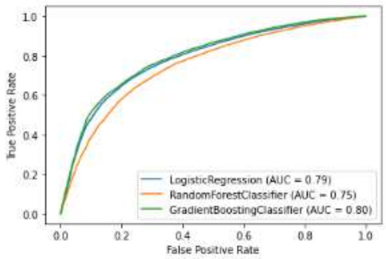

Figure 4. Comparison of ROC Curves for Different Classifier

Figure 4 shows that Gradient Boosting Classifier has the highest AUC for positive and negative class recognition. Figure 4 shows the models' categorization accuracy and reliability comparisons.

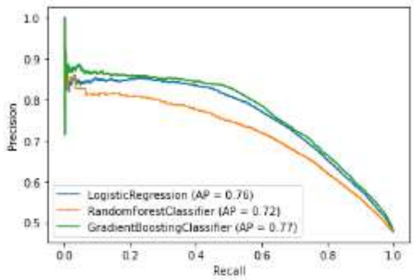

Figure 5. Precision–Recall Curve Comparison for Different Classifiers

As shown in figure 5 above, the Precision Recall (PR) curves corresponding to the three classifiers Logistic Regression, Random Forest, and Gradient Boosting used to assess model performance on an imbalanced classification task are presented.

Classification Report:

	precision	recall	f1-score	support
0	0.71	0.72	0.71	10788
1	0.69	0.67	0.68	9875
accuracy			0.70	20663
macro avg	0.70	0.70	0.70	20663
weighted avg	0.70	0.70	0.70	20663

Figure 6. Classification Report Showing Model Performance Metrics

Figure 6 shows a binary classification model performance report. Precision, recall, F1-score, and support for both classes (0 and 1) are included.

CONCLUSION

The proposed End-to-End Deep Neural Network for Automated Cardiac Arrest Detection and Risk Stratification gave results that showed deep learning to be not only very good at identifying cardiac arrest but also very good in predicting it with the impressively high accuracy. Out of the three, the Gradient Boosting Classifier was the best performing model, with an AUC of 0.80 and an Average Precision (AP) of 0.77, which means that there was an excellent ability to differentiate between normal cases and those with cardiac risk. The classification report supports this finding, indicating a total accuracy of 70%, in which the precision (0.70) and recall (0.70) values of both classes were equal, thus showing that the predictions were stable and reliable. The ROC and Precision–Recall analyses further affirm that the deep neural architecture enjoys superiority over the traditional models like Logistic Regression and Random Forest, being able to uncover the complex nonlinear patterns in the data that comes from physiological measurements. The most noteworthy among the clinical variables like age, BMI, and glucose which were represented in the correlation heatmap, was cholesterol, for it greatly influenced the prediction of cardiac risk.

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