Bed head ticket analysis for predicting inpatient cardiac arrest with machine learning

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***Abstract*—Cardiac arrest is a sudden loss of heart function with serious consequences. In Sri Lanka, healthcare professionals use bedhead tickets to track patient information. These tickets have been valuable for a research study that developed a cardiac arrest prediction model using data from paper records. The model achieved high accuracy using commonly recorded medical details. This approach is effective in identifying the risk of cardiac arrest in in-ward patients, even in the absence of electronic medical recording systems. The study evaluated 112 patients who were transferred from the Emergency Treatment Unit to the Cardiac Medical Ward. The developed model achieved 96% accuracy, 95.83% sensitivity, and 93.42% specificity in predicting the risk of developing cardiac arrest.**

***Index Terms*—Bed Head Tickets, Cardiac Arrest, Decision Tree Classification Model, Early Warning System, Deep Learning, Developing Country, Electronic Medical Recording Systems, Early Warning Systems, Machine Learning, Recurrent Neural Network (RNN).**

I. Introduction

Cardiac arrest often occurs due to dysfunction in the heart's conduction system, which can cause the heart to stop pumping blood. Ventricular fibrillation is the most common cause (65-80% of cases) [1]. Various heart-related causes include coronary artery disease, cardiomyopathy, inherited conditions, congenital heart disease, heart valve disease, acute myocarditis, and conduction disorders like long QT syndrome. Many patients may not recognize or ignore symptoms, with chest pain being the most common.

Ischemic coronary illness causes over 70% of cardiac arrests and is the leading cause of cardiac dysfunction. Risk factors include hypertension, hyperlipidemia, diabetes, smoking, age, and family history of coronary diseases [2]. In Sri Lanka, Cardiovascular Diseases (CVD) account for a high mortality rate of 534 deaths per 100,000 [3] and 22.64% of total deaths [4]. Cardiac arrest risk is 20-30% within the first 24 hours after a heart attack. Survival rates are around 25%, even with proper medical treatment.

The time to receive help and treatment is crucial for survival in sudden cardiac arrest cases.Early Warning System (EWS) can help identify deteriorating patients at risk of death from cardiac arrest [5]. Patients who experienced sudden cardiac arrest and were admitted to the ICU showed signs of deterioration hours before the event. Early detection and treatment can reduce mortality rates, and EWS is designed based on patients' vital signs to aid in this process [6]. This study makes several important contributions by,

- Publishing an Open Access bedhead ticket dataset.
- Introducing a machine learning model to predict the risk of fatal cardiac arrests, which has shown improved results.
- Analysing the data set with machine learning models to compare the usability of the dataset.

Repository links

- Dataset(Zenodo)
- Model(GitHub)

II. Related works

Marinkovic's study [7] demonstrated that patients with higher EWS scores before cardiac arrest had worse outcomes, emphasizing the importance of an EWS to predict cardiac arrest and closely monitor such patients. Sri Lanka's healthcare system, as a Low to Middle-Income Country (LMIC), is unfamiliar with EWS, Rapid Response Teams (RRT), and Dedicated Resuscitation Teams (DRT), often overcrowded and poorly resourced.

Adapting EWS from High-Income Countries (HIC) to LMIC settings can lose sensitivity and specificity in predicting deteriorating patients [8]. Most risk algorithms are based on European populations, and their validity for South Asian populations is unverified [9]. This highlights the need for an EWS tailored to Sri Lanka's healthcare system.

Developing an EWS to predict cardiac arrest risk can significantly reduce mortality among cardiac patients in Sri Lanka [8]–[10]. The objective of this study was to develop a model with high accuracy, suitable for Sri Lanka's medical care setup, predicting in-ward cardiac arrests using relevant data extracted from Bed Head Tickets (BHT) of cardiac patients [11]–[14].

This study demonstrates that, even in a healthcare setup with limited resources like Sri Lanka, it is feasible to develop an EWS to predict cardiac arrests using manually extracted

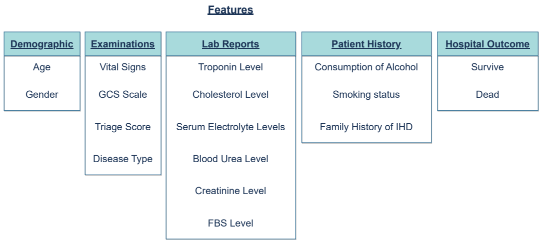


Fig. 1: *Categorization of extracted features into groups*

patient data from BHTs. The paper outlines the steps followed to collect and preprocess data, develop a high-accuracy deep learning model, and select suitable input features based on their high availability.

The results section elaborates on the final outputs of the model and the analysis of extracted data from BHTs. Finally, the study evaluates and validates the model to assess its predictive performance of the model, emphasizing the potential for implementing a tailored EWS in Sri Lanka's healthcare system.

III. Materials and Methods

A. Methodology

The research was designed as a retrospective cohort study, focusing on patients admitted to the cardiac ward between August 13th, 2018, and February 6th, 2020, at Teaching Hospital, Karapitiya (THK), Galle, Sri Lanka. The study population included patients who were transferred to the cardiac ward from the Emergency Treatment Unit (ETU), excluding other types of patients and pediatric patients. A total of 112 patients, aged 15-89 years, were included in the study, with 82 male patients and 30 female patients.

Ethical clearance was obtained from the Ethics Review Committee of the Faculty of Medicine, University of Ruhuna, Galle, Sri Lanka, and the study adhered to the relevant guidelines and regulations established by the committee. Permission to access data was granted by the Director of Teaching Hospital Karapitiya. As this was a retrospective study, obtaining informed consent from all subjects was not applicable.

Data collection involved extracting information from the BHTs records in the hospital's record room. Due to the absence of electronic clinical data, each BHT was manually examined to collect the necessary data. The BHTs contained information on patients' health status, clinical history, management actions, investigations, treatments, progress, and diagnosis.

The extracted BHT data were categorized into five main categories: demographic features, examinations, lab reports, patient history, and outcomes (Fig. 1). The extracted features were further analyzed to determine their availability concerning patients' hospital stays. Features with an availability rate of over 60% (Fig. 2) were selected for model development.

B. Data preprocessing

As illustrated in Fig. 3, the extracted clinical data were primarily divided into two categories: time-series data and

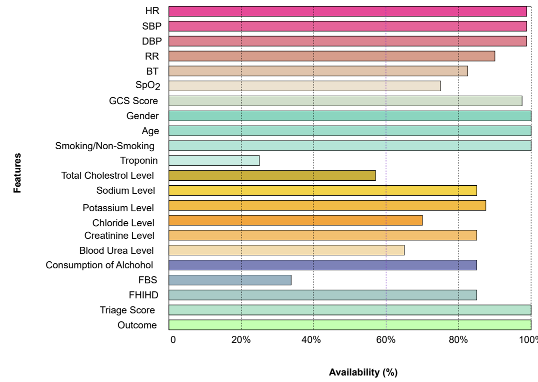


Fig. 2: *Feature availability of 112 patients*

non-time-series data. Time-series data consisted of patient information recorded in relation to time, while non-time-series data encompassed the remaining data. The clinical dataset contained 21 features: age, heart rate (HR), Systolic Blood Pressure (SBP), Diastolic Blood Pressure (DBP), Respiratory Rate (RR), Body Temperature (BT), Oxygen Saturation (SpO2), level of consciousness, troponin level, total cholesterol level, Fasting Blood Sugar level (FBS), serum electrolytes (Sodium, Potassium, Chloride), urea level, creatinine level, triage score (risk score on admission), alcohol consumption, smoking status, Family History of Ischemic Heart Diseases (FHIHD), and hospital outcome.

Out of the 21 features, 19 were selected for inclusion, while three were excluded from the final feature list. Troponin level, total cholesterol level, and fasting blood sugar level, which can be used to detect comorbidities in patients, were excluded due to insufficient records in the BHTs for the majority of patients. Data preprocessing consisted of two steps. First, 19 common features, including the patient's hospital outcome (target variable), were selected. Second, missing value imputation was performed for the selected features. If any feature data were missing, the most recent value was used; if no value was available, the median value was used.

Regarding time-series data (SBP, DBP, HR, RR, BT, SpO2), patients were monitored hourly throughout their hospital stay. In the selected dataset, patients were monitored for a minimum of one hour and a maximum of 266 hours (11 days). A suitable time step (time window) for observation was chosen from this range. The time step was determined based on the average observation time of a patient (52 hours). This 52-hour observational time window is considered the prediction window of the model. For non-time-series data, only the results from the patient's lab tests conducted on the hospital admission date were considered.

C. Model architecture

The integration of artificial intelligence into clinical practice has led to numerous studies focused on predicting adverse events, such as cardiac arrests before they occur. Evidence from these studies suggests that deep learning models are more efficient at identifying high-risk patients compared to existing EWSs [14]. Recurrent Neural Network (RNN) models are

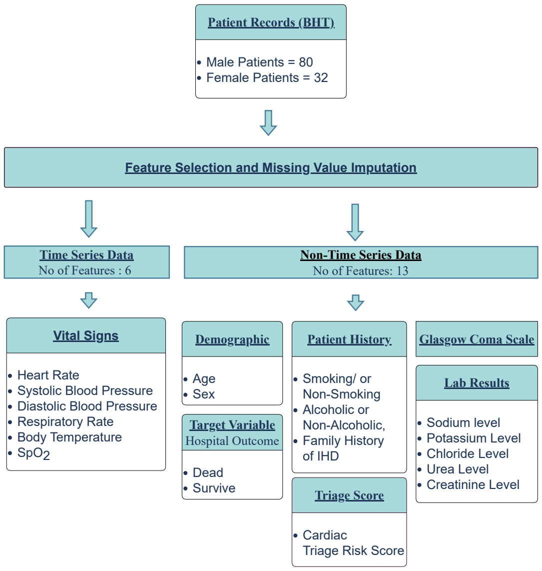


Fig. 3: *Data preprocessing workflow*

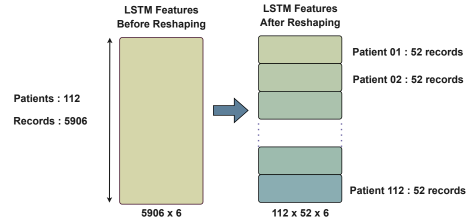


Fig. 4: *Data reshaping after oversampling*

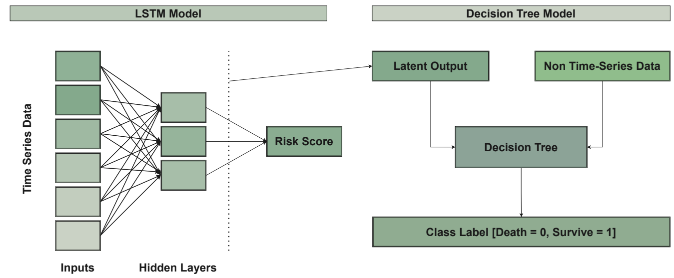


Fig. 5: *Model architecture*

particularly well-suited for handling temporal sequence data. Among RNN variants, Long Short-Term Memory (LSTM) has demonstrated remarkable performance in various sequence-based tasks [15]. Recent studies have also shown that deep learning models employing RNN architectures with LSTM outperform clinical prediction models developed using logistic regression [16], [17]. Consequently, we chose the LSTM structure to model the temporal relationships within data extracted from the BHT.

1) LSTM model: The Deep-Learning Cardiac Arrest Prediction Model (DLCAPM) consists of a LSTM designed to handle time-series data, followed by a dense layer. During the model's development, we employed a sigmoid activation function for the dense layer, the Adam optimizer with default parameters, and binary-cross entropy as the loss function. The complete dataset was divided into 30% for validation and 70% for training. Inputs to the LSTM model include Systolic Blood Pressure (SBP), Diastolic Blood Pressure (DBP), Heart Rate (HR), Respiratory Rate (RR), Body Temperature (BT), and Oxygen Saturation (SpO2) levels. Prior to oversampling, the input data fed into the LSTM comprised a three-dimensional array of $112 \times 52 \times 6$ (112 patient records), and after oversampling, the dimensions were $186 \times 52 \times 6$ (186 patient records), as illustrated in Fig 4. The first phase of the model aimed to handle temporal data, while the second phase combined the results of the time-series data with non-time-series data. This combined data was then input into the decision tree model to predict the final outcome based on the model's results.

2) Decision tree model: In the medical domain, the clinical practice involves continuous decision-making, where optimal decision-making strives to maximize effectiveness and minimize loss [18]. Clinical decision analysis (CDA) highlights the significant role of decision trees in this process [19]. Among the five methodologies employed for decision-making, designing a decision tree is considered one [20]. Owing to their reliability, effectiveness, and high accuracy in decision-making, decision trees are widely utilized in various medical decision-making studies [21]. These factors led us to select the decision tree as the model to handle non-time-series data, including the LSTM outcome. The LSTM model is designed to generate a risk score based on time-series data acquired within a time window of up to 52 hours.

3) Latent vector space: Latent vector space is employed in machine learning to analyze data that can be mapped to a latent space where similar data points are in close proximity. In simpler terms, it can be described as a representation of compressed data. This latent space representation retains all the essential information required to represent the original data points, thereby facilitating data analysis. Latent space representations are utilized to transform more complex forms of raw data, such as images and videos, into simpler representations, a concept implemented in Representation Learning.

In the context of the LSTM model, the latent vector space serves as an input parameter for the decision tree model. The decision tree inputs are a combination of non-time-series data, including demographic information, lab results, triage score, Glasgow Coma Scale (GCS) values, and patient history, as well as the latent output of the LSTM model (Fig 5). This approach allows for a more comprehensive analysis by integrating both time-series and non-time-series data, enhancing the model's decision-making capabilities.

4) Dealing with Data Imbalance Problem: Class imbalance is a common challenge in real-world data, particularly in medical fields, making it difficult to optimize machine learning algorithm performance. In this study, there were 93 majority-class (survived) and 19 minority-class (dead) patients, yielding a 1:5 ratio.

To address the class imbalance, Synthetic Minority Over-sampling Technique (SMOTE) was used to over-sample the minority class, generating synthetic data and achieving a 1:1 class ratio. SMOTE enhances model performance by properly

TABLE I: Hyperparameter values

No of Epochs	Learning Rate	Batch Size	LSTM Nodes	Optimizer
100	0.001	10	2	Adam

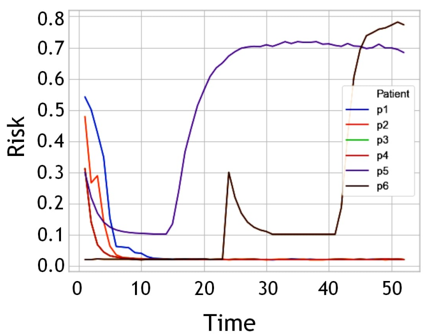


Fig. 6: *Prediction of the risk score with 52 hours*

representing and accounting for both classes during classification.

IV. Results

The DLCAPM model used an over-sampled dataset of 186 records, achieving 0.96 accuracy for the LSTM model and 0.76 for the decision tree model, with sensitivities of 0.96 and 0.69, respectively. Hyperparameters were optimized (Table I), and the decision tree classifier predicted patient outcomes.

Creatinine levels were the most critical predictor, followed by sodium and blood urea levels. Studies suggest that these markers relate to renal function, which is linked to cardiovascular diseases [22]. Additionally, potassium levels, FHIHD, and age played key roles in classifying cardiac patients, supporting the association between cardiovascular diseases and decreased potassium levels [23].

FHIHD is recognized as a well-established risk factor for cardiovascular diseases [24]. In the study's findings, the risk factor FHIHD emerged as one of the most reliable predictive features for cardiac arrests. (Fig 6) displays the probabilistic prediction window for six randomly selected patients (three from each of the two classes).

The LSTM model itself was proficient in providing predictions from the time of admission up to 52 hours later. In other words, the model's prediction window spanned 52 hours. The model demonstrated a prediction accuracy of 96% with a confidence interval of 95.01% to 95.85%.

A. Comparison with existing models

We assessed the performance of the developed Deep Learning Cardiac Arrest Prediction Model (DLCAPM) by comparing it with well-established machine learning algorithms, such as Logistic Regression, Random Forest, Naïve Bayes, and Support Vector Machine (SVM). The evaluation was carried out using all the features incorporated in the DLCAPM model. Table II presents the performance metrics, including Accuracy, Sensitivity, Specificity, Positive Predictive Value (PPV), Negative Predictive Value (NPV), and F-Score, for each of the compared models. The results demonstrate that the LSTM component of the DLCAPM model exhibits superior performance in comparison to the selected models.

TABLE II: Performance comparison with existing machine learning models (LSTM | Decision Tree)

Model	Accuracy	Sensitivity	Specificity	PPV	NPV	F-Score
DLCAPM	**0.96** | 0.76	**0.95** | 0.69	0.93 | 0.81	0.98 | 0.72	0.81 | 0.79	0.86 | 0.80
SVM	0.89	0.84	0.82	0.81	0.82	0.844
Logistic Regression	0.88	0.93	0.81	0.92	0.81	0.87
Random Forest	0.88	0.89	0.90	0.87	0.81	0.91
Naive Bayes	0.85	0.89	0.80	0.82	0.88	0.91

Fig. 7: *Correlation heatmap between time-series inputs*

B. Correlation analysis

Correlation analysis evaluates the relationships among model input features. Pearson's and Spearman's coefficients are commonly used; the former for normally distributed variables and the latter for skewed or ordinal variables. A coefficient near ±1 indicates a strong correlation, either positive or negative [25]. In this study, Spearman's rank correlation was used due to Gaussian distribution, and Fig 7 shows the heatmap of correlation coefficients. A high positive correlation exists between Systolic and Diastolic Blood Pressure.

C. Characteristics of the study population

In the cohort study, patient data was analyzed to assess the observed characteristics of the study population, as shown in Table III. From these observations, we can infer that males may have a higher susceptibility to cardiovascular diseases and cardiac arrests. This study also examined the impact of various risk factors that could potentially contribute to the development of CVDs. Among these risk factors, alcohol consumption, smoking, and a family history of ischemic heart disease (FHIHD) were identified as the most significant contributors. In the total population (comprising both males and females), 37% of individuals reported having an FHIHD. Notably, none of the female patients were documented to consume alcohol or smoke. Among the male patients, 73% (81 patients) were found to engage in at least one of these behaviors, with 69% (55 patients) consuming alcohol, 63% (51 patients) smoking, and 26% (21 patients) engaging in both alcohol consumption and smoking.

V. Discussion

The performance of the model was assessed using two optimization algorithms, 'Adam' and 'Admax'. Multiple iter-

TABLE III: Characteristics of the study population

Characteristic	Data
Study period	13th of August 2018 - 6th of February 2020
Hospital	Teaching Hospital Karapitiya, Galle, Sri Lanka
Total patients, n	112
Input vectors, n	19
Age group	59 – 76years
Male, n (%)	73%
Symptoms before admission	Chest pain on the left side (1/2 hour before the admission), Tightening of the chest, Vomiting, Sweating, Nausea, Cough, Fever
Patients with FHIHD, n (%)	37%
Consume alcohol, Male n (%)	69%
Smoking, Male n (%)	63%
Smoking & use alcohol, Male n (%)	26%

TABLE IV: Performance of the model with the oversampled dataset

Metric	LSTM				Decision Tree			
	Experiment number				Experiment number			
	01	02	03	**04**	01	02	03	**04**
Accuracy	0.93	0.85	0.94	**0.96**	0.80	0.83	0.80	**0.76**
Precision	1.0	1.0	1.0	**1.0**	1.0	1.0	1.0	**1.0**
Recall	1.0	1.0	1.0	**1.0**	1.0	1.0	1.0	**10**
F-Score	0.81	0.86	0.81	**0.86**	0.82	0.85	0.82	**0.80**
AUC score	0.97	0.95	0.97	**0.98**	0.79	0.83	0.79	**0.75**

TABLE V: Evaluation metrics of LSTM model

Statistic	Value		95% CI	
	LSTM Model	Decision Tree Model	LSTM Model	Decision Tree Model
Sensitivity	95.83%	69.57%	95.37% to 96.25%	47.08% to 86.79%
Specificity	93.42%	81.82%	92.07% to 94.61%	64.54% to 93.02%
Positive Predictive Value	98.71%	72.73%	98.44% to 98.93%	55.19% to 85.24%
Negative Predictive Value	81.04%	79.41%	79.37% to 82.60%	67.07% to 87.96%

ations were performed, altering hyperparameter combinations to identify the four most optimal configurations, which yielded the highest accuracy. Table IV presents the evaluation metrics for each of these four selected runs. Among these experiments, the best results were achieved in experiment number 04, which employed an oversampled dataset for training the model.

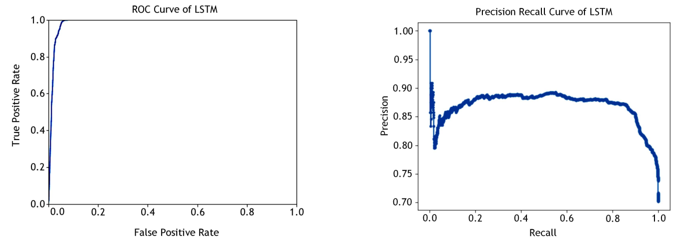
Table V shows the sensitivity, specificity, Positive Predictive Value (PPV), Negative Predictive Value (NPV), and accuracy measures for the outperformed LSTM model and decision tree model in experiment number 04, respectively.

The ROC curve is a graphical representation that demonstrates the diagnostic ability of binary classifiers by plotting sensitivity against specificity. A better-performing classifier will have a curve closer to the top-left corner. To compare classifiers' performance, a common approach is to calculate the area under the ROC curve. Figure 8a presents the ROC curve for the LSTM model.

However, visual interpretations and comparisons of ROC curves can be misleading for imbalanced datasets. To address this issue, precision-recall curves are utilized. Figure 8b illustrates the precision-recall curve for the LSTM model, and the supplementary figure shows the curve for the decision tree classifier model.

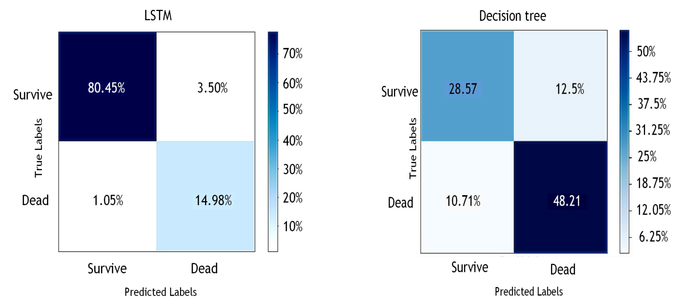
The confusion matrix, crucial for statistical classifications in machine learning, is a table describing a classification model's performance and identifying class confusion. Figure 9a and Figure 9b display the confusion matrices for the LSTM and decision tree models, respectively.

1) Comparison with existing EWS: DLCAPM was evaluated against existing cardiac arrest early warning scores, including Modified Early Warning Score (MEWS), Cardiac Arrest Risk Triage Score (CART), and National Early Warning



(a) *ROC curve* (b) *Precision-Recall curve*

Fig. 8: ROC curve and Precision-Recall curve of LSTM model



(a) *Confusion matrix for LSTM model* (b) *Confusion matrix for the decision tree model*

Fig. 9: *Confusion matrices for (a) LSTM model and (b) decision tree model*

Score (NEWS), based on research by [26], [27]. MDCALC calculator [28]–[30] was used to calculate risk scores for CART, MEWS, and NEWS using collected data (RR, SpO2, BT, SBP, DBP, HR, Age, Triage Score). Table VI displays the performance of each score.

TABLE VI: Performance comparison of DLCAMP, CART, MEWS and NEWS

Model	Accuracy	Sensitivity	Specificity	PPV	NPV	F-Score
DLCAPM	**0.96** | 0.76	**0.95** | 0.69	0.93 | 0.81	0.98 | 0.72	0.81 | 0.79	0.86 | 0.80
CART	0.60	0.50	0.75	0.75	0.75	0.60
MEWS	0.80	0.93	0.40	0.82	0.4	0.50
NEWS	0.80	0.84	0.66	0.94	0.66	0.66

2) Limitations: The THK record room utilizes Microsoft Excel to store limited data from bedhead tickets, making it necessary to manually review each patient's record to obtain the required information for this study, which was time-consuming. The small sample size, potential patient heterogeneity, and focus on a specific patient population within a single hospital unit limit the research's generalizability, making it potentially inapplicable nationwide. These limitations stem from the legacy methods of maintaining patient data and difficulties in retrieval.

Due to limited resources, only 112 patient records were extracted, which prevented reaching the desired sample size for the model. To address this limitation, the Synthetic Minority Over-sampling Technique (SMOTE) was employed to increase the minority sample size. Furthermore, the study faced constraints due to the scarcity of local research on the development of cardiac arrest EWSs in Sri Lanka [8], [10].

VI. Conclusion

An efficient deep-learning cardiac risk prediction model was developed using clinical features from THK cardiac patients' BHTs. This simple model uses accessible patient data, offering bedside support for healthcare workers and assisting decision-making. An open-access dataset was published to encourage further research.

Early and accurate predictions can aid in timely interventions and prevent cardiac events. Despite high accuracy, addressing data limitations could improve the model. Further research is needed to explore applicability in other healthcare settings and integration with existing patient monitoring tools for enhanced prediction.

Acknowledgment

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