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

L T W Rajapaksha[1], S M Vidanagamachchi[2], Sampath Gunawardena[2] and Vajira Thambawita[2]

[1]*University of Ruhuna, Sri Lanka*
[2]*SimulaMet, Norway*

***Abstract*—Cardiac arrest is an instantaneous loss of cardiac function in a person who may or may not be diagnosed with heart disease, and it has a significant impact on a patient's well-being and can also pose a threat to their life. In Sri Lanka, healthcare professionals use bed head tickets to keep track of important information about patients which allows quick access to identify patients' medical conditions and communicate patients' information effectively across different healthcare teams. The bed head tickets of cardiac patients have been a valuable source of data for our research study, particularly as these data were collected in a setting where electronic medical recording systems were not yet implemented. This research demonstrates the feasibility of implementing a cardiac arrest prediction model using data extracted from the bed head tickets. Additionally, it emphasizes the importance of preserving and using data from paper records where electronic medical recording systems are not available, highlighting the value of historical data and the need for global efforts to digitize and integrate medical records. This retrospective cohort study evaluates 112 patients who were transferred from the Emergency Treatment Unit to the Cardiac Medical Ward. A Deep-Learning Cardiac Arrest Prediction Model was developed using a Recurrent Neural Network and a decision tree classification model. The model used a total of nineteen commonly recorded medical details from patients' bed head tickets to predict the risk of developing a cardiac arrest. The Recurrent Neural Network model achieved 96% accuracy, 95.83% sensitivity, and 93.42% specificity, making it an effective approach in identifying the risk of developing a cardiac arrest in in-ward patients, than traditional Early Warning Systems. Our proposed model was developed in an environment that had no Electronic Medical Recording.**

***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 usually happens when there is a dysfunction in the heart's conduction system which could cause the heart to stop pumping blood. The most frequent cause of cardiac arrest is ventricular fibrillation (65 -80% of cases) [1]. There are many heart-related causes of cardiac arrests, such as coronary artery disease, cardiomyopathies, some inherited heart conditions, congenital heart disease, heart valve disease, acute myocarditis, and conduction disorders (e.g., long QT syndrome). In many patients, the symptoms of cardiac arrest are unrecognized or ignored by the individual. The most common symptom displayed by the above patients is chest pain, the cause of which could be acute coronary ischemia. More than 70% of cardiac arrests are caused due to ischemic coronary illness, which is considered the leading cause of cardiac dysfunction. Nevertheless, risk factors such as hypertension, hyperlipidemia, diabetes, cigarette smoking, increasing age, and family history of coronary diseases will play a major role in deaths caused by cardiac arrest [2]. Within the Sri Lankan population, the estimated mortality of 534 deaths per 100,000 is caused by cardiovascular diseases (CVD), which is a significantly high value when compared to developed countries [3]. According to the recent data published by WHO in 2018, CVD also accounts for 22.64% of total deaths in the country [4]. The chance of cardiac arrest after a heart attack, within the first 24 hours, is 20-30%. It is observed that the survival chance from a cardiac arrest is 25%, even if all the medical treatments are provided. The national data from Sri Lanka indicate that around 87% of hospital deaths are due to resuscitation attempts after a cardiac arrest. The chance of survival after resuscitation, even with full medical attention, is extremely slim and may cost the patient's life [2]. Time is of paramount importance when it comes to sudden cardiac arrest. The time it takes to receive help and treatment for a cardiac arrest is the determining factor between survival and death. Implementing an Early Warning System (EWS) could play a major role in the identification of deteriorating patients at risk of death due to cardiac arrest [5]. It was observed that the patients who underwent sudden cardiac arrest and were required to be admitted to the Intensive Care Unit (ICU) showed signs of deterioration several hours before the event. It is possible to reduce the mortality rate by early detection of these signs and providing appropriate treatments in time. For early identification of signs of deterioration, the EWS has been designed based on the major vital signs of patients [6].

II. Related works

A study carried out by O. Marinkovic [7] demonstrated that patients who had higher EWS scores before having a cardiac arrest experienced the worst outcome. This highlights the need for an EWS to predict a cardiac arrest before it occurs to keep such patients under more close supervision. As a Low to Middle-Income Country (LMIC), the healthcare system of Sri Lanka is not familiar with EWS, Rapid Response Teams (RRT), and Dedicated Resuscitation Teams (DRT). Additionally, the Sri Lankan healthcare setup is most often overcrowded and poorly resourced. Adapting EWS used in High- Income Countries (HIC) in an LMIC setting has been found to lose sensitivity and specificity in predicting deteriorating patients [8]. A previous study shows that most of the risk algorithms were generated based on European populations and, their validity for the South Asian populace has not yet been verified [9]. This highlights the importance of implementing an EWS that can meet the specific demands of the Sri Lankan healthcare system. With the use of available resources in Sri Lanka, developing an EWS to predict the risk of cardiac arrest in a patient can significantly reduce the mortality rate among cardiac patients. So far, several types of research related to the topic have been carried out in Sri Lanka. Most of them have explored the risk of coronary heart disease and mortality due to cardiovascular disease (CVD) and the feasibility of implementing an EWS within the healthcare setup of the country [8] [9] [10]. Most of the research work that has been done has developed their models based on the data from vital signs (Systolic Blood Pressure, Heart Rate, Respiratory Rate, Body Temperature, and Mental Status). Though the manual records of vital signs are usually available for evaluation, the data from Electronic Medical Records (EMR) are not widely available because the Sri Lankan healthcare system is not entirely familiar with EMR. The objective of this study was to develop a model with high accuracy in parallel with the state-of-the-art models, which will be suitable for the Sri Lankan medical care setup to predict in-ward cardiac arrests using relevant data extracted from the Bed Head Tickets (BHT) of cardiac patients. According to previous studies, single parameter and Aggregate Weighted Track and Trigger Systems (AWTTS) were used by multiple EWSs [11]. Modified Early Warning Score (MEWS), Standard Early Warning Score (SEWS), National Early Warning Score (NEWS), Vital PAC Early Warning System (ViEWS), and Cardiac Arrest Risk Triage Score System (CART) are some of them. These EWS were commonly used in High-Income Countries (HIC), such as the Netherlands, USA, Australia, and the UK. EWSs were developed by using a variety of approaches such as regression models, observation of vital signs, and statistical methods. Some researches show that the practice of these EWS models was scarce. They show that the poor development of the models and the inappropriate evaluation of these models have led to this situation. There is no common ground of agreement as to which EWS's performance is better than that of the other EWS [12]. The DEWS [13] model was stated as the first early warning score, which was developed using the deep learning technique. Similar research was carried out in the year 2019. They developed a model by using six major physiological features, and three major demographic features and excluded the laboratory data to develop a feasible application in wards. A total of nine feature data was retrieved through EMRs for this study [14]. Compared to Kim's research, the significance of our study is to develop this EWS by using manually extracted patient data from the BHTs. Through this study, we project that, even in a healthcare setup with limited resources like the one found in Sri Lanka, in which clinical data extracted using EMR systems are not commonly used, it is feasible to develop an EWS to predict cardiac arrests. The paper explores and discusses the steps that we followed to collect the data and pre-process it as the initial step of the methodology. Later on, we review the development of a high-accuracy deep learning model, which will cater to our main objective. Next, we review and select suitable input features for the developed model based on their high availability. The results section elaborates on the final outputs of the model as well as the analysis of extracted data from BHTs. Finally, we evaluate and validate the model to read the predictive performance of the model.

III. Materials and Methods

A. Methodology

The research was conducted as a retrospective cohort study with patients admitted to the cardiac ward between the period of the 13th of August 2018 to the 6th of February 2020 at Teaching Hospital, Karapitiya (THK), Galle, Sri Lanka. We considered only the patients who were transferred to the cardiac ward from the Emergency Treatment Unit (ETU), and all other types of patients were disregarded, including pediatric patients. In total, 112 patients aged between 15– 89 years stayed in the cardiac ward at THK during the selected period of the study. They comprised 82 male patients and 30 female patients. Ethical clearance was obtained from the Ethics Review Committee of the Faculty of Medicine, Unversity of Ruhuna, Galle, Sri Lanka. The study was carried out following the relevant guidelines and regulations of the above Ethics Review Committee. In addition, permission has been obtained from the Director of the Teaching Hospital Karapitiya to retrieve the data from the record room of the hospital. Since this study was carried out as a retrospective study, obtaining informed consent from all subjects was not applicable. Data collection for this study was carried out by extracting the BHT records from the hospital's record room. Since the clinical data of patients were not electronically recorded, we had to go through every BHT manually and extract the required data. When considering the BHT of a cardiac patient, we identified a number of information such as the patient's health status, clinical history, actions taken by management, investigations, treatments, patient's progress, and diagnosis. The extracted BHT data could be categorized into five main categories (Fig 1) Demographic features, Examinations, Lab Reports, Patient history, and the Outcome.

We further analyzed the extracted features to identify the availability of the features with respect to the patient's hospital stay. According to the availability (Fig 2), features that scored more than 60% were selected for the development of the model.

B. Data preprocessing

As depicted in Fig 3, extracted clinical data were categorized mainly into two, as time-series data and non-time-series data. The patient data recorded in relation to time were defined as time-series whereas the rest were defined as non-time-series data. The extracted clinical data set consisted of

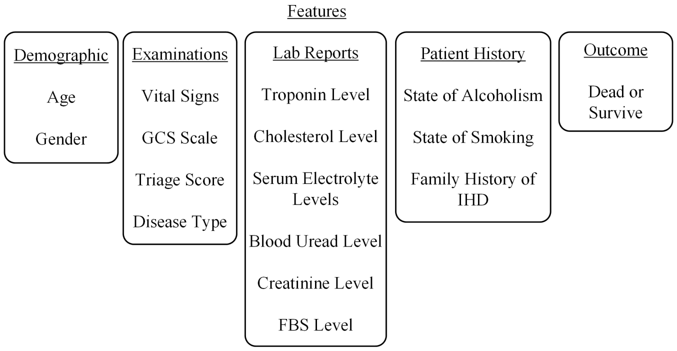

Fig. 1: *Categorization of extracted features into groups*

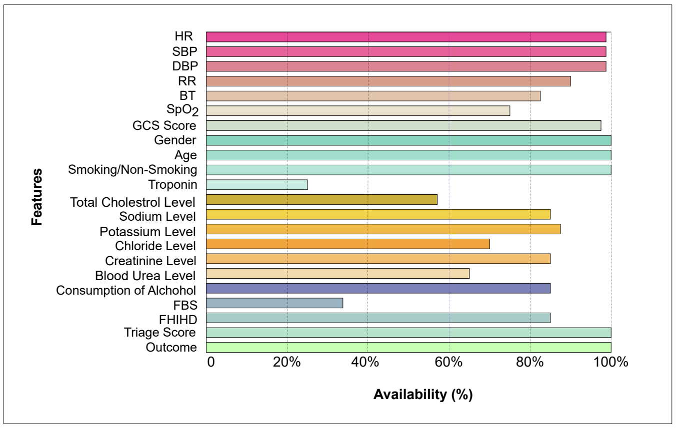

Fig. 2: *Feature availability of 112 patients*

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), alcoholic/nonalcoholic, smoker/non-smoker, Family History of Ischemic Heart Diseases (FHIHD), and hospital outcome.

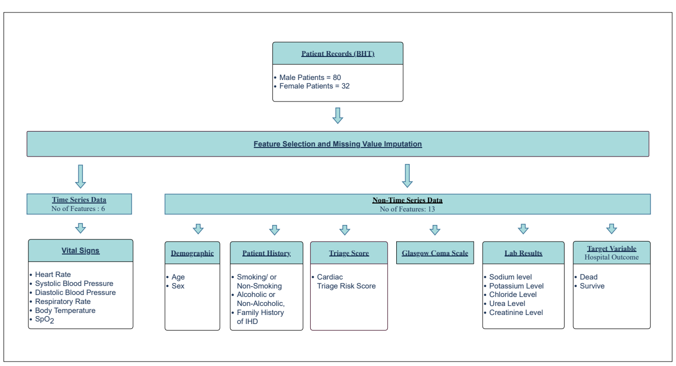

Fig. 3: *Data preprocessing workflow*

Of the 21 features, only 19 features were selected, and three were excluded from the final feature list. The features troponin level, total cholesterol level, and fasting blood sugar level which can be used to detect any comorbidity of patients were excluded due to the unavailability of records in the BHTs for most of the patients. The data preprocessing part underwent two steps. In the first step, 19 features that were common to all patients, including the patient's hospital outcome (target variable) were selected. In the second step, missing value imputation was carried out for the selected features. If any feature datum was missing, its most recent value was used. If there was no value present, the median value was used. When considering time-series data (SBP, DBP, HR, RR, BT, SpO2) patients were monitored on an hourly basis throughout their hospital stay. In the selected data set, patients have been monitored for a minimum of one hour up to a maximum of 266 hours (11 days). From the above time range, a proper time step (time window) was selected for observation. Time-step was deduced by considering the average observation time of a patient (52 hours). This 52-hour observational time window is considered the prediction window of the model. Only the results from the patient's lab tests carried out upon hospital admission date were taken into account when considering non-time-series data.

C. *Model architecture*

With the recent introduction of artificial intelligence into the clinical field, many studies have been carried out to predict adverse events such as cardiac arrests well before their occurrence. All the above studies indicate the deep learning model to be more efficient in detecting high- risk patients in comparison to the rest of the existing EWS [14]. When it comes to handling the temporal sequenced data, RNN models are considered the best-suited models for the purpose. Among developed RNN variants, long short-term memory (LSTM) displays an impressive performance in various sequence-based tasks [15]. Some recent studies also demonstrated that deep learning models equipped with RNN model architectures that utilize LSTM outperform the clinical prediction models developed from logistic regression [16][17]. Due to the above reasons, we used the LSTM structure to model the temporal relationship among data extracted from the BHTs.

1) LSTM model: The Deep-Learning Cardiac Arrest Prediction Model (DLCAPM) is comprised of a Long Short-Term Memory unit (LSTM), which deals with time-series data and is followed by a dense layer. For the development of the model, we used the activation function as a sigmoid function for the dense layer, the Adam optimizer with the default parameters, and a binary-cross entropy as a loss function. The model was trained by dividing the full data set; 30% for validation and 70% for training. SBP, DBP, HR, RR, BT, and SpO2 levels are input to the LSTM model. The input data delivered into the LSTM were a three-dimensional array of $112 \times 52 \times 6$ (112 patient records) before oversampling and the dimension of $186 \times 52 \times 6$ after oversampling the data set (186 patient records) as shown in Fig 4.

The goal of the first phase of the model was to deal with temporal data. In the second phase, the results of the time-

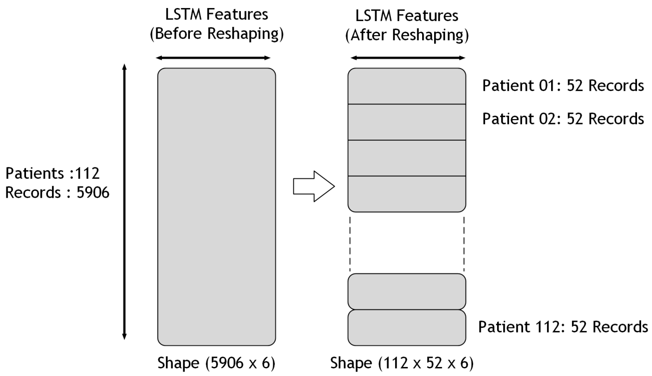

Fig. 4: *Data reshaping after oversampling*

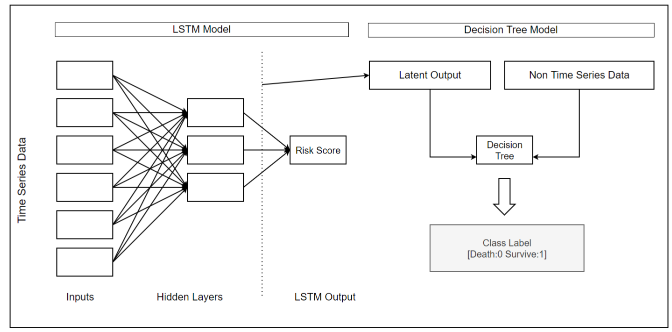

Fig. 5: *Model architecture*

series data were combined with the non-time-series data and then fed to the decision tree model to predict the final decision based on the outcome of the model.

2) Decision tree model: When it comes to the medical domain, clinical practice is a continuous act of making decisions where the best decision-making refers to a choice that maximizes effectiveness and minimizes loss [18]. According to clinical decision analysis (CDA), decision trees play a major role [19]. Designing a decision tree is considered to be one of the methods out of five methodologies that are used for decision-making [20]. Due to the reliability and effectiveness of decision-making with high accuracy, decision trees are used in many areas of medical decision-making studies [21]. These aforementioned reasons led us to choose the decision tree as the model that handles the non-time-series data including the LSTM outcome. The LSTM model was capable of generating a risk score based on the time-series data obtained within a time window of a maximum of 52 hours.

3) Latent vector space: Latent vector space is used in machine learning to observe data that can be mapped to a latent space where similar data points are close together. Simply, we can describe it as a representation of compressed data. This latent space representation of our data contains all the important information needed to represent our original data points and make it easier to analyze the data. The latent space representations are used to transform more complex forms of raw data like images and videos into simpler representations, and implementation of these methods can be seen in a concept called Representation Learning The latent vector space of the LSTM becomes an input parameter for the decision tree model. In the model, the decision tree inputs were a combination of the non-time-series data (demographic, lab results, triage score, GCS scale, patient history) and the latent output of the LSTM model (Fig 5).

4) Dealing with Data Imbalance Problem: In real-world data, the class imbalance is the most common problem that researchers face. In the medical field, it was very hard to find a well- balanced data set in their class labels, and it was a very difficult task to optimize the performance of a machine learning algorithm because the classification algorithms do not perform well on minority classes. Out of the total number of patients considered for the study, ninety-three patients belonged to the majority class (survived), and nineteen patients belonged to the minority class (dead). The ratio between majority and minority classes was approximately 1:5. To overcome the class imbalance problem in this study, we have used the Synthetic Minority Oversampling Technique (SMOTE) to oversample the minority class. Since this technique can be used to generate many synthetic data for the minority class as required, we were able to oversample the minority class and adjust the data set to 1:1 ratio in terms of class label.

IV. Results

DLCAPM's results were computed using the over-sampled data set, which consisted of 186 patient records. The model showed 0.96 accuracy for the LSTM model and 0.76 accuracy for the decision tree model with 0.96 and 0.69 sensitivities, respectively. These results were derived by adjusting the hyperparameter values, as shown in Table I.

TABLE I: Hyperparameter values

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

The decision tree classifier (Fig 6) would finally classify the patients' outcome as 'survive' or 'death.' The most crucial predicting feature for predicting cardiac arrest was the patients' 'creatinine.' The second most crucial predictors were the Sodium (Na) level and the blood urea level of the patient. A similar study stated that blood urea and creatinine levels could also be used to evaluate renal functions. Therefore, they stated that renal dysfunction was directly related to cardiovascular diseases [22]. When analyzing the first three levels of the decision tree, we could see that on behalf of the predictors of FHIHD and age, the Potassium (K) level also plays a key role in classifying cardiac patients. This result also endorses the finding; that cardiovascular diseases are associated with the draining of K levels in the heart [23].

FHIHD is considered a well-known risk factor for cardiovascular diseases [24]. In the results of the study, the risk factor FHIHD emerged as one of the best prediction features

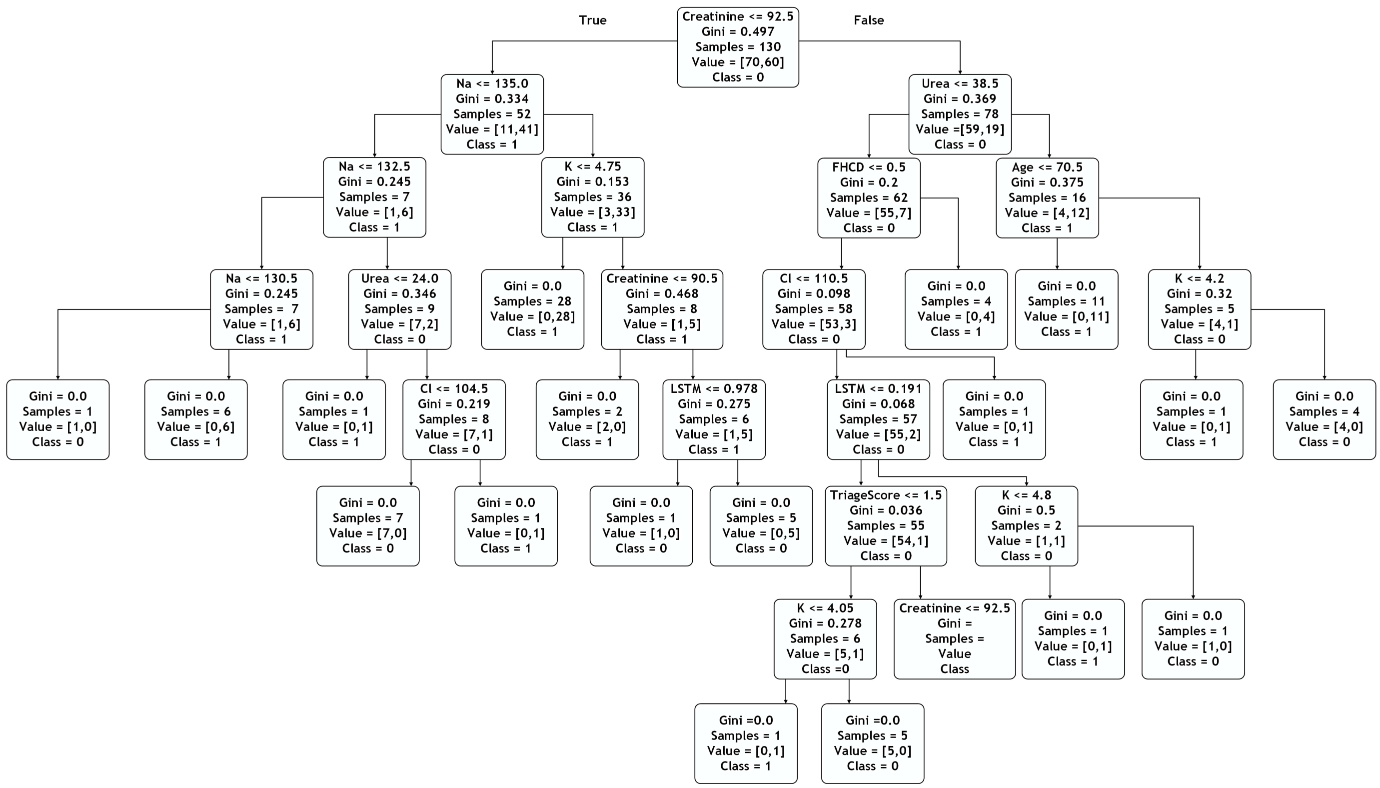

Fig. 6: *Decision tree classification*

for cardiac arrests. Fig 7 shows the probabilistic prediction window for six randomly selected patients (three from each of the two classes). The LSTM model itself was capable of providing predictions from admission time up to 52 hours onwards. In other words, the prediction window of the model was 52 hours. The model was capable of prediction accuracy of 96% with confidence of 95.01% - 95.85%.

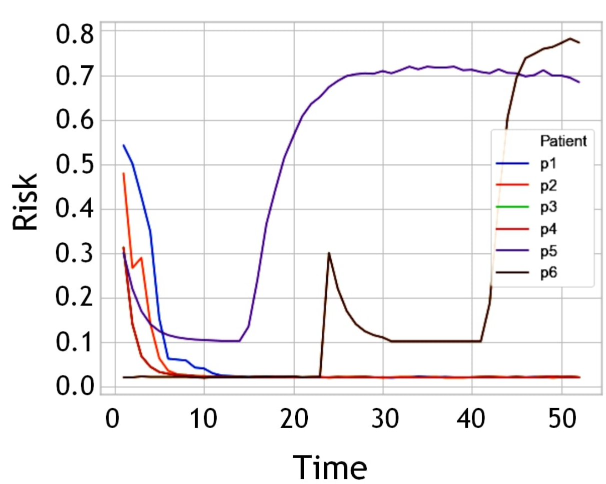

Fig. 7: *Prediction of the risk score with 52 hours*

A. Comparison with existing models

We evaluated the developed model (DLCAPM) against the machine learning algorithms/models such as Logistic Regression, Random Forest, Naïve Bayes, and Support Vector Machine (SVM) by using all features that we considered for the DLCAPM model. The following Table II shows the Accuracy, Sensitivity, Specificity, Positive Predictive Value (PPV), Negative Predictive Value (NPV), and F-Score of the above models. Based on the results we can see that the LSTM section of the DLCAPM model performance is better with respect to the selected models. Table II. Performance comparison with existing machine learning models (LSTM | Decision Tree)

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

B. Correlation analysis

It is important to conduct a correlation analysis for the selected input features for the model as it could be used to evaluate the strengths of the relationship among the selected features. Pearson's product-moment correlation coefficient and Spearman's rank correlation coefficient are the existing two types of correlation coefficients. Pearson's product-moment correlation coefficient was used when both variables were normally distributed, and Spearman's correlation coefficient was used when both variables were skewed or ordinal. When the correlation was strong, the coefficient comes to ±1. If a correlation coefficient was a positive number, the two variables were said to be directly correlated, and when a correlation coefficient was a negative number, the variables were inversely related [25]. This analysis was done using Spearman's rank correlation technique and we used this technique because the distribution of each and every input feature was Gaussian. Fig 8 shows the heat map of the correlation coefficient for the time-series features recorded. From the above matrix, it could be concluded that there is a very high positive correlation between Systolic Blood Pressure (SBP) and Diastolic Blood Pressure (DBP).

Fig. 8: *Correlation heatmap between time-series inputs*

C. Characteristics of the study population

When considering the patient data used in the cohort study, Table III shows the observed characteristics of the study population. Table III. Characteristics of the study population

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%

By this observation, we could infer that males have a higher tendency to be susceptible to cardiovascular diseases and cardiac arrests. In this study, we observed the influence of risk factors that could become a root cause of CVDs. Among them, alcohol consumption, smoking, and FHIHD were at the top of the list. Of the total population (including males and females), 37% recorded having an FHIHD. None of the female patients were recorded to consume alcohol or smoke. Patients who were recorded to be smoking and consuming alcohol were all male, and from 73% (81 patients) of male patients, 69% (55 patients) were found to consume alcohol, 63% (51 patients) were smokers, and 26% (21 patients) were found to consume both

V. Discussion

The model's performance was evaluated by using the optimizers 'Adam' and 'Admax' and ran multiple times by changing its hyper-parameter combinations until the best four combinations with the highest accuracy were discovered. Table IV shows each evaluation metric recorded for the selected four runs. Out of these four experiments, the best results were obtained from experiment number 04, which was done using the oversampled data set.

TABLE IV: Performance of the model with the oversampled data set

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 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.

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%

ROC curve is a graphical representation used to show the diagnostic ability of binary classifiers. It is a plot between the sensitivity (TPR) and the specificity (1-FPR). When a classifier performs better, the curves will become closer to the top left corner. When comparing the performance of the classifiers into a single measure, one common approach was to calculate the area under the ROC curve. Fig 9 shows the ROC curve of the LSTM model. (Refer to supplementary figure I for the ROC curve of the decision tree classifier model).

Visual interpretations and comparisons using ROC curves for an imbalanced data set could be misleading. To overcome this problem, precision-recall curves were used. Fig 10 shows the precision-recall curve for the LSTM model. (Refer to supplementary figure for the precision- recall curve of the decision tree classifier model)

The confusion matrix or error matrix in machine learning plays a major role when it comes to statistical classifications. It

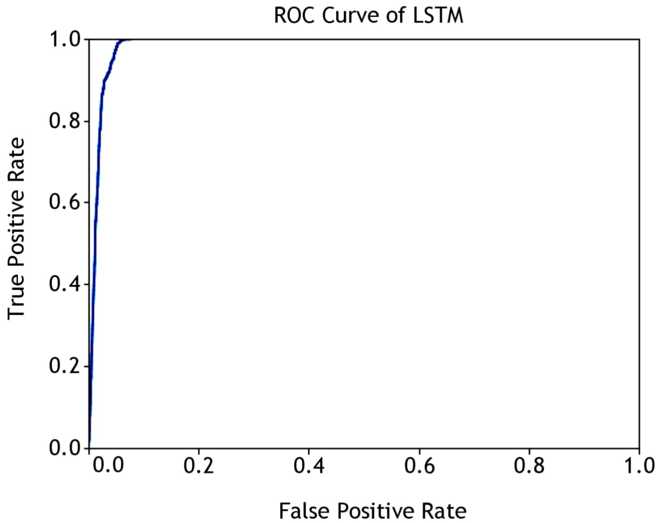

Fig. 9: *ROC curve of LSTM model*

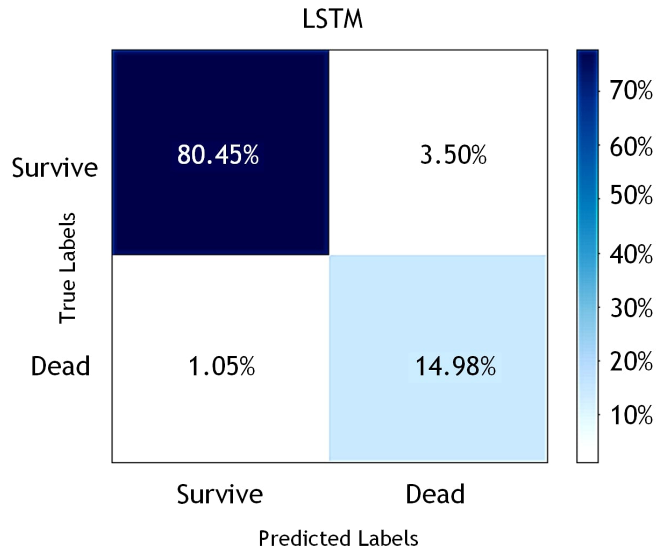

Fig. 11: *Confusion matrix for LSTM model*

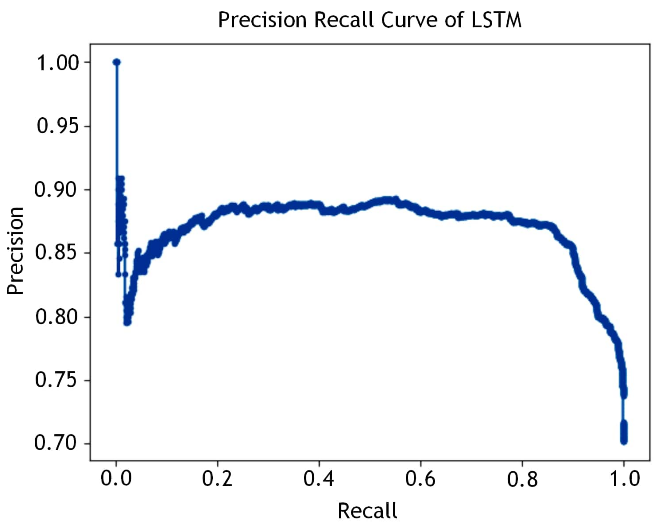

Fig. 10: *Precision-Recall curve of LSTM model*

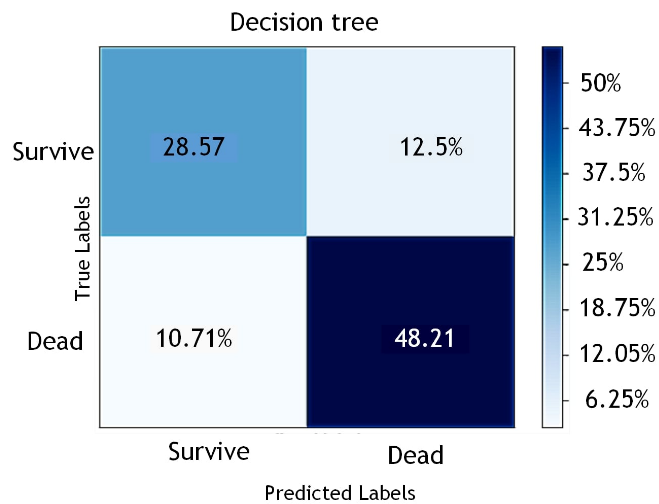

Fig. 12: *Confusion matrix for the decision tree model*

is a table used to describe the performance of the classification model. This allows us to identify the confusion between classes. Fig 11 and Fig 12 show the confusion matrix of the LSTM model and the decision tree model, respectively.

1) Comparison with existing EWS: DLCAPM was mainly evaluated against already existing cardiac arrest early warning scores. Modified Early Warning Score (MEWS), Cardiac Arrest Risk Triage Score (CART), and National Early Warning Score (NEWS) were considered for the evaluation of the developed cardiac arrest prediction model of the study. Choosing these existing models for evaluation was based on research done by [26] and [27]. These were existing models developed for predicting deteriorating patients. MDCALC calculator [28] [29] [30] was used to calculate the risk scores for CART, MEWS, and NEWS by using the data collected under each of the features; RR, SpO2, BT, SBP, DBP, HR, Age, and Triage Score. The following Table VI shows the performance of each of the above models.

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

In an article [31] by van der Ploeg, Austin, and Steyerberg, it is estimated that to have a very high chance of rigorously validating, many machine learning algorithms require 200 events per candidate feature (20 for logistic regression). Although longitudinal observation may lower this threshold, the inter-correction within the subject in the longitudinal data may not reduce the threshold significantly. And in medical prediction problems, these modern techniques should only be used if the data set is considerably large. But even with using a considerably lesser number of data, the DLCAPM in this research managed to outperform the existing machine learning models (Table II) and the existing EWS (Table VI) that it was compared with, with regard to its accuracy, sensitivity, specificity, PPV, NPV as well as F-Score. Therefore, given a higher number of data this model is sure to perform with significant efficiency and reliability. The research [8] and [9], which have been c arried out in Sri Lanka, were surveys that focus on evaluating the feasibility of implementing an EWS in the Sri Lankan context. These researches paved the way for the possibility of implementing an EWS but so far implementation has been a challenging task due to practicalities such as the limited access to EMR systems. Many EWS have been developed using statistical methods followed by observations, and some were developed based on clinical consensus [12]. Many recent studies [32] [33] [34] [35] have used several machine learning model architectures such as Gated Recurrent Unit (GRU), Convolutional Neural Networks (CNN), Long-Short-Term Memory (LSTM), decision tree models, and also combinations of the above models to develop each of their prediction models. When comparing the work done by J.M. Kwon [13] to the current study, it is evident that we combined highly available time-series and non-time-series data for prediction while Kwon uses only four vital signs to develop the model. Also, in the current study, generating cardiac arrest risk prediction via two models helped to verify the prediction accuracy of each model individually.

2) Limitations: The record room of the THK saves very little data from the bedhead tickets using Microsoft Excel as their data-capturing platform. Considering that such recorded data were significantly insufficient to fulfil the requirements of this study, because of that we had to go through each and every BHT of patients' manually in order to retrieve the required data and this process is time consuming. With the relative sample size of data compared to the potential heterogeneity of this type of patient and evidently high specific patient population in a single unit of single hospital can be considered as a major limitation of this research. Because of this it limits the generalizability of the findings and cannot apply for the whole country. The major reason for this limitation to occur can be consider as legacy methods of keeping patient's data and the difficulties of retrieving them. The limited resources in this aspect of the study only allowed the extraction of 112 patient records which hindered the required original sample size for the model. To mitigate this limitation to a certain extent we carried out SMOTE which is generally used to increase the minority sample size. Another limitation the study faced was the limited number of local researches carried out regarding the development of cardiac arrest early warning systems in Sri Lanka [8] [10].

A. Conclusion

We have successfully developed an effective deep-learning cardiac risk prediction model based on clinical features extracted from the BHT of cardiac patients in the Teaching Hospital Karapitiya. This simple prediction model was based on the highly available patient data features. This may provide bedside assistance for healthcare workers and also will impact decision-making for patients with deteriorating health. We hope the early and accurate prediction of cardiac arrests will directly assist in early intervention and prevention of cardiac arrest. Though we still observed a high accuracy in this proposed system with the available data, we strongly believe that the model could behave better with higher accuracy if the limitations of the data can be resolved. Further research is essential to discuss whether this developed model could be applied to other healthcare setups besides THK within the country. This study could also be extended to integrate the available patient monitoring tools within the Sri Lankan healthcare setup by utilizing this deep-learning model to predict cardiac arrests more accurately.

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