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Implementation of Machine Learning Algorithm for Cardiac Arrest Prediction

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ABSTRACT: Machine learning (ML) is a subfield of AI that uses statistical algorithms. Cardiac Arrest or heart failure has been implicated as one of the leading causes of death. The limited accuracy and the inherent invasiveness in diagnosis of this disease call for a revamp of the existing diagnostic protocol. In this study, we developed Machine learning (ML) algorithms for the prediction of cardiac arrest. Our protocol employs different methods for classification of the HD dataset using univariate and Bivariate analysis for prediction of cardiac arrest on input data which contains 11 features such as ChestPainType, age, gender etc and Pair plot to check the distribution of each variable and how it correlated with the target variable (Cardiac Arrest). Our result indicated that the ASY pain type was the highest ChestPainType that had cardiac arrest with 54% while NAP had 22%, ATA had 19% and TA 5%. The male genders were also observed to have the highest rate of cardiac arrest when compared to the female genders. Our protocol was able to predict the occurrence of cardiac arrest and at the same time recommend possible treatments, medication and exercises regime to the patient via the web application interface

KEYWORDS: Algorithms; Machine learning; Cardiac arrest; Diagnosis, Prediction models.

1.0 INTRODUCTION

Cardiac arrest is a sudden halt in the function of the heart that causes heartbeat to cease, as a result of loss of blood flow resulting from failure of the heart to pump blood effectively (Guyton and Hall 2011) It is usually as a result of variety of heart diseases such as coronary artery disease (McCullough, 2007) arising from infections and heart rhythm disorders called arrhythmias (Singh *et al*, 2020). Symptoms are known to include loss of consciousness and abnormal or difficulty in breathing (Gersh, Sliwa and Mayosi 2010). Although, radiating pain to one arm, chest pain, shortness of breath or nausea have also been reported to precede cardiac arrest (Gersh, Sliwa and Mayosi 2010).

Many techniques have been deployed for the diagnosis of heart diseases; including blood tests (Mayo, 2016), electrocardiogram (ECG) (Davie *et al*, 1996), Holter monitoring (Khongphatthanayothin 2018). Echocardiogram (Li, Hu and Zhang 2017), cardiac catheterization (Wyman, Safian, Portway, Skillman, McKay and Baim 1988), cardiac computerized tomography (CT) scan (Benjamins, Hendriks, Knuuti, Juarez-Orozco, and van der Harst, 2019) and cardiac magnetic resonance imaging (MRI) (Naghavi, Abajobir, and Abbafati, 2017).

Emerging communication and information technologies are presently used to improve health and for healthcare delivery (Al-sharqi *et al*, 2018). Recently, the internet of things and AI has been used for disease diagnosis and management in the healthcare setting (Mayo 2016, Seetharam *et al*., 2019 and Chandran, 2019 and Retson *et al*., 2019). The architecture of IoT medical applications consists of three layers: the sensing layer composed of sensors worn or carried by patients, the transport layer composed of connecters, and the application layer composed of remote server (Li, Hu and Zhang 2017).

Figure 1.1. Components of IoT: the sensor senses the temperature, pressure and sent the gate way to the cloud or server, which send the information to the mobile phone through the mobile App. (Retson *et al*., 2019).

Artificial intelligence (AI), though, defines the activities of computers that have been trained and programmed to mimic human intelligence (Seetharam *et al*., 2019; Narula *et al*, 2016 and Nature 2016). It uses machine-learning algorithms and language, heuristics, pattern matching and cognitive computing (Seetharam *et al*., 2019), using input data and deep learning (Nadrljanski and Foster 2022) to create their own logic (Murdoch and Detsky, 2013).

Increased hospitalizations (Kulkarni and Vijaykumar, 2016 and Krittanawong, Zhang and Wang 2017) and the high rates of morbidity and mortality resulting from cardiac arrest has necessitated the development of a novel protocol for the early detection and prediction of the disease, The potential of IoT-based devices stands out, as the traditional protocol remains expensive, invasive and characterized with uncertainty due to complicated symptoms. We therefore, present a non-invasive approach capable of using IoT to predict the occurrence of cardiac arrest. This will ensure early detection, drastically reduce hospitalization, the attendant cost and increase life expectancy in cardiovascular disease (CVD) patients.

2.0 MATERIALS AND METHODS

2.1 Software Packages

The following software packages were used for the study:

- **TensorFlow:**

TensorFlow is a free and open-source software library for machine learning and artificial intelligence.

- **Keras:**

Keras is an open-source software library that provides a Python interface for artificial neural networks. Keras acts as an interface for the TensorFlow library.

- **Scikit-Learn:**

Scikit-learn is a software machine learning library for the Python programming language. It features various classification, regression and clustering algorithms such as Random Forest, SVMs, etc.

- **Python:**

Python is a high-level, interpreted, general-purpose programming language.

- **Streamlit:**

Streamlit turns data scripts into shareable web apps in minutes. All in pure Python.

- **Pandas:**

pandas is a software library written for the Python programming language for data manipulation and analysis.

- **Numpy:**

NumPy is a library for the Python programming language, adding support for large, multi-dimensional arrays and matrices.

2.2 Input biological parameters contained in the dataset.

The dataset contains the following features or attributes with their corresponding description.

- Age: age of the patient [years]
- Sex: sex of the patient [M: Male, F: Female]
- ChestPainType: chest pain type [TA: Typical Angina, ATA: Atypical Angina, NAP: Non-Anginal Pain, ASY: Asymptomatic]
- RestingBP: resting blood pressure [mm Hg]
- Cholesterol: serum cholesterol [mm/dl]
- FastingBS: fasting blood sugar [1: if FastingBS > 120 mg/dl, 0: otherwise]
- RestingECG: resting electrocardiogram results [Normal: Normal, ST: having ST-T wave abnormality (T wave inversions and/or ST elevation or depression of > 0.05 mV), LVH: showing probable or definite left ventricular hypertrophy by Estes' criteria]
- MaxHR: maximum heart rate achieved [Numeric value between 60 and 202]
- ExerciseAngina: exercise-induced angina [Y: Yes, N: No]
- Oldpeak: oldpeak = ST [Numeric value measured in depression]
- ST_Slope: the slope of the peak exercise ST segment [Up: upsloping, Flat: flat, Down: downsloping]
- Cardiac Arrest: output class [1: cardiac arrest, 0: Normal]

2.3 Exploratory Data Analysis

To better understand the dataset, we carried out some basic data analysis to discover which features might be of a good target predictor variable and also to check if there were outliers and distributions of each feature.

2.4 Univariate Analysis

This was carried out to determine the number of people with cardiac arrest out of the total observation.

2.5 Bivariate Analysis

This analysis was used to check which gender is at most risk to have a cardiac arrest.

2.6 Multivariate Analysis

This analysis was performed to determine the distribution of each variable and how it correlated with the target variable (cardiac arrest).

2.7 Correlation Heatmap

A correlation plot of the dataset was computed to determine what features had a high positive or high negative correlation with the target column.

2.8 Artificial Neural Network

A simple feed forward artificial neural network with one input layer, one hidden layer and one output layer was implemented using TensorFlow library

2.9 WebApp Design and Deployment

In othe to make the model accessible by anyone, a web application interface was designed and deployed on the cloud using the Streamlit package. The WebApp was developed mainly using the python programming language.

```
model = Sequential([
    Dense(64, input_shape=(x_train.shape[1],), activation='relu'),
    Dense(32, activation='relu'),
    Dense(1, activation='sigmoid')
])

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
```

```
# Model summary
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 64)                768

 dense_1 (Dense)             (None, 32)                2080

 dense_2 (Dense)             (None, 1)                 33
```

Figure 3.16. Sequence model of the ANN

3.0 RESULTS

Table 3.1: Table of the cardiac arrest dataset.

Cardiac Arrest: output class [1: cardiac arrest, 0: Normal] showing the variables; age, sex, cholesterol, blood sugar, chest pain type, in the output, 0 is prediction for normal while 1 is the prediction for cardiac arrest occurring.

	Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxHR	ExerciseAngina	Oldpeak	ST_Slope	CardiacArrest
0	40	M	ATA	140	289	0	Normal	172	N	0.0	Up	0
1	49	F	NAP	160	180	0	Normal	156	N	1.0	Flat	1
2	37	M	ATA	130	283	0	ST	98	N	0.0	Up	0
3	48	F	ASY	138	214	0	Normal	108	Y	1.5	Flat	1
4	54	M	NAP	150	195	0	Normal	122	N	0.0	Up	0

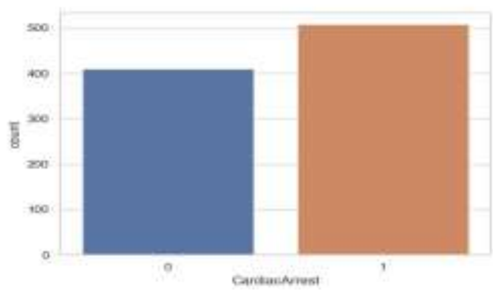

Figure 3.1: Distribution of the target individual column (univariate analysis)

The result aboved showed that there were slightly more people with cardiac arrest out of the total observations. [0] which predicts normal is 400 while [1] which predicts cardiac arrest is on the 500.

Figure 3.2: Distribution of the chest pain type from the univariate analysis

We noticed that people with the ASY type of chest pain had the highest ratio of 54% as seen in the pie chart above and are predicted for cardiac arrest, NAP had 22%, ATA had 19% while people TA are 5% and are predicted normal.

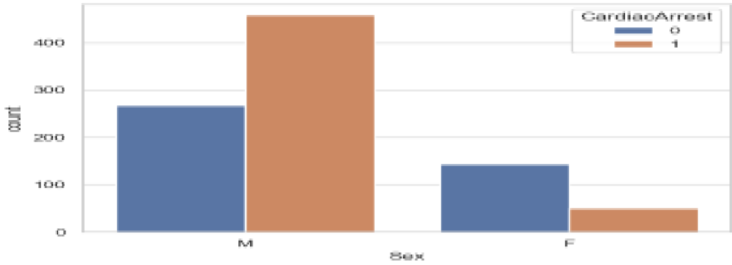

Figure 3.3: Bar chart showing the gender with high rate of cardiac arrest (Bivariate analysis)

Above, the male genders is shown to have the highest rate of cardiac arrest, compared to female.

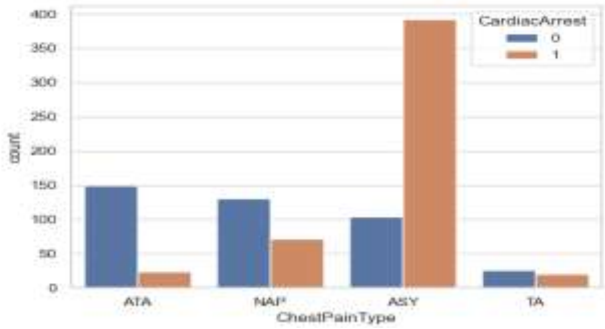

Figure 3.4: Bar chart showing the ChestPainType with high rate of cardiac arrest (Bivariate analysis). the ASY pain type was also the highest ChestPainType that had cardiac arrest.

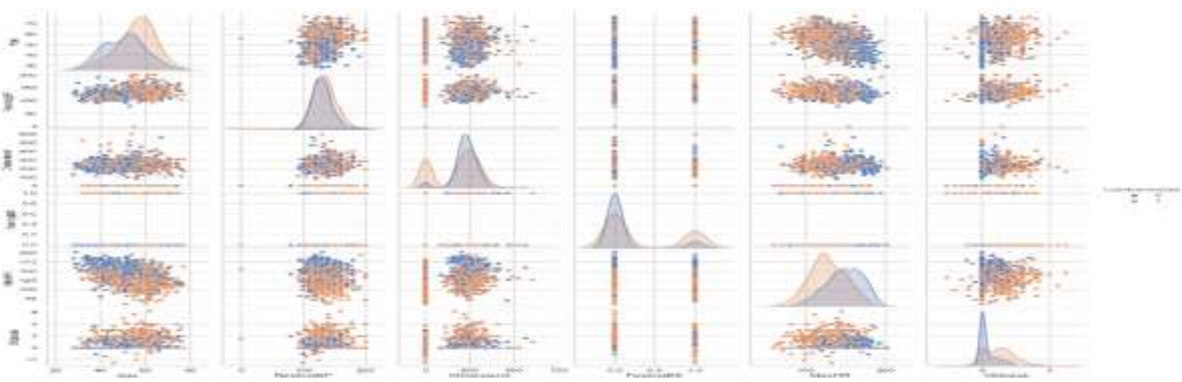

Figure 3.5: Pair plot of the dataset showing its distribution and correlation

We made a pair plot to check the distribution of each variable and how it correlated with the target variable (Cardiac Arrest). As seen above, the features are normally distributed with some features showing some correlation with the target column.

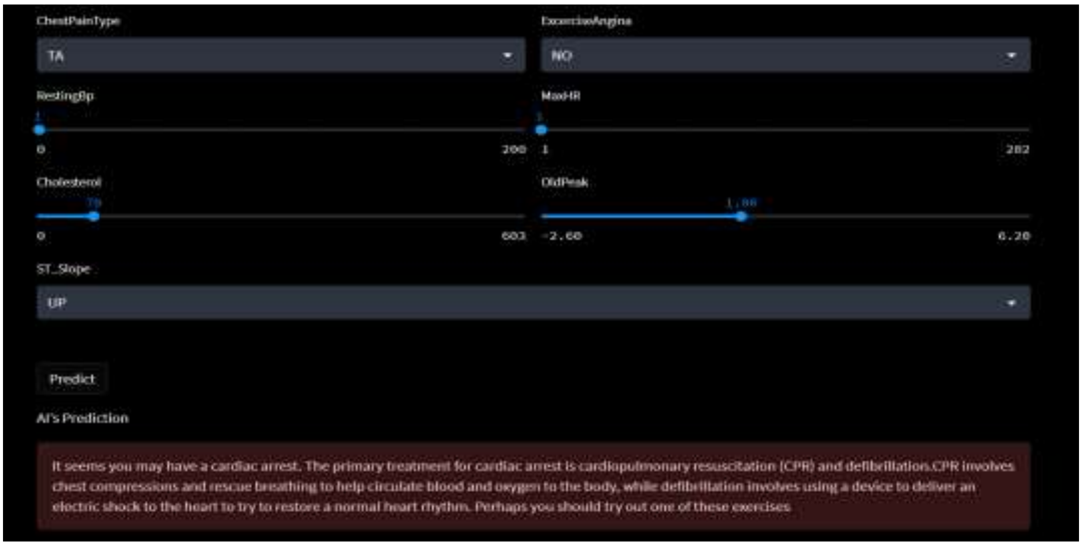

Figure 3.6: Screenshot of webapp prediction demo

4.0 DISCUSSION

Cardiac arrest is characterized by a sudden and unexpected loss of heart function (Davie *et al*, 1996), resulting from an electrical disturbance in the heart (Davie *et al*, 1996). The main symptom though, is loss of consciousness and unresponsiveness. This medical emergency needs immediate CPR or use of a defibrillator. Although there have been several machine learning approaches taken to predict the early risk of cardiac arrest (Chandran, 2019), our protocol does not only build a machine learning model, but also recommend possible treatments, medication and exercises regime to the patient via the web application interface (See Figure 3.6).

Cardiovascular diseases (CVDs) are the number 1 cause of death globally (McCullough, P. A. 2007), taking an estimated 17.9 million lives each year (WHO), which accounts for 31% of all deaths worldwide. Four out of 5 CVD deaths are due to heart attacks and strokes, and one-third of these deaths occur prematurely in people under 70 years of age (McCullough, P. A. 2007). Heart failure is a common event caused by CVDs, diagnosis has always been invasive, but we have developed a dataset which contains 11 features that can be used to predict a possible heart disease (See Table 3.1).

Our protocol employs different methods for classification of the HD dataset using different classifiers. We tested the data using univariate analysis (See figure 3.1), the distribution result showed that there were slightly more people with cardiac arrest out of the total observations as [0] which predicts normal is on the 400 while [1] which predicts cardiac arrest is on the 500. The univariate analysis pie chart, which analysed and gave the distribution for CestPainType feature column, showed that people with the ASY type of chest pain had the highest ratio of 54% and are predicted for cardiac arrest, NAP had 22%, ATA had 19% while people TA are 5% and are predicted normal (See figure 3.2).

Testing the same data using the Bivariate analysis to check what gender was prone to having cardiac arrest, it was observed that the male genders had the highest rate of cardiac arrest while the female genders are at the lowest risk to have a cardiac arrest (See figure 3.3). Although, predicting the rate of cardiac arrest by comparing the variable ChestPainType using Bivariate analysis, we discovered that the ASY pain type was also the highest ChestPainType that had cardiac arrest (See figure 3.4). This result collaborated the data from the univariate analysis.

Using Pair plot to test the data, to check the distribution of each variable and how it correlated with the target variable (Cardiac Arrest), we noticed that the features are normally distributed with some features showing some correlation with the target column (See figure 3.5). Studies in neuroscience have revealed much about the human brain since computer scientists first attempted the original artificial neural network.

Although big progress was made through the’90s and 2000s, it was only in 2012, when Krizhevsky and colleagues won the ImageNet ILSVRC contest, using a deep convolutional neural network to classify objects via graphics processing units (GPUs) to accelerate network training, that explosion of research activity in the neural network field started to happen (Murdoch and Detsky 2013). Our design, however, built on this, to analyse data such as age, resting BP, cholesterol, ChestPainType etc to predict the occurrence of cardiac arrest in a given subject, (See Table 4.1) using IoT and WedApp interface.

CONCLUSION

Based on this study, we conclude that; although, cardiac arrest occurrence is always sudden and its diagnosis is known to be time consuming and invasive. **T**here is a need to develop a protocol that will accurately predict the occurrence of the disease. Hence, we developed a machine learning algorithm that makes a prediction on the risks of the user having a cardiac arrest while suggesting common medication and exercise regime for the patient.

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