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CONGESTIVE HEART FAILURE PREDICTION USING DEEP LEARNING

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1. Abstract:

In early days the diagnosis and treatment were improved the quality and length of life for people who have congestive heart failure, since the heart failure was predictable after the very first attempt Myocardial Inflammation. The Congestive heart failure may cause of various reasons like age, anemia, Creatinine Phosphokinase, diabetics, Ejection Fraction, High BP, Platelets, Serum Creatinine, Serum Sodium, Sex, Smoking, Time and etc. Therefore, many techniques were used for diagnosing and for prediction the Congestive heart failure, here we using the Artificial Neural networks (ANN) to predict the early stage of heart failure. It consists of three different layers (input layer, multiple hidden layers and an output layer). In this ANN network nodes are in one layer that it is connected to another node in the next layer. The very first layer of ANN layer is an input layer which is train and validate data, second layer is a hidden layer are known as distillation layer, this layer which is help to extract the data. Final layer is the output layer this could be predicting the data of Heart Failure events of (Death Event) early stage. Here, the ECG or EKG dataset are used for heart failure prediction. By using the data mining technique, we predict the heart failure death event accuracy level of 89.92%. Here, the dataset was collected and used from Kaggle datasets (https://www.kaggle.com/).

Keywords: Congestive Heart Failure, Artificial Neural Network, Prediction, Heart disease.

2. Introduction:

In the era, Congestive Heart failure is more common in all over the world, according to Center for Disease Control and Prevention, America alone 6.2 million adults have a congestive heart failure have some certain medical conditions are can be increasing the risk for heart failures [1] [3]. The coronary artery disease (CAD) is the most common type of heart disease and for heart attacks, diabetes, high blood pressure, obesity and other conditions related to heart disease, and other unhealthy behaviors can also increase the heart failure, especially smoking tobacco, excessive alcohol intake, eating high in fat like cholesterol and sodium contain foods, less physical activities [1] [3]. In 2020, the congestive heart failure was mentioned on the 3,82,820 death cases certified in the center of disease control and prevention, US Department of health & human service. The heart failure cost of the nation which is estimated USD $229 billion in the year of 2017 and 2018, this total includes the cost of health care services, medicines to treat heart failure and so on [1] [3]. The heart which is can't be pumping the enough oxygen during the bloods flow for a body functioning. In this process the heart, it never has been stopping the pulsation. But it needs an enough blood to flow into the right atrium from the body, moves into the right ventricular and is pushed into the pulmonary arteries in the lungs. Our human heart basically made up of 4 different chambers they are 2 atriums and 2 ventricles. The top 2 chamber are known as right atrium and left atrium. The bottom 2 chambers are known as right and left ventricles. The major function of each chamber is helps to keep the heart pumping, it refreshes and recirculate the blood all through of human body at the normal resting rate of 60 to 100 beats per minute (bpm). The major cause of the heart failure which is strike one or both side (right- side and left side) of the heart. During the right side of the heart failure, the heart pumps enough blood to the lungs to getting an oxygen and the heart it's too weak. When the heart failure in the left sided, the heart not able to pump the blood to the body. In this case it occurs two major things was happening; first reason is human heart it's difficult to pump enough blood. Second reason is too thick or stiff so it's difficult to exhale and fill the enough blood [2]. Deep learning is the simplest method for medical signal processing to detect the congestive heart failure and feature extract the layers of input layer, hidden layer and output layer in Artificial neural network. In this project, the Data mining technique which is helps to extract the values from the database (samples) to predict the congestive heart failure in ANN [5][11].

Literature Survey

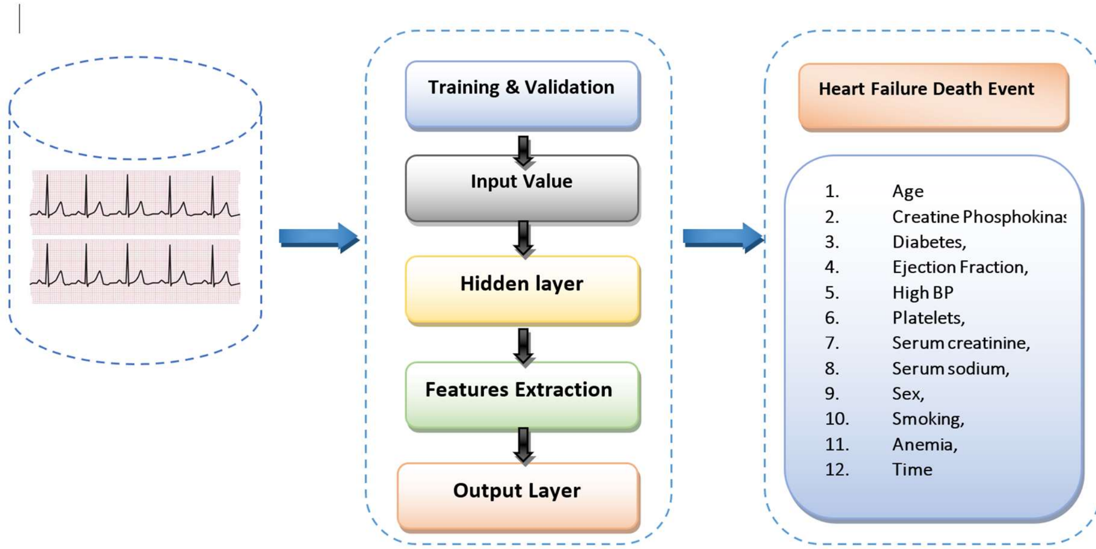
This paper mainly studied the early prediction of congestive heart failure and the cause of heart failure. This operation enables accurate heart signal and prediction using the congestive heart failure region of the heart chamber. The concept of this paper is to predict the various cause of heart failure. This experiment has conducted using the KAGGLE dataset on Google Colab which enables GPU. The bio signal of the heart chamber from human heart ECG datasets and it plotted in a 2D multigraph in the ECG signal. The approach has given an accuracy of 89.92 % and a loss of 18.50%. The aim of the process is to predict heart failure in the early stage. The proposed method of processing was drained and removed the unwanted signals of the ECG heartbeat were removed mainly to the comparison of the Artificial Neural Network (ANN) using the confusion matrix, ROC Curve, and AUC curve through this comparison to analyze the early prediction of the Congestive Heart Failure Prediction. A confusing matrix is used to define the early prediction algorithms. The one vs rest of the signals are using a regression classifier algorithm for binary classification. This project used various kinds of cases are creatine phosphokinase, diabetes, ejection fraction, high blood pressure, platelets, serum creatinine, serum sodium, sex, and smoking.

Material and Methodology

This paper used the Kaggle datasets which is collected from the various patients in the same duration. It included the ECG and EKG signals of patients who diagnosed with the previous history cognitive heart failure subjects. The ECE and EKG signals were diagnosed by the cardiologist and the cardio- thoracic surgeon. It contains of 12 various causes from the 5 different age group patients which is represented in Table 4.1. The Fig 4.1 represents the proposed methodology of this entire process and the methodology of the heart failure death event.

No of Patients	0	1	2	3	4
Causes of Death Events					
Age	75	55	65	50	65
Anemia	0	0	0	1	1
Creatinine Phosphokinase	582	7861	146	111	160
Diabetes	0	0	0	0	1
Ejection Fraction	20	38	20	20	20
High BP	1	0	0	0	0
Platelets	265000.00	263358.03	162000.00	210000.00	327000.00
Serum Creatinine	1.9	1.1	1.3	1.9	2.7
Serum Sodium	130	136	129	137	116
Sex	1	1	1	1	0
Smoking	0	0	1	0	0
Time	4	6	7	7	8
Heart Failure (Death Event)	1	1	1	1	1

Table 4.1 Data of Heart Failure patients.



ECG and EKG Signals Data Base

Dataset Classification **Classified**

ECG or EKG Signal

Fig 4.1 Proposed Methodology of (Cognitive Heart Failure) Death Events

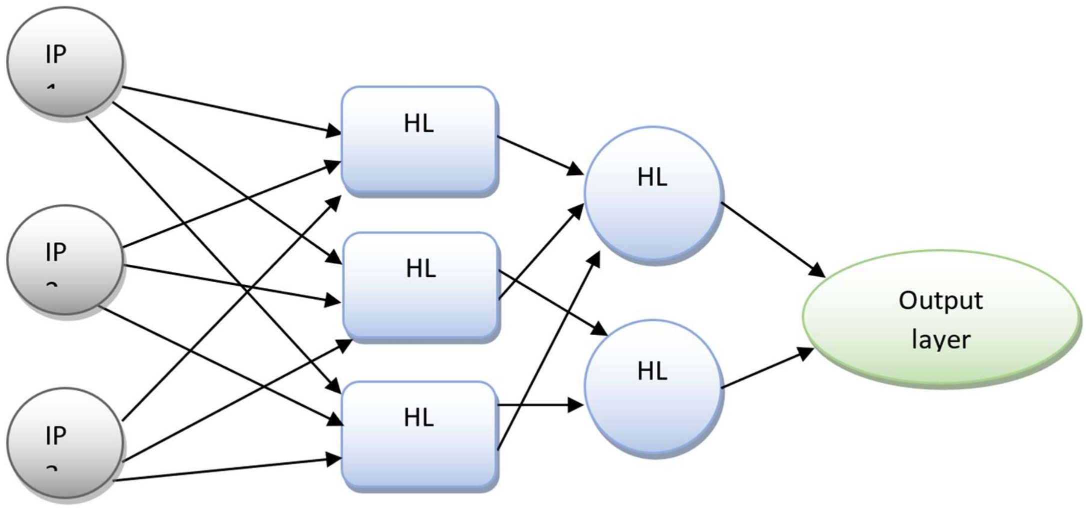


Fig 4.2 Architecture of Artificial Neural Network

The ANN network node architecture IP 1,2,3 (Input Layer), HL (Hidden Layer), OP (Output Layer) is representing in Fig 4.2. The datasets are containing 13 data columns, which is divided into 3 rows of attributes, Non-null Counts, D types. The range index of the total entries is 299 which means 0-298. The range index of the entire are shown in below Table 4.2.

Table 4.1 Range Index of the Entries

No of Entries	Attributes	Non- Null Count	D type
0	Age	299 non-null	float64
1	Anemia	299 non-null	int64
2	Creatinine Phosphokinase	299 non-null	int64
3	Diabetes	299 non-null	int64
4	Ejection Fraction	299 non-null	int64
5	High BP	299 non-null	int64
6	Platelets	299 non-null	float64
7	Serum Creatinine	299 non-null	float64
8	Serum Sodium	299 non-null	int64
9	Sex	299 non-null	int64
10	Smoking	299 non-null	int64
11	Time	299 non-null	int64

The Congestive Heart failure has been predicted and plotted between the total count and the death event due to heart failure. In the graph 0 are represented the Creatine Phosphokinase, Diabetes, Ejection Fraction, High Blood Pressure (High BP), Platelets, Serum creatinine, Serum sodium, Sex, Smoking Anemia, Time and the 1 represented the Heart Failure (Death Event). The bar graph was being plotted and shown in the below diagram.

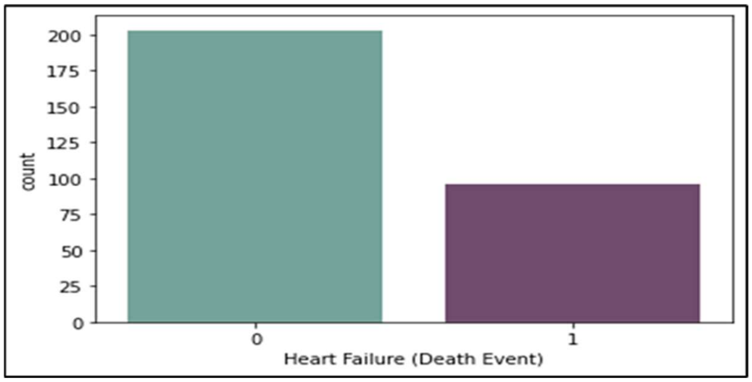


Fig 4.3 Range of Entries

5 Experiment and Result:

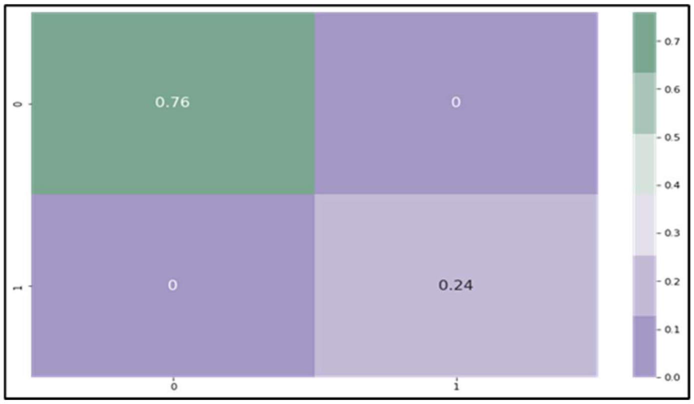
The Congestive Heart Failure of the death events which have been calculate the statistics module of mean and standard deviation. These statistics module represent the minimum to maximum possibility of heart failure- death event. The statistics module of the mean and standard deviation from value of (Min) 0%, 25%, 50%, 75%, 100% (Max). The total entries of each attribute are 299.0 (0-298). The Statistic module of the heart failure death events is shown in the below tabulation Table 5.1.

Table 5.1 Heart Failure Death events

Attributes	Count	Mean	Std	Min (0%)	25%	50%	75%	Max (100%)
Age	299.0	5.703353e-16	1.001676	-1.754448	-0.828124	-0.070223	0.771889	2.877170
Anemia	299.0	1.009969e-16	1.001676	-0.871105	-0.871105	-0.871105	1.147968	1.147968
Creatinine Phosphokinase	299.0	0.000000e+00	1.001676	-0.576918	-0.480393	-0.342574	0.000166	7.514640
Diabetes	299.0	9.060014e-17	1.001676	-0.847579	-0.847579	-0.847579	1.179830	1.179830
Ejection Fraction	299.0	-3.267546e-17	1.001676	-2.038387	-0.684180	-0.007077	0.585389	3.547716
High BP	299.0	0.000000e+00	1.001676	-0.735688	-0.735688	-0.735688	1.359272	1.359272
Platelets	299.0	7.723291e-17	1.001676	-2.440155	-0.520870	-0.013908	0.411120	6.008180
Serum Creatinine	299.0	1.425838e-16	1.001676	-0.865509	-0.478205	-0.284552	0.005926	7.752020
Serum Sodium	299.0	-8.673849e-16	1.001676	-5.363206	-0.595996	0.085034	0.766064	2.582144
Sex	299.0	-8.911489e-18	1.001676	-1.359272	-1.359272	0.735688	0.735688	0.735688
Smoking	299.0	-1.188199e-17	1.001676	-0.687682	-0.687682	-0.687682	1.454161	1.454161
Time	299.0	-1.901118e-16	1.001676	-1.629502	-0.739000	-0.196954	0.938759	1.997038

The total (val_acc) validate accuracy of the model is 88.92 % and the (val_loss) validate loss is 11.08 %. The total accuracy of the trained data is 86.67% and the loss is 18.50%. The

Confusion matrix of the data which is classifies the trained and test data of the heart failure death event attributes. Using the confusion matrix of the axes plot which helps to represent the data of various attributes in ECG signal. In the ECG signal 76% of the data are well-trained and 24% of them are tested. The Axel Plot and the accuracy table shown in below Fig 5.1 and Table 5.2.



Features	Trained	Validates
2	86.67%	88.92 %

Table 5.2

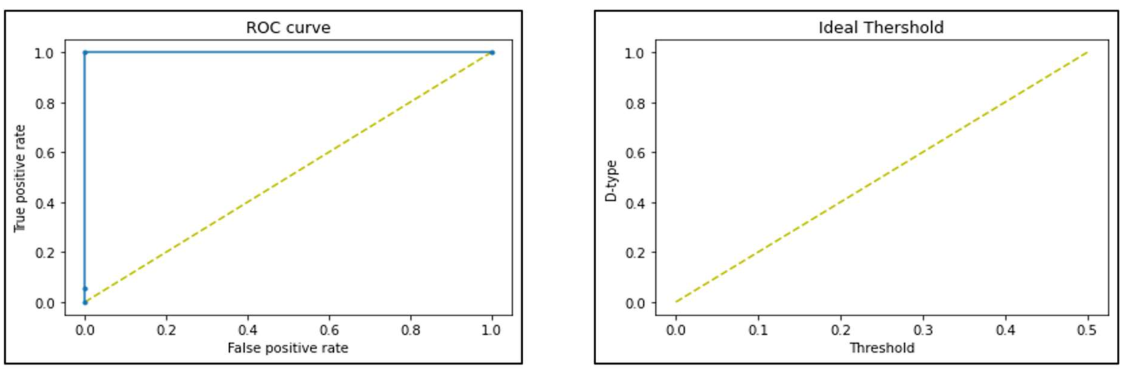
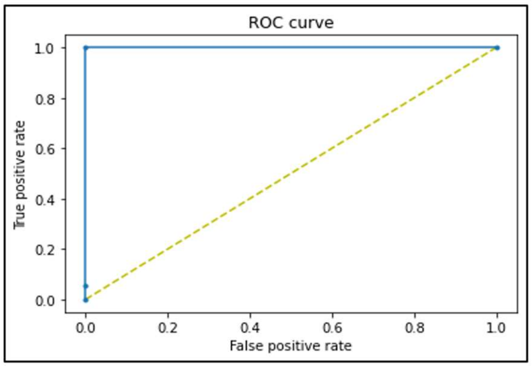


Fig 5.1 Axel Plot

The Receiver Operational Curve (ROC) which is represented the relationship between the false positive rate and the True Positive rate. The false positive rate model which is predicts incorrect positive outcome and the True Positive models rate model which is predicts the correct positive of the trained and validate data. These are the relationship between the true positive rate and the false negative rate. This summarized process is done by the help of confusion matrix and showed in the below plot diagram Fig 5.2. The ideal threshold which helps to projects the highest sum of the test selectivity and sensitivity. The graph plotted between the optimal threshold and D-type of the ROC data frames. The ideal threshold graph showed in below diagram Fig 5.3.



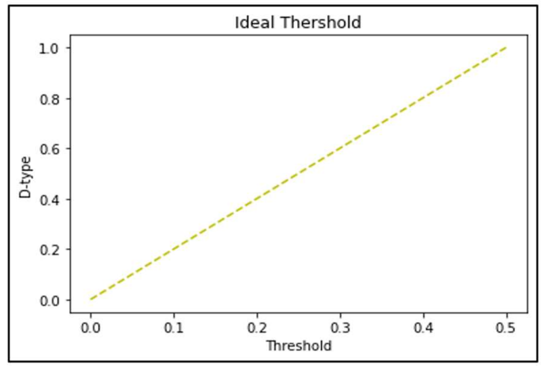


Fig 5.2 ROC curve of the Classifier. **Fig 5.3 Ideal Threshold of the Classifier**

The final graph represents the Area Under Curve (AUC), is summarize the ROC curve of the binary classifier. The AUC curve is distinguished between the true positive and False positive rate of the model performances. The AUC curve graph plotted in below diagram Fig 5.4.

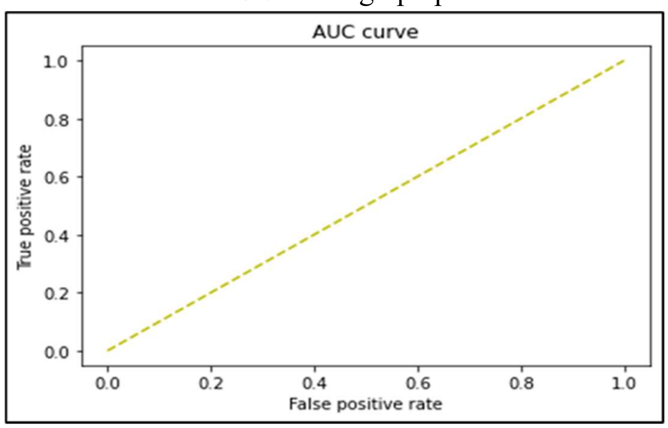


Fig 5.4 AUC of the Classifier

Conclusion:

This research project is showing the efficiency of predict the congestive heart failure for in the early stage. In this project, we are not used any patients directly so we took the existing data from the kaggle.com for our research work. In a future we planning to work in a CNN classifier to predicts the congestive heart failure for labor patients during delivery time with the real time data.

Declaration of Interests:

The authors declare that they have no known competing financial interests or personal relationship that could have appeared to influence the work reported in this paper.

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