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ANN Can Predict Survival of Patients with Heart Failure

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Abstract: *Cardiovascular diseases kill approximately 18 million people every year worldwide, and they mainly exhibit as myocardial infarctions and heart failures. Heart failure occurs when the heart cannot pump enough blood to meet the needs of the body. Artificial Neural Network (ANN) can predict patients' survival from their data and can individuate the most important features among those included in their medical records. Methods: In this paper, we analyze a dataset of 132 patients with heart failure collected from UCI machine Learning Repository. We applied ANN classifier to both predict the patient's survival, and rank the features corresponding to the most important risk factors. The results of the proposed ANN model in predicting patients' survival was 100%. This model has the potential to impact on clinical practice, becoming a new supporting tool for physicians when predicting if a heart failure patient will survive or not. Indeed, medical doctors aiming at understanding if a patient will survive after heart failure or not.*

Keywords: Cardiovascular heart diseases, Heart failure, ANN, Feature ranking

1. INTRODUCTION

Cardiovascular disease (CVD) is a class of diseases that involve the heart or blood vessels. CVD includes coronary artery diseases (CAD) such as angina and myocardial infarction (commonly known as a heart attack). Other CVDs include stroke, heart failure, hypertensive heart disease, rheumatic heart disease, cardiomyopathy, abnormal heart rhythms, congenital heart disease, valvular heart disease, carditis, aortic aneurysms, peripheral artery disease, thromboembolic disease, and venous thrombosis [3].

The underlying mechanisms vary depending on the disease. Coronary artery disease, stroke, and peripheral artery disease involve atherosclerosis. This may be caused by high blood pressure, smoking, diabetes mellitus, lack of exercise, obesity, high blood cholesterol, poor diet, and excessive alcohol consumption, among others. High blood pressure is estimated to account for approximately 13% of CVD deaths, while tobacco accounts for 9%, diabetes 6%, lack of exercise 6% and obesity 5%. Rheumatic heart disease may follow untreated strep throat [2].

It is estimated that up to 90% of CVD may be preventable. Prevention of CVD involves improving risk factors through: healthy eating, exercise, avoidance of tobacco smoke and limiting alcohol intake. Treating risk factors, such as high blood pressure, blood lipids and diabetes is also beneficial. Treating people who have strep throat with antibiotics can decrease the risk of rheumatic heart disease. The use of aspirin in people, who are otherwise healthy, is of unclear benefit.[5,6,7,8,9]

Cardiovascular diseases are the leading cause of death in all areas of the world except Africa. Together CVD resulted in 17.9 million deaths (32.1%) in 2015, up from 12.3 million (25.8%) in 1990. Deaths, at a given age, from CVD are more common and have been increasing in much of the developing world, while rates have declined in most of the developed world since the 1970s. Coronary artery disease and stroke account for 80% of CVD deaths in males and 75% of CVD deaths in females. Most cardiovascular disease affects older adults. In the United States 11% of people between 20 and 40 have CVD, while 37% between 40 and 60, 71% of people between 60 and 80, and 85% of people over 80 have CVD. The average age of death from coronary artery disease in the developed world is around 80 while it is around 68 in the developing world. Diagnosis of disease typically occurs seven to ten years earlier in men as compared to women [1]

There are many cardiovascular diseases involving the blood vessels. They are known as vascular diseases.

- Coronary artery disease (also known as coronary heart disease and ischemic heart disease)
- Peripheral arterial disease – disease of blood vessels that supply blood to the arms and legs
- Cerebrovascular disease – disease of blood vessels that supply blood to the brain (includes stroke)
- Renal artery stenosis
- Aortic aneurysm

There are also many cardiovascular diseases that involve the heart [4,5].

- Cardiomyopathy – diseases of cardiac muscle
- Hypertensive heart disease – diseases of the heart secondary to high blood pressure or hypertension

- Heart failure - a clinical syndrome caused by the inability of the heart to supply sufficient blood to the tissues to meet their metabolic requirements
- Pulmonary heart disease – a failure at the right side of the heart with respiratory system involvement
- Cardiac dysrhythmias – abnormalities of heart rhythm
- Inflammatory heart disease
    - Endocarditis – inflammation of the inner layer of the heart, the endocardium. The structures most commonly involved are the heart valves.
    - Inflammatory cardiomegaly
    - Myocarditis – inflammation of the myocardium, the muscular part of the heart, caused most often by viral infection and less often by bacterial infections, certain medications, toxins, and autoimmune disorders. It is characterized in part by infiltration of the heart by lymphocyte and monocyte types of white blood cells.
    - Eosinophilic myocarditis - inflammation of the myocardium caused by pathologically activated eosinophilic white blood cells. This disorder differs from myocarditis in its causes and treatments.
- Valvular heart disease
- Congenital heart disease – heart structure malformations existing at birth
- Rheumatic heart disease – heart muscles and valves damage due to rheumatic fever caused by Streptococcus pyogenes a group A streptococcal infection.

2. AN ARTIFICIAL NEURAL NETWORK

An Artificial Neural Network is a multilayer perceptron (MLP) is a class of feed forward[6-20]. The term MLP is used ambiguously, sometimes loosely to any feedforward [21-32] ANN, sometimes strictly to refer to networks composed of multiple layers[33-44] of perceptron (with threshold activation). Multilayer perceptron are sometimes colloquially referred to as "vanilla" neural networks, especially when they have a single hidden layer[45-57].

An MLP consists of at least three layers of nodes: an input layer, a hidden layer and an output layer. Except for the input nodes, each node is a neuron that uses a nonlinear activation function. MLP utilizes a supervised learning technique called backpropagation for training[58]. Its multiple layers and non-linear activation distinguish MLP from a linear perceptron. It can distinguish data that is not linearly separable [59].

If a multilayer perceptron has a linear activation function in all neurons, that is, a linear function that maps the weighted inputs to the output of each neuron, then linear algebra shows that any number of layers can be reduced to a two-layer input-output model. In MLPs some neurons use a *nonlinear* activation function that was developed to model the frequency of action potentials, or firing, of biological neurons[60].

The two historically common activation functions are both sigmoids, and are described by

$$y(v_i) = \tanh(v_i) \text{ and } y(v_i) = (1 + e^{-v_i})^{-1}$$

In recent developments of deep learning the rectifier linear unit (ReLU) is more frequently used as one of the possible ways to overcome the numerical problems related to the sigmoid [61].

The first is a hyperbolic tangent that ranges from -1 to 1, while the other is the logistic function, which is similar in shape but ranges from 0 to 1. Here y_i is the output of the i^{th} node (neuron) and v_i is the weighted sum of the input connections. Alternative activation functions have been proposed, including the rectifier and softplus functions. More specialized activation functions include radial basis functions (used in radial basis networks, another class of supervised neural network models)[62].

The MLP consists of three or more layers (an input and an output layer with one or more *hidden layers*) of nonlinearly-activating nodes. Since MLPs are fully connected, each node in one layer connects with a certain weight w_{ij} to every node in the following layer.

Learning occurs in the perceptron by changing connection weights after each piece of data is processed, based on the amount of error in the output compared to the expected result. This is an example of supervised learning, and is carried out through backpropagation, a generalization of the least mean squares algorithm in the linear perceptron [63].

We can represent the degree of error in an output node j in the n^{th} data point (training example) by:

$$e_j(n) = d_j(n) - y_j(n),$$

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Where d is the target value and y is the value produced by the perceptron. The node weights can then be adjusted based on corrections that minimize the error in the entire output, given by:

$$\mathcal{E}(n) = \frac{1}{2}\sum_j e_j^2(n).$$

Using gradient descent, the change in each weight is:

$$\Delta w_{ji}(n) = -\eta \frac{\partial \mathcal{E}(n)}{\partial v_j(n)} y_i(n)$$

Where y_i is the output of the previous neuron and η is the *learning rate*, which is selected to ensure that the weights quickly converge to a response, without oscillations [64].

The derivative to be calculated depends on the induced local field v_i, which itself varies. It is easy to prove that for an output node this derivative can be simplified to [65]:

$$-\frac{\partial \mathcal{E}(n)}{\partial v_j(n)} = e_j(n)\phi'(v_j(n))$$

Where ϕ' is the derivative of the activation function described above, which itself does not vary. The analysis is more difficult for the change in weights to a hidden node, but it can be shown that the relevant derivative is [66]

$$-\frac{\partial \mathcal{E}(n)}{\partial v_j(n)} = \phi'(v_j(n))\sum_k -\frac{\partial \mathcal{E}(n)}{\partial v_k(n)} w_{kj}(n).$$

This depends on the change in weights of the k^{th} nodes, which represent the output layer. So to change the hidden layer weights, the output layer weights change according to the derivative of the activation function, and so this algorithm represents a backpropagation of the activation function.

The term "multilayer perceptron" does not refer to a single perceptron that has multiple layers. Rather, it contains many perceptrons that are organized into layers. An alternative is "multilayer perceptron network". Moreover, MLP "perceptrons" are not perceptrons in the strictest possible sense. True perceptrons are formally a special case of artificial neurons that use a threshold activation function such as the Heaviside step function. MLP perceptrons can employ arbitrary activation functions. A true perceptron performs *binary* classification, an MLP neuron is free to either perform classification or regression, depending upon its activation function[67].

The term "multilayer perceptron" later was applied without respect to nature of the nodes/layers, which can be composed of arbitrarily defined artificial neurons, and not perceptrons specifically. This interpretation avoids the loosening of the definition of "perceptron" to mean an artificial neuron in general.

MLPs are useful in research for their ability to solve problems stochastically, which often allows approximate solutions for extremely complex problems like fitness approximation.

MLPs are universal function approximators as shown by Cybenko's theorem, so they can be used to create mathematical models by regression analysis. As classification is a particular case of regression when the response variable is categorical, MLPs make good classifier algorithms[68].

MLPs were a popular machine learning solution in the 1980s, finding applications in diverse fields such as speech recognition, image recognition, and machine translation software, but thereafter faced strong competition from much simpler (and related) support vector machines. Interest in backpropagation networks returned due to the successes of deep learning[69].

3. METHODOLOGY

We have collected the dataset from UCI Machine Learning repository that was developed by University of California, School of Information and Computer Science [70]. This dataset was prepared by Dr. Evlin Kinney, The Reed Institute, Maimi, FL, USA [70].

International Journal of Engineering and Information Systems (IJEAIS)
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3.1 Input and output Features

The Echocardiogram dataset consists of 132 samples and 13 features. The features: mult, name, and group were skipped. The remaining features either numeric or nominal (categories). All nominal Features were replaced with numeric values starting with 0 to maximal count of different values in the feature. The second step is normalizing all numeric values to be between 0 and 1 (as shown in Table 1). Table 2 shows the output attribute and its distribution.

Table1: Attribute description

S.N.	Attribute	Secription	Type	Category
1	survival	the number of months patient survived (has survived, if patient is still alive). Because all the patients had their heart attacks at different times, it is possible that some patients have survived less than one year but they are still alive.	Numeric	Input
2	still-alive	a binary variable. 0=dead at end of survival period, 1 means still alive	Boolean	Input
3	age-at-heart-attack	age in years when heart attack occurred	Numeric	Input
4	pericardial-effusion	Pericardial effusion is fluid around the heart. 0=no fluid, 1=fluid	Binary	Input
5	fractional-shortening	a measure of contractility around the heart lower numbers are increasingly abnormal	Numeric	Input
6	epss	E-point septal separation, another measure of contractility. Larger numbers are increasingly abnormal.	Numeric	Input
7	lvdd	left ventricular end-diastolic dimension. This is a measure of the size of the heart at end-diastole. Large hearts tend to be sick hearts.	Numeric	Input
8	wall-motion-score	a measure of how the segments of the left ventricle are moving	Numeric	Input
9	wall-motion-index	equals wall-motion-score divided by number of segments seen. Usually 12-13 segments are seen in an echocardiogram. Use this variable instead of the wall motion score.	Numeric	Input
10	mult	a derivate variable which can be ignored	Ignored	Input
11	name	the name of the patient (replaced them with "name")	Ignored	Input
12	group	meaningless, ignore it	Ignored	Input
13	alive-at-1	Boolean-valued. Derived from the first two attributes. 0 means patient was either dead after 1 year or had been followed for less than 1 year. 1 means patient was alive at 1 year.	Boolean	Output

Table 2: Class alive-at-1feature distribution

Class code	Class	Number of instances
1	Not Alive	50
2	Alive	24
3	?	58

3.2 Dataset preprocessing

There are some missing values in the 13 attributes of the Echocardiogram dataset. The missing values in all input attributes (the first 12 attributes) were replaced with average value of that attribute. But for the output attribute (alive-at-1feature), it was handled with a different way. There were 58 missing values in the output attribute as shown in Table 3. The missing values of the output attribute were replaced according to first and second attribute. If the second attribute value was zero, the corresponding missing value in the output value was replaced with a zero otherwise it was replaced with a one.

Table 3: Missing Attribute Values

Attribute #	Number of Missing Values:
1	2
2	1
3	5
4	1
5	8
6	15
7	11
8	4
9	1
10	4
11	0
12	22
13	58

We used the following equation to normalize the features in the Echocardiogram dataset:

$$X_i = (X_i - X_{min}) / (X_{man} - X_{min}) \qquad \text{eq.(1)}$$

For the nominal features we have done two things:

- Replaced the different values of that features with numeric values starting with 0
- We normalized the features using the above equation where the possible values between 0 and 1.

For all other features we normalized their values to be in the range of 0 to 1 using the normalized equation stated above.

3.3 Building the ANN Model

We used Just Neural Network (JNN) tool [71] to build a multilayer ANN model. The proposed model consists of four Layers: Input Layer with 9 nodes, First Hidden Layer with 3 nodes, Second Layer with 1 node, and Output Layer with one node as can be seen in Figure 3.

We have sat the parameters of the proposed model as follows: Learning Rate 0.6 and the Momentum to be 0.8, and Average Error rate to be 0.01 (as shown in Figure 2).

3.4 Evaluating the ANN model

The Echocardiogram dataset consists of 132 samples with 13 attributes as in Table 1 and Table 2. We imported the preprocessed CSV file of the Echocardiogram dataset into the JNN environment (as seen in Figure 1). We divided the imported dataset into two sets (Training and Validation) randomly using the JNN tool. The Training consists of approximately 67% (88 samples) and the validation set consists of 33% of the dataset (44 samples). After making sure that the parameter control was sat properly, we started training the ANN model and kept eye on the learning curve, error loss and validation accuracy. We trained the ANN model for 101 cycles. The best accuracy we got was 100% (as seen in Figure 4). We determined the most influential factors in the Echocardiogram dataset as in Figure 5. Figure 6 shows the summary of the proposed model.

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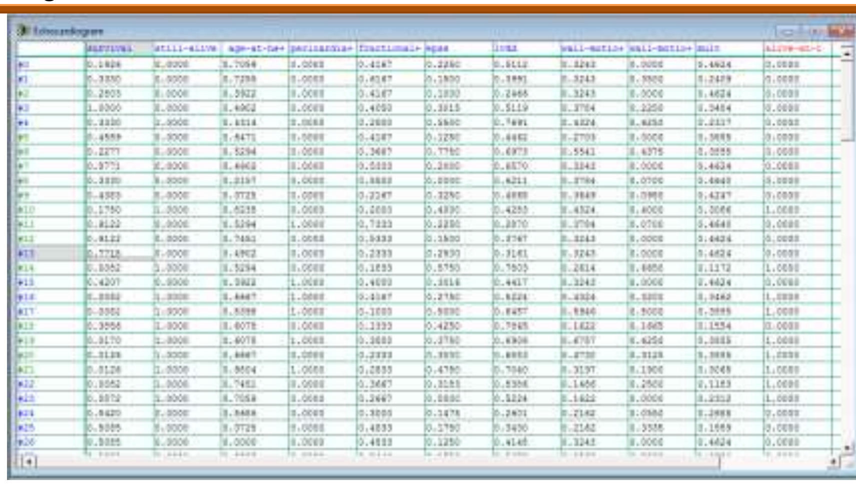

Figure 1: Imported dataset into JNN environment

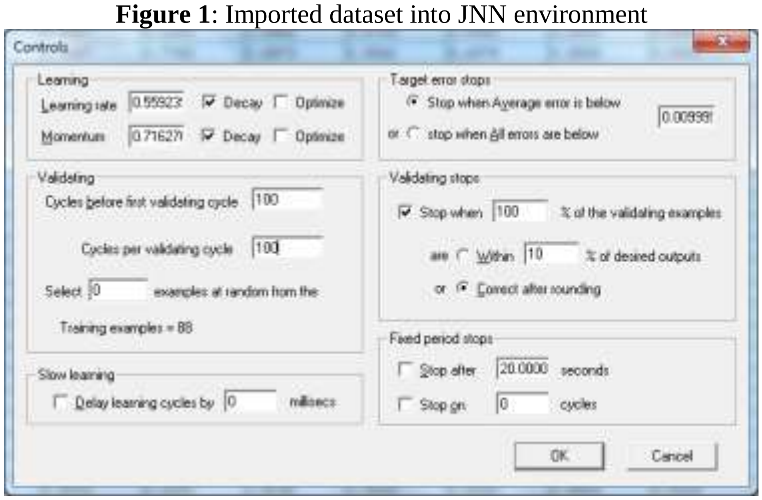

Figure 2: Control of the parameters of the proposed ANN model

International Journal of Engineering and Information Systems (IJEAIS)
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Vol. 5 Issue 4, April - 2021, Pages: 47-56

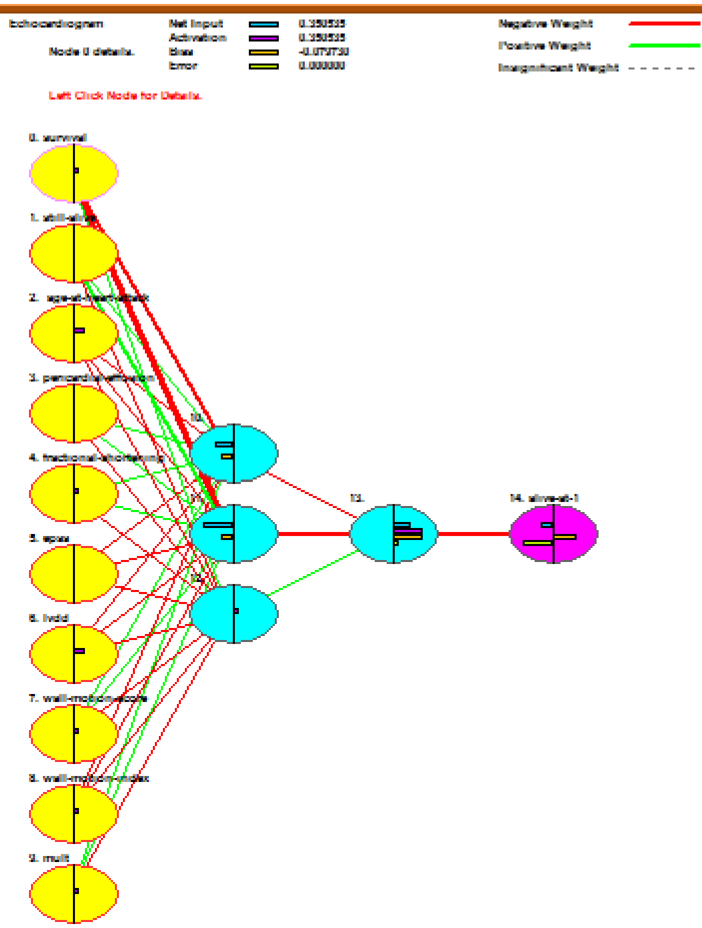

Figure 3: architecture of the final ANN model

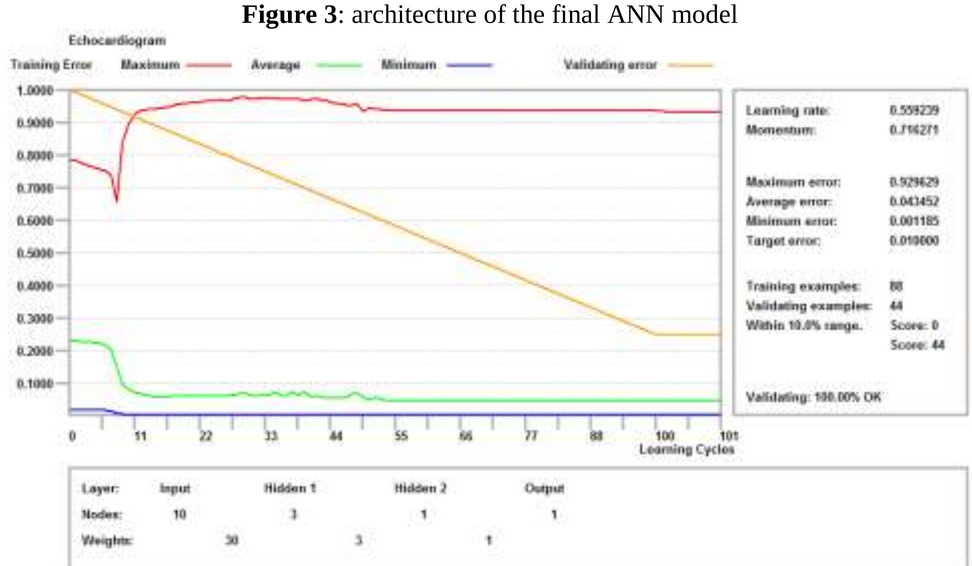

Figure 4: Training and validation curves of the proposed ANN model

Figure 5: The most influential Feature in the proposed ANN model

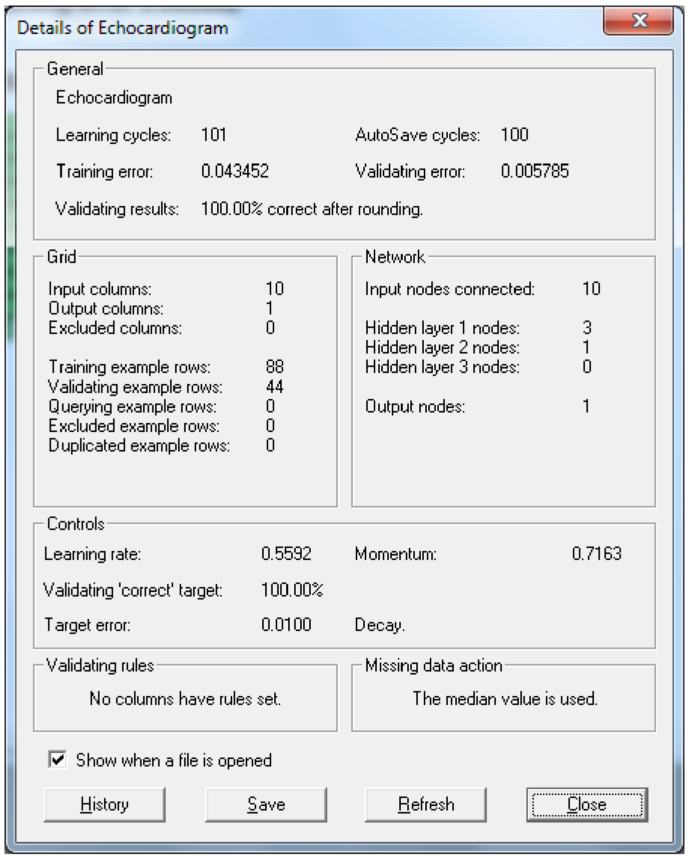

Figure 6: Details of the proposed ANN model

4. CONCLUSION

An Artificial Neural Network model for predicting two Echocardiogram dataset: Alive or Not Alive, using features obtained from UCI Machine Learning Repository was presented. The model used was feed forward backpropagation algorithm for training the proposed ANN model using JNN tool. The factors for the model were obtained from dataset which represents Echocardiogram features. The model was tested and the accuracy rate was 100%. This model has the potential to impact on clinical practice, becoming a new supporting tool for physicians when predicting if a heart failure patient will survive or not. Indeed, medical doctors aiming at understanding if a patient will survive after heart failure or not.

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