Risk Estimator using a Multi-Layer Perceptron Network for Coronary Artery Disease Prevention

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Abstract

One of the most prevalent heart disease is coronary artery disease (CAD).
We propose the use of Deep Learning (DL) Network Multi-Layer Perceptron (MLP) in order to obtain an early cardiovascular risk estimation at 10 year for CAD prevention in patients with the purpose of reduced rate of mistreatment.For this purpose, we designed a protocol for selecting eloquent data. We also designed a method which is using Deep Neural Network sequential model which has multiple inputs and three outputs. Data set are from a private clinic in South- West zone in Romania. Custom data set included a batch of 784 patients with 11 medical characteristics. The result of predicting the MLP network gives us the probability that the patient will develop a severe heart disease in the following 10 years.
By deploying a DL network, we were able to provide an unitary risk assessment method of CAD for physicians that allowed the "localization" of the medical European Society of Cardiology guidelines to Romania region.

Keywords
Coronary artery disease, deep neural network, multilayer perceptron network, cardiovascular risk estimator

1. Introduction

The importance of of early diagnosis and risk stratification of ischemic heart diseases is given by the fact that cardiovascular diseases is the leading cause of death in Europe. [eurostat - causes of death statistics 2019], and in the same time in the world [World Health Organization]. Among them, the most prevalent manifestation is ischemic heart disease given by coronary atherosclerosis pathology, which is associated with an increased mortality and morbidity rate.

Coronary artery disease is caused by cholesterol deposits that stick and narrow the walls of coronary arteries that supply blood to the heart.

Clinical presentation of ischemic heart disease includes silent ischemia, stable coronary artery disease, unstable angina, myocardial infarction, heart failure, and sudden cardiac death[1]. In Europe, the recommendations for treating cardiac diseases a[1]re described in the Guidelines of the European Society of Cardiology [www.escardio.org].

Those are covering a minimum of investigations that should be done to patients with coronary heart disease such as laboratory examinations (bio-markers, lipid profile, NTProBNP, D-Dimers), 12-lead electrocardiogram, the ECG and imaging effort test, echocardiography, coronarography and describes the cardiac risk scores that should be performed, but it leaves to the physician's discretion how these protocols will be implemented.

The diagnosis and cardiovascular risk assessment of stable coronary artery disease (SCAD) involves clinical evaluation, including identifying significant dyslipidemia, hyperglycaemia or other biochemical risk

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factors and specific cardiac investigations such as stress testing or coronary imaging. These investigations may be used to confirm the diagnosis of ischemia in patients with suspected SCAD, to identify or exclude associated conditions or precipitating factors, assist in stratifying risk associated with the disease and to evaluate the efficacy of treatment

Conventional risk factors for the development of SCAD are hypertension, hypercholesterolemia, diabetes,sedentary lifestyle, obesity,smoking and a family history.

Taking into consideration the fact that cardiac diseases have remained the leading causes of death globally in the last 15 years [2], there is need for a better strategy in improving the diagnostic and treatment.

Artificial Intelligence can help in order to have an early diagnosis and more accurate and also can reduce the rate of misdiagnosis. That leads to a decrease in mortality rate. In order to achieve this, is necessary to customized healthcare for each individual patient.

The cardiac risk scores used in traditional medicine are calculated on a generalized population at a very large level, and doesn't allow localized medicine with particularities from each zone. Neural networks can do customized healthcare, because they learn and so the cardiac risk scores is improved.

AI refers to those programs that computers may execute similar to human intelligence , learning and solving problems. The neural network are simulating the way that human brain is interacting in the learning process. Deep learning (DNN) is formulated as a mathematical neural network architecture consisting of multiple hidden layers with non-linear activation.[3] One architecture of DNN is Multilayer perceptron (MLP), in which every element of a previous layer, is connected to every element of the next layer and has an activation function at each hidden layer.[4]

In literature, there are different methods in medical research for SCAD classification using different learning and data mining techniques , like neural network (NN), support vector machine, random forest, decision tree, clustering, and Gaussian mixture model and others.

The purpose of this model was to obtain an early diagnosis of CAD with a good accuracy , that can be used in clinical practice for diagnosis of SCAD, using deep learning methods for combining results of clinical examination and other attributes recorded from the patients.

2. Methods

The main purpose was to help physicians in their practice by automatic predicting the cardiovascular risk for a particular patient, in other words to determine which patient will have in the near future (next 10 years) a major cardiovascular event such as sudden death, therefore the physicians will have to prescribe a more aggressive medical treatment.

We used private data from a private clinic in South- West zone in Romania. Data used were obtained between October 2017- September 2019. The patients enrolled received cardiology consult with electrocardiogram, different blood tests. The examination was Data were anonymized and patient consent was obtained.

Patient consultations, cardiac ultrasounds and exercise tests were performed by a cardiologist. Patients had previous blood tests .

We proposed a MLP network with 4 layers Deep Neural Network sequential model which has multiple inputs and three outputs because our model needs to predict cardiac overall risk for the patient.

We decided to use the most accessible deep network architecture that could fulfill our requirements.

Each hidden network layer used an rectifier function (ReLu) and we used the SoftMax function in our output layer, because we want a three output result (low, intermediate and high) therefore the number of categories in the output layer is more than two.

For the purpose of implementing and testing the MLP network we used a custom data set that included a batch of 784 patients.

The patient dataset was made of 8 medical characteristics:RegistryNumber, PatientName, PatientAge, Gender, Total Cholesterol,LDL Cholesterol, Glicemia, BMI, ABI,Mean Blood Pressure.After analyzing the medical data,we determined each medical input attribute and noticed that:

-some attributes like PatientAge, Glicemia, BMI and LDL attributes are integers; others are cathegorical attributes like Gender, RelativeRisk, Sex, etc.

-In the test population test we have more male , over 60 years old. According to eurostat 2016 standardised death rate were higher for man than for women for nearly all the main causes of death , including cardiac disease.

-Some attributes with zero value are non-existent values for that patient.

-The patient data set is small (for learning purposes) and contains 784 rows with 11 columns.The output/endpoint of the dataset consisted of 3 distinct

We also implemented a Graphical User Interface in order to enter the data.

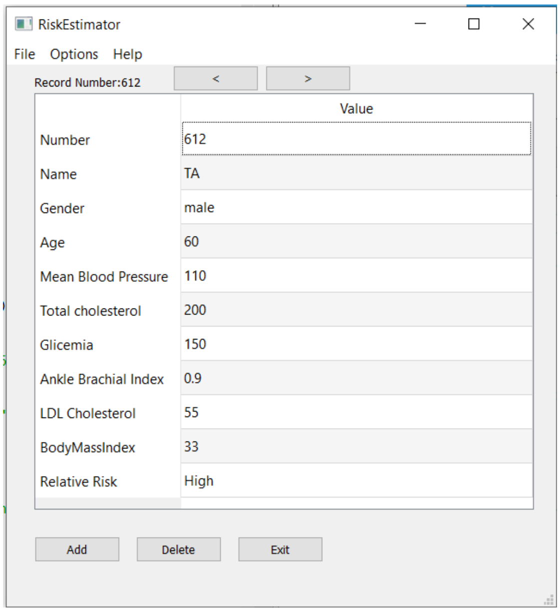


Figure 1: Screenshot of the Risk Estimator application Graphical User Interface

In order to load the data in the neural network we have implemented a XML file format specially created for our project.

The XML format contains metadata along with the structured data as follows:

```
<patient number=1>                                    (1)
<item>
Age
</item>
<value type=numeric>
50
</value>
<item>
Name
</item>
<value type=string>
ML
</value>
<item>
Gender
</item>
<value type=categorical>
male</value>
...
<item>
FinalRisk
</item>
<value type=string>
High risk
</value>
</patient>
```

For the implementation of the neural network that predicts risk and makes medical recommendations (intensive medical treatment and invasive cardiac procedures), we used Spyder content in the Anaconda library, which can be downloaded free from the Internet. It requires also to install the Tensorflow, Theano and Keras libraries in Spyder. Keras is the main library that implements Multilayer perceptron network models and it is built on Tensorflow and Theano, so that these two libraries work in back-end whenever we execute a program in Keras[5].

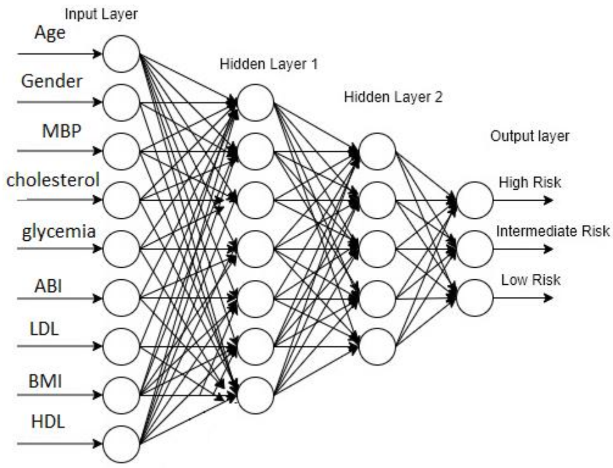


Figure 2:Proposed Deep Learning Network architecture

Keras is a high-level neural network API capable of running on Tensorflow, Theano and CNTK. It allows for fast experimentation through a high-user-friendly, modular and extensible API, as well as running on the processor and GPU[6].

The MLP network uses the efficient Adam gradient descent optimization algorithm with a logarithmic loss function, called "categorical_crossentropy"[7] .

The Adam optimizer used a LearningRateSchedule based on an exponential decay schedule with initial learning rate of

0.01, decay steps of 10000 and decay rate 0.9 and epsilon value of 0.01.[8]
In Machine Learning, we always divide medical data into a training part and a testing part[9]. So , we train the model on the training data and on the test data we check the accuracy of the model. The efficiency of the model is evaluated when we test the model on the test data using F1-score per each class, overall accuracy, macro-average accuracy, weighted-macro-average accuracy[10][11].

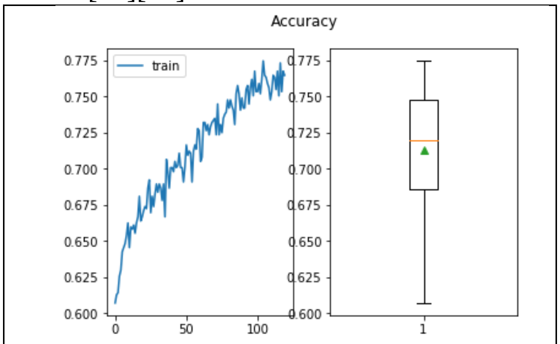
3. Results

Our study collected the data from 784 cases.
By training our Deep Learning Network we achieved two things:
-we calculated the accuracy of the final risk estimation
-we computed for a new patient the risk score based on previous patient historical data by deploying the trained network.
We trained our model using a batch size of 10 and 120 epochs.
Because we are modelling a multi-class classification problem using a MLP neural network, we decided to reshape the output attribute of a vector that contains value (high risk, intermediate risk and low risk) to a matrix with a boolean for each value by using hot coding or creating dummy variables from a categorical variable.
For example, in this problem the three class values are low risk, medium risk and high risk. We can turn this into a hot-coded binary matrix for each data instance that would look like this:

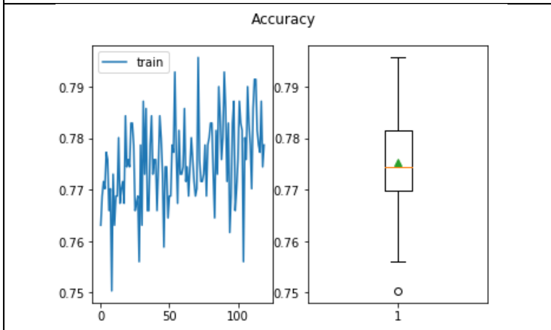
Table 1
Cardiovascular risk coding

Low risk	Intermediate risk	High risk
0	0	1
0	1	0

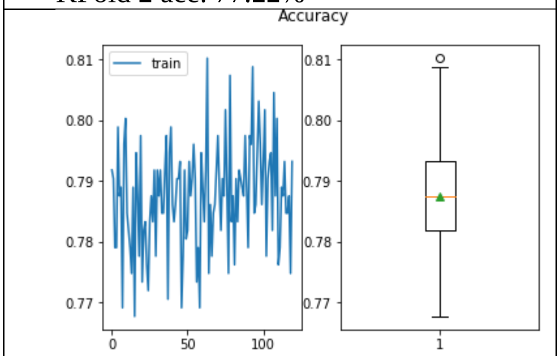
Because we used one-hot encoding for our cardiovascular data set, the output layer creates 3 output values, one for each class. The output value with the highest value will be taken as the class provided by the model.
We used a Softmax activation function in the output layer. This ensures that the output values are in the range 0 and 1 and can be used as predicted probabilities.
The result of predicting the MLP network will give us the probability that the patient will develop a severe heart disease. We will convert that probability into binary 0 and 1.
In following step we evaluated the performance of our MLP network model. We already have final results and thus we can classification reports to verify the accuracy of the model.
To test our model we used 10 fold stratified cross validation because we had a small dataset and we wanted to be sure that the results do not depend on the initialization of weights or on the order of presentation of training data vectors[12][13].



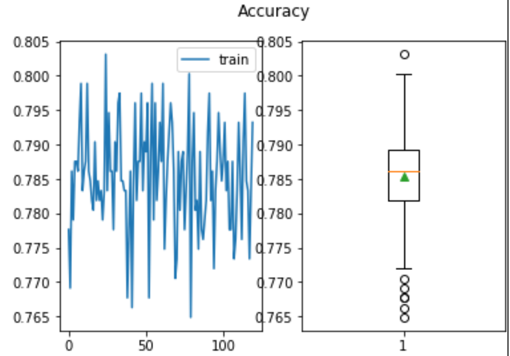
KFold 1 acc: 63.29%



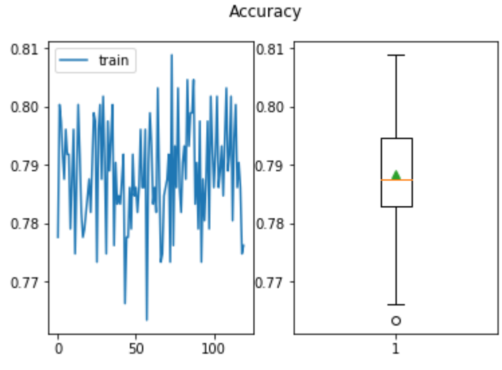
KFold 2 acc: 77.22%



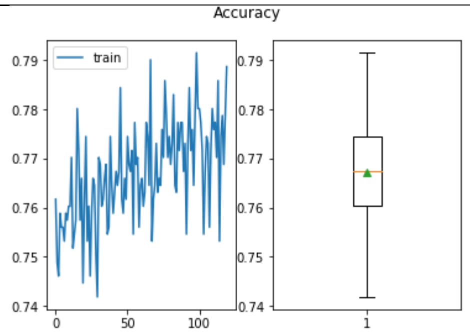
KFold 3 acc: 75.64%



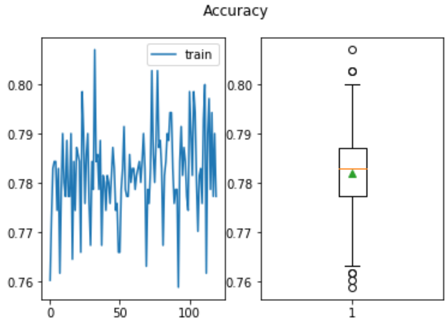
KFold 4 acc: 79.49%



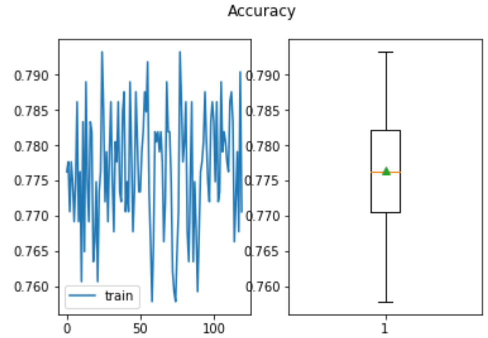
KFold 5 acc: 74.36%



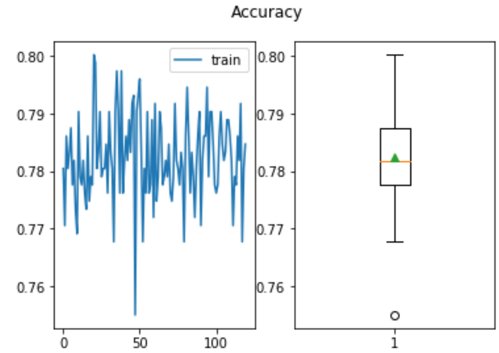
KFold 6 acc: 72.15%



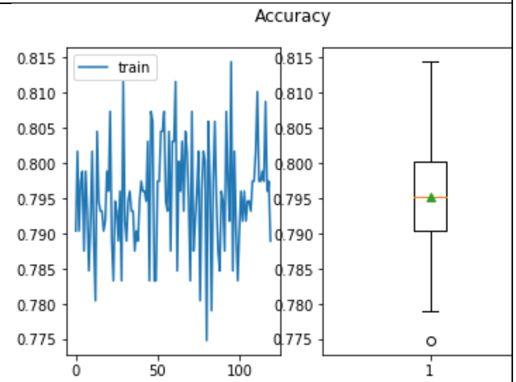
KFold 7 acc: 78.48%



KFold 8 acc: 80.77%



KFold 9 acc: 79.49%



KFold 10 acc: 73.08%

Figure 3:Ten intermediary results during k-fold validation from 10 runs

We have computed the average accuracy (ACA) as the percentage of correctly classified cases during the testing phase[14]. Besides the ACA, the standard deviation (SD) of the ACA and the 95% confidence interval were computed also[15].

Table 2

MLP performance indicators

Variable	ACA (%)	SD	95% CI
MLPNetwork	75.396	5.150	(71.711, 79.080)

We can see from Table 2 that on average the MLPNetwork performs with 75% average accuracy. Regarding the stability of the model, the SD is 5.150.

We also built a classification report showing the general classification metrics after complete MLP training.

Table 3

Overall Classification Report

Class	Precision	Recall	F1-score	support
0	0.81	0.96	0.88	479
1	0.72	0.46	0.56	213
2	0.84	0.76	0.80	92
Macro avg	0.79	0.73	0.75	784
Weighted avg	0.79	0.80	0.78	784
Accuracy			0.80	784

The reported averages in our testing included precision[16], recall, F1-score per risk class (low ,intermediate and high), macro average (averaging the unweighted mean per risk class, weighted average (averaging the support-weighted mean per risk class), and overall accuracy. Support parameter described number of patients included in each risk class.

This way we determine of the performance of our supervised learning algorithm.For computing these parameters we used all the instances in a predicted class, compared with the instances of the”true”class.T hese instances contained "actual" and "predicted" values.

We obtain an accuracy for our cardiac DL network model of 80%, which physicians consider is an acceptable accuracy.

Finally our model could be used to predict the cardiac risk for a new patient using classifier “predict_classes “ method.

4. Conclusion

Sometimes, the diagnosis of coronary heart disease can escape doctors. With the help of AI, even less experienced or tired doctors will have a high degree of accurate diagnosis. AI can help doctors improve the effectiveness of their treatment. AI is not perfect, but it has promising results. One of the outcome is that AI algorithms need a lot of data and time to be trained. Studies have suggested that the combination of clinicians and AI skills will provide patients with higher quality diagnostic results than experience alone.[17].Sooner or later, the development of deep learning applications will affect every aspect of health care.[18].

We consider that artificial intelligence can customizes healthcare for each patient because neural networks can learn and so the cardiac risk scores is improved.

Therefore using this innovative DL network, we were able to provide an unitary diagnosis method for physicians that allowed the “localization” of the medical ESC guidelines to Romania region. This way we created an method to transmit medical knowledge in a consistent way, therefore physicians will benefit from both ESC guidelines and “local” experience because a DL network has the ability to “learn” from previous medical patients data in diagnosis of coronary heart diseases.

We further plan to train our application and deep neural network with more clinical data, including ultrasound and cardiac 3D angiography data[20]. Also we plan to use more complex deep neural networks with multiple layers to test if we can further improve the overall accuracy of our risk estimator.

5. References

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