All Sciences Proceedings

5th International Conference on Applied Engineering and Natural Sciences

July 10-12, 2023 : Konya, Turkey

All Sciences Proceedings
http://as-proceeding.com/

https://www.icaens.com/

Effect of Parameter Selection on Heart Attack Risk Prediction in an RNN Model

Pınar Cihan [1*]

[1]Computer Engineering Department, Tekirdağ Namık Kemal University, Turkey

[*]pkaya@nku.edu.tr

Abstract – Heart attack has become a significant public health issue worldwide, and effective prediction methods, along with early diagnosis, are crucial for the prevention and treatment of this disease. Various machine learning and deep learning techniques have been employed in the literature to predict the risk of heart attack. In this study, the evaluation of heart attack risk was conducted using the Recurrent Neural Network (RNN) classification method with different parameters. By considering various parameters that affect the performance of the RNN model, the impact of proper parameter selection on classification accuracy was investigated. During the data preprocessing stage, the data was appropriately standardized, and 5-fold cross-validation was performed. Eleven RNN models were compared by altering different parameters such as the number of units, the number of training cycles, batch size, dropout rate, activation function, and number of units in the dense layer. The classification performance was evaluated using metrics such as accuracy, precision, recall, and F1 score. The results demonstrate that parameter selection influences the performance of the RNN classification model and that performance improvements can be achieved with appropriate parameter selections.

Keywords – RNN, classification, deep learning, heart attack, parameter selection

I. INTRODUCTION

Heart disease is one of the deadliest diseases worldwide and poses a serious threat to human health [1]. It can develop as a result of various risk factors such as high blood pressure, high cholesterol, obesity, smoking, and a sedentary lifestyle. Therefore, accurately assessing and classifying the risk of heart disease is of great importance [2].

The accurate assessment and classification of the risk of heart disease emphasize the significance of deep learning classification methods that go beyond traditional statistical approaches. Deep learning is an artificial intelligence approach that can detect complex relationships in large datasets and create high-performance models for predicting the risk of heart disease [3].

Deep learning classification methods can automatically learn complex data structures and important features contributing to heart disease. These methods can represent deep features within the data through neural networks and learn how to utilize these features to predict the risk of heart disease [4].

Deep learning classification methods can be employed to detect hidden relationships in large and complex datasets and accurately classify the risk of heart disease. These methods are based on neural networks and deep learning algorithms, enabling them to automatically learn deep features within the data [5]. This can assist doctors and healthcare professionals in better managing patients and formulating appropriate treatment plans.

In this study, the classification of heart disease risk is performed using the recurrent neural network (RNN) method, which is one of the deep learning classification methods. The classification performance of 11 RNN methods with different

parameters is compared. Accuracy, precision, recall, and F1 score metrics are utilized for evaluation.

II. Materials and Method

The Heart Attack Analysis & Prediction Dataset used in this study was obtained from the Kaggle website [6]. The dataset consists of 303 samples and includes 14 variables. The variables are as follows: age, sex, chest pain type (cp), resting blood pressure (trtbps), cholesterol level in mg/dl fetched via BMI sensor (chol), fasting blood sugar (fbs), resting electrocardiographic results (restecg), maximum heart rate achieved (thalach), exercise-induced angina (exang), ST depression induced by exercise relative to rest (oldpeak), the slope of the peak exercise ST segment (slope), the number of major vessels (ca), thalassemia (thalassemia), and the output (0 = less chance of heart attack, 1 = more chance of heart attack).

An example image of the dataset is presented in Fig. 1. The dataset contains important details such as the demographic information of patients, medical histories, symptoms, and test results. These pieces of information can contribute to understanding the risk factors for heart attack, the onset of symptoms, and changes in patients' conditions.

age	sex	cp	trtbps	chol	fbs	restecg	thalachh	exng	oldpeak	slp	caa	thall	output
63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
56	1	1	120	236	0	1	178	0	0.8	2	0	2	1
57	0	0	120	354	0	1	163	1	0.6	2	0	2	1
57	1	0	140	192	0	1	148	0	0.4	1	0	1	1
56	0	1	140	294	0	0	153	0	1.3	1	0	2	1
44	1	1	120	263	0	1	173	0	0	2	0	3	1
52	1	2	172	199	1	1	162	0	0.5	2	0	3	1
57	1	2	150	168	0	1	174	0	1.6	2	0	2	1

Fig. 1. An example section from the dataset

A. Method

In this study, Heart Attack prediction was performed using the Recurrent Neural Network (RNN) method. The RNN model was developed using the Python programming language. To evaluate the performance of the model, the 5-fold cross-validation (5-CV) method was employed. This method divides the dataset into 5 equal parts randomly, using each part sequentially as the test data while using the remaining 4 parts as the training data. The model is trained based on the training data and evaluated on the test data. This process is repeated 5 times, with a different part used as the test data each time. Performance metrics such as accuracy, precision, recall, and F1 score were calculated for each test set. These metrics were used to assess the overall performance of the model. Finally, the average of these metrics was computed since the tests were repeated 5 times and yielded different results each time.

In the study, classification results were examined for different parameters of the RNN method. Thus, the impact of parameter changes on the classification performance was observed. Based on the obtained results, the most suitable RNN method for Heart Attack prediction was determined.

Recurrent Neural Network (RNN) is an artificial neural network model used in the field of deep learning. Unlike traditional artificial neural network models, this model incorporates feedback connections, which allows RNN to have a structure capable of transferring information computed in previous steps to the current step [7].

The fundamental component of RNN is an artificial neural cell called a "cell." Each cell receives input data and the state information computed in the previous step and produces an output. The memory of the cell is a state vector that contains information from previous steps. This state vector influences the computed output in the current step and is updated for use in the next step.

RNN has a cyclic structure to model dependencies over time. This enables it to remember information from past steps and predict the outputs of future steps based on this information. This characteristic makes RNNs effective in tasks such as language processing, text generation, translation, sentiment analysis, and more.

The training of RNN is typically performed using an algorithm called backpropagation through time (BPTT). This algorithm calculates the gradient by

propagating dependencies among cells backward and updates the weights of the network.

In this study, the classification performance was compared by varying the parameters of RNN Units, Epoch, Batch Size, Dropout, Activation Function, and Dense Units. Brief descriptions of these parameters are provided below [8]:

RNN Units: It is a parameter that specifies the number of RNN units. It refers to the number of cells or neurons included in the RNN. These units contain information from previous time steps and process it along with the current input.

Epoch: Epoch represents the number of iterations in which the entire dataset is presented to the network during the training process. An epoch uses the entire dataset to update the weights of the network.

Batch Size: Batch size is a parameter that determines the number of samples processed in each step during training. A larger batch size utilizes more memory but can accelerate the training process. A smaller batch size uses less memory but can increase the training time.

Dropout: Dropout is a regularization technique used to prevent overfitting in the network. During training, dropout randomly disables connections, forcing the network to become more generalized. The dropout rate specifies the percentage of connections to be disabled at each step.

Activation Function: Activation function is a function used to compute the output of each neuron in a neural network. Activation functions introduce non-linearity to the neural network, allowing it to learn more complex relationships. Popular activation functions include sigmoid or tanh.

Dense Units: A dense layer, also known as a fully connected layer, is a type of layer used in a neural network. Dense units represent the number of neurons that connect the output of each neuron in the previous layer to the next layer. These units determine the capacity of the neural network and help in learning more complex models.

B. *Performance metrics*

In this study, accuracy, precision, recall, and F1 score metrics were used to evaluate the classification performance of the RNN methods. The formulas for these metrics are provided below [9, 10]:

$$Accuracy = \frac{T_p + T_n}{T_p + T_n + F_p + F_n}$$

$$Precision = \frac{T_p}{T_p + F_p}$$

$$Recall = \frac{T_p}{T_n + F_p}$$

$$F_1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Where (Tp) is True positive; (Tn), True negative; (Fp), False positive; and (Fn), False negative.

III. RESULTS

The RNN method was used for heart attack prediction in the study. Different parameters of the RNN method were experimented with to determine the most successful model. 5-fold cross-validation was used to assess the models' performance. After obtaining the results for each fold, their averages were calculated. Table 1 presents the classification performance of the RNN model with different parameters, including the average accuracy, average precision, average recall, and average F1 score values.

Table 1. RNN model's parameters and classification performance

Run	RNN Units	Epoch	Batch size	Dropout	ActFunc	Dense Units	Accuracy	Precision	Recall	F1 Score
1	64	100	32	0.2	sigmoid	32	0.762	0.786	0.786	0.781
2	64	100	32	0.2	tanh	32	0.765	0.729	0.917	0.810
3	64	100	32	0.3	tanh	32	0.792	0.791	0.858	0.819
4	32	50	32	0.3	tanh	32	0.788	0.781	0.845	0.810
5	32	50	32	0.3	sigmoid	32	0.798	0.810	0.836	0.820
6	64	50	32	0.2	sigmoid	32	0.801	0.797	0.860	0.825
7	64	150	64	0.2	sigmoid	32	0.759	0.794	0.755	0.774
8	64	150	64	0.2	tanh	32	0.801	0.792	0.861	0.823
9	32	200	32	0.2	sigmoid	32	0.752	0.787	0.758	0.766
10	32	100	32	0.2	tanh	32	0.801	0.784	0.892	0.830
11	**32**	**100**	**32**	**0.3**	**tanh**	**32**	**0.811**	**0.799**	**0.893**	**0.838**

When examining the RNN classification results in Table 1, it can be observed that when RNN units=32, epoch=100, batch size=32, dropout=0.3, activation function=tanh, and dense units=32 are selected, an accuracy of approximately 81% is achieved.

The precision value of our model is 0.799. Precision represents the ratio of true positives (correctly classified positives) to the total positive predictions. In other words, approximately 79.9% of the examples predicted as positive by our model are truly positive. This indicates that our model has good capability in making correct positive predictions.

Recall represents the ratio of true positives to the actual positives (positives in the true class). In this case, our model has correctly detected approximately 89.3% of the true positives. This indicates a low probability of our model missing true positives.

The F1 score represents the harmonic mean of precision and recall metrics. This metric indicates whether both precision and recall are balanced and performing well. With an F1 score of 0.838, the model demonstrates balanced high performance in both precision and recall values.

IV. CONCLUSION

This study employed various parameter selections to improve the performance of the RNN deep learning model in predicting the risk of heart attack. Standardization and 5-CV methods were used in the data pre-processing stage. With this method, the dataset is randomly divided into 5 equal parts. Each part is sequentially used as the test data while the remaining 4 parts are used as the training data. This step is repeated 5 times, with a different part serving as the test data each time. As a result, after calculating the accuracy, precision, recall, and F1 score metrics for each test set, the average of the 5 run results was taken.

The results demonstrated that the performance of the RNN classification model is dependent on parameter selection. The best performance, reaching an accuracy of approximately 81%, was achieved using the parameters RNN units=32, epoch=100, batch size=32, dropout=0.3, activation

function=tanh, and dense units=32. The precision value of the model was determined as 0.799, indicating that approximately 79.9% of the examples predicted as positive by the model were truly positive. The recall value was determined as 0.893, suggesting that the model correctly detected approximately 89.3% of the true positives. The F1 score was calculated as 0.838, indicating that the model exhibited balanced high performance in both precision and recall metrics. These findings emphasize the applicability of the RNN classification method in assessing the risk of heart attack. It was observed that parameter selection significantly affects the classification performance.

REFERENCES

[1] W. H. Organization, The world health report 2002: reducing risks, promoting healthy life. World Health Organization, 2002.

[2] J. Wang, C. Rao, M. Goh, and X. Xiao, "Risk assessment of coronary heart disease based on cloud-random forest," Artificial Intelligence Review, vol. 56, no. 1, pp. 203-232, 2023.

[3] P. Wang, Y. Li, and C. K. Reddy, "Machine learning for survival analysis: A survey," ACM Computing Surveys (CSUR), vol. 51, no. 6, pp. 1-36, 2019.

[4] N. Kagiyama, S. Shrestha, P. D. Farjo, and P. P. Sengupta, "Artificial intelligence: practical primer for clinical research in cardiovascular disease," Journal of the American Heart Association, vol. 8, no. 17, p. e012788, 2019.

[5] J. Zhang, L. Zi, Y. Hou, M. Wang, W. Jiang, and D. Deng, "A deep learning-based approach to enable action recognition for construction equipment," Advances in Civil Engineering, vol. 2020, pp. 1-14, 2020.

[6] Kaggle. "Heart Attack Analysis & Prediction Dataset." https://www.kaggle.com/datasets/rashikrahmanpritom/heart-attack-analysis-prediction-dataset (accessed 15.06.2023.

[7] C. Yin, Y. Zhu, J. Fei, and X. He, "A deep learning approach for intrusion detection using recurrent neural networks," Ieee Access, vol. 5, pp. 21954-21961, 2017.

[8] Ş. Öztürk and U. Özkaya, "Gastrointestinal tract classification using improved LSTM based CNN", Multimedia Tools and Applications, 79(39-40), 28825-28840, 2020.

[9] Z. B. Ozger and P. Cihan, "A novel ensemble fuzzy classification model in SARS-CoV-2 B-cell epitope identification for development of protein-based vaccine," Applied Soft Computing, vol. 116, p. 108280, 2022.

[10] P. Cihan and Z. B. Ozger, "A new approach for determining SARS-CoV-2 epitopes using machine learning-based in silico methods," Computational Biology and Chemistry, vol. 98, p. 107688, 2022.