Eureka Open Access Journals
Open Access | Peer Reviewed | International Journals | Multidisciplinary Areas

Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)

ISSN 2760-5000 (Online) Volume 2, Issue 3, March 2026

https://eurekaoa.com/index.php/11

NEURAL NETWORK PREDICTION OF THE FREQUENCY OF ADMISSION OF PATIENTS WITH CARDIOVASCULAR DISEASES TO CLINICAL INSTITUTIONS

Giyos Pulatov[1]
Gulxayo Pulatova [2]
"TIIAME" National Research University, Tashkent, Uzbekistan [1]
Ferghana State Technical University [2]
giyospulatov1987@gmail.com

Abstract

The issues of using recurrent neural networks with long short-term memory (LSTM) in predicting the admission of patients with cardiovascular diseases are considered. The forecast of the frequency of admission of patients with cardiovascular diseases (CVD) to medical institutions is based on meteorological (ambient temperature, atmospheric pressure, air humidity and wind speed) and heliogeophysical factors (geomagnetic activity index). The stages of architecture selection and training of LSTM neural networks are described in detail. The results of predicting the frequency of admission of patients with CVD to medical institutions in two cities of the Republic of Uzbekistan (Nukus, Samarkand) using the recurrent deep learning neural network LSTM implemented using the Keras library in the Python software environment are presented.

Keywords: Forecasting, time series, meteorological factors, heliogeophysical factors, cardiovascular diseases, LSTM neural network, neural network architecture, neural network training.

Eureka Open Access Journals
Open Access | Peer Reviewed | International Journals | Multidisciplinary Areas
Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 3, March 2026

https://eurekaoa.com/index.php/11

INTRODUCTION

According to the World Health Organization, about 18 million people die from cardiovascular diseases (CVD) every year, accounting for 32% of all deaths. One in three people over the age of 18 in the world has high blood pressure. Central Asia is one of the regions with the highest prevalence of these diseases.

Most people predisposed to or suffering from CVD (arterial hypertension, coronary artery disease, heart attacks, cardiac rhythm and conduction disorders, etc.) belong to a fairly large group of weather-dependent people. A large group of meteorological, heliogeophysical, environmental, and other factors affect their well-being, occurrence, exacerbation, and course of CVD. In this regard, one of the urgent tasks is the timely forecasting of the "quality of the day" for weather-dependent people. At the same time, the frequency of admission of patients with CVD to clinical institutions can serve as an estimated parameter, and a variety of meteorological and heliogeophysical factors can be influencing parameters. A correct and timely forecast of the "quality of the day" will prevent the occurrence or exacerbation of CVD by taking proactive preventive measures, optimizing the organization of emergency medical services for the population, and improving the efficiency of clinical institutions.

RELATED WORK

Recently, many studies have been conducted to identify the impact of weather factors on cardiovascular diseases, which occupies an important place in medicine. As observations show, weather factors affect human well-being and health. The following parameters were taken as factors: temperature, humidity, atmospheric pressure, wind speed and magnetic storms [1]. Many scientific papers have confirmed that these factors affect blood pressure, heart rhythm and can even cause heart attacks [2, 3]. However, data on the impact of magnetic storms on the cardiovascular system have not been sufficiently studied. Given this, the need for further research in this area is emphasized [5]. Deep learning

Eureka Open Access Journals
Open Access | Peer Reviewed | International Journals | Multidisciplinary Areas

Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)

ISSN 2760-5000 (Online) Volume 2, Issue 3, March 2026

https://eurekaoa.com/index.php/11

methods, such as the LSTM (long short-term memory) model, have shown higher efficiency in analyzing time series data compared to traditional methods, providing significant progress in identifying complex relationships between weather factors and health [4, 6]. This research work is intended to jointly analyze the gaps identified in scientific papers.

METHODS

In practice, a number of methods are widely used to solve the problems of forecasting complex dynamic processes: factual, expert, publication, scenario, matrix, mathematical modeling, analogy method, graph, etc. Until recently, statistical modeling methods remained the most traditional methods of predicting diseases in medicine.

The listed forecasting methods have one drawback in common with them - they are ineffective in conditions of weak formalizability of the task, incompleteness and vagueness of information. Therefore, machine learning methods and deep neural networks have recently been given greater preference in predicting complex processes [7]. Studies by many scientists show that the accuracy of predicting CVD using machine learning algorithms such as random forest [8], logistic regression, gradient boosting and neural networks [9] significantly exceeds the accuracy of doctors' predictions. Recurrent deep learning neural networks have proven themselves particularly well, which are successfully used in predicting dynamic processes described by multidimensional time series [9].

This article is devoted to solving the problem of creating an effective neural network model in the class of recurrent deep learning neural networks that ensure high accuracy in predicting the frequency of admission of patients with CVD to clinical institutions.

Step 1. Prepared a data set. For analysis, daily data on weather factors and visits to medical institutions were processed and exported in csv format, the data in which is shown in Table 1.

Eureka Open Access Journals
Open Access | Peer Reviewed | International Journals | Multidisciplinary Areas

Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 3, March 2026

https://eurekaoa.com/index.php/11

I Table. input and output data table

Num	Temperature	Pressure	Wind	Humidity	Magnetic storm	Number of applications
1	22.3	697.8	37	2.3	2.8	5.8
2	23.4	698.4	38.2	2.3	2.5	4.1
3	22.6	698.7	37.6	1.6	2	4.6
4	22.9	698.2	32.6	2.5	1.7	2.6
5	25	697.4	25	4.2	0.9	3.4
6	25.2	697.8	28.2	4	1.7	4.8
7	24.5	698.1	29.3	3.4	1	6.4
8	25.4	697.4	28	2.9	1.7	4
9	26	698.2	28.1	2.9	1	4.8
10	26.7	697.1	28.8	2.5	1.9	4
11	24.5	698.1	36.4	3.5	1.7	4.6
12	21.5	700.3	33	4.5	2	2.8
…	...	...	...	...	...	...
154	-8.9	700.9	88.5	3.2	1.2	8.8

Step 2. We define metrics such as MSE, MAE, R^2 in the LSTM model.
MSE (Mean Squared Error):

$$\text{MSE}=\frac{1}{\text{N}}\sum_{i=1}^{N}(y_i-\hat{y}_i)^2 \tag{1}$$

MAE (Mean Absolute Error):

$$\text{MAE}=\frac{1}{\text{N}}\sum_{i=1}^{N}|y_i-y_i| \tag{2}$$

RMSE:

$$R^2=1-\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\overline{y}_i)^2} \tag{3}$$

Eureka Open Access Journals
Open Access | Peer Reviewed | International Journals | Multidisciplinary Areas

Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 3, March 2026

https://eurekaoa.com/index.php/11

Where:

- y_i: actual value
- $\hat{y}_i$: predicted value
- N : total number of samples

Step 3. We will build an LSTM model based on the above csv table. First, we will load the numpy, pandas, and tensorflow libraries into the Python program and load the csv file.

LSTM model:

```
seq_length = 10
X, y = create_sequences(df[feature_cols].values, df[target_col].values, seq_length)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, shuffle=False)

model = Sequential([
    LSTM(200, activation='tanh', return_sequences=True, input_shape=(seq_length, len(feature_cols))),
    Dropout(0.1),
    LSTM(100, activation='tanh', return_sequences=True),
    Dropout(0.1),
    LSTM(50, activation='tanh', return_sequences=False),
    Dropout(0.05),
    Dense(25, activation='relu'),
    Dense(1)
])

history = model.fit(X_train, y_train, epochs=100, batch_size=64, validation_data=(X_test, y_test), callbacks=[early_stopping], verbose=1)
```

Eureka Open Access Journals
Open Access | Peer Reviewed | International Journals | Multidisciplinary Areas
Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 3, March 2026

https://eurekaoa.com/index.php/11

The model was trained for 50 epochs, with 20% of the data set allocated for validation. The data was split 80/20 using the Train-Test Split method. The LSTM model consisted of the following layers:

1. The first LSTM layer with 50 neurons (with relu activation function),
2. 20% Dropout layer,
3. The second LSTM layer with 50 neurons,
4. Another Dropout layer (20%),
5. Dense layer for output.

The model was compiled with the MSE loss function and the Adam optimizer.

RESULTS

In this study, an LSTM model was used to study the effects of weather factors on cardiovascular diseases. The MAE, MSE, and RMSE were determined using the LSTM model. The accuracy value was increased during model training. The error values were minimized. The results are shown in the table below.

II Table. MAE, MSE, and RMSE results

Metric	Value
MAE	0.23
MSE	0.057
RMSE	0.24

The importance of LSTM features is illustrated in Figure 1 below. This graph shows the contribution of each weather factor to the forecast.

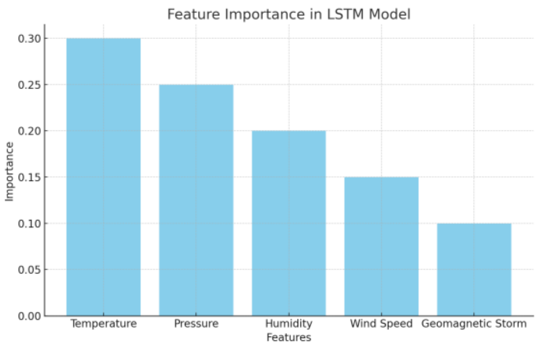

Figure 1. Importance of features in an LSTM model.

Eureka Open Access Journals
Open Access | Peer Reviewed | International Journals | Multidisciplinary Areas
Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 3, March 2026

https://eurekaoa.com/index.php/11

Residual analysis illustrates the differences between the model predictions and the actual values Figure 2. The normal distribution of the residuals indicates that the model performs well.

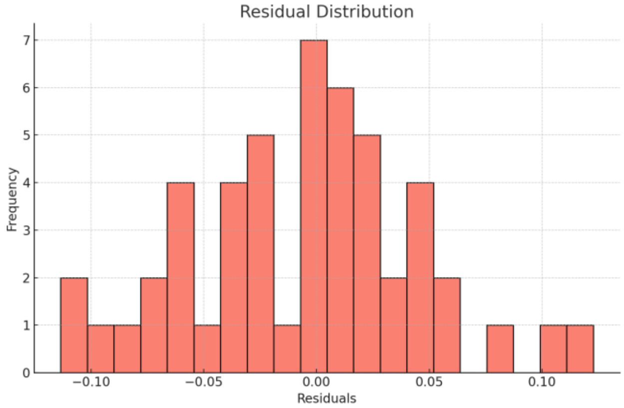

Figure 2. Residual distribution graph.

Figure 3 illustrates the dependence of the training and validation loss functions on epochs. This figure shows the decrease in the loss function during the training of the model and the values of the loss function during the validation process.

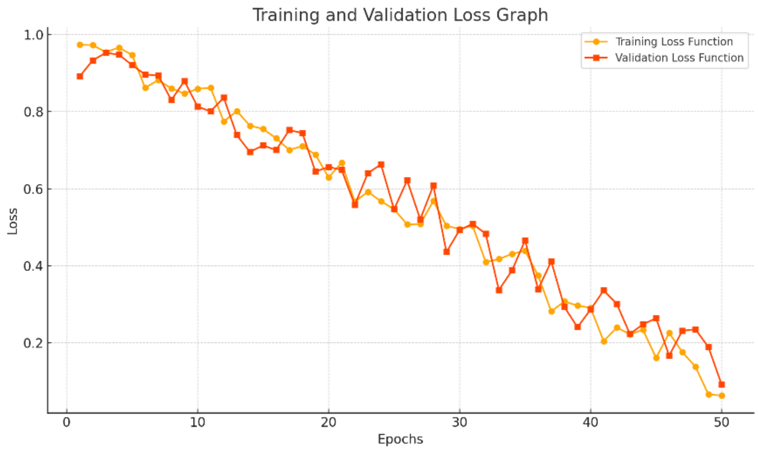

Figure 3. Training and validation losses

Eureka Journal of Artificial Intelligence and Data Innovation (EJAIDI)
ISSN 2760-5000 (Online) Volume 2, Issue 3, March 2026

https://eurekaoa.com/index.php/11

LSTM has been shown to be effective in detecting and predicting the impact of weather conditions on cardiovascular disease. The model's predictions were made with high accuracy, which statistically reliably indicates the impact of weather factors on cardiovascular disease. At the same time, the model's performance can be considered more effective than other algorithms.

CONCLUSION

The following research work has shown that the LSTM model has high efficiency in predicting weather factors affecting cardiovascular diseases. Also, the high accuracy of the LSTM model can be important not only in the analysis of cardiovascular diseases, but also in the prediction of other types of diseases. The ability of the LSTM model to effectively detect complex and long-term relationships in time series makes it a key tool for modern forecasting systems.

This research work provides several useful results: Taking timely measures by predicting disease risks, improving patient health by properly directing resources, and integrating medicine, artificial intelligence, and meteorology.

The application of the LSTM model opens up new perspectives. This will serve to solve other climate change, environmental, and societal problems in addition to healthcare systems.

It is recommended that future research consider other deep learning models and ensemble methods. We believe that this research work will serve as a foundation for future work.

REFERENCES

[1] A. S. Kabildjanov, G. G. Pulatov, and G. A. Pulatova, "Forecasting the impact of weather conditions on cardiovascular diseases using the LSTM model," Electronic Scientific Journal of the Fergana Branch of Tashkent University of Information Technologies named after Muhammad al-Khwarizmi, vol. 1, no. 4, pp. 251–255, 2024.

ISSN 2760-5000 (Online) Volume 2, Issue 3, March 2026

https://eurekaoa.com/index.php/11

[2] Stewart, S., Keates, A. K., Redfern, J., & McMurray, J. J. (2017). "The influence of weather on cardiovascular disease: A review." *Journal of Cardiology, 70(3), 209-215.
[3] Kim, J., Shin, J., & Park, S. (2019). "Impact of meteorological factors on cardiovascular mortality in South Korea." *Environmental Health Perspectives, 127(5), 057004.
[4] Wang, X., Zhang, L., & Chen, Y. (2021). "Deep learning approaches for predicting cardiovascular events using meteorological data." *Artificial Intelligence in Medicine, 115, 102057.
[5] Chen, R., Wang, C., & Meng, X. (2020). "Geomagnetic storms and their impact on cardiovascular health: A systematic review." *International Journal of Environmental Research and Public Health, 17(12), 4478.
[6] Li, Y., Liu, H., & Zhou, J. (2022). "Time-series forecasting of cardiovascular disease using LSTM and meteorological data." *Journal of Healthcare Informatics Research, 6(2), 123-138.
[7] Han C.W. Hsiao, Sean H.F. Chen, Jeffrey J.P. Tsai. Deep Learning for Risk Analysis of Specific Cardiovascular Diseases Using Environmental Data and Outpatient Records. 2016 IEEE 16th International Conference on Bioinformatics and Bioengineering (BIBE). 31 October 2016. P. 369-372. DOI 10.1109/BIBE.2016.75.
[8] Z. A. Enikeeva and D. S. Rafikov, "Predicting the risk of developing cardiovascular diseases using a fully connected deep neural network," Scientific and Educational Journal for Students and Teachers ‘StudNet’, no. 7, pp. 7274–7283, 2022.
[9] P. S. Onishchenko, K. Yu. Klyshnikov, and E. A. Ovcharenko, "Artificial neural networks in cardiology: Analysis of numerical and text data," Mathematical Biology and Bioinformatics, vol. 15, no. 1, pp. 40–56, 2020, doi: 10.17537/2020.15.40. [Online]. Available: https://www.researchgate.net/publication/339522128.