RESEARCH OF MODELS AND ALGORITHMS OF REMOTE MONITORING OF ARTERIAL PRESSURE

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Abstract. *Monitoring blood pressure is an important aspect of human health. Modern technologies for monitoring blood pressure allow for increased accuracy of measurements and facilitate the process of controlling this health indicator. The use of artificial intelligence and machine learning can help develop even more accurate and convenient monitoring methods, which will be beneficial for many people around the world.*

This article explores the tasks of developing a predictive algorithm for identifying individuals at high risk of developing hypertension without the need for invasive clinical procedures.

Keywords: *blood pressure monitoring, artificial intelligence, hypertension, neural network, blood pressure monitoring algorithm, model.*

1. Introduction

Instability of blood pressure is one of the key factors affecting human health, leading to various diseases, including hypertension. Hypertension is a common disease that has become a problem in today's world.

According to the World Health Organization (WHO), hypertension worldwide is responsible for 12.8% of total deaths and approximately 7.5 million deaths [1]. An estimated 1.28 billion adults aged 30–79 years worldwide have hypertension, the majority (two-thirds) of whom live in low- or middle-income countries.

An estimated 46% of adults with hypertension are unaware they have the condition. At the same time, less than half (42%) of adult patients with hypertension are covered by diagnostics and treatment. Among which, approximately one in five (21%) adult hypertensive patients controls the disease [2].

2. Theoretical foundations of the disease. Hypertension is part of the metabolic syndrome and is a multifactorial condition in which a person is diagnosed with a systolic blood pressure of ≥140 mmHg. and/or diastolic pressure ≥90 mmHg. Its exact causes are unknown, but genetic mutation, increased sodium intake, reduced physical activity, and obesity contribute to its progression [3]. Hypertension significantly increases the risk of heart, brain and kidney disease and is one of the leading causes of morbidity and mortality in the world.

In some cases, hypertension acts as a "silent killer", only noticed when it reaches dangerous levels [4]. At the same time, according to statistics, hypertension is one of the leading causes of death worldwide.

For some people, treatment for hypertension may only involve lifestyle adjustments without the use of medications. Lifestyle interventions include, but are not limited to, reducing salt intake, switching to a low-fat diet, eating more fruits and vegetables, becoming active, and quitting smoking [3]. One successful approach to prevention is to identify and target those at high risk. Studies have shown that the development of hypertension is influenced not only by prehypertensive status, but also by other factors, such as age [5], gender [6], diet [7], body mass index [8], literacy level [9], stress [10], co-morbidities [11], as well as clinical parameters [12-15].

In this regard, the development of a mathematical model for predicting and early diagnosis in blood pressure monitoring is a very complex and multi-factorial task that takes into account various medical and biological parameters of the patient, such as: age, gender, level of education, employment, tobacco use, physical activity, sufficient fruit consumption and vegetables, abdominal obesity, history of diabetes, history of high cholesterol, and history of maternal high blood pressure (see Fig. 1.) All of these biomedical parameters of the patient are important predictors of arterial hypertension.

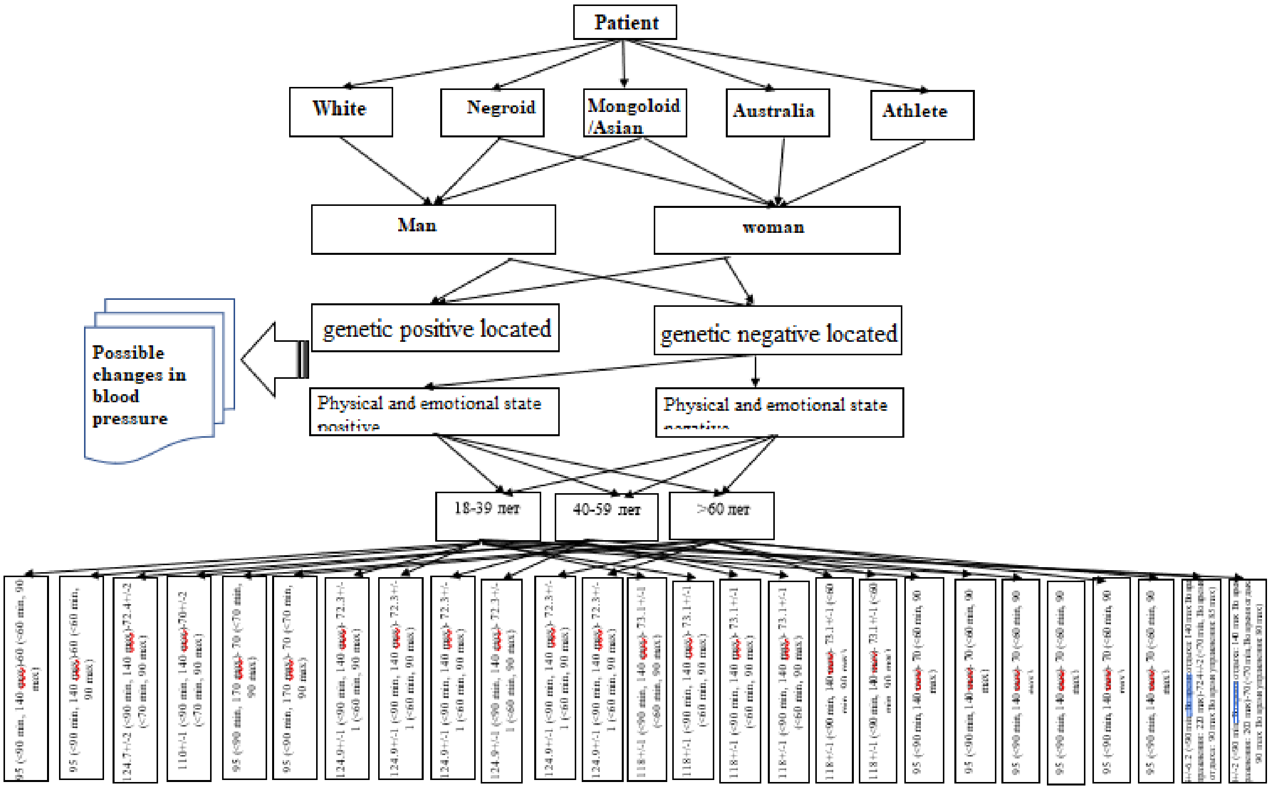

Fig. 1. Risk factors affecting hypertension.

This article explores the challenges of constructing a predictive algorithm to identify individuals at high risk of developing hypertension without the need for invasive clinical procedures.

3. Methods and means of monitoring. Constant monitoring of blood pressure is especially important for people with cardiovascular diseases, as well as for the elderly. Traditionally, blood pressure monitoring is carried out using manual blood pressure monitor, but modern technologies allow automating the process and increasing the accuracy of measurements.

One of the most common blood pressure monitoring technologies is the use of portable devices such as cuffs with an electronic sensor. These devices allow you to take pressure measurements anywhere and at any time without requiring the constant presence of medical personnel. Moreover, some device models can automatically send data to servers for further analysis. However, there are even more advanced blood pressure monitoring technologies based on the use of artificial intelligence and machine learning (see Fig. 2.).

(a)

(b)

Fig. 2. Portable devices for measuring blood pressure: a) cuffs with an electronic sensor; b) intellectual means.

For example, some companies are developing special applications for smart phones that allow you to take blood pressure measurements using a camera and a flash-light. Applications use machine learning algorithms to recognize pulse waves on the skin and determine pressure.

4. Analysis of the algorithms used. Modern artificial intelligence technologies allow the development of new blood pressure monitoring methods that can be even more accurate and convenient for patients, as well as save significant costs.

Due to the enormous costs of chronic diseases, studies have been conducted to assess the risk of hypertension in order to prevent further costly management and treatment of complications. Many of these studies used traditional logistic regression.

Predictive models are useful for predicting hypertension and are essential in medical practice due to their value in patient care [16]. The clinically used Framingham Hypertension Risk Index, a gender-specific algorithm, is used to predict the risk of developing cardiovascular disease after 10 years [17]. This is one of the main indicators used to determine arterial hypertension. Many methods using machine learning (ML) methods are used in hypertension risk models, such as artificial neural network, support vector machine, random forest, naive bayes classifier, gradient boosting machines, decision tree and logistic regression [18-20]. Echouffo-Tcheugui et al., a systematic review of the performance of such algorithms [20], and Krittanawong et al. gave a comprehensive overview of hypertension prediction using artificial intelligence [19].

Using several ML methods, a number of prognostic factors for predicting hypertension were identified, e.g., co-morbidities, medication history, age > 60 years, gender, smoking, family history of hypertension, body mass index, education level, salty diet, vegetables, fruits. meat consumption, regular exercise, low-density lipids, occupational status, depression and anxiety [21-24].

In addition, some studies show that the use of neural networks can improve the accuracy of blood pressure monitoring. For example, researchers at Johns Hopkins University have developed a neural network that can predict blood pressure based on data from heart rate and other physiological parameters.

Another example would be using a neural network to analyse ECG data and other physiological parameters to predict the likelihood of cardiovascular disease.

This technology can be especially useful for people with heart disease who need constant blood pressure monitoring.

5. Model of the functioning of the system. An abstract model of the functioning of the system for remote monitoring of blood pressure will be provided in the form of an undirected multi graph with weighted edges and vertices =<D,S> , D ≠ 0, D ∈ S × S. The set of two sets - a non-empty set D and a set S of unordered pairs of different elements of the set graph .

The sets D are called vertices, denoting equipment in a distributed system, and S is called a set of edges, denoting the connection between the equipment of a distributed monitoring system, indicating the direction of traffic transmission [25]; $D = \{d_i, i = 1,..., n_d\}$ - a set of peaks, consisting of various equipment of the remote monitoring system designed to remove the transmission and process the medical and biological data of patients connected to a single system; $S = \{s_l, l = 1,..., n_s\}$ - a set of edges represented by communication channels connecting all equipment into a single network (see Fig. 3.).

In the considered model of the functioning of the system, the elements of the complex of remote monitoring, the exchange of messages in the form of a stream of medical and biological data of a person can be implemented “in the many-to-one format” - when certain biometric information of the patient is transmitted from various measuring sensors to the central database of the system for collection and processing.

To describe the process of exchanging messages in the form of a data flow between vertices D_i^λ (equipment of a remote monitoring system), we construct an incidence matrix of the above graph.

The incidence matrix is a rectangular matrix of size, where are graph vertices, graph arcs, n is the total number of graph vertices, and m is the total number of arcs.

The incidence matrix $V_i^\lambda = \{V_{ij}\}$ $i = 1,2,...n,\ \ j = 1,2,..., m$ is denoted as follows

$$V_i^\lambda = \begin{vmatrix} V_{11} & V_{12} & \dots & V_{1m} \\ V_{21} & V_{22} & \dots & \dots \\ \dots & \dots & \dots & \dots \\ V_{1n} & \dots & \dots & V_{nm} \end{vmatrix}$$

where

$$V_i^\lambda = \begin{cases} \text{if } 1, \text{then } D_i^\lambda - \text{network node} - \text{transmitter} \\ \text{if } 0, \text{then the network node is not functioning} \end{cases}$$

The mathematical model of prediction and early diagnosis in blood pressure monitoring can be described as $X = \{x_i\}$ (where $i = 1, \dots, n$) the primary medical and biological data of the patient entering the monitoring system (age, gender, level of education, employment, tobacco use, physical activity, sufficient consumption of fruits and vegetables, abdominal obesity, history of diabetes, history of high cholesterol, and history of maternal high blood pressure (see Figure 1)), $Y = \{y_j\}$ (where $j = 1, \dots, m$) is a set of parameters (answers) dependent on the input data, and β are regression coefficients.

$$y_j = \beta 0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \varepsilon$$

It is assumed that there is an unknown target dependency —$y*: X \to Y$ a mapping whose values are known only on the objects of the final training sample $X^n = \{(x_1, y_1), \dots, (x_n, y_m)\}$ The task of supervised learning is to build an algorithm $a: X \to Y$, that would approximate the unknown target dependency both on the sample elements and on the entire set X.

In accordance with the general structural system (see Fig. 3.), we will describe the stages of the functioning of the system using the following applications and examples:

1. Data collection: It is necessary to use medical devices such as a blood pressure monitor to collect blood pressure data. For remote monitoring, you can use special devices that transmit data via the Internet or Bluetooth.

2. Data storage: the received data should be stored in a database for further analysis and processing. To do this, you can use various DBMS, for example, MySQL or MongoDB.

3. Data processing: after data is collected, it must be processed and analysed. To do this, you can use various machine learning algorithms such as linear regression or neural networks.

4. Data visualization: The results obtained can be visualized using graphs and charts so that the user can easily assess their health status.

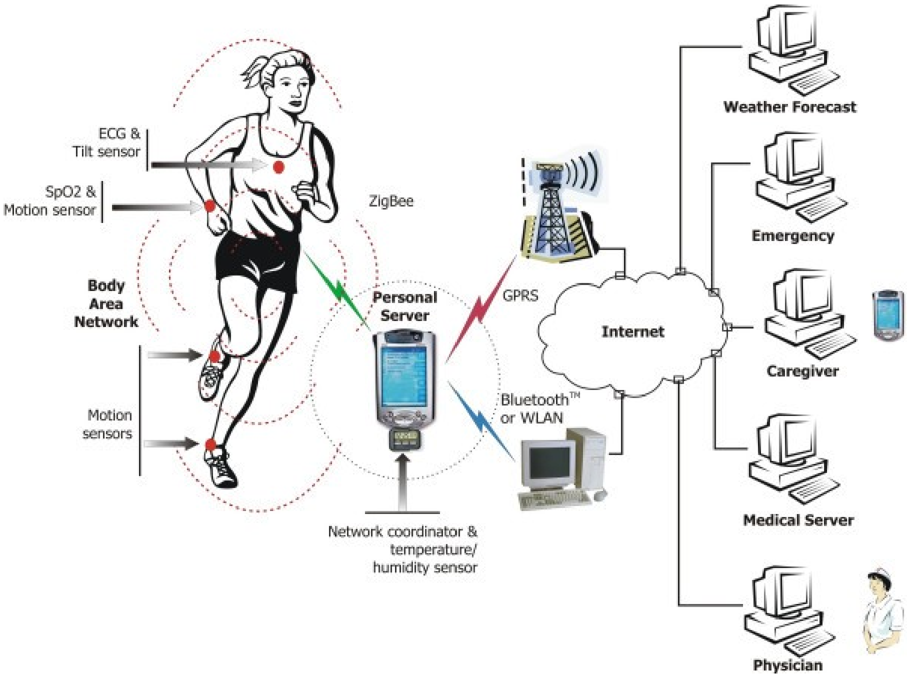

Fig.3. Structural diagram of the functioning of the blood pressure monitoring system.

6. Intelligent monitoring algorithm. The blood pressure monitoring algorithm may include the following steps:

1. Measurement of blood pressure using traditional methods such as tonometer or auscultation.

2. Data recording of pressure and other physiological parameters such as heart rate, respiratory rate and body temperature.

3. Data analysis using machine learning algorithms and neural networks to identify trends and predict future blood pressure values.

4. Providing pressure information and treatment recommendations to the patient or medical staff.

5. Evaluation of the effectiveness of monitoring and adjustment of the algorithm, if necessary.

It is important to note that blood pressure monitoring should be carried out under the supervision of qualified medical personnel, especially in case of serious illness.

7. The software implementation of the algorithm of the system for remote monitoring of blood pressure of patients can be provided based on the program code developed in the Python language. The provided program code is one of the possible software options for the patient blood pressure monitoring system and consists of four main steps described in the abstract model of the operation of the remote blood pressure monitoring system. Sample Python code for collecting data:

```
python
import serial
ser = serial.Serial('/dev/ttyUSB0', 9600) #
  specify the port and baud rate
while True:
    data = ser.readline().decode('utf-8') #
      read data from port
      print(data) # print data to console
```

Sample Python Code for Data Processing:

```
python
import pandas as pd
from sklearn.linear_model import
LinearRegression

df = pd.read_csv('data.csv') #loading data from a file
X = df['age'].values.reshape(-1, 1) # select features for training the model
y = df['pressure'].values

model = LinearRegression() # create a linear regression model
model.fit(X, y) # train the model on the selected features

new_data = [[40], [50], [60]] # new prediction data
predictions = model.predict(new_data) # predict values for new data
print(predictions) # output the predicted values to the console
```

Sample Python code for data visualization:

```
python
import matplotlib.pyplot as plt
import pandas as pd
df = pd.read_csv('data.csv') # loading data from a file
plt.plot(df['date'], df['pressure']) # build a graph of pressure by date
plt.xlabel('date')
plt.ylabel('Pressure')
plt.title('Dynamics of blood pressure')
plt.show() # display the graph on the screen
```

It should be noted that for the full and uninterrupted functioning of the described program code, it is necessary to configure a number of libraries of the Python programming language:

- Python programming language for writing scripts and machine learning algorithms;
- Pandas library for working with data and their processing;
- Matplotlib library for data visualization;

- Flask or Django to create a web application that will display pressure data;
- PySerial library for working with devices via COM or USB ports;
- Bluetooth library for working with devices that transmit data wirelessly.

The considered program code is one of the possible simple examples, it takes much more effort and knowledge to create a full-fledged application. However, the example considered in the paper will help to better understand how remote monitoring of blood pressure works and to implement more efficient systems.

8. Conclusion. Blood pressure monitoring is an important aspect of human health. Existing methods and means of monitoring blood pressure, such as the use of wearable devices that can measure blood pressure continuously throughout the day. These devices may be especially useful for people who need constant monitoring of their blood pressure, such as in the treatment of hypertension. In general, modern technologies for monitoring blood pressure can improve the accuracy of measurements and facilitate the process of monitoring this indicator of health. The use of artificial intelligence and machine learning can help develop even more accurate and user-friendly monitoring methods, which will be useful for many people around the world.

In addition, some studies show that the use of artificial intelligence can help improve the diagnosis of cardiovascular diseases, which may be associated with changes in blood pressure. However, research on models and algorithms using machine learning algorithms will help implement effective monitoring systems.

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