

# ALGORITHMS FOR INTELLIGENT DIAGNOSIS OF A PATIENT WITH HEART DISEASE: AN OVERVIEW

<sup>1</sup>Ismailov O.M., <sup>2</sup>Khojamurotov A.Sh.

<sup>1</sup>Professor at Tashkent University of Information Technologies named after Muhammad al-Khwarizmi, Department of Computer Systems

<sup>2</sup>Graduate student at Tashkent University of Information Technologies named after Muhammad al-Khwarizmi, Department of Computer Systems

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**Abstract.** Heart diseases stand as a leading cause of mortality worldwide, posing a particularly severe challenge in developing regions across Africa and Asia. Detecting heart diseases in their early stages not only empowers patients to take preventive measures but also equips healthcare practitioners to discern and mitigate the primary causes before an actual heart attack occurs. This paper introduces CardioHelp, a method devised to predict the likelihood of cardiovascular disease in patients. This method integrates a deep learning algorithm known as convolutional neural networks (CNN), specifically focused on temporal data modeling for early-stage heart failure prediction.

**Keywords:** artificial intelligence, heart diseases, ultrasound, genomics, accurate diagnosis, Machine learning, Convolutional neural networks.

## INTRODUCTION

Presently, a substantial number of global fatalities stem from heart attacks, posing a critical concern worldwide. Developing nations, particularly in Asia and Africa, grapple with a significant challenge in preserving lives due to delayed identification of the attack's severity [1, 2]. Early detection of a heart attack holds immense potential in averting its onset. Ongoing medical practices generate a wealth of datasets, ripe for analysis to discern crucial attributes pivotal in diagnosing heart attacks [3]. Regrettably, these datasets currently underutilized fail to fulfill their potential.

The primary aim of this research is to leverage these real-life datasets effectively, aiming to timely predict potential heart attacks. Various data analysis and mining techniques stand ready to facilitate this goal [4]. Tragically, many individuals succumb to symptoms that were previously unidentified or disregarded. The imperative now lies in predicting heart disease before its manifestation, emphasizing the urgency for proactive predictive measures to safeguard lives.

Heart disease stems from various primary causes, including elevated cholesterol levels, high blood pressure, smoking, excessive alcohol consumption, elevated sugar intake, sedentary lifestyle, cardiovascular disease (CVD), and hypertensive heart conditions [5].

In the contemporary era, the significance of data science and Big Data rivals that of the internet itself, particularly evident in online shopping, search engines, and multimedia platforms. Individuals seek comprehensive insights into their environment, prompting queries about ongoing events, their causation, and future predictions. Analyzers aspire not just to comprehend present occurrences but also anticipate future developments over time spans. For instance, a prospective loan applicant might seek to evaluate a bank's services, weighing potential costs and benefits before deciding on a loan. Similarly, an investor aims to optimize their financial investments, seeking real-time insights and trends. Big Data's impact extends to online shopping, where consumers grapple with numerous product choices amidst a plethora of brands.

Furthermore, some experts speculate that the Internet of Things (IoT) might surpass or even supplant Big Data as the foremost technological marvel in the future, hinting at a potential shift in the technological landscape.

Indeed, the evolution of IoT is intricately linked with the foundation of Big Data. Gartner defines Big Data as a collection of information assets characterized by extensive volumes, rapid velocity, and diverse variety, necessitating cost-effective and innovative information processing methodologies to facilitate advanced insights and decision-making capabilities [7]. In practical terms, much of the data generated in the contemporary world is voluminous. For instance, consider social media platforms like Facebook, boasting a staggering 800 million active members. Additionally, with approximately four billion mobile phones globally, over 25% of which are smartphones, and the proliferation of billions of RFID tags, the scale of data generation continues to expand exponentially.

### **METHODS AND MEANS OF MONITORING.**

Monitoring cardiac heart disease involves various methods and means to assess heart health and detect potential issues. Here are some common approaches:

1. **Electrocardiogram (ECG or EKG):** This is a primary diagnostic tool that records the electrical activity of the heart. It helps identify irregular heart rhythms (arrhythmias) and assesses heart damage.

2. **Holter Monitoring:** This involves wearing a portable ECG device for an extended period (24 to 48 hours or more) to track heart rhythms continuously. It helps detect irregularities that might not show up during a standard ECG.

3. **Echocardiogram:** This is an ultrasound of the heart that provides detailed images of its structure and function. It helps assess the pumping efficiency, valve function, and overall health of the heart.

4. **Stress Test:** This involves monitoring the heart's activity while the patient exercises to evaluate its performance under stress. It can help detect coronary artery disease and assess the risk of a heart attack.

5. **Cardiac CT or MRI:** These imaging techniques can provide detailed images of the heart's structure, blood vessels, and blood flow, helping to identify problems like blockages or structural abnormalities.

6. **Blood Tests:** Specific blood tests can indicate heart health by measuring cholesterol levels, cardiac enzymes (which increase after a heart attack), and other biomarkers associated with heart disease.

7. **Implantable Devices:** Devices like pacemakers or implantable cardioverter-defibrillators (ICDs) continuously monitor the heart's rhythm and can provide valuable data to manage heart conditions.

8. **Remote Monitoring Devices:** Wearable devices, such as smartwatches or patches, can continuously track heart rate, rhythm, and activity levels, providing ongoing data for assessment.

9. **Risk Assessments:** Assessing risk factors like family history, smoking habits, high blood pressure, diabetes, and cholesterol levels is crucial for monitoring and managing heart disease risk.

10. **Telemedicine:** Remote consultations and follow-ups with healthcare providers using digital platforms can aid in continuous monitoring and management of cardiac conditions.

Each method contributes to a comprehensive approach in monitoring and managing cardiac heart disease, allowing healthcare professionals to make informed decisions about treatment and lifestyle modifications to improve heart health.

### **MATERIALS AND METHODS**

The Least Absolute Shrinkage and Selection Operator (LASSO) constitutes a regression technique renowned for its effectiveness in both regularization and variable selection, enhancing predictive accuracy and the interpretability of resultant models. LASSO operates by shrinking data values towards a central point,  $P_c$ , facilitating parameter elimination and variable selection. This regression method particularly excels in addressing highly multicollinear models. Through LASSO regression, a penalty proportional to the absolute magnitudes of coefficients is imposed, leading some coefficients to ultimately reach zero and consequently, these variables are eliminated from the model. This elimination process results in a model with a reduced set of coefficients, offering enhanced interpretability and efficiency due to variable selection. Because of their quadratic nature, the solutions produced by LASSO aim towards a singular objective: to minimize a specific function:

$$\sum_{j=1}^n (y_j - \sum_j x_{jk} \gamma_k)^2 + \lambda \sum_{k=j}^q |\gamma_k| \quad (1)$$

As depicted in Eq. (1), this yields an interpretation readily comprehensible to the regression model, as a subset of values (denoted by  $\gamma$ ) becomes zero following the completion of the shrinking process. The equation incorporates a parameter  $\lambda$ , serving as a tuning parameter dictating the extent of shrinkage. When  $\lambda$  tends to zero, no parameters are excluded from the model. However, as  $\lambda$  increases, more coefficients are compelled towards zero, ultimately eliminating them from the model. A decrease in  $\lambda$  corresponds to heightened variance, while an increase in  $\lambda$  leads to increased bias.

The significance of variables, as gauged by their contribution to the underlying variation, is encapsulated in the  $\gamma$  value assigned to a variable or factor. Variables with  $\gamma$  values equal to or less than zero are regarded as inconsequential and consequently disregarded in the model.

It's important to highlight that an imbalanced dataset, characterized by data imbalance, can significantly skew results obtained through LASSO regression. This imbalance may potentially steer us towards an erroneous selection of crucial variables when employing LASSO on the entire dataset.

The impact of imbalance can be mitigated through a strategic approach that involves random subsampling of the dataset and multiple iterations of LASSO. This strategy incorporates majority voting based on  $\gamma$  values to select the non-zero variables across most iterations. To illustrate, consider a scenario where an  $N$  randomly subsampled dataset undergoes LASSO  $N$  times, each instance comprising an equal number of examples representing CHD or non-CHD. Assuming we have 45 variables denoted as  $\gamma_j = [\gamma_{j1} + \gamma_{j2} + \gamma_{j3} + \dots + \gamma_{j45}]$  at the  $j$ th instance. To determine a variable's inclusion in further analysis, we tally the count of non-zero instances for that variable, applying a manually set threshold value as an alternative criterion.

$$x(\gamma) = \begin{cases} 0 & \text{if } \gamma = 0 \\ 1 & \text{otherwise} \end{cases}$$

$$[x(\gamma_{1,d}), x(\gamma_{2,d}), x(\gamma_{3,d}) \dots \dots \dots x(\gamma_{N,d})] 1 \geq \frac{m}{\alpha} \Rightarrow d \text{ is selected} \quad (2)$$

**CONCLUSION.**

Cardiovascular disease (CVD) poses a mounting challenge to public health, persisting as a significant cause of global morbidity and mortality. To address this, frequent heart condition assessments through diverse devices have become imperative. Contemporary technologies for monitoring heart health not only enhance measurement precision but also streamline the monitoring process itself. The integration of artificial intelligence (AI) and machine learning (ML) stands poised to revolutionize monitoring methods, promising heightened accuracy and user convenience, benefiting countless individuals worldwide.

Furthermore, studies suggest that AI applications can notably enhance the diagnosis of cardiovascular diseases associated with fluctuations in blood pressure. Leveraging machine learning models and algorithms proves instrumental in implementing robust monitoring systems, offering effective tools for accurate diagnoses and proactive healthcare interventions.

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