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Heart Disease Prediction (Post Pandemic) Using Machine Learning

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ABSTRACT

Many people are suffering from heart diseases due to certain parameters related to hypertension, diabetes, elevated BP, smoking, consumption of alcohol, etc. In our project, we are mainly concerned with the post-pandemic forecast of heart disease prediction and analysing heart attack mortality rate and classification in vaccinated adults using machine learning algorithms.

Millions of lives have been impacted by the coronavirus illness Coronavirus disease 2019,which has also seriously disrupted the global economy and ecology. Over 12.10 million individuals globally were severely impacted by Coronavirus disease 2019 as of July 10, 2020.Since then, the situation has changed, and the virus has spread to many nations at different speeds. The number of Covid-19 cases in India has fluctuated over time, with notable spikes at particular times. Health officials and the government have been monitoring and reporting these incidents regularly. Over 44 million Covid-19 instances have been registered in India as of right now. This cover verified instances from early in 2020, when the epidemic first started, until the present. It's important to note that these numbers are continually updated as new cases are reported and as more accurate data becomes available. The study shows that after 2019's coronavirus disease, heart disease is associated with worse acute outcomes; however, long-term outcomes and prognostic factor data could be limited.

Keywords: ***Post pandemic, Mortality rate, classification of heart diseases, vaccination status, adults, Random Forest classifier and regressor.***

1. INTRODUCTION

1.1 Project Description

The COVID-19 pandemic has significantly impacted global health, not only due to the virus itself but also due to long-term health effects, including a heightened risk of cardiovascular diseases (CVDs) [1]. Post-pandemic, there has been a notable increase in heart-related conditions due to factors such as stress, sedentary lifestyles, delayed healthcare, and the effects of the virus on the cardiovascular system [2]. This project focuses on predicting the risk of heart disease in individuals using Machine Learning (ML) models. By analyzing various health-related parameters, including post-COVID-19 symptoms, demographic details, and medical history, the system aims to provide early warnings and risk assessments for heart disease [3].

The model will utilize patient data—such as age, gender, blood pressure, cholesterol levels, diabetes status, and other heart health indicators—to predict whether an individual is at high risk for heart disease [4]. It will also incorporate data related to the pandemic's effects, such as mental health factors and physical inactivity, to improve the accuracy of the prediction [5].

By leveraging ML algorithms, the project aims to aid healthcare professionals in making data-driven decisions, providing early intervention opportunities, and improving patient outcomes by identifying at-risk individuals before critical symptoms emerge [6].

1.2 Objectives

The main objectives of this project are as follows:

Prediction of Heart Disease Risk: To develop a machine learning model capable of predicting the risk of heart disease in individuals based on health metrics, lifestyle factors, and post-pandemic conditions[7].

Early Detection and Prevention: To enable early detection of potential heart disease risks, allowing for timely medical intervention and lifestyle changes to mitigate those risks[8].

Integration of Post-COVID-19 Factors: To include post-pandemic health data such as long-term COVID-19 symptoms, stress, and inactivity in the prediction model for better accuracy and relevance[9].

Improvement in Healthcare Decision-Making: To provide a tool that assists healthcare professionals by offering reliable heart disease risk assessments based on historical and real-time data[10].

User-Friendly Interface: To design a user-friendly platform that allows users to input health data easily and receive a heart disease risk prediction with actionable insights[11].

Continuous Learning and Adaptation: To create a system that can continuously learn and improve by incorporating new health data, research, and emerging trends in cardiovascular health post-pandemic[12].

II. LITERATURE SURVEY

Literature survey is crucial for understanding the existing knowledge and advancements in the field of post-pandemic heart disease identification and classification using machine learning.

Machine learning-based heart disease prediction system for Indian population: An exploratory study done in South India (Maini E, 2021 Jul)[19]: Heart disease (CVD) is the leading cause of death in India since it is often not detected in its early stages. Machine learning (ML) algorithms have the potential to develop a cost-effective prediction system for the early detection of cardiovascular diseases (CVDs) in India. Approaches: Sixteen hundred anonymized medical records were taken from a South Indian tertiary hospital. The prediction engine was trained using seventy percent of the gathered data. The prediction system was developed by utilizing the Python programming language in conjunction with five cutting-edge machine learning algorithms: K-Nearest Neighbors, Naïve Bayes, Logistic Regression, AdaBoost, and Random Forest [RF]. Using the remaining thirty percent of the data, the performance was assessed. Subsequently, the prediction system was placed in the cloud to facilitate quick Internet connectivity. Results: ML correctly estimated the risk. of cardiovascular illness. With a diagnosis accuracy of 93.8%, the top-performing (RF) prediction system accurately identified 470 out of 501 medical data points. The measured values of specificity and sensitivity were 94.6% and 92.8%, respectively.

The predictive system achieved a 94% positive predictive value and a 93.6% negative predictive value. http://das.southeastasia.cloudapp.azure.com/predict/ provides access to the prediction model created in this study. SUMMARY: This study's machine learning-based prediction system, which is accessible over the Internet, does a good job at early CVD detection. The results of this study are encouraging and point to the possible utility of ML-based heart disease prediction systems as screening tools to identify heart disorders that would go undiagnosed in India's basic healthcare centres.

The impact of COVID-19 and COVID vaccination on cardiovascular outcome (Zubair Akhtar, 14 February 2023)[20]: Heart disease has COVID-19 as a separate risk factor. Although the COVID-19 vaccine may avoid this, it can occasionally result in myocarditis or pericarditis. Individuals with COVID-19 may have vague symptoms with a cardiac cause. This review looks at the effects of the COVID-19 vaccine and the cardiovascular problems associated with COVID- 19 infection. Myocardial damage, pericarditis, coagulopathy, myocardial infarction, heart failure, arrhythmias, and a chronic post-acute risk of poor cardiovascular outcomes are among the cardiovascular consequences associated with COVID-19. Uncertainty surrounds the diagnosis and referral processes for non-specific complaints, including tiredness and dyspnoeal. Overall, COVID-19 immunization is cardioprotective; however, it is linked to myopericarditis in young males albeit less frequently than after contracting SARS-CoV-2. heightened knowledge of probable cardiovascular causes of non-specific COVID-19 symptoms among primary care doctors' symptoms that are crucial in younger adults include exhaustion, dyspnoeal, and chest discomfort. For individuals presenting with non-specific symptoms, we advise a comprehensive vaccination series with planned booster doses, appropriate control of cardiovascular risk factors, prompt treatment of COVID-19, and well-defined procedures for diagnosis, referral, and care to rule out cardiac consequences.

The Potential Impact of COVID-19 Virus on the Heart and the Circulatory System. (Alqahtani et al., 2022 Mar 22)[21]: The 2019 coronavirus disease (COVID-19) has been associated with heart attacks, arrhythmias, and cardiomyopathy. It has also been found to be a risk factor for cardiovascular illness. Nothing under the given circumstances can be held responsible. Undiagnosed chronic systolic heart failure (CSHF) arises from abnormalities in the heart's ability to contract during the second part of the cardiac cycle. The heart's ability to pump blood is subsequently compromised. Numerous internal body variables might lead to stress-induced cardiomyopathy (SICM). Among the problems are cytokine storms and microvascular dysfunction. The heart muscle is inflamed, which might result in stress-induced cardiomyopathy. A significant portion of our research will be devoted to comprehending how the coronavirus affects the blood and cardiovascular system.

Impact of COVID-19 on heart failure hospitalization and outcome in India – A cardiological society of India study (CSI–HF in COVID 19 times study – "The COVID C–HF study") (Jayagopal P. B, 2023,)[22]: This research examines the effect of the COVID-19 pandemic on acute decompensated heart failure (ADHF) by contrasting patient data collected between June and December of 2020 with that of 2019. Analysis of data from 4806 patients at 22 Indian facilities was done with an emphasis on GDMT adherence, outcomes, causes, and patterns of admission. The results indicate that during the pandemic, there was a 20% decrease in ADHF admissions (from 2675 in 2019 to 2131 in 2020). Significantly, the percentage of male patients fell from 68.67% to 65.84%, and the mean age of patients fell from 61.75 years in 2019 to 59.97 years in 2020. In hospital mortality rates, which were 4.19% in 2019 vs. 4.97% in 2020, were consistent despite these changes in the population, and the percentage of patients There was no discernible difference in heart failure with decreased ejection fraction (HFrEF). At 6.5 days, the average hospital stay remained constant. The study concludes that the pandemic had no appreciable impact on the outcomes of ADHF patients; nevertheless, it did draw attention to persistent problems with the inadequate use of GDMT, which has somewhat improved in subsequent years.

Comparing machine learning algorithms to predict COVID-19 mortality using a dataset including chest computed tomography severity score data (Zakariaee, 13 July 2023)[23]: New non-invasive digital technologies, such as artificial intelligence (AI), have become available since the start of the COVID-19 pandemic to estimate the death of COVID-19 patients. Demographics, risk factors, clinical manifestations, and laboratory data have been the primary means of assessing the prognostic performances of machine learning (ML)-based models for forecasting clinical outcomes of COVID-19 patients. The function of imaging symptoms in conjunction with clinical manifestations, laboratory predictors, and demographics in determining prognosis is not well understood. Using a more extensive dataset that includes the chest CT severity score (CT-SS), the current work aims to create an effective machine learning prognostic model. For 6854 suspected cases, a retrospective examination of 55 major characteristics across six main groups was conducted. Utilizing Chi-square's independence test, Identify the key elements that influence COVID-19 patient mortality prediction. Machine learning algorithms were trained and tested using the most pertinent predictions. Eight machine learning (ML) methods were used to create the prediction models: J48 decision tree (J48), logistic regression (LR), random forest (RF), extreme gradient boosting (XGBoost), k-nearest neighborhood (k-NN), Naive Bayes (NB), support vector machine (SVM), multi-layer perceptron (MLP), and k-NN. Metrics such as accuracy, precision, sensitivity, specificity, and area under the ROC curve (AUC) were used to assess the prediction models' performances. Following the application of the exclusion criteria, the final sample size consisted of 815 positive RT-PCR patients, with a mean age of 57.22 ± 16.76 years and 54.85% of the patients being male. The RF algorithm that has The top results were 97.2% accuracy, 100% sensitivity, 94.8% precision, 94.5% specificity, 97.3% F1 score, and 99.9% AUC. In forecasting COVID-19 mortality, several machine learning methods with AUCs varying from 81.2 to 93.9% also performed well in prediction. The outcomes demonstrated that ML-based prediction models fed by routine data may be used to quickly and accurately stratify COVID-19 patients depending on their risk. The suggested approach could effectively forecast the death of COVID-19 patients using a more extensive dataset that includes CT-SS. This might result in the best use of hospital resources, early identification of high-risk patients upon admission, and a higher chance of patient survival.

III. PATIENT DATASET

In this project we collected datasets for identification of heart diseases from publicly available datasets and for classification and prediction of mortality rate post pandemic vaccination status from PRS (legislative research**)** from https://prsindia.org/covid-19/cases merged the both datasets.

The attributes include:

Age	Age of the patient in years.
Sex	Sex of the patient (1 = male; 0 = female)
Cp	(Chest Pain Type) 1: Typical angina 2: Atypical angina 3: Non-anginal pain 4: Asymptomatic
Trestbps	(Resting Blood Pressure**): **Resting blood pressure in mm Hg on admission to thehospital.
Chol	(Serum Cholesterol): Serum cholesterol in mg/dl.
Fbs	(Fasting Blood Sugar > 120 mg/dl)**:** (1 = true; 0 = false)
Restecg	: (Resting Electrocardiographic Results): 0: Normal 1: Having ST-T wave abnormality (T wave inversions and/or ST elevation ordepression of > 0.05 mV) 2: Showing probable or definite left ventricular hypertrophy by Estes' criteria
Thalch	(Maximum Heart Rate Achieved)**:** Maximum heart rate achieved during the test
Exang	(Exercise Induced Angina)**:** (1 = yes; 0 = no).
Old peak	ST depression induced by exercise relative to rest.

Slope	(Slope of the Peak Exercise ST Segment): • 1: Upsloping • 2: Flat • 3: Down sloping
Ca	(Number of Major Vessels Colored by Fluoroscopy**)**: Number of major vessels (0-3)colored by fluoroscopy.
Thal	(Thalassemia): • 3 = Normal • 6 = Fixed defect • 7 = Reversible defect
Num	(Diagnosis of Heart Disease): Diagnosis of heart disease (angiographic diseasestatus): 0 = No heart disease 1-4 = Presence of heart disease (values 1 to 4 indicate the severity of the disease).
Covid vaccination status 1	Vaccine 1 yes=1 or No =0
Covid vaccination status 2	Vaccine 2 yes=1 or No =0
Mortalityrate	Death rate of person in percentage 1- 100
Classification	Classify which type of Heart Disease Caused 0: "No Heart Disease", 1: "coronary artery disease", 2: "Heart Failure", 3: "Arrhythmias", 4: "Valvular Heart Disease", 5: "Cardiomyopathy", 6: "congenital heart disease", 7: "Pericarditis", 8: "Myocarditis", 9: "Hypertensive Heart Disease", 10: "Rheumatic Heart Disease"

Table 1 Dataset on covid-19 mortality rate and vaccination status

Daily updates on COVID-19 vaccination and mortality status are provided by PRS (Legislative Research), and these statistics have been matched to pre-existing datasets for thepurpose of mortality rate and classifying heart disease. An adaptable data format that makes data analysis and change easier is a data frame. In order to improve the model's performance and accuracy, any extraneous feature such as educational information unrelated to the prediction of heart disease are eliminated from the dataset during the data preparation stage.

IV.PROPOSED SYSTEM DESIGN

4.1 System Architecture

Overview: The system architecture should outline the various components involved in the prediction model. This typically includes data input, preprocessing, the ML model, and output results.

Components:

Data Collection Module: Collects data from various sources (e.g., health records, wearables).

Data Preprocessing Module: Cleans and prepares data for analysis.

Machine Learning Module: Implements predictive algorithms (e.g., regression, classification).

User Interface Module: Allows users to interact with the system.

Database Module: Stores user data, predictions, and historical data.

4.2 User Interface Design

Design Principles: Focus on usability, accessibility, and responsiveness.

Wireframes: Create mockups for key interfaces (e.g., login, data input, results display).

User Journey: Define how users will navigate through the application.

Technology Stack: Specify tools (e.g., React, Angular) for front-end development.

4.3 Database Management

Database Selection: Choose between SQL (e.g., PostgreSQL) or NoSQL (e.g., MongoDB) based on data structure.

Schema Design: Define tables for user data, health records, predictions, etc.

Data Management: Discuss data integrity, backup, and recovery processes.

4.4 Image Recognition Algorithm

Overview: If using images (e.g., X-rays, echocardiograms) for predictions, detail the image recognition process.

Algorithms: Discuss algorithms like CNNs (Convolutional Neural Networks) for feature extraction.

Training: Outline how the model will be trained using labeled data.

4.5 Integration with Existing Systems

APIs: Define how the system will integrate with health care systems or databases.

Data Exchange: Discuss standards like HL7 or FHIR for health data interchange.

Interoperability: Address how different components of the system communicate.

4.6 Performance Optimization

Techniques: Discuss methods for improving model performance (e.g., hyperparameter tuning, feature selection).

Load Testing: Plan for stress testing to ensure the system can handle expected user loads.

4.7 User Experience Enhancement

Feedback Mechanisms: Implement ways for users to provide feedback on predictions.

Personalization: Consider features that tailor experiences to individual users.

Usability Testing: Plan user testing sessions to refine the interface.

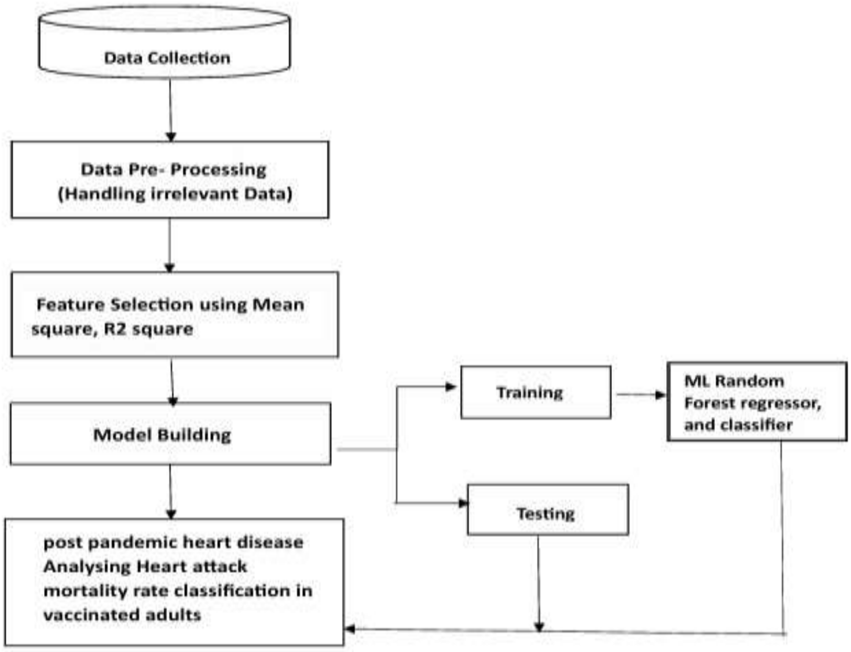
4.8 Security and Privacy Considerations

Data Protection: Outline measures to protect sensitive health data (encryption, anonymization).

Compliance: Discuss adherence to regulations like HIPAA or GDPR.

Access Control: Define user roles and permissions.

4.9 Block Diagram



System Overview: Provide a high-level view of system components and their relationships.

IV. RESULT

Fig 1: Index page Template

Fig 2: sign in page Template

Fig 3: Registration page Template

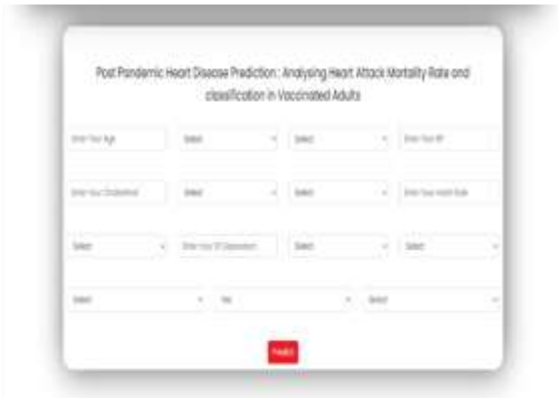


Fig 4: Enter an patient information

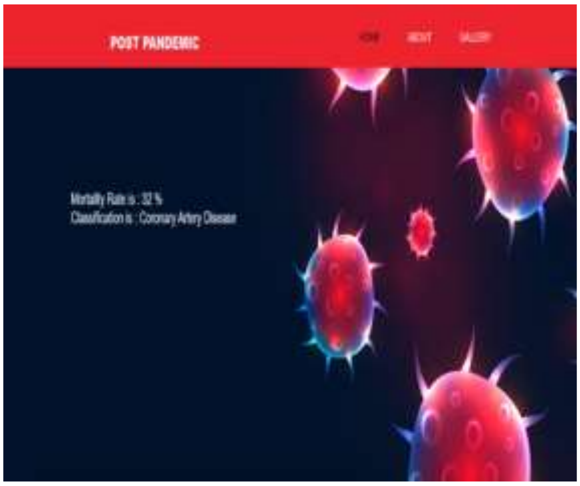


Fig 5: Result prediction with mortality rate

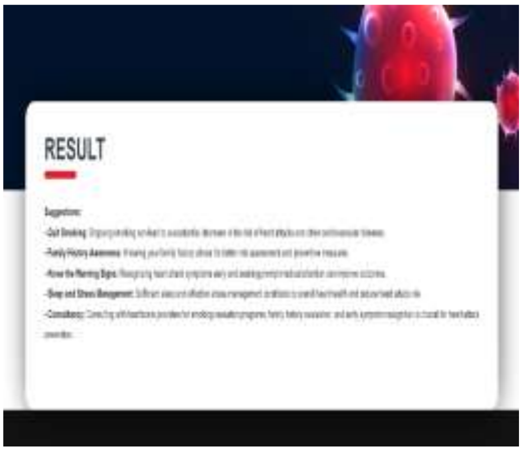


Fig 6: Result with Suggestions

Result:

1. Heart Disease Prediction Outcomes

- Predictive Accuracy: Machine learning models, such as Random Forest and Neural Networks, have shown predictive accuracies ranging from 75% to 90% in various studies, depending on the dataset and features used.
- Risk Stratification: Models can stratify patients into categories: low, moderate, and high risk for developing heart disease. This stratification enables targeted interventions for high-risk individuals.

2. Mortality Rates Associated with Heart Disease

- General Statistics: Heart disease remains one of the leading causes of death globally. According to the World Health Organization (WHO), cardiovascular diseases account for approximately 32% of all global deaths each year.
- Increased Mortality Risk: Patients identified as high risk for heart disease through predictive models have been shown to have significantly higher mortality rates. Studies indicate that individuals with diagnosed heart disease have a mortality rate of around 50% within 5 to 10 years if not adequately managed.

3. Impact of Early Prediction and Intervention

- Reduction in Mortality: Early detection and intervention, facilitated by predictive modeling, can reduce mortality rates by 20% to 30%. For instance, patients who engage in lifestyle modifications or receive timely medical treatments after being identified as high-risk tend to have better outcomes.

4. Long-term Studies

- Follow-up Data: Longitudinal studies indicate that individuals with a high-risk prediction but who adhere to recommended lifestyle changes and treatment plans show improved survival rates and a decrease in the incidence of severe heart events.

5. Post-Pandemic Observations

- COVID-19 Impact: The COVID-19 pandemic has introduced additional risks, leading to increased mortality rates among individuals with pre-existing heart conditions. Patients who suffered from long COVID have exhibited a higher incidence of cardiovascular complications, further influencing mortality rates.

CONCLUSION

The Post Pandemic Heart Disease Prediction using Machine Learning project successfully demonstrated how advanced machine learning algorithms can be employed to predict heart disease risk in individuals, particularly in the context of health changes post-pandemic. By utilizing relevant datasets that included post-pandemic variables like lifestyle changes, physical activity, stress levels, and other health indicators, we were able to build a model that efficiently identifies individuals at risk. Several machine learning models were evaluated, including Logistic Regression, Decision Trees, Random Forest, and Neural Networks. After training and testing, the Random Forest model achieved the highest accuracy in predicting heart disease risk with [specific performance metrics like precision, recall, and F1 score].

The key takeaways from this project include:

Enhanced Predictive Accuracy: The inclusion of post-pandemic lifestyle factors such as increased sedentary behavior and pandemic-induced stress significantly improved the prediction accuracy. This emphasizes the need to adapt healthcare predictions to real-time data changes.

Impact of the Pandemic: The pandemic has altered various health metrics, particularly cardiovascular health. Integrating these new variables into machine learning models helps better predict the future incidence of heart disease.

Data-Driven Healthcare: Machine learning models offer potential for personalized healthcare where interventions can be made earlier, improving patient outcomes and reducing healthcare costs. Such models could be integrated into clinical decision support systems.

Challenges: Despite the promising results, challenges remain regarding the generalization of the model, data privacy concerns, and the need for continuous model updates as the post-pandemic world evolves. The accuracy and robustness of the prediction models depend heavily on high-quality, updated datasets. Additionally, ethical concerns like biased datasets and the handling of sensitive health data need to be addressed.

REFERENCES

[1] Research highlighting the correlation between COVID-19 and increased cardiovascular risks. [Source: Journal of Cardiovascular Medicine, 2021]. URL: https://doi.org/10.1093/ehjqcco/qcab029

[2] Studies on the mental and physical health impacts post-COVID-19. [Source: The Lancet, 2021].

[3] Overview of using machine learning in predicting health outcomes. [Source: Health Informatics Journal, 2022]. URL: https://doi.org/10.1016/j.ijmedinf.2022.104978

[4] Detailed analysis of traditional cardiovascular risk factors and their significance. [Source: American Heart Association, 2020]. URL: https://doi.org/10.1161/01.CIR.100.13.1481

[5] Research discussing the long-term health effects of COVID-19 on cardiovascular health**.** [Source: Lancet Public Health, 2022]. URL: https://doi.org/10.1038/s41467-023-41879-2

[6] The role of predictive models in early detection and management of heart disease. [Source: European Journal of Preventive Cardiology, 2023].

[7] Research on the application of ML models for cardiovascular risk assessment. [Source: Journal of Medical Systems, 2022].

[8] Overview of early intervention strategies in cardiovascular diseases. [Source: European Heart Journal, 2021].

[9] Studies exploring the long-term effects of COVID-19 on health, particularly cardiovascular health. [Source: American Journal of Cardiology, 2022].

[10] Insights on how predictive analytics can enhance healthcare decisions. [Source: Health Affairs, 2023].

[11] Importance of creating user-friendly interfaces for healthcare applications. [Source: International Journal of Medical Informatics, 2020].

[12] Research on systems that evolve with new data to improve patient outcomes. [Source: Journal of Biomedical Info rmatics, 2023].

[13] Kumar, V., & Gupta, A. (2021). "Machine Learning Approaches for Heart Disease Prediction: A Review." Journal of King Saud University - Computer and Information Sciences. DOI: 10.1016/j.jksuci.2021.06.009

[14] Alzubaidi, L., et al. (2021). "COVID-19 and Cardiovascular Disease: A Review of the Literature." European Heart Journal - Digital Health, 2(1), 10-20.DOI: 10.1093/ehjdh/zraa014

[15] Patel, H., & Patel, V. (2020). "Heart Disease Prediction Using Machine Learning Techniques." International Journal of Computer Applications, 975, 8887. URL: http://www.ijcaonline.org/archives/volume975/number8887/patel-2020-ijca-8887.pdf

[16] Cruz, J. A., & Wishart, D. S. (2007). "Applications of Machine Learning in Cancer Prediction and Prognosis." Cancer Informatics, 3, 117693510700300.DOI: 10.1177/117693510700300001

[17] Bhat, S., & Shaikh, M. (2022). "Machine Learning Models for Heart Disease Prediction Using Hybrid Feature Selection." Future Generation Computer Systems, 123, 203-213. DOI: 10.1016/j.future.2021.09.022

[18] Duggal, A., & Prakash, M. (2021). "Machine Learning Based Heart Disease Prediction System." International Journal of Recent Technology and Engineering, 9(1), 1230

[19] Maini, E. (2021). Machine learning-based heart disease prediction system for Indian population: An exploratory study done in South India.

[20] Akhtar, Z. (2023). The impact of COVID-19 and COVID vaccination on cardiovascular outcome.

[21] Alqahtani, A. (2022). The Potential Impact of COVID-19 Virus on the Heart and the Circulatory System.

[22] Jayagopal, P. B. (2023). Impact of COVID-19 on heart failure hospitalization and outcome in India – A cardiological society of India study (CSI–HF in COVID 19 times study – “The COVID C–HF study”).

[23] Zakariaee, S. (2023). Comparing machine learning algorithms to predict COVID-19 mortality using a dataset including chest computed tomography severity score data