2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT) | 979-8-3503-7024-9/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICCCNT61001.2024.10725488

Deep Learning Based Framework for Cardio Vascular Disease Risk Prediction

Dr.V.Baby Shalini,
Department of Information Technology,
Kalasalingam Academy of Research and Education,Krishnankoil,
Virudhunagar,Tamil Nadu
v.babyshalini@klu.ac.in

T.Befrin Moofina,
Department of Information Technology,
Kalasalingam Academy of Research and Education,
Krishnankoil,
Virudhunagar,Tamil Nadu
befrin003@gmail.com

S.Sowmya,
Department of Information Technology,
Kalasalingam Academy of Research and Education,Krishnankoil,
Virudhunagar,Tamil Nadu
sowmya.s050620@gmail.com

S.Venkat Bharathi,
Department of Information Technology,
Kalasalingam Academy of Research and Education,
Krishnankoil,
Virudhunagar,Tamil Nadu
venkatbharathi392@gmail.com

T. Backialakshmi
Department of Information Technology,
Kalasalingam Academy of Research and Education,Krishnankoil,
Virudhunagar,Tamil Nadu
blakshmi2210@gmail.com

***Abstract*— Depressive and anxiety disorders stem from an unhealthy lifestyle perpetuated by the hectic lives of the modern world. In an effort to manage these symptoms, there is a tendency to turn to drug usage, smoking, and binge drinking. All of these things are the main causes of cardiovascular disease, tumors, and other major ailments. The World Health Organization, which is part of the UN has established that cardiovascular disease (CVD) is the primary cause of death worldwide. They have proliferated throughout time and are currently overtaxing national healthcare systems. Clinical evaluation of the illness severity that is prompt, precise, and accurate is essential at this point. This article presented an efficient deep learning-based approach for CVD prediction to improve making choices and logistical preparation in healthcare systems. Cytokines are regarded as a crucial component for the forecast. This work acknowledges the urgency and suggests a remedy: using deep learning to quickly and correctly forecast the severity of CVD. The work shows the efficacy of a Long Short Term Memory (LSTM) classification in CVD prediction by evaluating publically accessible information from the MIMIC-II database. Findings show a significant increase in prediction accuracy, providing crucial assistance for medical decision-making and logistics scheduling. To summarize, this study shows the critical need to address cardiovascular disease (CVD) and provides a viable approach using sophisticated prediction methods, with the ultimate goal to decrease the strain on health care systems while improving patient outcomes.**

Keywords*— *Long Term Short Memory, anxiety, depression, cardiovascular disease, death rates, deep learning,cytokiness

I. Introduction

Cardiac heart rate variability, myocardial infarction, angina pectoris, coronary heart disease, and other circulatory system disorders are collectively referred to as cardiovascular disease (CVD), and they are usually connected with atherosclerosis[4]. The aging population, growing urbanization, and the growth of China's social economy have all contributed to changes in national lifestyles that have increased the prevalence of CVD. In all, over 290 billion individuals suffering from CVD were reported in 2016.

They has been 4.344 million deaths in China as a result of it, with 1.736 million deaths from coronary heart disease and 2.098 million losses from stroke. These deaths have a significant social and economic impact. Cardiovascular disease (CVD) is a preventable and managed condition that can be effectively controlled in its progression with early intervention[6].

Several improvements in the evaluation associated with the cardiovascular disease (CVD) prediction model have been established in recent years, however the model has some demographic specificity due to the potential variability in the effects of epidemiologic risk variables and diagnostics in different populations[5]. Furthermore, no research on a large cohort based on populations CVD risk prediction system has been conducted in eastern China.

However, a majority of the present CVD prediction models only show modest predictive accuracy, particularly for certain subpopulations. This is because many of the models are built in a linear fashion using the multivariable regression method[1]. Random forest (RF) and other machine learning (ML) approaches can be used to find new risk indicators and more complex relationships between them, which could lead to a reduction in risk forecast accuracy through the use of huge data archives.

In the field of cardiovascular medicine[7], machine learning (ML) is one area of artificial intelligence (AI) and is being used more and more. It is basically the process by which computers interpret data and determine how to classify a task, whether or not human supervision is involved. The foundation of machine learning is its conceptual framework, which is based on models that take in input data (like text or images) and forecast outputs (like positive, negative, or neutral) using a combination of statistical analysis and mathematical optimization. A variety of machine learning methods have been implemented in routine tasks. An example of a popular machine learning technique is the Support Vector Machine (SVM), which is capable of identifying non-linear patterns and applying them to various applications such as credit card fraud detection, handwriting interpretation, and facial recognition. Only statistics and data mining methods and procedures for CVDs using cardiology records are the subject of this work.

The healthcare industry is producing enormous amounts of data at a very quick pace [2, 3]. Data is growing as a result of the electronic records of healthcare information, which includes social media, biomedical signals, genomic data, clinical text, biomedical images, Electronic Health Records, and sensing data. This process creates a significant amount of both primary and secondary information for the healthcare sector. By 2025, 175 zeta bytes of data will have been generated globally, representing a compound annual growth rate of 61%. This represents a sharp increase in data generation over the next few years.

Only 22% of the total data could be analyzed, according to the International Disease Classification's 2012 Digital Universe Study. By 2020, the proportion of useful data would rise to 37%. This has led to a great deal of interest in using access to healthcare data to improve patient quality and save costs. The rapid increase in temporary or archived data has made it essential to develop automated tools and innovative methods that can help effectively transform massive amounts of data into useful knowledge and information. These days, the health care industry produces a lot of detailed information about a patient's condition and detection.

It is challenging to analyze healthcare and medical device data resources manually, and loading them into a conventional database with relationships for analysis takes time and money. Finding hidden information to make wise decisions is made easier for the empowered individual thanks to the main disciplines of study in statistics and data mining. Quantification and result evaluation have a solid foundation thanks to statistics. Still, statistics-based algorithms must be adjusted and expanded before being used in data analysis.

One of the best methods for people, companies, and researchers to extract information is through data mining large data sets that include useful information. To find patterns and trends that go beyond straightforward analytical techniques, it involves automatically scanning through enormous information warehouses. In order to predict the probability of future events, it employs intricate mathematical formulas for the data segments. Numerous techniques from other fields, including as artificial intelligence, machine learning, statistics, pattern recognition, visualization, data bases, and data warehouse systems, have also been utilized in this. Evaluating the massive progress that has been accomplished in recent decades is challenging due to the vastness of these domains.

II. RELATED WORKS

Azam et al. [8] utilized a novel approach known as the in order to improve achievement, the Principal Components of Heart Failure (PCHF) feature design approach identified the most salient aspects and recommended a comparison of nine machine learning-based approaches. The author created a new feature set to improve the recommended procedure in an inventive attempt to achieve the highest accuracy ratings. The newly created dataset, which is based on eight of the best-fit characteristics, was tested for algorithmic efficiency through numerous runs.

Huazhong et al. [9] the most sophisticated hyper parameter optimization framework (OPTUNA), was used to optimize the prediction model's hyper parameters. The focused loss (FL) is the term used to describe the improved loss function. The Framingham Heart Institute's CHD data was used in this study to assess a prediction model. AUC, sensitivity, specificity, recall, F score, accuracy, Matthew's correlation coefficient, precision, and accuracy were among the metrics used to assess the prediction model's performance.

Ankit et al. [10] used python to create a cardiovascular disease clinical decision-making system (HDCDSS), with Flask serving as the Python web server Management Interface and Bootstrap offering data visualization. Data was stored in MongoDB. The HDCDSS makes it simple and useful for healthcare providers to assess a patient's potential. The two publicly accessible datasets used in this study are Cleveland and Stat Logs. The calculations include irregular forest land, decision trees, multi-facet perceptual neurons, strategy relapse, Naive Bayes, and SVM.

Mana et al. [11] proposed Hybrid Deep Neural Network (HDNN) system has a lot of potential to be integrated into healthcare systems in order to create sophisticated and trustworthy the prediction of heart disease models that can greatly aid in diagnosis and enhance patient care.

Nadeen et al. [12] developed an innovative stacking model called PaRSEL, which combines four different classifiers at the center layer: At the base layer, the classifiers are a passive aggressive Classification (PAC), Range Classifiers (RC), sequential Gradient Descent Classifiers (SGDC), and excessive gradient boost (XGBOOST). Logit Boost is utilized for the final prediction at the meta layer. It improves comprehension of the model's internal operations.

Abdulwahab et al. [13] objective is to make the simulation applicable and user-friendly in practical instances, expanding on earlier work by devising a fresh and original method of model creation.

Ghulab et al. [14] determined that the Extreme gradient booster Classification with Guided Searching CV provides the highest and nearly identical training and testing accuracies of 100% and 99.03% for the two sets of data (the country of Hungary, Switzerland & Long Beach, respectively V and UCI).

Ghulab et al. [15] studied different datasets have distinct attribute categories, the performance of different layer combinations differs as well. The final results of the suggested framework are evaluated through a thorough testing process. The study's findings demonstrate that, in comparison to individual models and other ensemble approaches, the deep learning model proposed in this research paper achieves greater precision, specificity, and sensitivity when compared across all heart disease datasets.

III. EXISTING SYSTEM

Multiple variables have given rise to the application of neural networks. This covers a range of topics, from comprehending and modeling the human brain to more general ones. That is the imitation of human functions like speech and application in several domains. Neural networks are often made up of layers upon layers of connected nodes. The nonlinear function of each node's input is produced. Furthermore, a node's input can originate from its own input data or from other nodes. A few nodes are additionally recognized by the network's output. This explains the variety of uses for neural networks that exist today.

1. Clinical Decision Support: The clinical decision-making system tools that healthcare professionals employ have certain integrated CVD prediction systems. These technologies let healthcare workers make well-informed judgments about treatment plans and preventive measures based on patient danger profiles.

2. Personalized Risk Assessment: Personalized risk assessment—where prediction algorithms consider individual attributes and adjust risk estimations accordingly—is becoming more and more prevalent. More precise risk assessment as well as targeted procedures are made possible by this method.

3. Integration of Genetic Information: Certain sophisticated prediction systems integrate genetic data into their models, such as SNPs, which are single nucleotide linked to heightened risk of cardiovascular disease (CVD). In order to increase predictive accuracy, genetic risk scores are mixed with conventional risk variables, which are derived from an individual's genetic profile.

4. Validation and Calibration: To make sure that prediction models are accurate and can be used to a variety of populations, validation is essential. The receiver's characteristic area under its operating curve (AUC-ROC). Sensitivity, and specificity are examples of performance metrics that are usually measured when validating models using different datasets. The agreement between the observed and expected risks—referred to as calibration—is also assessed.

5. Predictive Models and Scores: To calculate a person's chance of getting cardiovascular disease (CVD) over a specific time frame, several prediction models and scores have been created and verified. A few examples are the Reynolds Risk Score, the Framingham Risk Score, the Pooled Longitudinal Equations, and the SCORE (Systematic Coronary Risk Evaluation) algorithm. To give a thorough risk assessment, these models frequently incorporate a number of risk factors.

That include identifying patterns and coming to basic conclusions about them. The appropriate accuracy of heart disease prediction can be predicted using a variety of various sorts of algorithms.

IV. PROPOSED SYSTEM

A significant dataset of patient data, including demographics, medical histories, lab test results, and may be genetic information, was collected for this project. Take care of missing numbers, discrepancies, and outliers to guarantee the quality of the information you have. Scaled numerical features and carried out immediate encoding for variables with categories as part of the preprocessing step. Raw data can be used to teach deep learning models new characteristics. Domain expertise, however, might be applied to provide new characteristics that could enhance model performance. Divide the data into sets for testing, validation, and training. Utilizing the validation set to optimize hyper parameters, train the model on the training set. Keep an eye on the training process to make sure the prediction generalizes well and avoid overfitting.

Explore methods that include transfer learning, which optimizes a previously trained model for CVD risk prediction on an analogous task. By doing so, performance may be enhanced by utilizing the power of big datasets. Provide a smooth way for the deep learning model to be integrated into the current clinical processes so that doctors may use it with ease. To improve the accuracy of risk prediction, take into account additional sources of information such as social media, socioeconomic variables, and environmental factors. Use cutting-edge XAI techniques to learn more about the model's process of decision-making and help patients and medical professionals trust and understand its forecasts. Make certain that the deep learning framework complies with all applicable laws on the creation and use of medical devices.

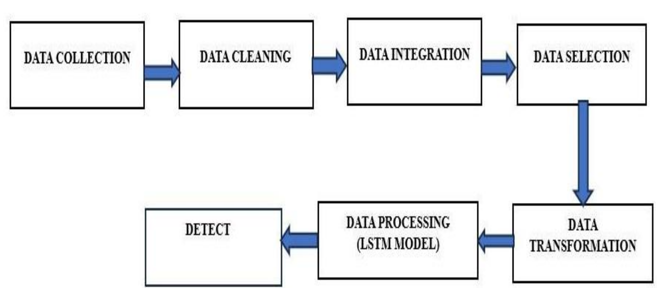


Fig 1: Workflow of Cardio Vascular Disease Prediction

1. Data Collection

When utilizing deep learning for cardiovascular disease (CVD) risk prediction, gathering data is essential for multiple reasons:

1. Training Data: To create a representative and diverse dataset is the primary objective of data collection with pertinent details regarding people's health, way of life, and medical background. With the help of this dataset, deep learning models are trained to correctly predict the risk of cardiovascular illness from input feature data.

2. Feature Representation: In order for deep learning models to identify intricate patterns and connections between input features and the target variable (in this example, CVD risk), a substantial quantity of data is needed. Gathering data makes sure that many aspects, including lifestyle choices, physiological measurements, medical history, and demographics, that may impact the risk of CVD are sufficiently varied and covered.

3. Model Generalization: Gathering information from a heterogeneous population makes it more likely that the deep learning models that have been trained will make a good generalization to unobserved individuals or communities. The models have the potential to yield precise forecasts for different patient groups since they encompass a broad spectrum of demographic, regional, and clinical data.

4. Model Calibration: In order to account for biases or fluctuations in the data, deep learning models can also be more easily calibrated with the help of data collecting. Researchers can handle problems like data imbalance, selection bias, or data drift, which could impair the performance of the model, by gathering data from several sources or changing the sampling technique.

5. Model Evaluation: To assess how well deep learning models are performing, gathered data is necessary. The accuracy, sensitivity, specificity, and other performance parameters of the model are evaluated by researchers using distinct validation and test datasets. The validity and reliability of these assessment metrics are directly impacted by the caliber of the data that was gathered.

6. Improving Model Interpretability: To encourage deeper learning models to be more interpretable, data collection activities may involve gathering more annotations or labels. Researchers may be able to determine which factors most significantly influence CVD risk projections by, for example, compiling expert annotations for particular features or results.

Overall, the goal of data collection in a deep learning-based cardiovascular disease risk prediction system is to supply the required inputs for training, assessing, and refining predictive models that aid medical personnel in identifying people who are at high risk of developing cardiovascular disease and successfully implement preventive interventions.

2. Data Cleaning

In order to forecast the risk of cardiovascular disease using deep learning, data cleaning aims to remove errors, inconsistencies, and missing values from the dataset. There are multiple steps involved in data cleansing, which include:

Eliminating Duplicates: Finding and removing duplicate entries to prevent the model from becoming biased.

Managing Missing Values: To keep missing data points from impairing the performance of the model, impute or remove them.

Error Correction: Finding and fixing typos and outliers in the dataset to guarantee data accuracy.

Formatting Standards: To make model training and interpretation easier, it is important to maintain uniformity in data formats and units across various variables.

In order to train the deep learning model on high-quality data and produce more accurate and dependable predictions of the risk of cardiovascular disease, researchers can ensure that data cleaning is performed. Data that is noisy or inconsistent is removed.

3. Data Integration

Integrating data from various sources, including demographics, medical histories, genetic information, lifestyle factors, and clinical measurements, into a single dataset is the goal of data integration in deep learning-based cardiovascular disease risk prediction. Numerous data are merged from various sources. Because of this integrated dataset, deep learning models are able to learn more intricate linkages and patterns, which improves the accuracy of risk predictions. The model can improve its predictive power and capture a wider range of risk factors by utilizing a variety of data sources.

4. Data Selection

When using deep learning to predict the risk of cardiovascular disease, data selection seeks to find and include pertinent features or variables that are most instructive for the prediction task. Data that are closely related to one another are examined and extracted from the database

This procedure entails choosing characteristics or data points, such as age, gender, blood pressure, cholesterol, smoking status, and family history of heart disease, that significantly affect cardiovascular health outcomes. Data selection enhances the efficacy and efficiency of the deep learning model by concentrating on the most pertinent information while minimizing noise and extraneous information that may otherwise impair prediction accuracy. It can also aid in reducing problems with overfitting and data imbalance, which will ultimately result in more accurate risk assessments.

5. Data Transformation

Data transformation has multiple uses in the deep learning-based risk prediction of cardiovascular disease:

The procedure of normalization involves adjusting numerical properties to a reference range, like between 0 and 1, in order to keep characteristics with bigger magnitudes from taking center stage during training. Normalization guarantees that every feature contributes equitably to the prediction and enhances the convergence of deep learning algorithms. Applying aggregate or summary procedures to the data in order to reinforce and transform it.

Encoding Categorical Variables: Transferring categorical variables to a numerical representation so deep learning algorithms can handle them. In order to enable the model to interpret categorical input as meaningful numerical representations, usually one-hot encoding or label encoding approaches are used.

Feature Engineering: Increasing the model's capacity for prediction by adding new features or changing current ones. Polynomial features, interaction terms, and transformations such as logarithmic or square- root transformations can be employed in feature engineering techniques to capture nonlinear interactions between variables.

Dimensionality Reduction: Minimizing the number of characteristics in the dataset while keeping the most crucial data. Without compromising predictive performance, strategies such as feature selection and principal component analysis, or PCA techniques assist lessen the effects of dimensionality and increase computational efficiency.

6. Data Processing (LSTM model)

Sequential data in networks with LSTM (long short-term memory) needs to be prepared through data processing for validation, training, and testing. Speech recognition, processing of natural language, and time series prediction are just a few of the sequence prediction applications that frequently use recurrent neural networks, or RNNs, with short-term and long-term memory (LSTMs).

Improving the understanding as well as effectiveness of Long Short-Term Memory (LSTM) frameworks for cardiovascular disease (CVD) risk prediction, an attention mechanism can be a useful addition. An LSTM model for CVD risk prediction may include an attention layer for a number of reasons:

1. Importance of Features: It can be useful to determine which characteristics—such as age, blood pressure, cholesterol, and so on—have a greater bearing on the likelihood of developing cardiovascular illnesses. Understanding which characteristics contribute more significantly to a patient's risk profile can be critical for clinicians.

2. Temporal Attention: In the context of Long Short-Term Memory (LSTM), attention processes might assist the model in concentrating on specific time steps or intervals that are more important for making predictions. This is crucial for the prediction of CVD because specific trends or variations in health markers across time may be more suggestive of risk.

3. Interpretable Prediction: Clinicians are able to comprehend the reasoning behind the model's specific forecast for a patient by observing the attention weights. For machine learning algorithms to be adopted in healthcare settings and to foster trust, openness is essential.

4. Performance Improvement: By permitting the model to selectively concentrate on pertinent data while disregarding noise or extraneous characteristics, attention mechanisms can enhance the prediction performance of the model.

In order to incorporate an attention layer into an LSTM model for predicting CVD risk, algorithms that dynamically assess the significance of input characteristics or time steps must be added to the LSTM architecture. This is often accomplished by attaching attention weights to the hidden states of the LSTM, which are determined using parameters that have been learned.

An LSTM model for CVD risk prediction could be implemented with an attention layer in the following general ways:

1. Input Processing: Prepare the data for the LSTM model by processing the input (such as patient demographics, vital signs, and test results).

2. LSTM Layer: Employ an LSTM layer to identify temporal correlations within the data.

3. Attention Mechanism: To calculate attention weights across the LSTM outputs, create an attention mechanism. This can entail a number of techniques, including additive attention, dot product attention, and other attention mechanisms.

4. Weighted Sum: To create a weighted sum that highlights the most pertinent information, combine the attention weights and the LSTM outputs.

5. Prediction: For the ultimate risk prediction, feed the weighted total into layers that come after (like fully linked layers).

The effectiveness of LSTM models in predicting risk of CVD can be improved, new information about risk variables can be obtained, and forecasts can be easier for doctors and patients to understand when attention processes are included.

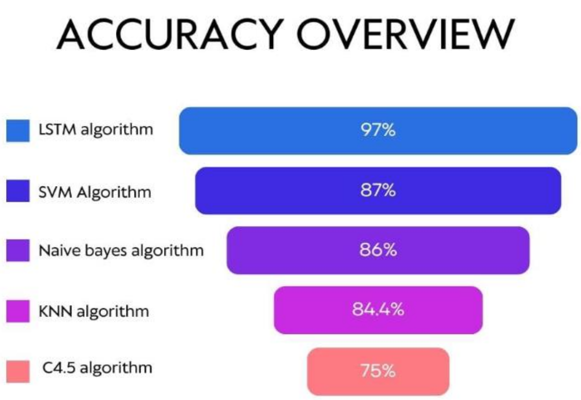
You can enhance model performance, obtain knowledge of the variables impacting risk, and improve the readability of forecasts for patients and doctors by adding attention mechanisms to LSTM models for CVD risk prediction.

7. Detect:

Users may be able to provide detailed reviews or comments about specific search results. These qualitative remarks may offer valuable insights into the reasons behind people's perceptions of the relevance or utility of specific content.

V. RESULT AND DISCUSSION

We used Keras 2.2.2 to execute all of the strategies based on data that was taken from the Xiangya Medical Dataset. The testing, validation, and training subsets also have their own sizes of 102,407, 14,630, and 29,259 after we divided the dataset at random into these three subsets (0.7:0.1:0.2). 100 iterations and 1,024 sequences per epoch are used to train each predictive model in a mini-batch fashion. Our work involved dividing the data into independent groups and testing and training each model ten times in order to improve its generalization performance. The mean assessment metrics for the ten test results are finally reported.



When compared to other methods like SVM algorithm, Navies Bayes Algorithm algorithm and C4.5 algorithm, our proposed method achieved the accuracy 97%.

VI. CONCLUSION AND FUTURE WORK

This work builds an Attention-LSTM model by appending an attention layer to the pre-existing LSTM model. Furthermore, experiments confirm the accuracy of long-sequence data prediction. We presented the Attention-LSTM model construction process and used actual CVD data sets to validate the model's performance. Experiments demonstrate that our suggested plan increases prediction accuracy. This study solely looked at using the attention layer model on time series data. We can apply attention mechanisms to the spatial correlation of traffic flow in future studies.

REFERENCES

[1] Nidhi Sinha, M. A. Ganesh Kumar, Amit M. Joshi, Linga Reddy Cenkeramaddi, "DASMcC: Data Augmented SMOTE Multi-Class Classifier for Prediction of Cardiovascular Diseases Using Time Series Features" ,Volume 11 ,IEEE Access, 2023.

[2] Rushuang Zhou, Lei Lu, Zijun Liu, Ting Xiang, Zhen Liang, David A. clifon, Yining Dong, Yuan-Ting Zhang," Semi-Supervised Learning for Multi-Label Cardiovascular Disease Prediction: A Multi-Dataset Study", Volume 46, Issue 5, IEEE,2024.

[3] Gihun Joo, Yeongjin Song, Hyeonseung Im, Junbeom Park ,"Clinical Implication of Machine Learning in Predicting the Occurrence of Cardiovascular Disease Using Big Data ",Volume 8,IEEE,2020.

[4] Christos P. Loizou, Efthyvoulos Kyriacou, Maura N. Nicolaides, Constantinos, "Association of Intima-Media Texture with Prevalence of Clinical Cardiovascular Disease", Volume 68,Issue 9,IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control ,2021.

[5] Sara Ghorashi, Khunsa Rehman, Anam Riaz, Hend Khalid Alkahtani, Ahmed H. Samak, Van Cherrez-Ojeda, Amna Parveen," Leveraging Regression Analysis to Predict Overlapping Symptoms of Cardiovascular Diseases", Volume 11, IEEE,2023.

[6] Ying An, Nengjun Huang, Xianlai Chen, Fangxiang Wu, Jianxin Wang," High-Risk Prediction of Cardiovascular Diseases via Attention-Based Deep Neural Network", Volume 18, Issue 3, IEEE,2021.

[7]AqsaRahim,YawarRasheed,Farooque,Azam,Muhammad,WaseemAnwar Muhammad Abdul Rahim,Abdul Wahab Muzaffar," An Integrated Machine Learning Framework for Effective Prediction of Cardiovascular Diseases", Volume 9,IEEE,2021 .

[8] Azam Mehmood Qadri, Ali Raza, Kashif Munir, Mubarak S. Almutairi," Effective Feature Engineering Technique for Heart Disease Prediction With Machine Learning", Volume 11,pp.56214-56224,IEEE,2023.

[9] Huazhong Yang, Zhongju Chen, Huajian Yang, Maojin Tian," Predicting Coronary Heart Disease Using an Improved LightGBM Model: Performance Analysis and Comparison",IEEE,2023.

[10] Ankit Kumar, Kamred Udham Singh, Manish Kumar," A Clinical Data Analysis Based Diagnostic Systems for Heart Disease Prediction Using Ensemble Method" ,Volume 6,Issue 4,IEEE,2023.

[11] Mana Saleh Al Reshan, Samina Amin, Muhammad AliZeb, Adel Sulaiman, Hani Alshahrani, Asadullah Shaikh, "A Robust Heart Disease Prediction System Using Hybrid Deep Neural Networks", Volume 11,IEEE,2023.

[12] Nadeem Javaid, Nadeem Javaid, Nabil Alrajeh, Babar Mansoor, Ali Khaqan, Safdar Hussain Bouk, "Heart Disease Prediction Using Stacking Model With Balancing Techniques and Dimensionality Reduction", Volume 11, IEEE Access, 2023.

[13] Abdulwahab Ali Almazroi, Eman A. Aldhahri, Saba Bashir, Sufyan Ashfaq, "A Clinical Decision Support System for Heart Disease Prediction Using Deep Learning", Volume 11,IEEE Access,2023.

[14] Ghulab Nabi Ahmad, Hira Fatima, Shafi Ullah, Abdelaziz Salah Saidi, Imdadullah,"Efficient Medical Diagnosis of Human Heart Diseases Using Machine Learning Techniques With and Without GridSearchCV", Volume 10, IEEE Access, 2022.

[15] Ghulab Nabi Ahmad, Shafi Ullah, Abdullah Algethami, Hira Fatima, Syed Md. Humayun Akhter," Comparative Study of Optimum Medical Diagnosis of Human Heart Disease Using Machine Learning Technique with and without Sequential Feature Selection", Volume 10, IEEE Access, 2022.