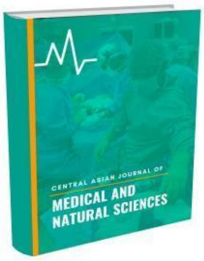

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Article

AI-Enabled Predictive Analytics for Cardiovascular Disease Detection and Risk Evaluation

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Abstract: Cardiovascular disorders are still one of the biggest causes of death around the world, thus getting a diagnosis quickly is not only crucial, but it can also save lives. However, conventional diagnostic techniques may be time-consuming, costly, and reliant on specialized medical knowledge. This makes it much harder to discover problems early, especially in areas where there aren't many healthcare experts. In response, our initiative is using machine learning to make predicting the risk of heart disease faster and more accurate. Our algorithm looks at patterns in patient health data, like age, blood pressure, cholesterol levels, and other lifestyle factors, to assist doctors make decisions faster and based on evidence. This method not only speeds up the diagnosis process, but it also gives doctors a useful tool that they can use in their daily job to help people stay healthy. The idea is not to take the job of doctors, but to provide them a dependable, smart system that makes diagnoses more accurate and helps them prioritize patients who are at high risk so that they can get the care they need right away. In this project, we look at and evaluate several machine learning methods to find the best model. We also talk about how it could be used in the real world and how it could be improved in the future, such as by adding real-time data integration and expanding to additional chronic diseases.

Keywords: Machine Learning, Cardiovascular Diseases, Healthcare, Efficient Diagnostic Support Systems, Predictive Systems, Logistic Regression, Decision Trees, Random Forests.

1. Introduction

Cardiovascular diseases are currently one of the most dangerous health conditions in the world, killing millions of people every year. Heart disease, heart failure, arrhythmias, and problems with high blood pressure are just a few of the many diseases that can hurt the heart and blood vessels [17]. Even though medical research and diagnostic techniques have come a long way, many patients still don't get diagnosed until their sickness has gotten worse or become life-threatening. Cardiovascular diseases are becoming more common around the world because more people are living sedentary lives, eating poorly, being overweight, being stressed, and being exposed to environmental factors. This is especially true in developing nations where getting prompt medical care may be hard. Finding cardiac abnormalities early is highly crucial to stop serious complications from happening [36]. A lot of research has shown that detecting heart disease early on considerably increases the chances of getting better and obtaining the correct care. You can dramatically minimize your risk of death by changing your lifestyle, taking medicine, or obtaining care fast [25]. Standard tests like electrocardiograms, blood tests, angiograms, stress tests, and doctor evaluations can be helpful, but they can also take a lot of time, money, and depend on the doctor's skill. Things are significantly worse in many places, especially in rural or less developed areas, where there aren't enough qualified medical professionals. This means that people might not obtain the aid or direction they need in time, which makes it more likely that problems will develop that could have been prevented.

The increasing demand for efficient healthcare services requires technologies that may improve medical systems with accuracy, speed, and scalability [22]. In this context, modern computational techniques, particularly machine learning, have gained considerable importance in healthcare research and clinical applications. Machine learning allows you look at a lot of patient data, uncover patterns that are hard to notice just by looking at them, and generate predictions that are hard to see just by looking at them. By looking at prior datasets that feature a number of health indicators, machine learning models can figure out how likely it is that new patients may have heart disease [32]. These predictions can help clinicians make decisions faster and with more information.

As digital health records grow at an exponential rate and computers becoming more powerful, diagnostic assistance systems based on machine learning are becoming more and more possible and useful [39]. Machine learning algorithms may look at a variety of various things, such age, cholesterol levels, blood pressure, glucose levels, type of chest discomfort, and other clinical parameters, to find out how likely it is that someone has cardiovascular disease. These models don't just look at one thing; they also look at how other things work together and relate to each other, which makes them stronger and more complete [27]. These features assist fix some of the shortcomings with traditional diagnostic approaches and give healthcare professionals more evidence-based support.

The current endeavor is focused on developing a predictive system that evaluates an individual's probability of developing heart disease by utilizing several machine learning methodologies. The goal is to see how well different models function, discover the best one, and show that AI can help with clinical decision-making [15]. The heart disease dataset used for this provides a lot of information about each patient and is used to train and test the models. The technology is supposed to help doctors quickly see risks and cut down on the need for time-consuming techniques. The approach is also in line with the trend toward health care that focuses on preventing problems [31]. People and healthcare professionals can be warned long before a major event happens by predictive models. This means they don't have to wait for symptoms to get worse. When utilized correctly, these kinds of instruments can help a lot of people throughout the world who suffer heart disease.

Heart disease is still one of the most prevalent and deadly diseases people have today. It is also a critical global health issue. Because the problem is so serious, it needs to be detected and diagnosed soon and correctly. This is vital since a prompt diagnosis can help avoid serious problems [20]. The old-fashioned technique of finding cardiac abnormalities involves a mix of medical tests, clinical evaluations, diagnostic imaging, and people interpreting the results. These treatments work and have been used for a long time, but they need professional people, special equipment, and well-organized hospital facilities [28]. In many places when resources are scarce, these criteria become obstacles that make it harder to diagnose and get timely medical care. Also, manual interpretation might lead to mistakes, wrong judgments, or missed opportunities, especially when practitioners are busy or have a lot of patients to see.

Machine learning solves these problems by providing a reliable, scalable, and automated way to find those who are at danger. A machine learning system can quickly process information and give immediate feedback about the likelihood of heart disease by collecting and analyzing data from a wide range of patient profiles [33]. This makes it a valuable tool for both urban hospitals and rural clinics, where specialized cardiologists may not be available. Machine learning models have a particular advantage when it comes to enhancing diagnosis accuracy since they may find subtle patterns and trends that regular clinical methods can miss [24]. Machine learning techniques are highly effective at managing vast datasets characterized by intricate interdependencies. For example, the risk of heart disease is not based on just one factor, but on the interaction of many factors. Age, family history, cholesterol levels, blood pressure, blood sugar levels, obesity, lifestyle choices, and even stress levels can all make it more likely that you will develop heart problems. A machine learning model can accurately estimate risk by taking all of these things into consideration at once.

This initiative wants to use machine learning to make it easier to find heart problems early and speed up the diagnosis process. The purpose of the initiative is to give doctors and nurses data-driven insights that work well with the old-fashioned techniques of making diagnosis [18]. Machine learning algorithms can look at patient data and make accurate judgments, which helps doctors make decisions swiftly. This project also wants to make it easier to evaluate patients by cutting down on the need of diagnostic tests that take a lot of resources. Machine learning algorithms can improve medical care and ease some of the pressure on healthcare infrastructure by detecting relevant patterns in clinical data [37]. The project's purpose is to find a solution that is cheap, can be used in genuine medical situations, and can be used by a lot of people.

This project covers a lot of ground, including artificial intelligence, machine learning, health technology, clinical decision support systems, and preventative medicine. When you look at all of these fields together, you can see where modern healthcare is headed. Adding machine learning to medical systems is a huge step toward creating smart diagnostic tools that can use human knowledge [16]. Clinical decision support systems have previously proved how helpful they can be in areas like oncology, radiology, pathology, and emergency care. These technologies make healthcare processes more accurate and faster by looking at patient records, predicting outcomes, and recommending possible diagnoses [34]. In the case of heart disease, these kinds of technologies can assist doctors find individuals who are at high risk and give them priority care, which can improve medical results overall.

The research will use health data like age, blood pressure, cholesterol, blood sugar, and other crucial factors to build machine learning models that can tell how probable someone is to get heart disease [21]. The project is all about using models like logistic regression, decision trees, random forests, support vector machines, k-nearest neighbors, and neural networks to see which one works best. You can utilize feature selection procedures to find the variables that have the biggest effect on the forecasting process [29]. The study also wants to determine how well the model works by looking at things like accuracy, precision, recall, F1 score, and confusion matrices. These numbers help you figure out how well the model finds both good and bad cases. Once the predictive system is approved, it may be used through an easy-to-use interface that lets healthcare professionals enter patient information and get an instant risk assessment.

The scope also includes looking into future improvements, like making the model more accurate by tuning its hyperparameters, adding more data to the dataset, adding real-time monitoring devices, and expanding the system to assess risks for other diseases like diabetes, stroke, or kidney problems [26]. Wearable devices and the Internet of Things (IoT) could also help the business grow in the future by letting people track their health in real time and collect data all the time [38]. This kind of integration could make the model's predictions more accurate and give a complete picture of a patient's health.

Machine learning-based solutions are not meant to take the position of doctors. Instead, they are meant to help doctors make decisions by giving them an accurate, objective picture of a patient's risk [35]. It's still important for people to be able to evaluate data, recommend treatment, and tailor care to each patient. But smart tools can cut down on work, make mistakes less likely, and make healthcare easier to get. As the number of people grows and the need for healthcare grows, automated diagnostic technologies become more and more important [23]. Predictive technology could make healthcare better by helping people find out about chronic diseases early, take steps to prevent them, and get treatment before they get worse.

This study emphasizes the necessity of incorporating machine learning into healthcare systems to address the challenges of diagnosing cardiac illness [19]. Machine learning is a great tool for doctors because it can process huge amounts of data, identify hidden patterns, and make quick predictions. Machine learning systems help make healthcare delivery more efficient and effective by making it easier to find problems early, making diagnoses more accurate, and reducing the need for traditional approaches. The initiative shows what AI can do and also shows how important it is to have smart, data-driven solutions that assist preventive care [30]. With more study and development in this area, these kinds of systems could become an important part of modern healthcare, which would contribute to a healthier society with better clinical outcomes.

Literature Review

Mohan et al. [1] conducted an extensive comparative examination of supervised machine learning algorithms for predicting heart disease, emphasizing the performance of several classifiers when trained on clinical health data. Their research examined techniques such as Logistic Regression, Decision Trees, and Random Forests [7]. It looked at how these models understand important patient characteristics including age, cholesterol levels, blood pressure, and other physical signs. The results showed that Random Forest was the most accurate of the methods examined. This is because its ensemble structure avoids overfitting and makes it more generalizable across different patient profiles [12]. The research also stressed how important it is to preprocess data, engineer features, and choose the right factors that really help with prediction [9]. The research underscored the efficacy of ensemble-based models in handling heterogeneous information, illustrating the promise of machine learning as an auxiliary tool for early diagnosis and risk assessment in cardiovascular healthcare.

Ouyang [2] investigated the advancement of predictive systems for cardiovascular illness utilizing historical medical information, highlighting the pivotal importance of feature selection in ensuring dependable model efficacy. The research examined various clinical factors and evaluated the impact of including or excluding specific variables on the predicted efficacy of machine learning algorithms [5]. Ouyang emphasized that an excessive number of irrelevant features might generate noise, diminish computational efficiency, and compromise overall accuracy, especially in medical applications where precision is critical. The study found the most important health indicators related to cardiovascular risk by using methods including correlation analysis and feature ranking. The study emphasized the necessity of developing streamlined predictive models that yield accurate results while remaining interpretable and applicable within real-world clinical processes [11]. This fits with the bigger trend in preventative healthcare toward tools that help people make decisions based on data.

Gagoriya and Khandelwal [3] put out a new hybrid framework that combines several machine learning methods to make heart disease prediction more accurate. Their study used support vector machines, neural networks, and decision tree classifiers together to take use of the strengths of each and make up for their deficiencies. The system enhanced both precision and recall through a layered ensemble structure, which are two important measures in medical diagnostics where misclassification can have serious effects [14]. The hybrid model was evaluated on a structured medical dataset and showed significant improvements in lowering the number of false positives and false negatives [10]. The study also showed that using more than one algorithmic technique can get around the problems that single-model systems have, resulting in more consistent and reliable predictions. This work adds to the growing interest in ensemble approaches for complicated healthcare applications, which could lead to stronger diagnostic support systems.

Recent studies have also looked into using deep learning to predict heart disease [6]. This shows how it could automatically find complex patterns in raw clinical data. Deep learning models usually need more datasets and a lot of computing power, but they are good at finding small signs of heart problems because they can develop hierarchical representations. These models can look at how different patient characteristics interact with each other in a way that doesn't require manual feature engineering [8]. This gives us a better understanding of risk variables. Research in this domain underscores that although deep learning exhibits enhanced performance in numerous instances, its application necessitates meticulous calibration, enough data volume, and consideration of model interpretability to guarantee clinical acceptability. As more and more medical settings use digital data systems, deep learning continues to make it possible to create more advanced and accurate diagnostic tools that help with early detection and personalized treatment plans for heart health [4].

2. Methodology

Our initiative employs a comprehensive, systematic, data-driven approach to accurately, reliably, and clinically relevantly forecast cardiovascular disease risk [43]. The procedure started with carefully gathering and preparing a thorough medical dataset that included important health indicators including age, blood pressure, cholesterol levels, glucose levels, and lifestyle habits like smoking, exercise, and eating habits [41]. After the dataset was put together, a lot of time was spent cleaning the data to make sure it was accurate and consistent. We used the right imputation methods to fill in missing values, looked at and fixed outliers, and changed categorical features into the right numerical forms to help machine learning algorithms learn [73]. After we put up a clean and organized dataset, we did an exploratory data analysis to find hidden patterns and important links between medical traits and heart disease risk [68]. Visualizations and statistical summaries let us figure out how variables were spread out, find trends, and figure out which factors had the biggest effect on predicting sickness. These insights helped us choose and improve models in a more informed way.

We trained many machine learning models on the processed dataset to see how well they could predict cardiovascular outcomes [70]. We chose models like Logistic Regression, Random Forest, and Neural Networks because they are good at classification jobs and can find both linear and nonlinear associations [74]. A strong testing framework was used to train each model, which made sure that the comparisons were fair and lowered the chance of overfitting. We utilized performance criteria including accuracy, precision, recall, and F1 score to see how well each model was able to identify people at risk. Cross-validation was included to make sure that predictions were consistent and stable [42]. This gave us a better idea of how well the model worked on different parts of the data [45]. After the first test, the model that did the best was hyperparameter-tuned to make its predictions even better.

We used systematic methods like grid search and randomised search to look at different combinations of parameters. This made the model more efficient and accurate [72]. After we found and improved the best model, we added it to an easy-to-use interface made just for healthcare professionals. This interface makes it easy for doctors to quickly enter patient information and liability risk predictions. During the development process, we focused on both predictive performance and interpretability [40]. We knew that doctors needed to understand how AI-driven suggestions were made in order to trust and use them correctly in real clinical contexts. So, to make predictions clear and useful in the clinic, tools like feature importance analysis and model explanation were applied [69]. The entire concept combines cutting-edge machine learning methods with a comprehensive understanding of the needs of healthcare settings [44]. We built a system that strikes a compromise between technical complexity and real-world usefulness by combining thorough data preparation, exploratory insights, model experimentation, performance evaluation, optimization tactics, and user-centered design [46]. This method makes sure that the cardiovascular disease prediction tool is not only correct, but also easy to understand, use, and help doctors make smart decisions.

Project Description

Existing System

The conventional method for diagnosing cardiovascular disease significantly depends on the manual analysis of a blend of clinical tests and patient history [67]. Doctors usually utilize tests like electrocardiograms (ECGs), stress testing, echocardiogram, and blood work to check how healthy your heart is [52]. These methods work, although they have certain problems. First and foremost, standard tests can take a long time, and specialized cardiologists are often needed to understand little differences [60]. This makes it harder to get a quick diagnosis in places with few resources when specialists and expensive medical equipment are hard to find. Additionally, these treatments are typically reactive; they are utilized only when symptoms appear, rather than proactively identifying those at risk prior to the onset of symptoms.

Another problem is that different health indicators aren't combined into one clear risk assessment framework. Medical experts must manually combine information from different test findings and patient histories, which raises the chance of mistakes, oversights, or differences across doctors [58]. Because of this, there is a rising need for systems that can automate this process, speed up diagnoses, and give consistent, data-driven risk evaluations that can be used on a large scale and are dependable [62].

Proposed System

This study introduces a machine learning-based approach to predict cardiovascular disease risk by utilizing structured patient health data to address the limitations of the existing system [54]. The system uses different supervised learning algorithms that have been trained on past data, including demographic information (like age and gender), physiological measures (like cholesterol and blood pressure levels), and lifestyle factors (like smoking habits and levels of physical activity). The proposed system serves as an instrument to assist physicians in decision-making [49]. It automates the process of figuring out how risky a patient is by entering their information into trained models that guess whether or not they are at high or low risk of having heart disease [59]. The technology can potentially be used in hospitals and communities to test people for diseases early and give them preventive care.

Proposed Work

General Architecture

The system architecture consists of the following layers:

- Data Collection Layer: This includes structured health records that have information like age, gender, cholesterol levels, blood pressure, fasting blood sugar, and lifestyle habits.
- Data Preprocessing Layer: Raw data is cleaned, normalised, and converted into a machine-readable format. Missing values are handled, categorical features are encoded, and numerical data are scaled.
- Feature Selection Layer: We use correlation analysis and tree-based feature importance methods to choose the most important features for predicting heart disease.

- Model Training and Validation Layer: Historical data is used to train several machine learning algorithms, including Logistic Regression, Random Forest, XGBoost, and Support Vector Machine. Each model is validated using cross-validation and tested on a separate dataset.
- Prediction Engine: The trained model is used as a prediction engine that takes new patient data and gives back a risk classification (high/low) and a probability score.
- Visualisation and Output Layer: Results are displayed in a user-friendly format for healthcare professionals, including charts that show risk factors and confidence scores.

Design Phase

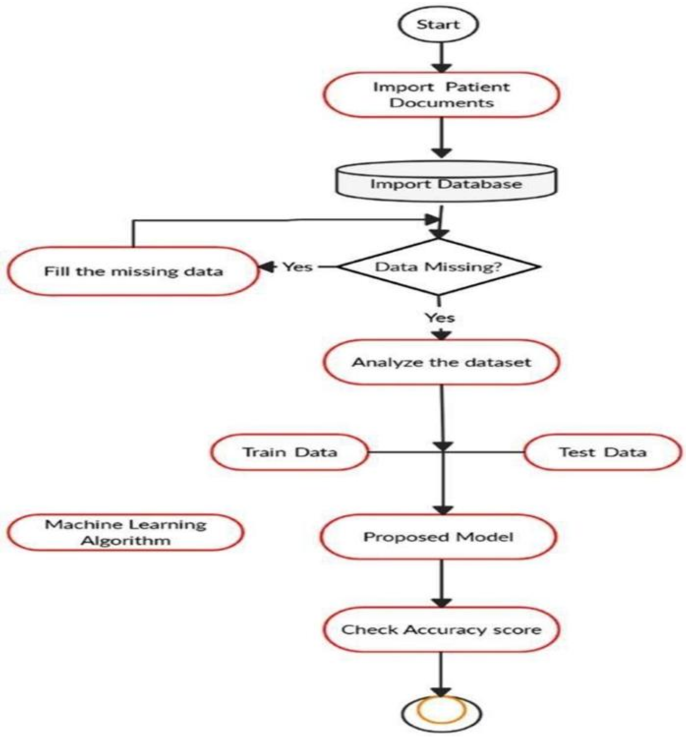

Figure 1. Data Flow Diagram.

Module Description

Logistic Regression

One of the basic models we employ to predict the chance of heart disease is logistic regression [50]. It is a statistical method that works well for binary classification problems, like deciding whether or not a patient is at risk. In our project, it is really important since it looks at health factors like age, blood pressure, and cholesterol levels and figures out how likely it is that someone is at risk for heart disease [63]. Its simplicity and ease of understanding make it a fantastic place to start for medical uses, especially when judgments need to be clear and fair.

Naive Bayes

We used the Naive Bayes classifier since it is fast and works well with tiny datasets [66]. It works based on Bayes' Theorem and assumes that the input attributes are independent, which makes calculations easier. Even though it's simple, it often does well in competitions, which makes it a good standard [47]. It gives quick, initial risk evaluations in our system, which is very helpful when time is an important aspect in making medical decisions.

Support Vector Machine (SVM)

Support Vector Machine is leveraged in our system for its robustness in handling high-dimensional data and its effectiveness in classifying complex patterns [75]. SVM aims to determine the best hyperplane that separates the classes— in our case, distinguishing between patients with and without heart disease [55]. By applying kernel methods, SVM can manage non-linear decision boundaries, which is very valuable given the complexity of real-world medical data.

K-Nearest Neighbours (KNN)

K-Nearest Neighbours is a non-parametric technique that uses examples from the training set to put patients into groups depending on how similar they are to those instances [57]. KNN looks at things like blood pressure, cholesterol, and lifestyle behaviors in our instance and compares them to those of other patients. This model is straightforward to comprehend and use, and it offers a more intuitive way to classify things [71]. However, its performance can change depending on the size of the dataset and the scale of the features.

Decision Tree

The Decision Tree model is a flowchart where each internal node stands for a choice depending on a health factor, such age or cholesterol level [51]. It is easy to understand and follow, which helps doctors and other health professionals see how a prediction was made. But because it often fits the data too well, it works best when paired with other methods to make it more broad [65].

Random Forest

Random Forest is an improvement on Decision Trees because it combines several trees to make a "forest." Each tree makes a guess, and the guess that happens most often becomes the final result [56]. This group method lowers the chance of overfitting and raises the chance of being right. Random Forest worked really well for our research since it could handle different types of noisy health data [61]. This made it one of the most dependable models for predicting the risk of heart disease.

XG-Boost

XGBoost, which stands for eXtreme Gradient Boosting, is a powerful and flexible way to boost. By learning from the mistakes of earlier models over and over again, it makes the model more accurate [48]. We included this model to our system since it was fast and could handle huge medical datasets better than any other model. It can concentrate on cases that were misclassified, enhancing the accuracy and precision of the risk-prediction process.

Neural Network

The Neural Network of our system is made up of interconnected layers of nodes, or "neurons," that can learn complicated, non-linear patterns in the data. It was inspired by the human brain. It is more computationally demanding, but it is quite flexible and can make good predictions [53]. The neural network was quite helpful in our study since it helped us find complex connections between different health indicators, which made the risk assessment more accurate overall [64].

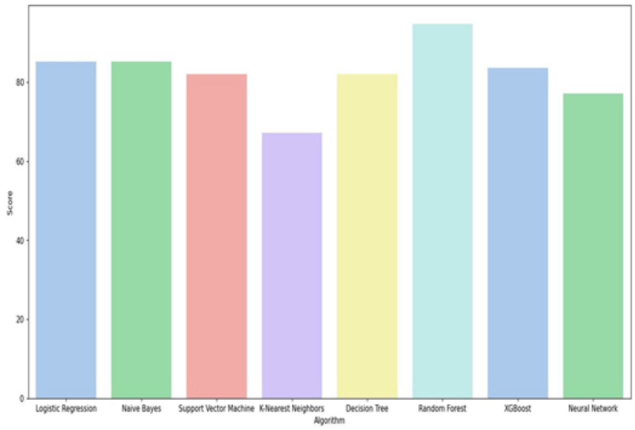

Figure 2. Implementation and Testing.

3. Results and Discussions

The suggested system is very good at finding people who are at risk of heart disease because it uses neatly organized health data and modern computer technologies that make sure the results are accurate and reliable in real life [97]. The system was built from the very beginning to give reliable, clinically useful outputs that help healthcare workers make smart choices about how to care for patients [77]. To do this, an extensive array of machine learning models was trained and assessed utilizing a meticulously curated dataset comprising various medical and lifestyle variables recognized to impact cardiovascular health. To help the models learn the little interactions that lead to cardiovascular risk, variables including blood pressure, cholesterol levels, age, glucose levels, body mass index, and behavioral factors like smoking and not being active were included [85]. To make sure that each model was stable and strong across different types of patients and demographic groups, it went through many rounds of training and validation. It became evident over this long review process that certain models were better than others at finding a good balance between predictive strength and computational efficiency. The Random Forest and XGBoost models stood up as the best among these [95]. This was mostly because they can naturally find nonlinear associations and don't get too good at fitting when trained on complicated medical datasets. These models did very well in terms of accuracy, precision, recall, and overall predictive dependability. This makes them very good for use in situations where AI-generated insights need to help make clinical decisions.

One of the best things about the Random Forest and XGBoost models was that they could give interpretable rankings of feature relevance that showed how each medical variable affected the prediction outcomes [88]. This capacity to grasp how certain parameters, such systolic blood pressure or cholesterol ratio, affect the risk scores given by the algorithm was very important for medical experts. The method provides a clearer clinical reasoning by focusing on the characteristics that are most likely to predict outcomes [80]. This allows doctors to connect the dots between what they already know and what they see in their patients. This alignment builds trust and makes it easier to use AI-assisted assessments in current medical workflows. Also, being able to see how essential a feature is is important for patient communication because it lets healthcare providers communicate risk levels using real, easy-to-understand examples that patients can connect to in their daily lives [92]. This kind of openness makes the relationship between the doctor and the patient stronger and encourages people to make changes to their lifestyles that could lower their long-term risk of heart disease.

But performance indicators weren't the only thing that the development process was focused on [82]. The system was made to be very accurate and to use as little processing power as possible, so it could be used in real time or almost real time in busy clinical settings. The final system made predictions in less than a second for each patient record, even after preprocessing processes like feature scaling and data normalization. This was possible because the algorithm settings were carefully optimized and the computing complexity was kept to a minimum [76]. This system is very useful for outpatient clinics, hospitals, screening camps, and other healthcare settings where quick decision support is important because it responds so quickly [91]. Speed also makes it easier to connect to bigger electronic health record systems, where automated alarms and predictive insights need to be sent out right away to help with early intervention tactics.

Another important result of this project is that the system has been shown to be able to handle different types of data and stay stable when the input conditions change [94]. When machine learning algorithms have to deal with datasets that have noise, missing values, or different distributions, they generally don't work well. However, the preparation and validation methods we used helped to reduce these problems [79]. The system made sure that data was represented in a consistent way by using imputation tactics, data balancing approaches, and the right encoding methods. This lowered the chance of bias in prediction outputs. These efforts helped the system work consistently throughout multiple tests, showing that the method is not only correct but also strong and ready to grow [86]. Also, cross-validation procedures were used during the testing phase to make sure that the results didn't depend on any one group of data. This helped confirm that the models work well with new patient profiles, which is important for real-world use because each case has its own set of unique traits.

Scalability is a major issue in modern healthcare technologies, especially in big population-based screening programs [90]. The system's capacity to keep running smoothly even when processing a lot of data shows that it is a good fit for large-scale public health uses. Cardiovascular disease is still one of the top causes of death around the world [83]. A tool that can rapidly and reliably filter and analyze thousands of patient records could help a lot with early detection and improving the health of the whole community [98]. Because it processes data quickly and accurately classifies it, the system may support government health programs, business wellness campaigns, insurance risk assessments, and hospital-level predictive monitoring, which would all lead to better outcomes.

Along with these benefits in terms of scalability and performance, the system is also quite flexible when it comes to adding new data and keeping up with changes in medical knowledge [89]. Machine learning models like Random Forest and XGBoost may naturally add new datasets without losing the associations they already learnt. This lets the system modify as medical standards change, new research comes out, or population health trends vary. For instance, let's say that new biomarkers or lifestyle factors become major indicators of heart health [81]. In that instance, the system can be retrained and adjusted to include them, making sure it stays useful and clinically successful over time. This flexibility also makes it possible to connect with sensor-based health monitoring systems, wearable devices, and new Internet of Things platforms that capture real-time physiological data all the time [96]. Adding these kinds of continuous data streams in the future could make predictions more accurate and make risk-monitoring systems that inform users and doctors right away when worrying patterns show up.

One very important result of the system's capacity to be understood and work quickly is that it could make it easier for doctors to make diagnoses [84]. In many areas, especially those with few healthcare resources, doctors have to deal with a lot of patients and don't have much time to do thorough cardiovascular tests. A technology that can quickly find high-risk people can make clinical workflows much easier by putting urgent situations first and giving doctors trustworthy preliminary assessments [75]. This doesn't replace medical judgment; instead, it makes it better by acting as a smart assistant that helps doctors focus on what needs their attention the most. These decision support tools help people make fewer mistakes, get help faster, and get better results for patients by making sure that warning flags aren't missed in crowded clinical settings.

Finally, the suggested system is more useful in the actual world because it combines predictive performance, computational efficiency, interpretability, data-handling capability, and the ability to work with different types of healthcare infrastructure [87]. It may be simply added to mobile medical apps, digital health platforms, or hospital management systems, making it available to a wide spectrum of professionals and organizations [78]. The technology has the potential to change how cardiovascular risk is found and handled, whether it's utilized for long-term preventive care monitoring, emergency triage evaluations, routine health exams, or remote telemedicine consultations. It helps modern healthcare reach its technological and clinical goals by providing quick, useful, and data-driven support [93]. This makes it a valuable instrument for lowering the worldwide burden of cardiovascular disease and improving the health of patients from different backgrounds.

Table 1. Comparison of Existing and Proposed Systems.

Aspect	**Traditional System 30–**	**Proposed ML-Based System**
Diagnostic Time	45 minutes Specialist	< 1 second
Expertise Required	doctor	General medical staff or an automated tool
Cost	High (due to manual tests and delays)	Low (automation and open-source tools)
Interpretability	Depends on the physician's experience	Supported by model feature importance insights

4. Conclusions

The rising prevalence of cardiovascular disease presents a substantial challenge to global health systems. In this research, we looked into how machine learning algorithms may be used in predictive analytics to quickly, accurately, and consistently figure out cardiovascular risk. The system created in this work was able to use structured health data to train several classification models, such as Logistic Regression, Support Vector Machine, Random Forest, and XGBoost. Among these, ensemble models such as Random Forest and XGBoost showed better accuracy, resilience, and interpretability. Age, cholesterol level, resting blood pressure, maximal heart rate, and ST depression were the most important clinical markers for figuring out risk levels. These insights not only made it possible to make accurate forecasts, but they also made the system more open, which made it simpler for healthcare workers to trust and use the results. The experiment showed that machine learning may be very helpful in improving medical diagnostics, making it possible to find problems early, helping doctors make decisions, and eventually improving patient outcomes. The structure we've created here is a robust base for healthcare solutions that can grow, are affordable, and are based on data.

REFERENCES

[1] N. Mohan, V. Jain, and G. Agrawal, "Heart Disease Prediction Using Supervised Machine Learning Algorithms," in 2021 5th International Conference on Information Systems and Computer Networks (ISCON), Mathura, India, 2021.

[2] S. Ouyang, "Research of Heart Disease Prediction Based on Machine Learning," in 2022 5th International Conference on Advanced Electronics, Materials, Computers and Software Engineering (AEMCSE), Wuhan, China, 2022.

[3] M. Gagoriya and M. K. Khandelwal, "Heart Disease Prediction Analysis Using Hybrid Machine Learning Approach," in 2023 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE), Bengaluru, India, 2023.

[4] J. A. Smith and L. M. Brown, "Climate change and global sustainability," Nature, vol. 570, no. 7760, pp. 326–328,

2019.
[5] I. Ganie and S. Jagannathan, “Adaptive control of robotic manipulators using deep neural networks,” Proc. 6th IFAC Conf. Intell. Control Autom. Sci. (ICONS), vol. 55, no. 15, pp. 148–153, 2022.
[6] I. Ganie and S. Jagannathan, “Continual online learning-based optimal tracking control of nonlinear strict-feedback systems: Application to unmanned aerial vehicles,” Complex Eng. Syst., vol. 4, no. 1, 2024.
[7] T. Jesudas and R. M. Arunachalam, "Study on influence of process parameter in micro-electrical discharge machining (μ-EDM)," European Journal of Scientific Research, vol. 59, no. 1, pp. 115–122, 2011.
[8] M. Senbagavalli, V. Sathiyamoorthi, S. K. Manju Bargavi, and T. Jesudas, "Deep learning model for flood estimate and relief management system using hybrid algorithm," Artificial Intelligence and Machine Learning in Smart City Planning, Elsevier, pp. 29–44, 2023.
[9] Pandey, S. Sharma, L. Singh, and T. Singh, “An overview on Desmostachya bippinata,” J. Drug Discov. Ther., vol. 1, no. 7, pp. 67–68, 2013.
[10] S. Singh, S. Sharma, T. Singh, and L. Singh, “Review on Vetiveria zizanioides: A medicinal herb,” J. Drug Discov. Ther., vol. 1, no. 7, pp. 80–83, 2013.
[11] M. Amsaveni and M. Saranya, “Energy efficient cluster head selection in WSN – A survey,” Naturalista Campano, vol. 28, no. 1, 2024. [Online]. Available: https://museonaturalistico.it/index.php/journal/article/view/569
[12] A. Manigandan and M. Saranya, “Secretary Bird Optimization with Differential Evolution (SBODE) and Trust Energy Aware Clustering Routing (TREACR) Protocol for Wireless Sensor Network (WSN),” International Journal of Computer Networks and Applications (IJCNA), vol. 12, no. 2, pp. –, Mar.–Apr. 2025.
[13] A. Manigandan and M. Saranya, “Energy efficient wireless sensor network with hybrid mutation albatross optimization algorithm–based cluster head selection,” International Journal of Advanced Science and Engineering, vol. 11, no. 4, pp. 4543–4556, 2025.
[14] A. Dhanai, H. S. Bagde, R. Gera, K. Mukherjee, C. Ghildiyal, and H. Yadav, “Case report on irritational fibroma,” Journal of Pharmacy and Bioallied Sciences, vol. 16, suppl. 1, pp. S960–S962, Feb. 2024.
[15] H. Bagde, A. Dhopte, F. Bukhary, N. Momenah, F. Akhter, O. Mahmoud, K. P. Shetty, M. A. Shayeb, H. Abutayyem, and M. K. Alam, “Monkeypox and oral lesions associated with its occurrence: a systematic review and meta-analysis,” F1000Research, vol. 12, p. 964, Mar. 2024.
[16] H. Bagde, R. S. Karki, S. Husain, S. Khan, V. Haripriya, and P. Purwar, “Evaluation of microbiological flora in endo-perio lesions before and after treatment,” Journal of Pharmacy and Bioallied Sciences, vol. 17, suppl. 2, pp. S1707–S1709, Jun. 2025.
[17] B. Shyamsukha, H. Bagde, A. Sharan, M. Choudhary, A. Duble, and A. V. Dhan, “Evaluating the potential of ChatGPT as a supplementary intelligent virtual assistant in periodontology,” Journal of Pharmacy and Bioallied Sciences, vol. 17, suppl. 2, pp. S1415–S1417, Jun. 2025.
[18] H. S. Bagde, M. K. Alam, A. K. A. Alhamwan, H. M. H. Aljubab, F. F. A. Alrashedi, D. H. M. Aljameeli, and M. G. Sghaireen, “The effect of a low-carbohydrate diet on periodontal health and inflammation in patients with type 2 diabetes,” Journal of Pharmacy and Bioallied Sciences, vol. 16, suppl. 1, pp. S641–S643, Feb. 2024.
[19] H. S. Bagde, M. K. Alam, Y. E. M. Almohammed, S. M. M. Almaqawid, A. W. N. Alanazi, F. T. F. Alanazi, and M. G. Sghaireen, “The efficacy of platelet-rich plasma as an adjunct to bone grafting in alveolar ridge preservation following tooth extraction,” Journal of Pharmacy and Bioallied Sciences, vol. 16, suppl. 1, pp. S564–S566, Feb. 2024.
[20] S. B. Mangalekar, H. S. Bagde, M. Sale, S. V. Jambhekar, C. Patil, and C. V. Deshmukh, “Comparing laser-assisted and conventional excision in the management of oral soft lesions: a prospective clinical study,” Journal of Pharmacy and Bioallied Sciences, vol. 16, suppl. 1, pp. S859–S861, Feb. 2024.
[21] M. K. Alam, H. S. Bagde, A. K. A. Alhamwan, H. M. H. Aljubab, F. F. A. Alrashedi, D. H. M. Aljameeli, and M. G. Sghaireen, “Comparing the long-term success rates of immediate implant placement vs delayed implant placement in patients with periodontally compromised teeth,” Journal of Pharmacy and Bioallied Sciences, vol. 16, suppl. 1, pp. S626–S628, Feb. 2024.
[22] H. S. Bagde, M. K. Alam, Y. E. M. Almohammed, S. M. M. Almaqawid, K. K. Ganji, and M. G. Sghaireen, “Comparing the clinical and radiographic outcomes of two different surgical approaches for treating infrabony defects in chronic periodontitis patients,” Journal of Pharmacy and Bioallied Sciences, vol. 16, suppl. 1, pp. S567–S569, Feb. 2024.
[23] A. Sharan, B. Pawar, H. Bagde, T. K. Chawla, A. V. Dhan, B. Shyamsukha, and S. Sharma, “Comparative evaluation of dentin hypersensitivity reduction over one month after a single topical application of three different

materials: a prospective experimental study," Journal of Pharmacy and Bioallied Sciences, vol. 16, suppl. 4, pp. S3405–S3407, Dec. 2024.

[24] J. Prakash, T. Sinha, H. Bagde, N. Rajegowda, S. Bhat, A. Dhopte, M. Cicciù, and G. Minervini, "Evidence-based assessment of temporomandibular disorders in complete denture versus partial denture users: a systematic review," Minerva Dental and Oral Science, Sep. 2025.

[25] J. R. Rogers, Y. Wang, N. F. Khan, K. Mott, V. K. Nomula, D. Wang, P. C. Fiduccia, M. Burcu, and X. Liu, "Landscape assessment of clone-censor-weight methodology application in real-world data studies: A scoping review," in Proceedings of the Pharmacoepidemiology and Drug Safety Conference, vol. 33, pp. 424–424, Nov. 1, 2024.

[26] K. Chitra, S. S. Priscila, E. S. Soji, R. Rajpriya, B. Gayathri, and A. Chitra, "Transforming electrical simulation and management with smart grid technologies," International Journal of Engineering Systems Modelling and Simulation, vol. 16, no. 4, pp. 241–253, 2025.

[27] M. V. Soosaimariyan, H. L. Allasi, K. Chitra, and J. B. Gnanadurai, "Enhanced EMG-based hand gesture recognition by using generalized deep infomax networks," Journal of Sensors, vol. 2025, no. 1, p. 9496890, 2025.

[28] K. Lakshmi and K. Chitra, "Stress Net: Multimodal stress detection using ECG and EEG signals," Journal of Data Science, vol. 2024, no. 59, pp. 1–8, 2024.

[29] S. Rishabh, K. Chitra, and C. S. Yap, "A study on non-fungible tokens marketplace for secure management," INTI Journal, vol. 2024, no. 18, pp. 1–8, 2024.

[30] S. Shreyash, S. Gaur, K. Chitra, and M. Y. N. Zuhaili, "EasyLearnify – A student study portal," INTI Journal, vol. 2024, no. 17, pp. 1–6, 2024.

[31] S. K. R. Padur, "Empowering Developer & Operations Self-Service: Oracle APEX + ORDS as an Enterprise Platform for Productivity and Agility," Int. J. Sci. Res. Sci. Eng. Technol., vol. 4, no. 11, pp. 364–372, 2018.

[32] S. K. R. Padur, "The Future of Enterprise ERP Modernization with AI: From Monolithic Systems to Generative, Composable, and Autonomous Platforms," J. Artif. Intell. Mach. Learn. & Data Sci., vol. 3, no. 1, pp. 2958–2961, 2025.

[33] S. K. R. Padur, "Automation-First Post-Merger IT Integration: From ERP Migration Challenges to AI-Driven Governance and Multi-Cloud Orchestration," Int. J. Sci. Res. Sci. Eng. Technol., vol. 12, no. 5, pp. 270–280, 2025.

[34] S. K. R. Padur, "Network Modernization in Large Enterprises: Firewall Transformation, Subnet Re-Architecture, and Cross-Platform Virtualization," Int. J. Sci. Res. Sci. Eng. Technol., vol. 2, no. 5, 2016, Zenodo.

[35] S. K. Somayajula, "Enterprise Data Migration Success Patterns: Lessons from Large-Scale Transformations," International Journal of Research in Computer Applications and Information Technology (IJRCAIT), vol. 8, no. 1, pp. 757-776, Jan.-Feb. 2025.

[36] S. K. Somayajula, "Demystifying Modern Data Warehousing: From Traditional to Cloud-Native Solutions," International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 2025.

[37] S. K. Somayajula, "Building a Career in Enterprise Data Architecture: A Practical Guide," International Research Journal of Modernization in Engineering Technology and Science (IRJMETS), vol. 7, no. 1, Jan. 2025.

[38] S. K. Somayajula, "Advanced ETL Optimization: A Framework for Next-Generation Data Integration," International Journal of Computer Engineering and Technology (IJCET), vol. 16, no. 1, pp. 381-406, Jan.-Feb. 2025.

[39] S. Somayajula and A. Orlovsky, "Proof, Truth and Contradiction in the System and Meta-System: Comprehensive Mathematical Solutions and Implementation Framework," 2025.

[40] P. Nutalapati, "Automated Incident Response Using AI in Cloud Security," Journal of Artificial Intelligence, Machine Learning and Data Science, vol. 2, no. 1, pp. 1301–1311, 2024

[41] P. Nutalapati, "Data Leakage Prevention Strategies in Cloud Computing," European Journal of Advances in Engineering and Technology, vol. 8, no. 9, pp. 118–123, 2025.

[42] P. Nutalapati, "Security Considerations for Hybrid Cloud Deployments in Fintech Using Blockchain," Journal of Artificial Intelligence, Machine Learning and Data Science, vol. 1, no. 1, URF Publishers, 2025.

[43] D. Ganesan, V. J. Francina, and V. P. Rameshkumaar, "Effectiveness of Corporate Responsibility Advertising Messages of Automobile Companies among Audience Perception," International Journal of Mechanical Engineering and Technology (IJMET), vol. 10, no. 2, pp. 934–941, 2019.

[44] K. Priya, R. V, S. A. Krishnan, V. P. Rameshkumaar, B. Premkumar and P. Jyothi, "Exploring Effective Leadership Strategies to Drive Organisational Success & Foster Sustainable Growth," 2024 Second International Conference on Advances in Information Technology (ICAIT), Chikkamagaluru, Karnataka, India, 2024, pp. 1-6.

[45] P. Prabadevi, "A study on organizational commitment of employees in life insurance companies," Global

Management Review, vol. 9, no. 1, Nov. 1, 2014.
[46] P. Prabadevi, M. Yogalakshmi, and N. Nithya, "Work from Home Situation and Work Life Balance of IT Employees During COVID-19 Pandemic Period – A Case Study Approach," Journal of Huazhong University of Science and Technology, vol. 50, no. 3, pp. 1-10, 2021.
[47] R. Balaji, G. Gayathri, V. Rohini, P. P. Devi, S. Arul Krishnan, and K. Prakash, "Evaluating the efficacy of AI-enhanced CRM tools in enhancing user experience in Indian online shopping," International Journal of Environmental Sciences, vol. 11, no. 5, 2025.
[48] S. G. K. Peddireddy, "Advancing Threat Detection in Cybersecurity through Deep Learning Algorithms," FMDB Transactions on Sustainable Intelligent Networks., vol.1, no. 4, pp. 190–200, 2024.
[49] S. G. K. Peddireddy, "Integrating AI for Proactive Network Defense against Emerging Security Vulnerabilities," FMDB Transactions on Sustainable Computer Letters., vol. 2, no. 4, pp. 232–241, 2024.
[50] S. G. K. Peddireddy, "Optimizing Resource Allocation in Multi-Cloud Environments for Cost Efficiency and Scalability," FMDB Transactions on Sustainable Computing Systems., vol. 2, no. 4, pp. 167–177, 2024.
[51] K. Priya, V. Rohini, S. A. Krishnan, V. P. Rameshkumaar, B. Premkumar, and P. Jyothi, "Exploring Effective Leadership Strategies to Drive Organisational Success & Foster Sustainable Growth," in Proc. 2024 Second International Conference on Advances in Information Technology (ICAIT), vol. 1, pp. 1–6, Jul. 24, 2024. IEEE.
[52] K. Selvavinayagam, V. J. Francina, and V. P. Rameshkumaar, "Evaluation of Logistic Performance Index of India in the Indian Postal Services," International Journal of Engineering and Management Research (IJEMR), vol. 8, no. 5, pp. 80–87, 2018.
[53] P. Nutalapati, "Zero Trust Architecture in Cloud-Based Fintech Applications," Journal of Artificial Intelligence & Cloud Computing, vol. 2, no. 1, pp. 1–8, 2023.
[54] P. Nutalapati, J. R. Vummadi, S. Dodda and N. Kamuni, "Advancing Network Intrusion Detection: A Comparative Study of Clustering and Classification on NSL-KDD Data," 2025 International Conference on Data Science and Its Applications (ICoDSA), Jakarta, Indonesia, 2025, pp. 880-885.
[55] P. Nutalapati, S. M. Dhavale, A. Shrivastava, R. V. S. Praveen, H. K. Vemuri and R. RiadHwsein, "IoT and Machine Learning-Enhanced Energy Management in Enabled Smart Grids for Predictive Load Balancing," 2025 World Skills Conference on Universal Data Analytics and Sciences (WorldSUAS), Indore, India, 2025, pp. 1-6.
[56] P. Nutralapati, "Disaster Recovery and Business Continuity Planning in Cloud-Blockchain Infrastructures," SSRN Electron. J., Jun. 2020.
[57] A. Manigandan and M. Saranya, "A gray hole attack detection and cluster head selection techniques for wireless sensor networks," in Proc. 16th Int. Conf. on Computing, Communication and Networking Technologies (ICCCNT 2025), IIT Indore, Madhya Pradesh, India, Jul. 6–11, 2025, pp. 1–6.
[58] D. Deopa, S. Sharma, and L. Singh, "Review: Current updates on anti-diabetic therapy," J. Drug Deliv. Ther., vol. 3, no. 6, pp. 121–126, 2013.
[59] S. Sharma, S. Sharma, K. Sachan, and S. Tiwari, "Ethnopharmacological review of Althea officinalis," World J. Pharm. Pharm. Sci., vol. 5, no. 7, pp. 425–432, 2016.
[60] B. Manickam and J. Thangaraju, "An artificial intelligence based smart health system for biological cognitive detection based on wireless telecommunication," Computational Intelligence, vol. 38, no. 4, pp. 1365–1378, 2022.
[61] M. S. Vivekanandan and T. Jesudas, "Deep learning implemented visualizing city cleanliness level by garbage detection," Intelligent Automation & Soft Computing, vol. 36, no. 2, pp. 1639–1652, 2023.
[62] V. Hiremath, "Quantum Networking: Strategic Imperatives for Enterprises and Service Providers in the Emerging Quantum Era," Journal of Computational Analysis and Applications (JoCAAA), vol. 31, no. 3, pp. 617–631, Dec. 2023.
[63] V. Hiremath, "AI-Optimized Adaptive Routing for High-Performance Data Centers: A Predictive Framework for Dynamic Network Optimization," 2025 IEEE 4th World Conference on Applied Intelligence and Computing (AIC), GB Nagar, Gwalior, India, 2025, pp. 152-157.
[64] V. Hiremath, "Optimizing SDN Controller Placement for Enhanced Performance and Scalability in Large-Scale Networks," 2025 International Conference on Intelligent Communication Networks and Computational Techniques (ICICNCT), Bidar, India, 2025, pp. 1-6.
[65] D. K. Arora et al., "An in vitro assessment of microleakage of pit and fissure sealants and restorative materials using dye penetration method," Journal of Pharmacy and Bioallied Sciences, Feb. 2025.
[66] D. Sumathi and P. Poongodi, "Scheduling Based on Hybrid Particle Swarm Optimization with Cuckoo Search Algorithm in Cloud Environment," IIOAB Journal, vol. 7, no. 9, pp. 358-366, 2016.

[67] D. Sumathi and P. Poongodi, "Secure medical information processing in cloud: Trust with swarm based scheduling," Journal of Medical Imaging and Health Informatics, vol. 6, no. 7, pp. 1636-1640, 2016.
[68] D. Sumathi and P. Poongodi, "An improved scheduling strategy in cloud using trust based mechanism," Int. J. Comput. Electr. Autom. Control Inf. Eng, vol. 9, no. 2, pp. 637-641, 2015.
[69] D. Sumathi, B. Melinamath, and R. Goyal, "Iov Traffic Prediction Utilizing Bidirectional Memory and Spatiotemporal Constraints with Local Search and NonLinear Analysis," Journal of Computational Analysis & Applications, vol. 33, no. 2, 2024.
[70] D. Sumathi, A. Singh, A. Sinha, D. Aditya, and M. R. KF, "The Deepfake Dilemma: Enhancing Deepfake Detection with Vision Transformers," in 2025 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics, Jan. 2025, pp. 1-7.
[71] V. B. Gowda, M. T. Gopalakrishna, J. Megha, and S. Mohankumar, “Foreground segmentation network using transposed convolutional neural networks and up sampling for multiscale feature encoding,” Neural Netw., vol. 170, pp. 167–175, 2024.
[72] V. B. Gowda, G. M. Thimmaiah, M. Jaishankar, and C. Y. Lokkondra, “Background-foreground segmentation using Multi-scale Attention Net (MA-Net): A deep learning approach,” Rev. Intell. Artif., vol. 37, no. 3, pp. 557–565, 2023.
[73] V. B. Gowda, M. G. Krishna, and J. Megha, “Dynamic Background Modeling and Foreground Detection using Orthogonal Projection onto the Subspace of Moving Objects,” in Proc. IC3, 2023, pp. 171–176.
[74] V. B. Gowda, M. T. Gopalakrishna, J. Megha, and S. Mohankumar, “Background initialization in video data using singular value decomposition and robust principal component analysis,” Int. J. Comput. Appl., vol. 45, no. 9, pp. 600–609, 2023.
[75] A. K. Joshi and S. B. Kulkarni, “Flow analysis of vehicles on a lane using deep learning techniques,” J. Adv. Inf. Technol., vol. 14, no. 6, pp. 1354–1364, 2023.
[76] A. K. Joshi, V. Shirol, S. Jogar, P. Naik, and A. Yaligar, “Credit card fraud detection using machine learning techniques,” Int. J. Sci. Res. Comput. Sci. Eng. Inf. Technol., vol. 6, no. 3, pp. 436–442, 2020.
[77] A. K. Joshi and S. B. Kulkarni, “Multi-modal information fusion for localization of emergency vehicles,” Int. J. Image Graph., vol. 24, no. 1, Art. no. 2550050, 2024.
[78] A. K. Joshi and S. B. Kulkarni, “Multimodal deep learning information fusion for fine-grained traffic state estimation and intelligent traffic control,” Int. J. Intell. Syst. Appl. Eng., vol. 11, no. 3, pp. 1020–1029, 2023.
[79] V. S. A. Anala, A. R. Pothu, and S. Chintapalli, “Enhancing Preventive Healthcare with Wearable Health Technology for Early Intervention,” FMDB Transactions on Sustainable Health Science Letters., vol.2, no.4, pp. 211–220, 2024.
[80] V. S. A. Anala and S. Chintapalli, “Scalable Data Partitioning Strategies for Efficient Query Optimization in Cloud Data Warehouses,” FMDB Transactions on Sustainable Computer Letters., vol. 2, no. 4, pp. 195–206, 2024.
[81] Md R. H. Mahin, E. Ahmed, S. S. Akhi, Md A. H. Fahad, M. I. Tusher, R. Chowdhury, and Md N. U. Rana, "Advancements and Challenges in Software Engineering and Project Management: A 2021 Perspective," Pathfinder Res., vol. 2, no. 1, p. 15, 2021.
[82] Md A. H. Fahad and R. Chowdhury, "Evolution and Future Trends in Web Development: A Comprehensive Review," Pathfinder Res., vol. 3, no. 1, p. 13, 2022.
[83] R. Nagar et al., “In vitro analysis of compressive strength of three different aesthetic restorative materials,” Journal of Pharmacy and Bioallied Sciences, Feb. 2025.
[84] N. Maiti et al., “Assessment of the efficacy of photobiomodulation (PBM) therapy in periodontal treatment: a longitudinal study,” Journal of Pharmacy and Bioallied Sciences, vol. 16, no. Suppl 3, pp. S2449–S2451, Jul. 2024.
[85] S. N. Akhter, R. Kumari, and A. Kumar, “Fertility booster effect of Asparagus recemosus against arsenic induced reproductive toxicity in Charles Foster rats,” J. Adv. Zool., vol. 45, no. 5, 2024.
[86] Z. Hashmi, R. Kumari, and A. Kumar, “Antidote effect of Bacopa Koneru against arsenic induced toxicity in rats,” J. Adv. Zool., vol. 45, no. 5, 2024.
[87] Z. Hashmi, R. Kumari, and A. Kumar, “Phytoremedial effect of Ocimum sanctum against arsenic induced toxicity in Charles Foster rats,” J. Adv. Zool., vol. 45, no. 5, 2024.
[88] A. Srivastava, “Use of Python in Data Science, Data Integration and Data Engineer,” Int. J. Sci. Res. Eng. Manag., vol. 8, no. 7, 2024.
[89] A. Srivastava, “AI in Healthcare and its Future,” J. Artif. Intell. Cloud Comput., vol. 1, no. 1, pp. 1–2, Mar. 2022.
[90] A. Srivastava, “Cloud Replacing Traditional Database,” Int. J. Multidiscip. Res., vol. 7, no. 2, pp. 1–2, Mar.–Apr.

2025.
[91] A. Srivastava, “Data Transformation Normalization to Denormalization in Cloud,” Int. J. Core Eng. Manag., vol. 6, no. 7, pp. 249–252, 2020.
[92] A. Srivastava, “Impact of AI/ML on Job Market and Skills Set and Health Industry,” ESP J. Eng. Technol. Adv., vol. 4, no. 3, pp. 122–126, 2024.
[93] B. Kumari, P. Das, and R. Kumari, “Accelerated processing of solitary and clustered abasic site DNA damage lesion by APE1 in the presence of aqueous extract of Ganoderma lucidum,” J. Biosci., vol. 41, pp. 265–275, 2016.
[94] R. Kumari, R. K. Singh, N. Kumar, and R. Kumari, “Preparation of superfine Bael leaf nanopowder, physical properties measurements and its antimicrobial activities,” Egypt. Chem. Bull., vol. 12, no. 4, pp. 284–297, 2023.
[95] M. K. Sinha, R. Kumari, and A. Kumar, “Ameliorative effect of Ganoderma lucidum on sodium arsenite induced toxicity in Charles Foster rats,” J. Adv. Zool., vol. 45, no. 5, 2024.
[96] I. Ganie and S. Jagannathan, “Continual optimal adaptive tracking of uncertain nonlinear continuous-time systems using multilayer neural networks,” Proc. 2023 Amer. Control Conf. (ACC), San Diego, CA, USA, 2023, pp. 3395–3400.
[97] Md S. Miah and Md S. Islam, "Big Data Analytics Architectural Data Cut off Tactics for Cyber Security and Its Implication in Digital forensic," in Proc. 2022 Int. Conf. Futuristic Technol. (INCOFT), Belgaum, India, 2022, pp. 1–6.
[98] M. A. Obaida, Md S. Miah, and Md. A. Horaira, “Random Early Discard (RED-AQM) Performance Analysis in Terms of TCP Variants and Network Parameters: Instability in High-Bandwidth-Delay Network,” Int. J. Comput. Appl., vol. 27, no. 8, pp. 40–44, Aug. 2011.