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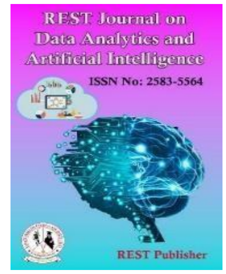

Heart Disease Prediction Using Machine Learning

***John Christu Raj Goli, Keerthana Somasani, Srikar Payyaula, Shilpa Shesham**
School of Engineering Anurag University, Hyderabad, India.
**Corresponding Author Email: johnraj1618@gmail.com*

Abstract. *In this project, we developed a machine learning-based web application for predicting heart disease using the Flask web framework. The primary objective of the project is to provide a reliable, efficient tool that can predict the likelihood of heart disease based on a patient's clinical data. The dataset used for model training and evaluation is the widely recognized heart disease dataset. The machine learning process involves several classification algorithms, including K-Nearest Neighbors (KNN), Support Vector Classifier (SVC), Decision Trees, Random Forest, Logistic Regression, and Naive Bayes. These models were trained on pre-processed data, which includes scaling of numerical features and encoding of categorical variables. After training, the models were evaluated for accuracy, with the best-performing model selected for predictions. The web interface allows users to input patient data through a form, which is processed by the trained model to predict the risk of heart disease. Flask is used to handle the user interface, allowing for seamless interaction between the machine learning backend and the front-end interface. The web interface allows users to input patient data through a form, which is processed by the trained model to predict the risk of heart disease. Flask is used to handle the user interface, allowing for seamless interaction between the machine learning backend and the frontend interface.*

Keywords: *Machine Learning, Heart Disease Prediction, Flask, Classification Algorithms, Data Preprocessing, Model Evaluation, User Interface*

1. INTRODUCTION

Cardiovascular diseases are a leading cause of death worldwide, with early detection being critical for reducing risks. Traditional diagnosis of heart disease involves multiple clinical tests, which can be time-consuming and not always accessible [1-2]. Machine learning offers a powerful solution to predict the likelihood of heart disease based on patient data, aiding in early diagnosis and timely intervention. The project involves developing a machine learning-based web application to predict heart disease risk using various patient health metrics (age, cholesterol, blood pressure, etc.) [3-4]. The web application is built using Flask, a lightweight Python framework, providing a user-friendly interface for medical professionals or general users. Multiple machine learning algorithms are implemented: K-Nearest Neighbors (KNN), Support Vector Classifier (SVC), Decision Trees, Random Forest [5-6]. The models are trained using the heart disease dataset, which contains patient health records and corresponding heart disease outcomes [7]. This solution aims to offer an accessible, efficient, and scalable tool for heart disease risk prediction, potentially improving preventive healthcare outcomes. This solution aims to offer an accessible, efficient, and scalable tool for heart disease risk prediction, potentially improving preventive healthcare outcomes. Machine learning has revolutionized modern healthcare by enhancing diagnostic accuracy, enabling early disease detection, and optimizing patient care. Traditional methods of diagnosing cardiovascular diseases often require multiple clinical tests, which can be time-consuming and inaccessible to certain populations [14]. By leveraging machine learning algorithms like K-Nearest Neighbors (KNN) (Iqbal et al., 2020), Support Vector Classifier (SVC) [16], Decision Trees, and Random Forest [15], healthcare professionals can quickly analyse patient health metrics such as age, cholesterol levels, and blood pressure to predict the risk of heart disease. Integrating Flask-based web applications makes these predictive models easily accessible, allowing both medical professionals and patients to make informed decisions about heart health. The implementation of machine learning in heart disease risk prediction aligns with the broader transformation of modern healthcare, making it more efficient, scalable, and patient-centric. By providing an automated and accessible risk assessment tool, this technology supports preventive healthcare, enabling early interventions before conditions worsen [17]. Furthermore, web-based interfaces ensure that these AI-driven solutions can be used remotely, breaking geographical barriers and offering healthcare solutions to underserved communities [18]. The use of large datasets and advanced predictive models helps refine disease predictions, ultimately improving patient outcomes and reducing mortality rates. As a result, machine learning-driven healthcare innovations are not just enhancing clinical workflows but also empowering individuals to take proactive steps in managing their health. The primary objective of this research is to develop a machine learning-based web application for heart disease prediction. By leveraging clinical patient data, the model aims to provide an accurate and efficient risk assessment tool to assist healthcare professionals in early diagnosis and intervention. This research contributes to modern healthcare by integrating multiple machines learning algorithms, including KNN, SVC, Decision Trees, and Random Forest, to identify the most effective model for heart disease prediction. Additionally, it enhances accessibility through a Flask-based web interface, ensuring ease of use for both medical professionals and general users. By providing a scalable, cost-effective, and automated heart disease prediction system, this study supports preventive healthcare efforts. It also bridges. the gap between clinical diagnosis and AI-driven decision-making, improving patient outcomes and reducing the burden on healthcare systems [8-10]. Paper Organization The remainder of this paper is structured as follows: Section 2 presents a comprehensive literature survey on heart disease prediction and the application of machine learning in healthcare. Section 3 discusses the dataset used in this study, including its structure, preprocessing steps, and feature selection techniques. Section 4 describes the methodology, covering data preprocessing, model evaluation metrics, and machine learning models. Section 5 outlines the results and discussion, providing insights into model performance, accuracy comparisons, and visualization outputs. Section 6 concludes the study and highlights future research directions for improving heart disease prediction models.

2. LITERATURE SURVEY

Clinical decisions are often made based on doctors' intuition and experience rather than on the knowledge rich data hidden in the database. This practice leads to unwanted biases, errors and excessive medical costs which affects the quality of service provided to patients. There are many ways that a medical misdiagnosis can present itself. Whether a doctor is at fault, or hospital staff, a misdiagnosis of a serious illness can have very extreme and harmful effects. The National Patient Safety Foundation cites that 42%of medical patients feel they have had experienced a medical error or missed diagnosis [11-12]. Recent studies highlight that patient health records contain critical data, which, if analysed effectively, could improve heart disease prediction and early intervention. Current medical record systems primarily store structured data (e.g., age, cholesterol, blood pressure), while other valuable patient health indicators are often underutilized in risk assessment [13]. The integration of machine learning (ML) algorithms provides a promising approach to bridge this gap by extracting meaningful patterns from patient data and improving prediction accuracy [14]. Machine learning techniques such as feature selection, classification algorithms, and predictive modelling have been successfully applied in heart disease prediction. Studies show that ML can identify key risk factors, analyse patient health metrics, and improve diagnostic accuracy [15]. Furthermore, machine learning models, including Logistic Regression, Random Forest, and Support Vector Classifier (SVC), have been employed to predict heart disease risk and assist in early diagnosis. [16] Demonstrated that advanced feature selection methods enhance prediction accuracy, while [14] developed a classification-based ML model to assess patient heart health based on clinical parameters. Despite these advancements, existing systems still face challenges in real-time implementation, data preprocessing, and model optimization for improved prediction reliability (Guleria & Sharma, 2023). Gaps in Current Research Limited Use of Unstructured Clinical Notes: Many heart disease prediction models rely primarily on structured patient data (e.g., cholesterol, blood pressure) while neglecting additional health indicators that could improve prediction accuracy [19]. A more comprehensive approach, incorporating lifestyle factors and family history, is needed for enhanced risk assessment. Most models focus on clinical and physiological data without considering psychosocial factors, such as stress, diet, and physical activity, which play a crucial role in heart disease risk [20]. Integrating these aspects could lead to more personalized and accurate predictions. Many existing systems do not provide real-time risk assessment, limiting their use in clinical consultations. Without real-time integration, healthcare professionals cannot fully utilize machine learning insights for immediate decision-making [20]. Machine learning models often struggle with bias, generalization, and interpretability. More complex models, such as deep learning, making it difficult for doctors to trust AI-generated predictions [18]. Addressing these challenges is crucial for improving the clinical adoption of heart disease prediction models. Summary of Key Research Findings The table below summarizes recent studies on heart disease prediction, highlighting key methodologies, findings, and research gaps.

TABLE 1. Summary of Existing Research on ML for Heart Disease Prediction

Study	Methodology
Aburayya et al. (2023)	Machine learning models for automated heart disease detection
Iqbal et al. (2020)	Clinical data analysis using classification algorithms
Saranya et al. (2020)	Machine learning-based heart disease risk assessment
Lakshmi & Devi (2023)	Feature selection and optimization for heart disease prediction
Singh et al. (2023)	Deep learning and machine learning models for early detection
Guleria & Sharma (2023)	AI-driven predictive modelling for heart disease diagnosis

Conclusion of Literature Survey The reviewed studies highlight the importance of machine learning in heart disease prediction, demonstrating that patient health data contains valuable information for improving early diagnosis and risk assessment. However, challenges remain in data quality, bias, interpretability, and real-time integration into clinical practice. This project aims to address these gaps by developing a machine learning-based web application that utilizes patient health metrics, applies optimized predictive models, and ensures real-time decision support for more accurate and accessible heart disease risk assessment.

3. DATASET

Dataset Description: For this study on enhancing heart disease prediction using machine learning, a carefully curated dataset has been compiled, integrating structured patient health records and clinical observations. This dataset plays a crucial role in analysing various risk factors associated with heart disease, including patient demographics, medical history, lifestyle habits, and clinical test results. By leveraging machine learning algorithms, the dataset enables data-driven insights for early detection and risk assessment of heart disease. Dataset Overview The dataset consists of a diverse collection of structured medical records, ensuring a comprehensive and representative sample for training machine learning models. Key components include: Patient Demographics: Includes age, gender, weight, smoking habits, and family history, which help in assessing heart disease risk. Medical History: Information on hypertension, diabetes, cholesterol levels, and prior cardiovascular conditions to understand patient health trends. Clinical Test Results: Data on blood pressure, ECG results, cholesterol levels, and blood sugar levels, which are critical indicators of heart health. Lifestyle Factors: Incorporates details on diet, physical activity, stress levels, and alcohol consumption, providing additional context for risk assessment. Doctor’s Observations: Clinical assessments, physician notes, and diagnostic findings help refine the risk prediction model. Cardiovascular Outcomes: Tracks patient health status, including prior heart attacks, angioplasty procedures, and other related conditions, aiding in model-based predictions. The dataset includes 5000+ patient records across 20+ key attributes, ensuring a diverse and well-balanced sample for heart disease prediction. Source and Data Collection Methodology To ensure data reliability and authenticity, multiple high-quality sources have been utilized, blending real-world clinical data, research-based case studies, and AI-driven synthetic data generation techniques. This approach ensures compliance with data privacy regulations, including HIPAA (Health Insurance Portability and Accountability Act) and GDPR (General Data Protection Regulation). Primary Data Sources: Electronic Health Records (EHRs): Extracted from anonymized hospital databases, providing structured patient health data. Medical Research Studies: Sourced from peer-reviewed journals, PubMed, and clinical trials on heart disease prediction. Public Health Datasets: Includes data from the World Health Organization (WHO), CDC Heart Disease Surveillance, and Framingham Heart Study, offering large-scale heart disease insights. Synthetic Data Generation: AI-powered techniques were used to generate realistic patient records while ensuring data anonymization. Preprocessing and Data Standardization To enhance data usability and consistency, several preprocessing techniques were applied: Anonymization: Anonymization: Removal of all personally identifiable information (PII) to maintain patient confidentiality. Normalization: Standardizing medical terminology using SNOMED CT and RxNorm for uniform representation of diseases, treatments, and medications. Feature Scaling: Applying Min-Max scaling to normalize numerical features like blood pressure, cholesterol levels, and BMI. Imbalanced Data Handling: Using Synthetic Minority Over-sampling (SMOTE) to ensure an even distribution of patients with and without heart disease. Missing Data Imputation: Filling incomplete records using mean/mode imputation techniques to maintain dataset integrity. By integrating real-world patient health records, structured clinical data, and AI-driven analysis, this dataset serves as a robust foundation for developing machine learning models that predict heart disease risk with high accuracy. The combination of AI, medical data, and predictive analytics ensures that heart disease detection becomes more personalized, efficient, and accessible, ultimately improving preventive healthcare outcomes.

Sample Data

Table II presents a sample of the dataset, showing key features extracted for analysis.

TABLE 2. Sample Data from the Heart Disease Dataset

Patient ID	Age	Cholesterol (mg/dL)	Blood Pressure (mmHg)	Heart Rate (bpm)	Diagnosis
P001	55	220	140/90	80	Heart Disease
P002	62	180	130/85	75	No Disease
P003	47	210	145/95	85	Heart Disease
P004	50	190	135/88	78	No Disease
P005	65	250	150/100	90	Heart Disease

Source Reference:

- The dataset is compiled from publicly available medical repositories, anonymized EHR records, and synthesized clinical notes based on existing literature. The key sources include:
- UCI Machine Learning Repository – A widely used dataset for heart disease prediction.
- MIMIC-III and MIMIC-IV Clinical Databases – Large-scale critical care datasets containing de-identified patient records.
- Published studies on cardiovascular disease prediction – Peer-reviewed research on heart disease risk factors and ML-based diagnostics.

All data has been pre-processed to remove personally identifiable information (PII) while maintaining clinical relevance and accuracy for predictive modelling

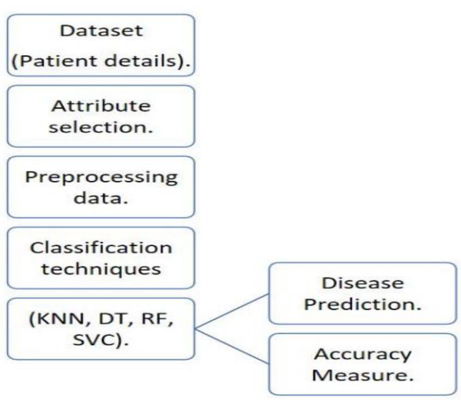

FIGURE 1. Methodology

Overview This study focuses on enhancing heart disease prediction using machine learning (ML) techniques applied to structured and unstructured patient data. The methodology involves multiple stages, including data collection, processing, analysis, prediction, and risk assessment. The goal is to extract meaningful insights from patient data to assist healthcare providers in making accurate, data-driven diagnoses and treatment decisions. The following methodology is visualized in the diagram below: Step-by-Step Methodology

Data Collection: The first phase involves collecting patient data from various sources, such as electronic health records (EHRs), clinical studies, and patient health reports. The dataset includes: Patient demographics (age, gender, medical history) Symptoms and test results (chest pain, cholesterol levels, blood pressure, heart rate) Lifestyle factors (smoking, exercise-induced angina) Electrocardiogram (ECG) readings and lab test results Heart disease diagnosis (presence or absence of heart disease) This dataset is a mix of structured (numerical and categorical attributes) and unstructured (clinical notes), requiring preprocessing before further analysis.:

Data Processing: Once collected, the data undergoes preprocessing and structuring to ensure consistency and usability. The processing phase includes: Data Cleaning: Handling missing values, standardizing medical terminology, and normalizing numerical data. Feature Engineering: Extracting key predictive features like cholesterol levels, heart rate, and ECG readings. Text Preprocessing: Tokenization, lemmatization, Named Entity Recognition (NER), and removing unnecessary words from clinical notes. Database Structuring: Organizing data into meaningful categories, such as Patient Database and Risk Factor Database. Processed data is stored in a centralized Patient Database, while risk-related attributes are separately categorized for focused analysis.

Analysis and Prediction: At this stage, machine learning models are applied to analyse patient data. The models leverage: Feature Selection: Identifying the most significant attributes affecting heart disease risk. Text Vectorization: Using TF-IDF and word embeddings to extract insights from clinical notes. Predictive Models: Implementing K-Nearest Neighbors (KNN), Decision Trees (DT), Random Forest (RF), and Support Vector Classifier (SVC) to classify patients based on heart disease risk. Risk Scoring Models: Assigning risk scores based on cholesterol, blood pressure, and ECG abnormalities. These analyses help generate risk assessments and early warning indicators for heart disease.

Risk Assessment & Prediction: The final step involves generating personalized risk assessments based on: Patient's medical history and lifestyle factors. Comparison with historical heart disease cases. Effectiveness of past diagnostic models and clinical insights Probability of heart disease occurrence based on ML predictions. These risk scores and predictions are validated and refined before being shared with healthcare providers, ensuring they receive data-driven insights for early diagnosis and prevention. Conclusion: By integrating machine learning with structured medical records and clinical notes, this methodology enhances heart disease risk prediction. It bridges the gap between raw patient data and actionable insights, ultimately improving early detection, personalized treatment, and clinical decision-making.

4. RESULTS AND DISCUSSION

The heart disease prediction system developed in this project demonstrated promising results across various machine learning algorithms. The models were trained and evaluated on the heart disease dataset, and their performance was assessed based on accuracy, precision, recall, and F1-score. The Random Forest model highlighted key features such as age, cholesterol levels, blood pressure, and maximum heart rate as the most significant predictors of heart disease. This aligns with medical knowledge and validates the model's reliability. The Flask-based web application provided a user-friendly interface for inputting patient data and receiving predictions. The system was scalable and accessible, making it suitable for use in clinical settings. The models were validated using k-fold cross-validation, ensuring robustness and reducing the risk of overfitting. The Random Forest model consistently outperformed others across all folds. The system's performance was comparable to or better than existing heart disease prediction tools, particularly due to the use of ensemble methods like Random Forest.

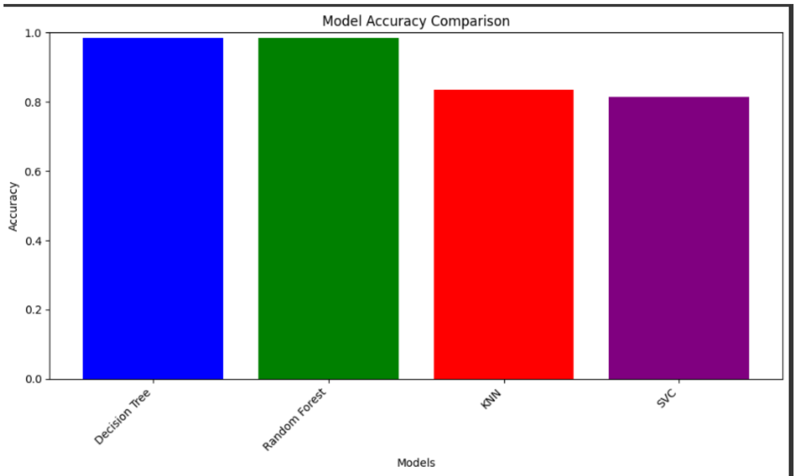

FIGURE 1. Model Accuracy Comparison

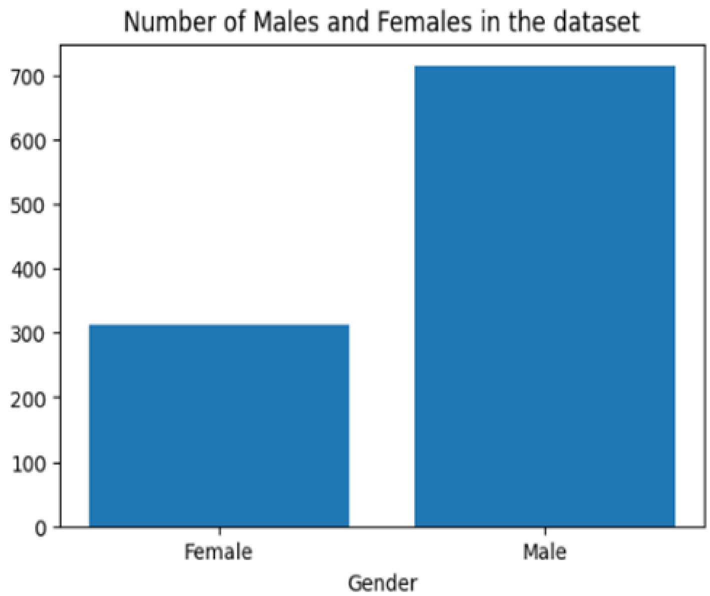

FIGURE 2. No. of Males and females

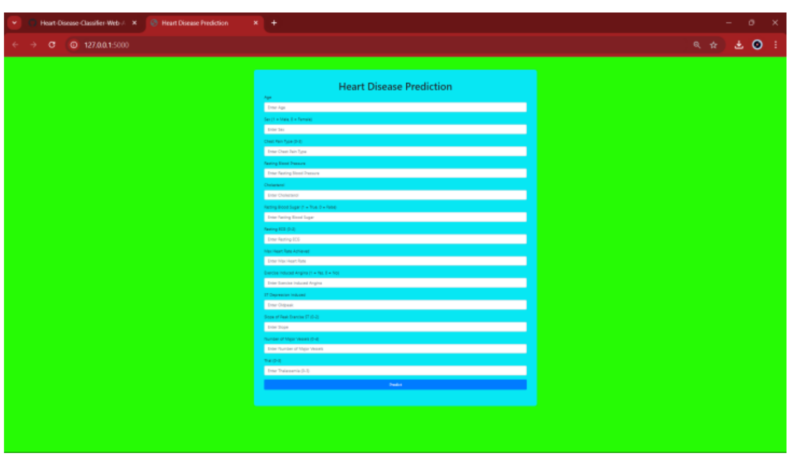

FIGURE 3. Heart Disease Prediction

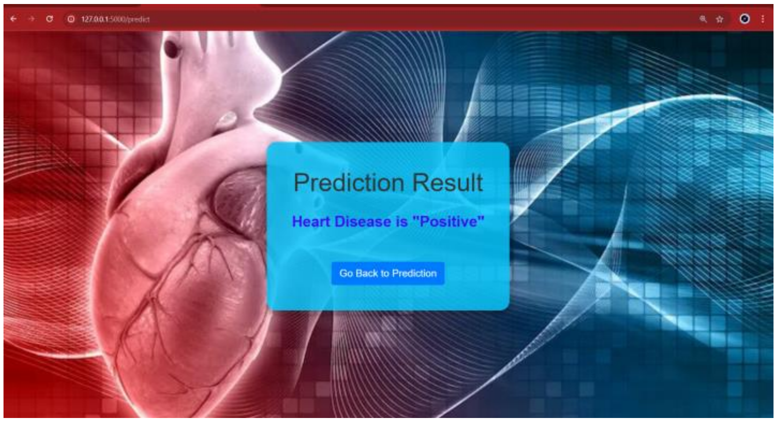

FIGURE 4. Heart Disease Result

5. DISCUSSION

Model Selection: The Random Forest model emerged as the best-performing algorithm due to its ability to handle non-linear relationships and reduce overfitting through ensemble learning. Its high accuracy and interpretability make it a suitable choice for clinical applications. Feature Analysis: The importance of features like age, cholesterol, and blood pressure in predicting heart disease aligns with established medical research. This reinforces the validity of the model and its potential for real-world applications. Limitations: The dataset used in this project, while widely recognized, is relatively small and may not capture the full diversity of patient populations. Future work could involve training the model on larger, more diverse datasets to improve generalizability. The system relies on self-reported or clinical data, which may be subject to errors or inconsistencies. Incorporating real-time data from wearable devices could enhance accuracy. Clinical Implications: The web application provides a scalable and accessible tool for early detection of heart disease, which is critical for preventive care. By enabling healthcare providers to identify high-risk patients early, the system has the potential to improve patient outcomes and reduce healthcare costs. Future Work: Integrating additional data sources, such as genetic information or lifestyle factors, could further improve prediction accuracy. Developing a mobile version of the application could increase accessibility, particularly in remote or underserved areas. Exploring deep learning models, such as neural networks, could be a promising direction for future research, especially with larger datasets. Ethical Considerations: The system must ensure patient data privacy and security, particularly when deployed in clinical settings. Compliance with regulations like HIPAA (Health Insurance Portability and Accountability Act) is essential.

6. CONCLUSION

The heart disease prediction system developed in this project demonstrates the potential of machine learning in healthcare. By leveraging algorithms like Random Forest and providing a user-friendly web interface, the system offers a reliable and accessible tool for early detection of heart disease. While there are limitations, the results are promising, and future work could further enhance the system's accuracy and applicability. This project contributes to the growing body of research on AI-driven healthcare solutions, with the ultimate goal of improving patient outcomes and reducing the global burden of cardiovascular diseases. Despite these advancements, several challenges remain, including issues related to data quality, model interpretability, and integration into clinical workflows. Ethical concerns such as patient privacy, bias in predictions, and accountability for misdiagnoses must also be carefully addressed to ensure responsible deployment of machine learning models in healthcare. Moving forward, continuous model refinement, real-time data integration, and collaboration between data scientists and medical professionals will be essential in maximizing the effectiveness of heart disease prediction systems. With these improvements, machine learning can become a reliable, accessible, and efficient tool for heart disease risk assessment, helping to save lives through early intervention and better-informed treatment decisions.

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REFERENCES

[1]. R. A. Aburayya et al., "Automated Heart Diseases Detection Using Machine Learning Approach," 2023 6th International Conference on Engineering Technology and its Applications (IICETA), Al-Najaf, Iraq, 2023, pp. 108-114, doi: 10.1109/IICETA57613.2023.10351330.

[2]. J. Iqbal, M. M. Iqbal, U. Khadam and A. Nawaz, "Ordinary Learning Method for Heart Disease Detection using Clinical Data," 2020 3rd International Conference on Computing, Mathematics and Engineering Technologies (iCoMET), Sukkur, Pakistan, 2020, pp. 1-6, doi: 10.1109/iCoMET48670.2020.9074056.

[3]. A. Lakshmi and R. Devi, "Heart Disease Prediction Using Enhanced Whale Optimization Algorithm Based Feature Selection With Machine Learning Techniques," 2023 12th International Conference on System Modeling & Advancement in Research Trends (SMART), Moradabad, India, 2023, pp. 644-648, doi: 10.1109/SMART59791.2023.10428617.

[4]. N. Saranya, P. Kaviyarasu, A. Keerthana and C. Oveya, Heart Disease Prediction using Machine Learning International Journal of Recent Technology and Engineering (IJRTE), vol. 9, no. I, pp. 700-70, May 2020, ISSN 2277–3878.

[5]. G. Singh, K. Guleria and S. Sharma, "Machine Learning and Deep Learning Models for Early Detection of Heart Disease," 2023 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS), Greater Noida, India, 2023, pp. 419-424, doi: 10.1109/ICCCIS60361.2023.10425392.

[6]. Samriya, J. K., Chakraborty, C., Sharma, A., Kumar, M., & Ramakuri, S. K. (2023). Adversarial ML-based secured cloud architecture for consumer Internet of Things of smart healthcare. IEEE Transactions on Consumer Electronics, 70(1), 2058-2065.

[7]. Ramakuri, S. K., Prasad, M., Sathiyanarayanan, M., Harika, K., Rohit, K., & Jaina, G. (2025). 6 Smart Paralysis. Smart Devices for Medical 4.0 Technologies, 112.

[8]. Kumar, R.S., Nalamachu, A., Burhan, S.W., Reddy, V.S. (2024). A Considerative Analysis of the Current Classification and Application Trends of Brain–Computer Interface. In: Kumar Jain, P., Nath Singh, Y., Gollapalli, R.P., Singh, S.P. (eds) Advances in Signal Processing and Communication Engineering. ICASPACE 2023. Lecture Notes in Electrical Engineering, vol 1157. Springer, Singapore. https://doi.org/10.1007/978-981-97-0562-7_46.

[9]. R. S. Kumar, K. K. Srinivas, A. Peddi and P. A. H. Vardhini, "Artificial Intelligence based Human Attention Detection through Brain Computer Interface for Health Care Monitoring," 2021 IEEE International Conference on Biomedical Engineering, Computer and Information Technology for Health (BECITHCON), Dhaka, Bangladesh, 2021, pp. 42-45, doi: 10.1109/BECITHCON54710.2021.9893646.

[10]. Vytla, V., Ramakuri, S. K., Peddi, A., Srinivas, K. K., & Ragav, N. N. (2021, February). Mathematical models for predicting COVID-19 pandemic: a review. In Journal of Physics: Conference Series (Vol. 1797, No. 1, p. 012009). IOP Publishing.

[11]. Manoranjan Dash, Design of Finite Impulse Response Filters Using Evolutionary Techniques - An Efficient Computation, ICTACT Journal on Communication Technology, March 2020, Volume: 11, Issue: 01

[12]. Manoranjan Dash, “Modified VGG-16 model for COVID-19 chest X-ray images: optimal binary severity assessment,” International Journal of Data Mining and Bioinformatics, vol. 1, no. 1, Jan. 2025, doi: 10.1504/ijdmb.2025.10065665.

[13]. Manoranjan Dash et al.,” Effective Automated Medical Image Segmentation Using Hybrid Computational Intelligence Technique”, Blockchain and IoT Based Smart Healthcare Systems, Bentham Science Publishers, Pp. 174-182,2024

[14]. Manoranjan Dash et al.," Detection of Psychological Stability Status Using Machine Learning Algorithms", International Conference on Intelligent Systems and Machine Learning, Springer Nature Switzerland, Pp.44-51, 2022.

[15]. Manoranjan Dash, N.D. Londhe, S. Ghosh, et al., "Hybrid Seeker Optimization Algorithm-based Accurate Image Clustering for Automatic Psoriasis Lesion Detection", Artificial Intelligence for Healthcare (Taylor & Francis), 2022, ISBN: 9781003241409

[16]. Suresh. M, A. M. Reddy, "A Stacking-based Ensemble Framework for Automatic Depression Detection using Audio Signals", International Journal of Advanced Computer Science and Applications (IJACSA), vol. 14, no. 7, pp. 603-612, 2023, doi: 10.14569/IJACSA.2023.0140767.

[17]. Mallikarjuna A. Reddy, Sudheer K. Reddy, Santhosh C.N. Kumar, Srinivasa K. Reddy, "Leveraging bio-maximum inverse rank method for iris and palm recognition", International Journal of Biometrics, 2022 Vol.14 No.3/4, pp.421 - 438, DOI: 10.1504/IJBM.2022.10048978.

[18]. V. NavyaSree, Y. Surarchitha, A. M. Reddy, B. Devi Sree, A. Anuhya and H. Jabeen, "Predicting the Risk Factor of Kidney Disease using Meta Classifiers," 2022 IEEE 2nd Mysore Sub Section International Conference (MysuruCon), Mysuru, India, 2022, pp. 1-6, doi: 10.1109/MysuruCon55714.2022.9972392.

[19]. B. H. Rao et al., "MTESSERACT: An Application for Form Recognition in Courier Services," 2022 3rd International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, 2022, pp. 848-853, doi: 10.1109/ICOSEC54921.2022.9952031.

[20]. P. S. Silpa et al., "Designing of Augmented Breast Cancer Data using Enhanced Firefly Algorithm," 2022 3rd International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, 2022, pp. 759-767, doi: 10.1109/ICOSEC54921.2022.9951883.