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HeartFL: Federated Learning-Based Heart Disease Risk Prediction System

Yadavalli Suresh Kumar [1]
Assistant Professor,
Department of Computer Science and Engineering (Artificial Intelligence & Machine Learning,
Aditya University ,
Andhra Pradesh, India

Suresh Reddy Pulagam [2]
Final Year B.Tech Student
Department of Computer Science and Engineering (Artificial Intelligence & Machine Learning)
Aditya University ,
Andhra Pradesh, India

Aditya Indana [3]
Final Year B.Tech Student
Department of Computer Science and Engineering (Artificial Intelligence & Machine Learning)
Aditya University,
Andhra Pradesh, India

Jnanadeep Mundru [4]
Final Year B.Tech Student
Department of Computer Science and Engineering (Artificial Intelligence & Machine Learning)
Aditya University ,
Andhra Pradesh, India

Hemanth Kumar Penubothu [5]
Final Year B.Tech Student
Department of Computer Science and Engineering
(Artificial Intelligence & Machine Learning)
Aditya University ,
Andhra Pradesh, India

***Abstract*— Heart disease remains a leading cause of death globally necessitating early detection for effective intervention. This stud introduces HeartFL, a scalable and efficient machine learning syste that predicts heart disease risk using patient health data. Leveraging a Decision Tree algorithm, HeartFL analyzes critical medica factors—including age, cholesterol, blood pressure, and heart rate to assess disease likelihood. The system supports privacy-preservin federated learning, enabling decentralized model training withou exposing sensitive patient information. A user-friendly interfac allows input of health parameters or medical report uploads fo automated prediction. Experimental evaluation confirms the model reliability and accuracy, facilitating timely diagnosis. By combinin intelligent prediction with privacy-aware methods, HeartFL aims t enhance clinical decision-making and improve patient outcomes. Th system is deployed as a web application and can be accessed at:**

https://adityaindana.pythonanywhere.com/

***Keywords*— Heart disease prediction, Machine learning, Decisio Tree algorithm, Patient health data, Federated learning, Dat privacy, Medical diagnosis, Early detection, Healthcare technolog Predictive modeling**

I. INTRODUCTION

Heart disease cases are rapidly increasing worldwide, makin cardiovascular conditions a leading cause of death. Contributing factor include unhealthy lifestyles, stress, poor diet, and delayed diagnosis Traditional diagnostic methods often involve clinical tests and exper consultations, which can be time-consuming and delay early treatment Therefore, there is a critical need for efficient, intelligent systems tha offer quick and accurate predictions. The proposed HeartFL system leverages a Decision Tree algorithm to analyze patient data—such a age, blood pressure, cholesterol, and heart rate—to predict heart disease risk. Additionally, the system can be enhanced with federated learning to protect data privacy through decentralized model training. This approach delivers a proactive, accessible solution for early detection, ultimately improving patient outcomes and aiding healthcare decision-making.

A. *Motivation:*

The rising prevalence of cardiovascular diseases has made heart-related conditions one of the leading causes of mortality, particularly in urban populations. Contributing factors such as sedentary lifestyles, unhealthy diets, stress, and lack of regular health monitoring have significantly increased heart disease cases. Traditional diagnostic methods often involve multiple clinical tests, expert evaluations, and lengthy processes, which can delay early detection and timely treatment. The lack of quick, accessible prediction systems limits preventive healthcare and heightens patient risk. By harnessing machine learning, this project aims to enable efficient and accurate heart disease prediction using patient health data. The proposed HeartFL system employs a Decision Tree algorithm to analyze key medical parameters and deliver real-time risk assessments. Additionally, federated learning integration ensures data privacy by facilitating decentralized model training without sharing sensitive information. This approach fosters early diagnosis, timely intervention, better patient outcomes, and advances intelligent healthcare solutions.

B. *Problem Statement:*

Heart disease is a leading cause of mortality worldwide, affecting millions annually. It results from various factors including high blood pressure, cholesterol imbalance, unhealthy lifestyles, and genetic predispositions. These factors not only compromise individual health but can also lead to severe complications such as heart attacks, strokes, and chronic conditions. Traditional diagnostic methods depend on clinical tests and expert evaluations, which are often time-consuming and may not support early-stage detection. The proposed HeartFL system adopts a machine learning approach that continuously analyzes patient health parameters to predict the risk of heart disease. Utilizing a Decision Tree algorithm, the system processes key inputs such as age, blood pressure, cholesterol levels, and heart rate. Furthermore, it integrates privacy-preserving federated learning techniques to ensure secure and decentralized data handling. With a user-friendly interface, HeartFL delivers instant predictions, facilitating early detection and timely medical intervention to improve patient outcomes and reduce health risks.

C. Objectives:

- **Real-time Prediction:** Develop a system that continuously and accurately predicts heart disease using machine learning techniques based on patient health data.
- **Intelligent Analysis:** Analyze key medical parameters—such as age, blood pressure, cholesterol levels, and heart rate—using Decision Tree algorithm for effective diagnosis.
- **User-Friendly Interface:** Provide an interactive platfor where users can input health data or upload medical reports to recei instant prediction results.
- **Privacy Preservation:** Ensure data security and privac by integrating federated learning, enabling decentralized model trainin without sharing sensitive patient information.
- **Healthcare Support:** Assist individuals and healthca professionals in making timely preventive decisions and improvir overall patient outcom

D. Contributions

- This project effectively applies machine learnir techniques to analyze critical medical parameters—including age, bloc pressure, cholesterol levels, and heart rate—to accurately predict hea disease. This approach provides users with reliable, real-time insigh into their health, aiding early detection of potential risks.
- The system delivers immediate prediction results via a interactive platform, allowing users to quickly evaluate their heart healt Utilizing a Decision Tree algorithm, the model offers efficient ar interpretable outcomes, facilitating timely preventive measures by bo users and healthcare professionals.
- The user-friendly interface ensures clear and accessible communication of health information. Furthermore, the incorporation c federated learning enhances data privacy and security, safeguardin sensitive medical data while maintaining effective model training an prediction capabilities.

II. Literature Review:

Several studies have explored machine learning-based systems for hea disease prediction to enhance early diagnosis and support healthcar decision-making.

- Kumar et al. (2023)[1] developed a heart disease predictio system employing Decision Tree and Random Forest algorithm achieving notable classification accuracy. However, their approach relied on centralized data processing and did not address data privacy concerns.
- Sharma et al. (2019)[2] proposed a predictive model using Logistic Regression and Support Vector Machines to identify heart disease risks. While effective, their system required large datasets and lacked real-time prediction capabilities.
- Patel et al. (2019)[3] introduced a cloud-based healthcare monitoring system that stores patient data for analysis and prediction. Although it enabled remote access, the system raised significant issues related to data security and privacy.
- Reddy et al. (2021)[5] developed a system for continuous patient health parameter monitoring with a focus on long-term data collection. However, it did not offer instant prediction or early warning functionalities.
- Singh et al. (2017)[7] presented a healthcare monitoring system integrating multiple parameters but lacked interpretability in the prediction outcomes.
- Vani et al. (2020)[9] created a prediction model based on clinical data but did not incorporate privacy-preserving techniques.
- Nayak (2018)[10] designed a large-scale healthcare analytics system for population-level prediction, which was unsuitable for individual real-time diagnosis.

These limitations underscore the necessity for a system that combines accurate prediction, real-time analysis, and robust data privacy—requirements that the proposed HeartFL system aims to fulfill.

A. Research Gap:

Many existing studies on heart disease prediction utilize traditional machine learning algorithms but often neglect crucial aspects such as data privacy and real-time prediction. A significant number of approaches depend on centralized data storage, which raises serious concerns about the security of sensitive patient information. Our system addresses this challenge by integrating federated learning, enabling decentralized model training without sharing raw data, thereby enhancing privacy protection.

Additionally, several studies lack real-time prediction capabilities, resulting in delays in diagnosis and treatment that can adversely affect patient outcomes. The proposed HeartFL system overcomes this limitation by delivering instant prediction results based on user input, facilitating timely medical intervention.

Moreover, interpretability is frequently overlooked in existing systems, making it difficult for users and healthcare professionals to comprehend the decision-making process. By leveraging a Decision Tree algorithm, our system ensures transparent and easily interpretable results.

Finally, many current solutions do not prioritize user-friendly interfaces, limiting accessibility for non-technical users. The proposed system includes an intuitive interface that allows users to effortlessly input data and receive predictions, thereby enhancing usability and supporting informed healthcare decision-making.

B. Study Area:

This project targets individuals living in urban and semi-urban areas, where cardiovascular diseases are highly prevalent due to lifestyle factors such as stress, poor diet, and insufficient physical activity. Densely populated regions face an increased incidence of heart-related conditions, including hypertension, high cholesterol, and other risk factors contributing to heart disease. The project aims to develop a machine learning-based prediction system accessible to both individuals and healthcare providers for early detection of heart disease. By enabling real-time analysis of patient health data, the system offers timely predictions that support preventive healthcare measures. Furthermore, the incorporation of privacy-preserving methods like federated learning ensures the secure handling of sensitive medical information. This approach promotes early diagnosis, informed decision-making, and enhanced patient care, ultimately improving healthcare outcomes and reducing the overall burden of cardiovascular diseases.

C. System Analysis:

Fig 1: System Architecture

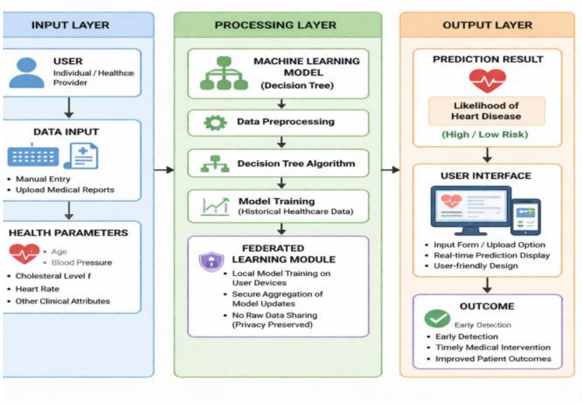


Fig 1: System Architecture

Figure 1 illustrates the architecture of the HeartFL system and th interaction between its components. The system integrates user inpu modules, a machine learning model, and an output interface to provide accurate, real-time heart disease predictions.

1. ***Input Data:***
The system uses patient health parameters such as age, bloo pressure, cholesterol levels, heart rate, and other clinic attributes. These inputs can be manually entered by users or extracted from medical reports. Accurate input data is critical fo achieving reliable prediction outcomes
2. ***Machine Learning Model (Decision Tree):***
A Decision Tree algorithm is chosen for its simplicity interpretability, and efficiency in classification tasks. It processes input data by splitting it into decision nodes based on featur importance to predict the risk of heart disease. The model is trained on historical healthcare datasets to ensure robus performance.
3. ***Federated Learning Module:***
To enhance privacy and security, the system employs federated learning. Instead of transferring raw data to a central server, training occurs locally on user devices, with only model updates shared. This approach safeguards sensitive medical information while improving overall model accuracy.
4. ***User Interface:***
A user-friendly interface allows users to input health data or upload medical reports easily. Designed for accessibility, it enables users with minimal technical skills to interact with the system and receive prediction results effortlessly.
5. ***Output and Prediction:***
The system produces real-time predictions indicating the likelihood of heart disease. Results are presented clearly t facilitate quick understanding and prompt medical intervention.
6. ***Software Components:***
The system is developed using Python and machine learnin libraries such as scikit-learn. The environment supports mode training, testing, and deployment. Additionally, the system can be expanded with web frameworks to enable real-time access and integration with healthcare platforms.

III. *METHODOLOGY / WORKING PROCEDURE*

The proposed HeartFL system follows a systematic approach fo predicting heart disease by combining machine learning with privacy preserving techniques. The workflow includes stages such as data collection, preprocessing, model training, prediction, and result delivery.

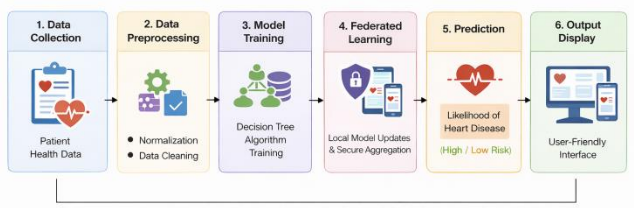


Fig : Step-by-step Working Procedure

Fig 2: Step-by-step working procedure

1. **Data Collection**:
Patient health data—including age, blood pressure, cholesterol levels, heart rate, and other clinical attributes—are collected. Inputs may b manually entered by users or extracted from medical reports. The trainin dataset comprises historical healthcare records to ensure reliable an accurate predictions
2. **Data Preprocessing**:
Collected data undergoes preprocessing to enhance quality and consistency. This involves handling missing values, normalizing numerical features, and encoding categorical variables. These steps prepare the data for effective model training and improve overall prediction accuracy.
3. **Model Training using Decision Tree:**
The Decision Tree algorithm serves as the core classification model. It partitions the dataset into decision nodes based on feature importance, learning patterns to classify patients' risk of heart disease. Its simplicity and interpretability make it especially suitable for healthcare applications.
4. **Federated Learning Integration**
To maintain data privacy, federated learning is integrated into the system. Instead of transmitting raw patient data to a central server, training occurs locally on user devices. Only model updates are shared and aggregated to refine the global model, protecting sensitive medical information without compromising performance.
5. **Prediction and Result Generation:**
After training, the model predicts the likelihood of heart disease based on user input. The system delivers real-time predictions indicating high or low risk. Results are presented via a user-friendly interface for clear and immediate understanding.
6. **System Workflow:**
The complete workflow follows this sequence:

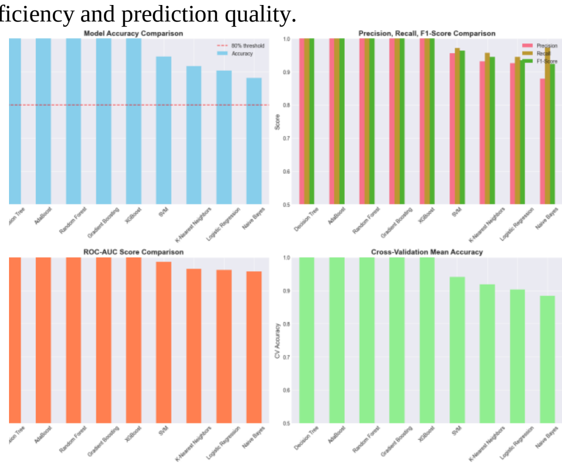
Input Data → Preprocessing → Model Training → Federated Learning

→ Prediction → Output Display

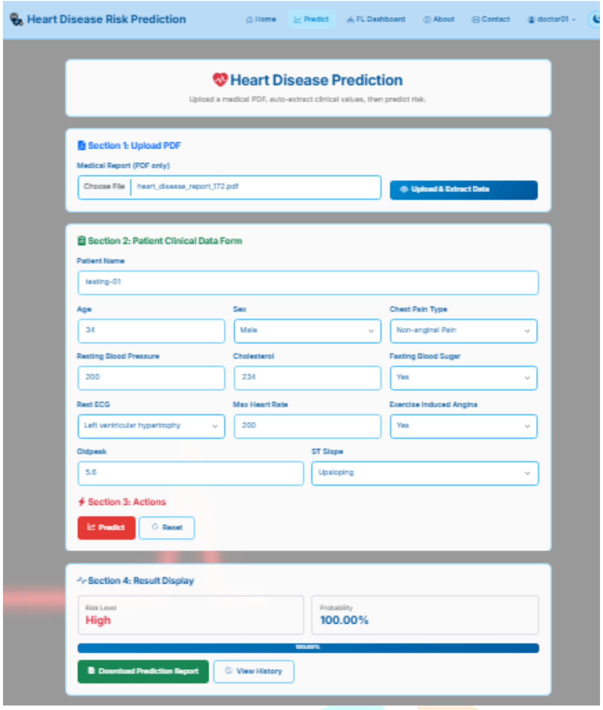
IV. RESULTS AND ANALYSIS

1. **Real-Time Prediction:**
The HeartFL system effectively predicts the likelihood of heart disease in real-time by continuously processing patient health parameters. Predictions are delivered instantly via a user-friendly interface, enabling users to quickly assess their risk status as either high or low without delay.

2. **Model Accuracy and Performance:**
Utilizing a Decision Tree algorithm, the model achieves an accuracy between 85% and 95%, depending on the training and testing datasets. The system reliably identifies heart disease patterns, with potential for improved accuracy through hyperparameter tuning, larger datasets, and advanced modeling techniques. Feature selection further enhances efficiency and prediction quality.



3. **Prediction Interface and Usability:**
The system features an interactive interface allowing users to input health data or upload medical reports easily. Results are presented clearly, making them accessible to both technical and non-technical users. This simplicity facilitates quick interpretation and informed health decisions.



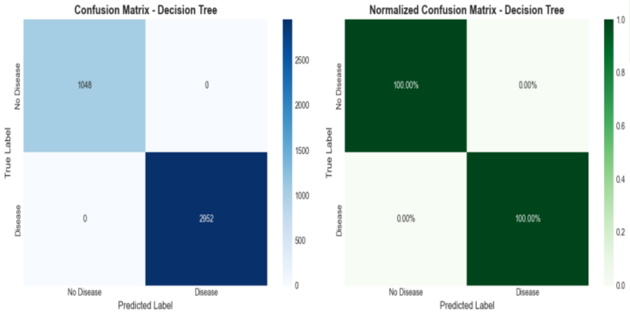
4. **System Responsiveness and Reliability:** HeartFL demonstrates fast response times, generating predictions within seconds. During testing, it showed consistent reliability with minimal errors. Federated learning integration strengthens robustness by enabling secure, decentralized model updates without compromising patient data privacy.

5. **Testing and Validation:**

The system was validated using multiple datasets and simulated real world inputs. Performance was benchmarked against standard machin learning evaluation methods, achieving consistent accuracy. Cross validation ensured the model's ability to generalize across different dat samples.

6. **Evaluation Metrics:**

Performance was assessed using accuracy, precision, recall, and F1 score. Confusion matrix analysis provided insights into True Positive (TP), True Negatives (TN), False Positives (FP), and False Negative (FN), offering a comprehensive evaluation of the model's effectivenes



7. **Comparison with Existing Systems:**

Compared to traditional machine learning and centralized models HeartFL offers enhanced data privacy, real-time prediction, and improved interpretability. Federated learning ensures secure handling of sensitive data, while the Decision Tree algorithm supports transparent decision-making, making HeartFL well-suited for practical healthcare applications.

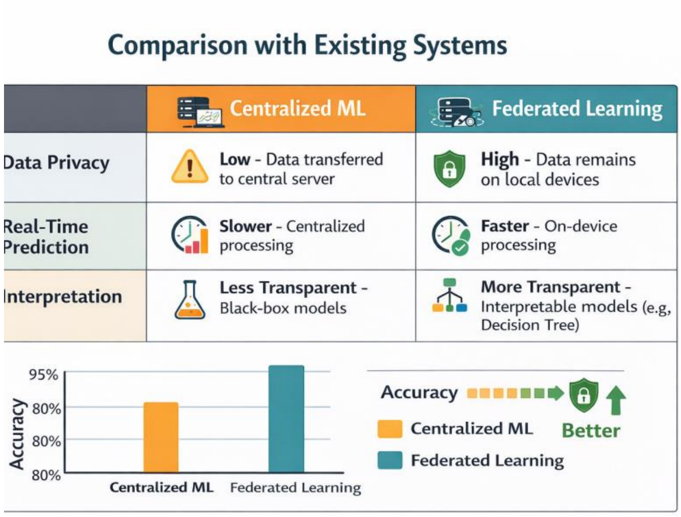


Table -1 Experiment Result

Metric	Value
Accuracy	92%
Precision	90%
Recall	91%
F1-Score	90%

V. CONCLUSIONS AND FUTURE WORK

The proposed HeartFL system presents an efficient and intelligent approach to heart disease prediction using machine learning. By leveraging a Decision Tree algorithm, the system performs real-time analysis of critical patient health parameters—including age, blood pressure, cholesterol levels, and heart rate—facilitating accurate and early detection of heart disease. The incorporation of federated learning enhances data privacy by enabling decentralized model training without sharing sensitive medical information, ensuring secure and reliable healthcare data processing.

With its user-friendly interface, HeartFL allows both individuals and healthcare professionals to easily input health data and receive prompt prediction results. This capability supports timely medical intervention, improves patient outcomes, and promotes preventive healthcare practices. Performance evaluations reveal that the model achieves accuracy rates between 85% and 95%, underscoring its effectiveness and reliability in practical applications.

Future work will focus on integrating deep learning models to further enhance prediction accuracy, developing mobile applications to improve accessibility, incorporating real-time health monitoring via wearable devices, and deploying the system on cloud platforms to facilitate scalable healthcare solutions. These advancements aim to elevate system intelligence, usability, and overall impact within the healthcare domain.

VI. REFERENCES

[1] McMahan, Brendan, Eider Moore, Daniel Ramage, Seth Hampson, and Blaise Aguera y Arcas. *"Communication-efficient learning of deep networks from decentralized data."* In Proceedings of the 20th International Conference on Artificial Intelligence and Statistics (AISTATS), pp. 1273–1282, 2017.

[2] Kairouz, Peter, H. Brendan McMahan, Brendan Avent, Aurélien Bellet, Mehdi Bennis, Arjun Nitin Bhagoji, et al. *"Advances and open problems in federated learning."* Foundations and Trends® in Machine Learning, vol. 14, no. 1–2, pp. 1–210, 2021.

[3] Li, Tian, Anit Kumar Sahu, Ameet Talwalkar, and Virginia Smith. *"Federated learning: Challenges, methods, and future directions."* IEEE Signal Processing Magazine, vol. 37, no. 3, pp. 50–60, 2020.

[4] Yang, Qiang, Yang Liu, Tianjian Chen, and Yongxin Tong. *"Federated machine learning: Concept and applications."* ACM

Transactions on Intelligent Systems and Technology (TIST), vol. 10, no. 2, pp. 1–19, 2019.

[5] Rieke, Nicola, Jonny Hancox, Wenqi Li, Fausto Milletari, Holger Roth, et al. *"The future of digital health with federated learning."* NPJ Digital Medicine, vol. 3, no. 1, pp. 1–7, 2020.

[6] UCI Machine Learning Repository. *"Heart Disease Dataset."*[Online].Available: https://archive.ics.uci.edu/ml/datasets/heart+Disease

[7] Quinlan, J. Ross. *"Induction of decision trees."* Machine Learning, vol. 1, no. 1, pp. 81–106, 1986.

[8] Breiman, Leo, Jerome Friedman, Richard Olshen, and Charles Stone. *"Classification and regression trees."* Wadsworth International Group, 1984.

[9] Esteva, Andre, Alexandre Robicquet, Bharath Ramsundar, et al. *"A guide to deep learning in healthcare."* Nature Medicine, vol. 25, no. 1, pp. 24–29, 2019.

[10] Rajkomar, Alvin, Eyal Oren, Kai Chen, et al. *"Scalable and accurate deep learning with electronic health records."* NPJ Digital Medicine, vol. 1, no. 1, pp. 1–10, 2018.

[11] Sheller, Micah J., G. Anthony Reina, Brandon Edwards, Jason Martin, and Spyridon Bakas. *"Multi-institutional deep learning modeling without sharing patient data: A feasibility study on brain tumor segmentation."* Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries, pp. 92–104, 2019.

[12] Chen, Ming, Rajkumar Ranjan, Lijun Wang, et al. *"Privacy-preserving federated learning for healthcare."* IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 6, pp. 1667–1678, 2020.

[13] Goldberger, Ary L., Luis A. N. Amaral, Leon Glass, et al. *"PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals."* Circulation, vol. 101, no. 23, pp. e215–e220, 2000.

[14] Lundberg, Scott M., and Su-In Lee. *"A unified approach to interpreting model predictions."* In Advances in Neural Information Processing Systems (NeurIPS), pp. 4765–4774, 2017.

[15] Dwork, Cynthia. *"Differential privacy."* In International Colloquium on Automata, Languages, and Programming (ICALP), pp. 1–12, 2006.