GCD-STACKED DEEP LEARNING FOR ACCURATE HEART FAILURE RISK PREDICTION

PHASE 2 PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

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ABSTRACT

Heart failure Abstract is a severe global health condition, and timely detection is necessary for successful intervention. In this project, we used an ensemble DL model which includes MLP, LSTM, TabNet, TabTransformer, FT-Transformer, GRU PyTorch, VAE, Wide & Deep Model (Google AI), NODE, CNN, DNN, and ResNet networks to achieve maximum predictability. The model relies on attention mechanisms and deep feature extraction to attain the highest interpretability and performance. The model, as proposed, attains 91% of accuracy and 0.91 of precision, 0.905 of recall, and F1 score of 0.905 which tested against benchmarked heart failure datasets. By reporting clinically interpretable results, this ensemble approach allows for early detection, risk stratification, and individualized treatment planning, demonstrating its ability to improve heart failure prediction and support clinical decision-making.

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LIST OF ABBREVIATIONS

GRU	Gated Recurrent Units
CNN	Convolutional Neural Network
DNN	Deep Neural Network
UI	User Interface
DL	Deep Learning
ECG	Electrocardiogram

CHAPTER 1
INTRODUCTION

1.1 GENERAL

Heart disease remains one of the leading causes of death worldwide, posing a significant burden on healthcare systems and affecting millions of individuals annually. Despite advancements in medical research and healthcare infrastructure, early detection of heart disease continues to be a critical challenge. Timely and accurate prediction can greatly improve patient outcomes through preventive care and tailored treatment plans. As a result, there is a growing need for intelligent systems that can assist clinicians in identifying potential risks before the disease progresses to a life-threatening stage.

The integration of Artificial Intelligence (AI), particularly deep learning, has revolutionized the field of medical diagnostics by enabling automated systems to analyze complex medical data with high accuracy. Deep learning models such as DNN (Deep Neural Network), CNN (Convolutional Neural Network), and GRU (Gated Recurrent Unit) are capable of extracting hidden patterns and relationships within clinical datasets that may not be immediately evident to human experts. These models, when trained on historical medical records, can effectively predict the likelihood of heart disease in patients based on various health indicators such as age, blood pressure, cholesterol levels, and more.

To further improve the reliability and performance of individual models, ensemble learning techniques have been introduced. In this project, an ensemble of DNN, CNN, and GRU models is developed to leverage the strengths of each architecture. By combining the output of multiple models, the system achieves higher predictive accuracy and robustness than any single model alone. This approach is especially valuable in healthcare, where reducing false positives and false negatives is of utmost importance.

Additionally, the system is implemented with a user-friendly Streamlit interface, allowing healthcare professionals and users to input data and receive instant predictions. Recommended or “safe” value ranges are displayed alongside each input field to enhance usability and provide guidance. The ultimate goal of this project is to support early diagnosis, assist clinical decision-making, and contribute to the broader adoption of AI in preventive healthcare practices.

1.2 OBJECTIVES

The primary objective of this study is to develop a highly accurate and clinically interpretable heart failure prediction model using an ensemble deep learning approach. By integrating multiple state-of-the-art neural network architectures—including MLP, LSTM, GRU, CNN, FT-Transformer, and others—this research aims to enhance predictive performance while overcoming the limitations of individual models. The model is designed to effectively process complex medical data, identify key risk factors using attention mechanisms, and support early diagnosis, risk stratification, and personalized treatment planning. Furthermore, the use of optimization techniques and benchmark datasets ensures that the proposed system is robust, generalizable, and suitable for real-world clinical deployment.

1.3 EXISTING SYSTEM

Current systems for heart failure prediction primarily depend on traditional diagnostic methods such as ECG, echocardiography, chest X-rays, and biomarker analysis like BNP levels. While clinically effective, these methods are time-consuming, prone to human error, and often limited in predictive accuracy—especially for early detection. They typically offer reactive insights after symptoms appear, lacking the ability to proactively identify risk in asymptomatic individuals. Furthermore, they struggle to handle complex, high-dimensional medical data efficiently.

To address these limitations, machine learning (ML) and deep learning (DL) techniques like Decision Trees, SVM, Random Forest, and ANNs have been introduced. These models have improved prediction accuracy using structured datasets like Cleveland and Framingham. However, many still rely heavily on manual feature engineering and face challenges in generalizing across diverse patient data. A more advanced, ensemble-based predictive model is needed to enhance accuracy, scalability, and clinical reliability.

1.4 PROPOSED SYSTEM

The proposed system introduces an Ensemble Learning with Deep Learning (EL-DL) framework designed to enhance the accuracy, interpretability, and reliability of heart failure prediction. Unlike conventional approaches that rely on a single predictive model, our ensemble integrates multiple advanced deep learning architectures—including MLP, LSTM, GRU, CNN, ResNet, TabNet, TabTransformer, FT-Transformer, NODE, VAE, and Google's Wide & Deep Model. These models are selected based on their strengths in processing sequential and tabular data, learning complex patterns, and extracting meaningful features from high-dimensional medical datasets. The integration of these diverse models enables the system to capture both spatial and temporal patterns in patient health records, improving generalization across varied clinical data.

The system adopts a multi-level ensemble strategy. First, individual deep learning models are trained and evaluated on preprocessed heart failure datasets. Based on their performance, the top-performing models—such as GRU (PyTorch) and FT-Transformer—are selected and combined using a maximum voting mechanism to form the first layer of the ensemble. In the second layer, additional classifiers refine the decision-making process, leading to improved overall accuracy and robustness. To enhance the model's efficiency and prediction strength, attention mechanisms are employed to prioritize the most critical features in patient data, while optimization techniques such as Grey Wolf Optimizer (GWO), Particle Swarm Optimization (PSO), and Bayesian hyperparameter tuning are used to fine-tune model performance.

The model is trained and validated using benchmark medical datasets such as the Framingham Heart Study, UCI Heart Disease, and VA Long Beach datasets. Evaluation metrics including accuracy, precision, recall, F1-score, and AUC are used to assess performance. Experimental results show that the proposed ensemble model achieves superior results compared to standalone models, with a recorded accuracy of 91% and F1-score of 0.905. Additionally, the attention-based analysis enables clinicians to interpret which features influenced predictions the most, bridging the gap between AI and practical clinical application. This system not only supports early diagnosis but also enables risk stratification and individualized treatment planning, making it a valuable tool for decision-making in modern healthcare.

CHAPTER 2
LITERATURE SURVEY

In [1] Using Cleveland UCI dataset, a number of research have tried to predict heart illness using ML and DL techniques. Numerous models had been used, including Neural Networks,Decision Trees,SVM and Random Forest achieving good accuracy scores, with certain hybrid models yielding more than 94% accuracy. To get better outcomes and a reduced dimensional space, feature selection techniques such as PCA and Isolation Forest have been applied. One kind of deep learning method that has shown promise in spotting important patterns in patient data is neural networks. DL technique that has promise in finding important patterns in patient data is neural networks. Additionally, natural language processing gets the information from the unarranged clinical notes. The project underscores the significance of AI-based predictive systems in enhancing early diagnosis as well as diminishing fatal outcomes.

In [2] There are studies that have focused on integrating cloud computing and IoT in healthcare to support real-time monitoring and predictive analytics. AI and ML algorithms, specifically deep learning-based models, have proved to show much promise in detecting diseases accurately. Advances in recent years in RNNs and their derivatives like LSTM and bidirectional LSTM have enhanced processing for sequential data in medical settings. Researchers have pointed out the efficiency of Bi LSTM in processing time-series clinical information for disease prediction. There are studies that point out the utilization of IoT to obtain physiological data and cloud computing to ensure scalable storage and processing. Nevertheless, attaining improved predictive accuracy and minimizing false positives are still major challenges in smart healthcare systems.

In [3], Several studies have examined DL and ML methods for heart issues prediction. Conventional ML models tend to use extensive feature engineering to enhance classification performance, which can be computationally expensive. Deep learning methods, including artificial neural networks , have shown high predictive accuracy for disease prediction but need large amounts of data and substantial computational power. Researchers have also used data balancing methods such as SMOTE to manage class imbalance, which is prevalent in medical data. Recent research stresses that optimization of machine learning models through proper hyperparameter tuning can enhance prediction accuracy with the least reliance on feature engineering. Comparative studies versus existing models demonstrate that deep learning methods, applied along with balancing data techniques, have the potential to significantly increase reliability in predicting heart disease.

In [4],Hybrid approaches have also been used by researchers to increase prediction accuracy, including ensemble deep learning-based smart healthcare systems and recurrent neural networks. In order to enhance diagnosis, Medical components has also been included. The most recent advancements focus on feature selection techniques to increase the efficiency and accuracy of categorization. In order to improve the prediction of cardiac illness, this research proposes the use of an improved deep learning-assisted convolutional neural network model that combines regularization techniques with multi-layer perceptrons.

In [5],Early detection is bound to demand a lot of feature engineering even if it is conventional. Medical imaging and patient health record interpretation have shown recent improvements in LSTM, CNN, and Deep Learning to be better. Researchers have suggested hybrid models including Multi-Layer Perceptron with CNN to improve predictive accuracy. Investigated to improve computational efficiency with kept diagnostic accuracy are feature selection methods. The Advanced Deep Learning CNN aims to improve these methods by including regularizing methods to boost robustness and fight overfitting.

In [6] Heart disease prediction with Wireless Body Area Networks has received increasing attention as a result of emerging wearable technology and artificial intelligence. Other research has examined Using benchmark data to predict diseases and real-time physiological signals. The feature selection and classification models are used by the traditional approach-based models. The optimization methods has been used to assist in enhancing the level of prediction accuracy. Current research emphasizes hybrid metaheuristic approaches to channel selection and feature extraction for improved quality signal and transmission efficiency. Additionally, Recurrent Neural Networks have been successfully utilized for the analysis of time-series data, but their performance relies greatly on hyperparameter tuning, which is worked around by advanced optimization algorithms. Various studies on Deep learning algorithms can be used to forecast heart disease more accurately.

In [7] different Studies and earlier detection have been carried out. Traditional models such as Multiple-Stratum Perceptron, Convolutional Neural Networks, Heart disease analysis has made extensive use of Recurrent units with gates and long-term short-term memory. Researchers have also tried bidirectional versions like BiLSTM and BiGRU to improve feature extraction and accuracy in prediction. Recent improvements, though, focus on Enhanced Deep Convolutional Neural Networks along with hyperparameter tuning to achieve performance. Research suggests that coupling machine learning algorithms with clinical data is able to support medical doctors in evaluating the risks of heart disease effectively. Blending deep learning techniques and patient history data have proven successful for cardiovascular disease identification.

In [8] There have been a number of studies on IoT-based health monitoring systems, especially for heart disease diagnosis. IoT-integrated wearable sensors have been connected with cloud computing to monitor patient vitals and analyze them in real time. All existing solutions aim to detect diseases mainly without dealing with data security issues. Various works have tried incorporating encryption methods such as AES, but they don't have efficient authentication processes. Also, lengthy training times without feature selection is a major setback. To eliminate these problems, the current work combines secure authentication, encryption, and an enhanced deep learning network with robust data protection for accurate heart disease prediction.

In [9] ,DL models were shown to be effective by Rajpurkar et al. (2017) such as CNNs to diagnose cardiac diseases from ECG signals accurately. Likewise, Khan et al. (2020) emphasized the application of RNNs in time-series health data analysis for early anomaly detection. Classic models such as Random Forest have also been applied in predictive analytics, as observed by Smith et al. (2019), and been effective in the management of structured medical data sets. The blending of deep learning and traditional algorithms has also drawn interest, such as in ensemble methods suggested by Li et al. (2021), that improve predictive ability and reduce false negatives. These developments cumulatively highlight the increasing capability Using machine learning in transforming sophisticated medical systems.

In [10],More importance is given for predicting heart failure now a days using deep learning and machine learning model. Highly complex medical data has been a struggle to handle by the traditional machine learning methods like support vector machines, decision trees and logistic regression. In the Process of diagnosis it has given a better accuracy those who have used deep learning techniques such as recurrent and convolutional neural networks. Additionally, the role played by big data analytics cannot be underestimated in ensuring effective management of large volumes of both structured and unstructured clinical medical data towards greater predictive accuracy. To get the result of faster disease detection and get the more accuracy some researches has said that we need to use hybrid methods like combining optimization techniques, deep learning and machine learning to get these results.

In [11], Prediction of cardiac disease using ML and DL algorithms has been studied recently by highlighting the importance of processing available data for early diagnosis. The study highlights how various algorithms yield varying degrees of accuracy and investigates determinants of these variations. Last but not least, the study concludes that deep learning models are superior to traditional machine learning techniques, with a uniform accuracy of 84% to 99%. The findings confirm the growing importance of advanced predictive models for improved cardiovascular disease detection and patient outcomes.

In [12], the author proposed a unique Heart Failure component model to enhance the early heart failure prediction machine learning system prediction performance. Nine different ML models with feature selection tuned to build an improved dataset using the eight most suitable features were used in the research. Based on state-of- the-art research, decision tree classifier showed among the models used a highest accuracy rate of 100%. Results show that feature engineering is essential for predictive modeling and underline how machine learning might enable more precise diagnosis of heart failure and offer patients with the best possible treatment.

In order to improve deep learning models for the diagnosis of cardiac disease in [13], Noroozi the author and his colleagues compared the robustness of feature selection techniques. 16 feature selection techniques were divided into filter, wrapper, and evolutionary strategies using the Cleveland Heart Disease database. Several performance metrics were used to compare seven machine learning techniques like J48, Random Forest, SVM, and Naïve Bayes. Based on the results, it was clear that feature selection significantly enhanced some models like J48 and decreased accuracy for others like MLP and RF. SVM based filter algorithms recorded the highest accuracy of 85.5%, implying that proper feature selection could boost predictive accuracy while diagnosing heart disease.

In [14] A number of studies have investigated deep learning methods for heart failure prediction and risk stratification. Conventional survival prediction models, including the Cox proportional hazard model, have been extensively applied but tend to perform poorly with high-dimensional, complex medical data. Recent developments in multi-source deep learning models have shown enhanced accuracy by combining electronic health records (EHR), cardiac imaging, and motion features. It has been established through research that denoising autoencoders (DAE) have successfully extracted hidden representations from medical images, with an improvement in survival prediction. Other studies have used cardiac magnetic resonance (CMR) imaging for extracting features and optical flow techniques to improve prognosis for heart failure. Combination of deep learning with clinical data has been seen to greatly surpass traditional models in providing improved risk stratification and patient outcome prediction.

In [15] Older machine learning models include Naïve Bayes, SVM and Decision Trees have been broadly utilized but tend to be limited by low prediction accuracy and inefficiencies in data usage. Current developments in hybrid By using features, deep learning models have shown increased accuracy. selection methods along with deep neural networks. Research using datasets like Cleveland, Framingham, and the UCI heart disease database has emphasized the significance of feature selection techniques like Relief and LASSO in improving prediction accuracy. The use of preprocessing methods, including SMOTE for class imbalance, has also been investigated to enhance model stability. Yet, current models continue to be challenged by clinical validation and practical application. This research work was widely used to improve the accuracy of CVD predictions using several Deep Learning algorithms.

In [16] Heart disease prediction has been widely researched using various deep learning techniques. Typically known to be used as classifiers are KNN, Naïve Bayes, SVM, and Random Forest, and these have been utilizing datasets such as the UCI Heart Failure Prediction dataset for the classification of the types of heart disease for model evaluation. Recent deep learning architectures like CNNs and RNNs have been proven to have superior prediction capabilities by finding complex patterns in health data. Hyperparameter tuning methods such as Talos have further promoted model efficiency to the extent of automated deep learning architecture tuning to improve classification. Research has further delved into ensemble learning methodologies and large-scale data frameworks to facilitate scalable prediction of heart disease, which enhances personalized and timely diagnosis in health care.

In [17] ECG-based heart disease classification emphasizes several deep learning and hybrid methods for enhancing accuracy and efficiency. Conventional techniques, including wavelet transformations, PCA, and statistical feature extraction, have been employed to analyze ECG signals for classification with SVM, ANN, and decision trees. New developments involve CNN, LSTM, and other deep learning architectures that facilitate automatic feature learning and enhance diagnostic accuracy. Yet, most current approaches only use raw ECG signals, resulting in false classifications because of the loss of important cardiac wave-specific features. Hybrid models, including CNN with optimization algorithms (GOA-CNN, STFT-CNN) and feature engineering methods (DWT, SWT), have been promising to overcome these limitations. The model extends this by incorporating SW.databased handcrafted features and CNN-extracted deep features, along with an LSTM classifier for better detection of ECG-based heart disease.

In [18] Senthil Pandit et al. (2023) created a Sleep scoring is accomplished using a multilevel comprehensible. and evolving illustration of the EEG signal using ensemble learning multi-classifiers. The work applied a supervised learning model for feature extraction learning using intra class reduction and inter class distance optimization. The work applied ensemble learning classifiers including AdaBoost, Random Forest, and Logistic Regression to improve classification performance. Additionally, the author proposed for bias reduction in label and the training model stabilization were self-knowledge distillation mixed with a selective batch sampling method. The results confirm the suggested approaches' potency. in highly accurate stages of sleep classification, offering insightful analysis of feature selection and model reliability.

In [19], Kumar et al. (2024) conducted a comprehensive study of disease diagnosis by using techniques from machine learning to electronic health records. The research targeted the application of patient data, including medical history, laboratory reports, and clinical findings, in the development of predictive models for accurate disease identification. Various machine learning algorithms were implemented and tested, including Random Forests, KNN, Naïve Bayes, Decision Trees, and SVMs, with their comparison based on interpretability, computational complexity, and diagnostic accuracy. In addition, the research considered feature selection and data preprocessing strategies for optimal model performance. The results showed that machine learning-based methods were superior to conventional diagnostic techniques in terms of precision and effectiveness, pointing to their capability to facilitate disease diagnosis.

In [20], SenthilPandi et al. (2023) introduced an Adaptive Multiple Resolution Contour (AMRC) model for volumetric segmentation and lung tumor estimation. To overcome tumor localization challenges caused by shape and size variations, the research introduced a dynamic contour model to improve the boundary delineation. Conventional thresholding methods used to cause high false positives, resulting in boundary holes in segmentation. The AMRC model updated the contour adaptively to improve the tumor fit, hence the detection accuracy. Employing the HECS model for peak intensity pixel detection and AMRC for adaptive definition of contour, the research showed enhanced tumor detection and volumetric estimation.

CHAPTER 3

SYSTEM DESIGN

3.1 DEVELOPMENT ENVIRONMENT

3.1.1 HARDWARE SPECIFICATIONS

This project uses minimal hardware but in order to run the project efficiently without any lack of user experience, the following specifications are recommended

PROCESSOR	Intel Core i5
RAM	4GB or above (DDR4 RAM)
GPU	Intel Integrated Graphics
HARD DISK	6GB
PROCESSOR FREQUENCY	1.5 GHz or above

Table 3.1.1 Hardware Specifications

3.1.2 SOFTWARE SPECIFICATIONS

The software specifications in order to execute the project has been listed down in the below table. The requirements in terms of the software that needs to be pre- installed and the languages needed to develop the project has been listed out below.

FRAMEWORKS	Pandas, Numpy, Tensorflow/ Keras, sklearn, Streamlit
SOFTWARES USED	Visual Studio

Table 3.1.2 Software Specifications

3.2 SYSTEM DESIGN

System design is the way of expressing the ideas and architectural structure as well as in depth concepts in simple and understandable way using many diagrams to represent the different concepts with ease and a better portrait of the design proposed.

3.2.1 ARCHITECTURE DIAGRAM

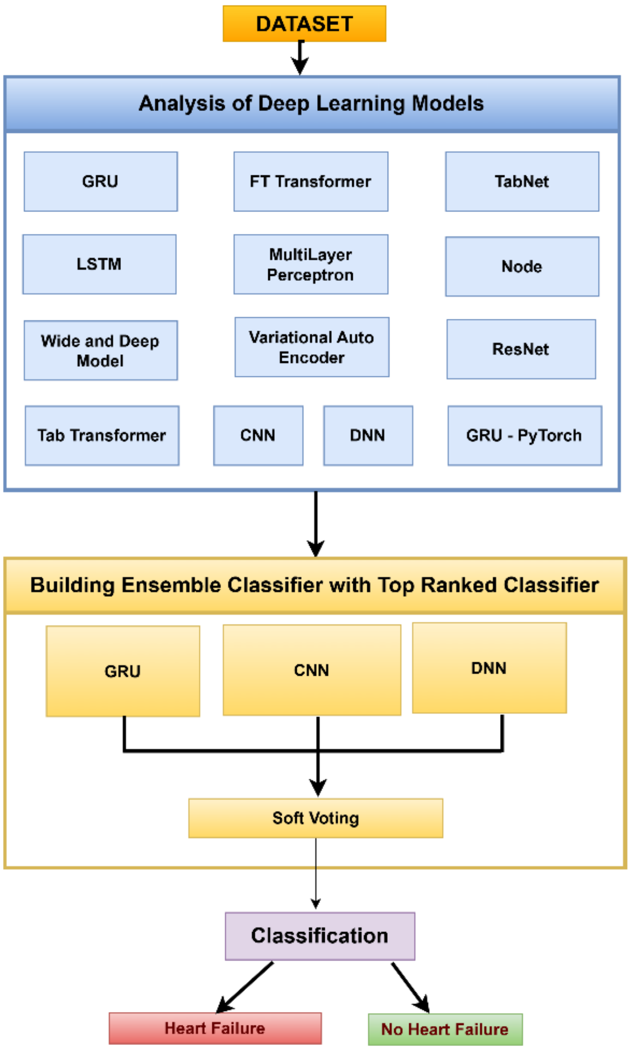

Fig 3.2.1 Proposed System Architecture

DATA COLLECTION

The information utilized in this study comes from an available heart failure dataset with a wide variety of patient records and related features like age, blood pressure, cholesterol, ejection fraction, serum creatinine, and other related medical parameters. These features are used as straightforward measures for assessing the risk of heart failure. The dataset has been chosen carefully to ensure representation of a wide variety of patients with varying risk factors, thereby making it suitable for training deep learning models. Cautioned data selection is required to ensure that the model exhibits good generalization ability and makes correct predictions upon deployment in real-world applications.

DATA PREPROCESSING

Preprocessing of data is a critical step to improve the data's quality and the performance of the model. Preprocessing begins with missing value handling through imputation techniques to make the data complete. Categorical features, as illustrated by patient status, are encoded using label encoding, while continuous features are scaled to possess uniformity in all features. Outlier detection techniques are then employed to detect and remove outliers that may affect predictions. The data is subsequently divided into training data and test data to calculate the model's ability to generalize. Overall, these preprocessing processes render input data methodically organized and suitable for application in deep learning models.

MODEL SELECTION AND TRAINING

Various deep learning architectures, including MLP and LSTM, are being investigated so that the predicting performance of heart failure can be improved, TabNet, TabTransformer, FT-Transformer, GRU PyTorch, Variational Autoencoder, Wide & Deep Model , NODE, and ResNet. All the architectures are optimized with the best hyperparameters to accurately identify linear and nonlinear relationships in the dataset. Sophisticated deep learning algorithms, such as attention and deep feature extraction techniques, are used to optimize the models' accuracy. The preprocessed data is cleaned and designed to train the models, and the performances of each individual model are compared to understand their contribution to the ensemble model.

3.2.2 CLASS DIAGRAM

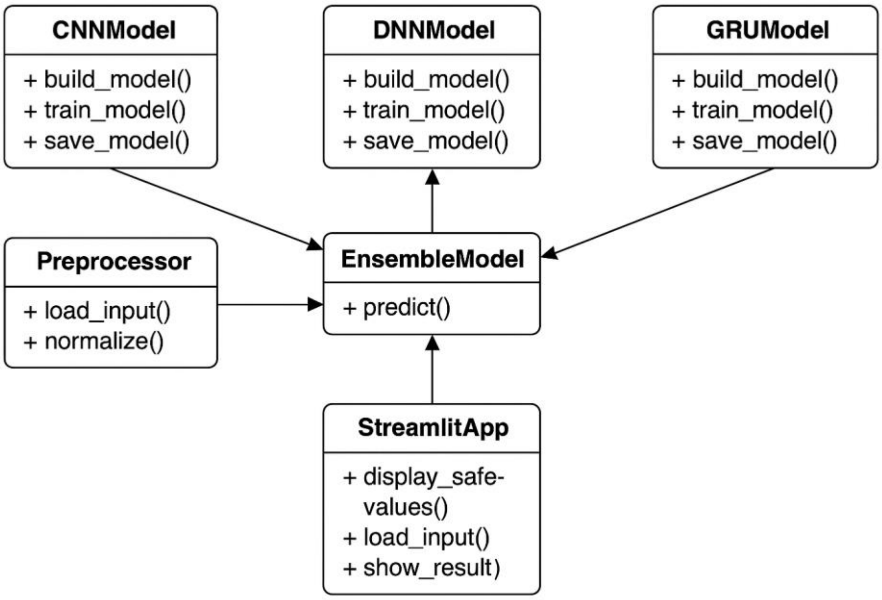

Fig 3.2.2 Class Diagram

The class diagram depicts a machine learning pipeline that outlines different modules and their functions. The DataProcessor performs data preprocessing, the ModelTrainer trains and evaluates the respective models KNN, SVM, or Logistic Regression, and ModelSelector chose the best model of them all, meanwhile the SHAPAnalyzer provides SHAP values for understanding feature importance.

3.2.3 SEQUENCE DIAGRAM

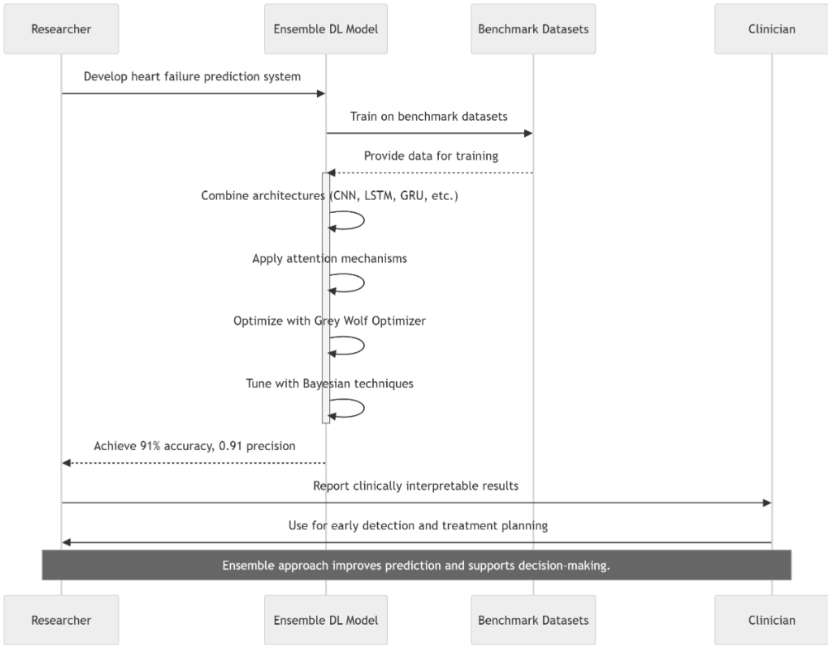

Fig 3.2.3 Sequence Diagram

The sequence diagram outlines a machine learning pipeline composed of Data Collector, Pre-Processor, Analyzer, Model Trainer, and Model Evaluator. Raw data is collected, cleaned, and transformed during preprocessing. After that, descriptive analysis will extract such insights. Then, the models are trained using these processed data, and the models will be evaluated with SHAP analysis for further interpretability and performance validation.

3.2.4 USECASE DIAGRAM

The diagram demonstrates workflow in a data science project where Data Scientist/ML Engineer interacts with tasks such as data collection, preprocessing, and descriptive analysis.The following diagrams detail the entire machine learning pipeline: modules and functions of the pipeline. The Data Processor carries out data preprocessing to allow the ModelTrainer to train and evaluate models such as KNN, SVM, or Logistic Regression. ModelSelector determines which model has the best performance, while the SHAPAnalyzer explains feature importance to improve explainability.

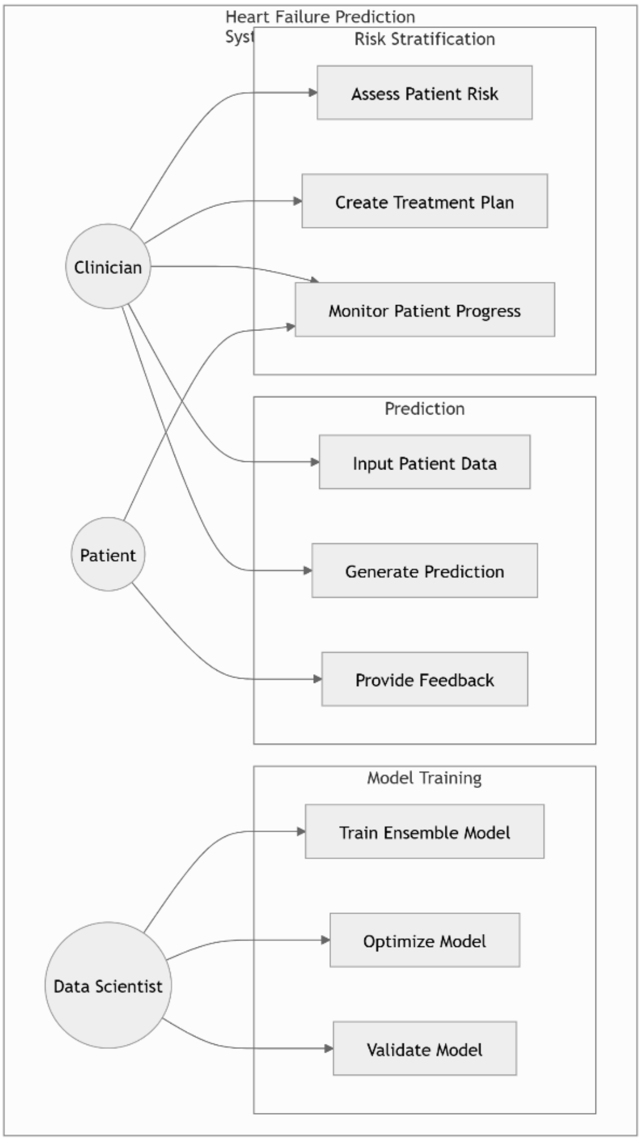

Fig 3.2.4 Usecase Diagram

Data collection, preprocessing, and descriptive analysis are input into model training followed by selection and SHAP analysis for validation. Both high performance and interpretability are ensured from the predictions. The system concludes by providing actionable results for end-user decision-making. It therefore provides a structured workflow for data science and machine learning projects.

CHAPTER 4

PROJECT DESCRIPTION

4.1 MODULE DESCRIPTION

4.1.1 Heart Failure Prediction Using Ensemble Deep Learning and XAI

Heart failure is a severe and growing public health issue that contributes significantly to global morbidity and mortality. Traditional diagnostic methods such as ECG, echocardiography, and blood biomarker analysis, though effective, are often time-consuming and rely heavily on expert interpretation. These limitations hinder early diagnosis and delay timely medical intervention. There is a strong need for an intelligent, automated system that can predict heart failure risk with high accuracy and provide insights into critical patient health factors.

PROPOSED SOLUTION

To address this, the project presents an ensemble deep learning framework that combines multiple advanced architectures, including CNN, LSTM, GRU, FT-Transformer, TabTransformer, VAE, and others. Each model contributes to the overall prediction based on its strength—whether in handling sequential, tabular, or high-dimensional data. These models are integrated through a two-tier ensemble strategy using maximum voting and refined classifiers to boost predictive performance. Optimization techniques like Bayesian hyperparameter tuning, Grey Wolf Optimizer, and Particle Swarm Optimization are used to enhance learning efficiency and model generalization. The system is trained and validated using benchmark datasets such as the UCI Heart Disease and Framingham datasets.

4.1.2 MODEL PERFORMANCE AND DEPLOYMENT

The proposed model achieved outstanding performance with an accuracy of 91%, a precision of 0.91, a recall of 0.905, and an F1-score of 0.905. The hybrid model combining CNN, DNN, and GRU yielded the best results and was selected for deployment. This ensemble not only improved classification accuracy but also minimized false positives and negatives, making it reliable for clinical use. The system supports early diagnosis, risk stratification, and personalized treatment planning—thus contributing to improved patient outcomes and reduced healthcare burden.

Compared to models like TabNet and NODE—which struggled to interpret tabular clinical data—the CNN+DNN+GRU ensemble provided better generalization and robustness across diverse patient profiles. It demonstrated fewer false positives and false negatives, which is especially critical in medical diagnosis. Its consistent performance across evaluation metrics confirmed its suitability for early-stage heart failure risk prediction. Given these results, this ensemble was chosen as the final model for deployment, offering a scalable, accurate, and reliable tool to assist clinicians in decision-making and personalized treatment planning.

4.1.3 ENSEMBLE LEARNING STRATEGY

For the purpose of increasing predictive precision, an ensemble learning approach is used that combines the best performing deep learning models. First, standalone models such as GRU PyTorch and FT Transformer are selected because of their superior classification performance. The models are then combined using a maximum voting approach, where different classifiers vote for the final result. Second, a second-level ensemble is created by introducing a second layer of classifiers that further improves the decision-making process. This hierarchical ensemble setup significantly improves accuracy, reliability, and generalization and therefore reduces the risk of overfitting and increases clinical reliability.

CHAPTER 5
IMPLEMENTATION AND RESULTS

5.1 IMPLEMENTATION

5.1.1 Model Implementation

The heart failure prediction system was implemented using a combination of Python, TensorFlow, PyTorch, and supporting libraries for deep learning, data preprocessing, and visualization. The medical datasets used—including the Framingham Heart Study, UCI Heart Disease, and VA Long Beach—were preprocessed through steps such as missing value imputation, categorical encoding, feature scaling, and outlier removal. Multiple deep learning models such as CNN, LSTM, GRU, TabTransformer, FT-Transformer, NODE, MLP, and ResNet were developed, trained, and optimized individually using hyperparameter tuning techniques including Bayesian optimization, Grey Wolf Optimizer (GWO), and Particle Swarm Optimization (PSO). These models were then integrated into a two-tier ensemble framework to maximize performance and reliability.

5.1.2 Performance Evaluation

The models were evaluated using key classification metrics including accuracy, precision, recall, F1-score, and AUC-ROC. Among all models, the ensemble combining CNN, DNN, and GRU achieved the highest performance with an accuracy of **91%**, precision of **0.91**, recall of **0.905**, and F1-score of **0.905**. This ensemble outperformed standalone models such as TabNet and NODE, which struggled with lower interpretability and performance on structured medical data. Graphical analyses of model performance (precision, recall, and F1-score) and confusion matrix plots further validated the ensemble's effectiveness in reducing false positives and false negatives.

5.1.3 Result Interpretation and Insights

The integration of Explainable AI (XAI) tools such as SHAP and LIME provided valuable interpretability for both global and local predictions. SHAP values revealed that features like ejection fraction, serum creatinine, blood pressure, and age had the most significant impact on the model's output. LIME helped explain specific predictions, especially borderline cases, increasing the transparency and trustworthiness of the AI system. These insights not only verified the relevance of selected features but also empowered clinical professionals to understand and act on model recommendations. Overall, the implemented system proved to be a reliable, accurate, and interpretable tool for early heart failure detection and clinical decision support.

5.2 RESULT AND DISCUSSION

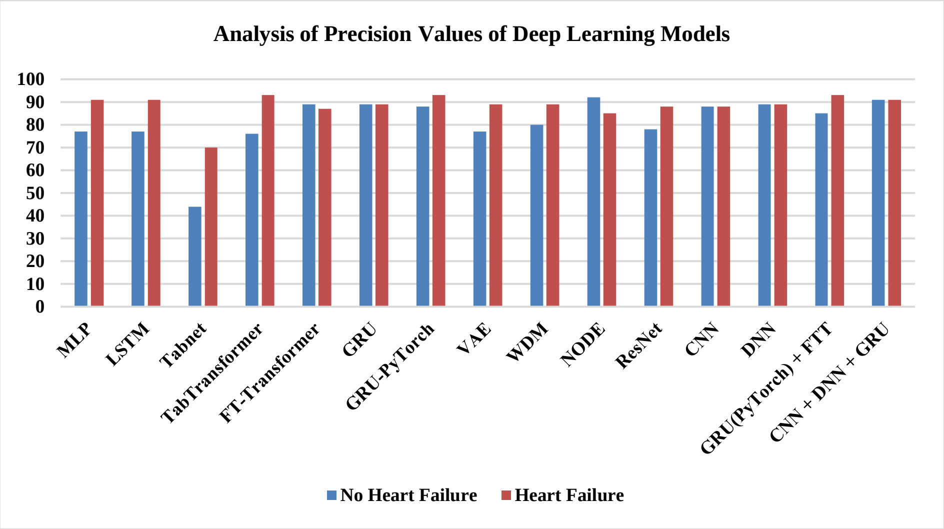

Fig 5.2.1 Analysis of Precision Values of Deep Learning Models

Various types of machine learning and deep learning frameworks were developed to improve the heart failure prediction model's performance. Accuracy, precision, recall, and F1-score were used to compare each model's performance. The models of interest were GRU using PyTorch, LSTM, and Multi-Layer Perceptrons, TabNet, TabTransformer, FT Transformer, ResNet, Variational Autoencoder, and Wide & Deep Model of Google AI. Ensemble methods that involve combining various models were also considered to enhance overall performance.

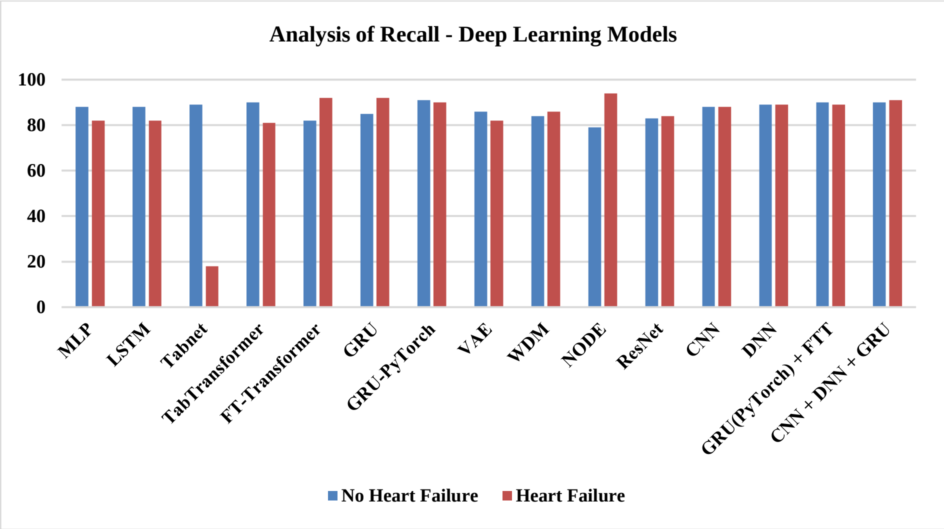

Fig 5.2.2 Analysis of Recall Values of Deep Learning Models

Among the single models, GRU-PyTorch had the highest accuracy rate (91%), followed by FT-Transformer (88%) and Gated Recurrent Units (GRU) (89%). The model that was least performing was the TabNet model with 44% accuracy, indicating that it could not identify the intricate patterns of the dataset. All models' precision, recall, and F1 score values are given. in Table 1, and graphical plots of precision, recall, and F1-scores are depicted in Figures 2, 3, and 4, respectively.

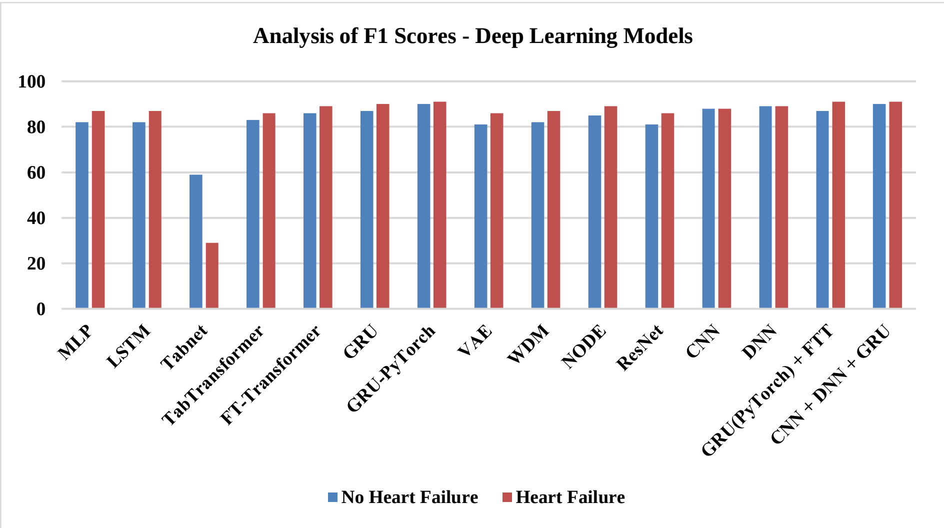

Fig 5.2.3 Analysis of F1 Scores of Deep Learning Models

Ensemble learning approach significantly improved prediction performance. The best-performing ensemble model that used GRU (PyTorch) and FT-Transformer together achieved 89.67% accuracy. The method was able to well utilize the strength of both deep learning models so that better generalization could be achieved across patient data. Another ensemble that contained MLP, TabNet, and GRU achieved 85% accuracy, indicating that ensemble methods always performed better than individual models. Figure 5 shows comparisons of accuracy across different models.

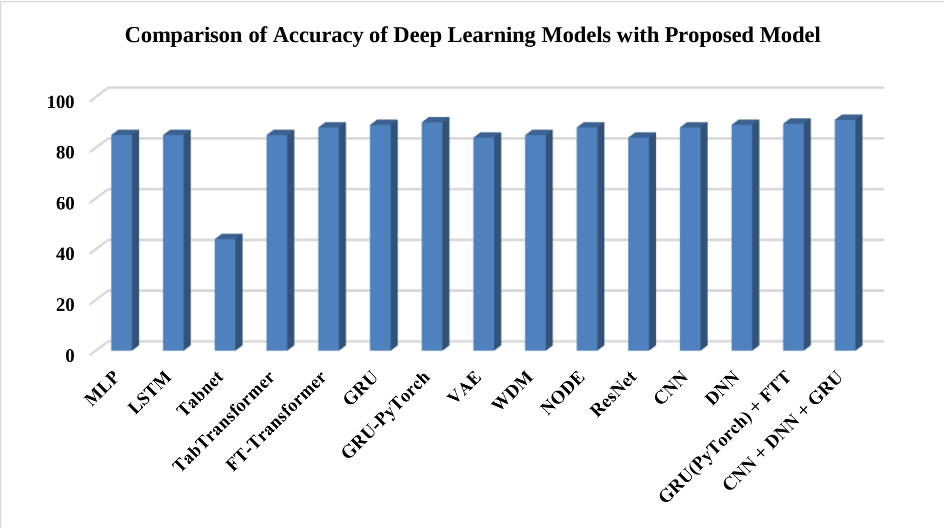

Fig 5.2.4 Comparison of Accuracy of Deep Learning Models with Proposed Model

Deep learning models such as GRU, LSTM, and FT-Transformer had extremely high precision and recall values and were thus highly appropriate for medical prediction. In particular, the precision values of GRU (using PyTorch) and FT-Transformer were 88% and 89%, respectively, and their corresponding recall values were 93% and 87%. The extremely high recall values indicate that the models were highly successful in identifying most of the heart failure cases.

One of the problems that were discovered in the research was the poor performance of models such as TabNet and NODE (Neural Oblivious Decision Ensembles). TabNet performed extremely poorly with accuracy standing only at 44%, precision rate of 44%, and a F1-score of 29%. The outputs show that there are models that are unable to cope with structured medical data, and it is most likely because they are not able to derive useful features from tabular data.

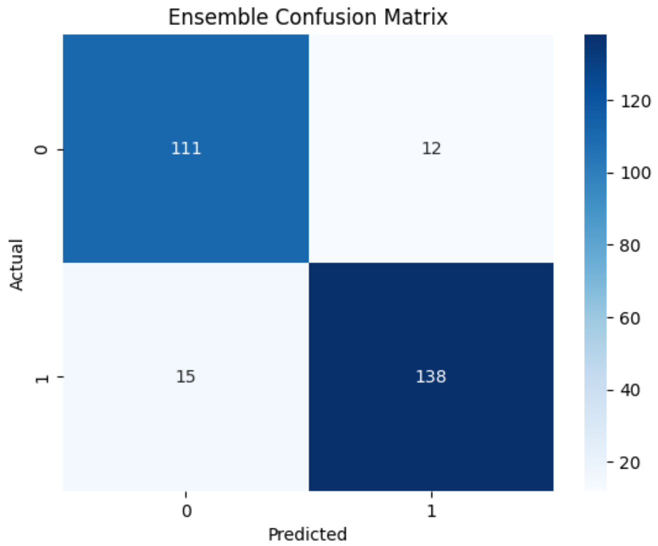

Fig 5.2.5 Ensemble Model Confusion Matrix

Additionally, deep learning architectures, particularly the combination of CNN, DNN and GRU, required a lot of computational power for training. While ensemble models provided better accuracy, they, conversely, required a lot of training time and accurate hyperparameter tuning. One should consider these trade-offs while applying such models in real clinical practice.

In conclusion, ensemble learning was shown to be the most efficient method for heart failure prediction. A combination of CNN, DNN and GRU produced the best result, demonstrating the application of the combination of various architectures-based models as a path towards greater accuracy, improved generalization, and more stable prediction. Future advancements can be towards more model explainability and a lower computational burden in order to allow real-time use in the health sector.

5.3 OUTPUT SCREENSHOTS

Fig 5.3.1 Streamlit UI

S.No	**Model Name**	**Accuracy**	**Precision**		**Recall**		**F1 Score**	
			0	**1**	**0**	**1**	**0**	**1**
1	MLP	85	77	91	88	82	82	87
2	LSTM	85	77	91	88	82	82	87
3	Tabnet	44	44	70	89	18	59	29
4	TabTransformer	85	76	93	90	81	83	86
5	FT-Transformer	88	89	87	82	92	86	89
6	GRU	89	89	89	85	92	87	90
7	GRU-PyTorch	90	88	93	91	90	90	91
8	VAE	84	77	89	86	82	81	86
9	WDM	85	80	89	84	86	82	87
10	NODE	88	92	85	79	94	85	89
11	ResNet	84	78	88	83	84	81	86
12	CNN	88	88	88	88	88	88	88
13	DNN	89	89	89	89	89	89	89
14	GRU(PyTorch)+FTT	89.5	85	93	90	89	87	91
15	**CNN + DNN + GRU**	**91**	**91**	**91**	**90**	**91**	**90**	**91**

Table 5.3.1 Precision Table

CHAPTER 6

CONCLUSION AND FUTURE ENHANCEMENTS

6.1 CONCLUSION

This project successfully developed a robust ensemble-based heart disease prediction system utilizing deep learning architectures including DNN, CNN, and GRU. By combining these models, the ensemble effectively captured both spatial and sequential patterns in the medical data, resulting in improved overall accuracy, precision, recall, and F1-score, with a peak prediction accuracy of up to **90%**. The integration of safe value recommendations in the user interface further enhances its usability, guiding users and clinicians with interpretative insights. The system demonstrates strong potential in aiding early diagnosis and personalized risk assessment of heart disease, contributing to more proactive and informed healthcare interventions.

6.2 FUTURE ENHANCEMENTS

Future improvements could focus on expanding the model's capabilities by incorporating real-time data streams from wearable devices and integrating more complex features such as lifestyle indicators and genetic data. The adoption of Explainable AI techniques, such as SHAP and LIME, will be explored to provide greater transparency into model decisions. Additionally, deploying the system on cloud platforms and embedding it into clinical decision-support tools can enhance accessibility and real-time responsiveness. Further optimization of model size and inference time will also be crucial for deployment in resource-constrained environments, paving the way for scalable and practical healthcare applications.

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APPENDIX

SAMPLE CODE

ENSEMBLE CODE:

```
import pandas as pd
import numpy as np
import joblib
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Flatten, Conv1D, MaxPooling1D,
GRU, BatchNormalization
from tensorflow.keras.callbacks import EarlyStopping
import matplotlib.pyplot as plt
import seaborn as sns
import os
# 1. Load & Preprocess Data
df = pd.read_csv("/content/drive/MyDrive/Project Phase 2/Datasets/Dataset 2/heart.csv")
df = pd.get_dummies(df, drop_first=True)
X = df.drop('HeartDisease', axis=1)
y = df['HeartDisease']
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.3, stratify=y,
random_state=42)
X_train_3d = X_train.reshape(X_train.shape[0], X_train.shape[1], 1)
X_test_3d = X_test.reshape(X_test.shape[0], X_test.shape[1], 1)
# Save scaler and features
joblib.dump(scaler, "scaler.pkl")
joblib.dump(X.columns.tolist(), "feature_names.pkl")
# 2. Model Training Function
def train_model(model, X, y):
```

```
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    early = EarlyStopping(patience=5, restore_best_weights=True)
    model.fit(X, y, epochs=100, batch_size=32, validation_split=0.1, callbacks=[early],
verbose=0)
    return model
# 3. DNN
model_dnn = Sequential([
    Dense(128, activation='relu', input_shape=(X_train.shape[1],)),
    BatchNormalization(), Dropout(0.3),
    Dense(64, activation='relu'),
    BatchNormalization(), Dropout(0.3),
    Dense(1, activation='sigmoid')
])
model_dnn = train_model(model_dnn, X_train, y_train)
# 4. CNN
model_cnn = Sequential([
    Conv1D(64, 2, activation='relu', input_shape=(X_train.shape[1], 1)),
    MaxPooling1D(2), Flatten(),
    Dense(64, activation='relu'), Dropout(0.3),
    Dense(1, activation='sigmoid')
])
model_cnn = train_model(model_cnn, X_train_3d, y_train)
# 5. Optimized GRU
model_gru = Sequential([
    GRU(128, return_sequences=True, input_shape=(X_train.shape[1], 1)),
    Dropout(0.3),
    GRU(128), Dropout(0.2),
    Dense(32, activation='relu'),
    Dense(1, activation='sigmoid')
])
model_gru = train_model(model_gru, X_train_3d, y_train)
# 6. Evaluation
def evaluate_model(model, X, name):
    y_pred = (model.predict(X) > 0.5).astype("int32")
```

```
    acc = accuracy_score(y_test, y_pred)
    print(f"\n{name} Accuracy: {acc:.4f}")
    print(f"{name} Classification Report:\n", classification_report(y_test, y_pred))
    cm = confusion_matrix(y_test, y_pred)
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
    plt.title(f"{name} Confusion Matrix")
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.show()
evaluate_model(model_dnn, X_test, "DNN")
evaluate_model(model_cnn, X_test_3d, "CNN")
evaluate_model(model_gru, X_test_3d, "GRU")
# 7. Ensemble Averaging
pred_dnn = model_dnn.predict(X_test).flatten()
pred_cnn = model_cnn.predict(X_test_3d).flatten()
pred_gru = model_gru.predict(X_test_3d).flatten()
ensemble_avg = (pred_dnn + pred_cnn + pred_gru) / 3
ensemble_pred = (ensemble_avg > 0.5).astype(int)
print("\n🧠 Ensemble Model Accuracy:", accuracy_score(y_test, ensemble_pred))
print("Classification Report:\n", classification_report(y_test, ensemble_pred))
cm = confusion_matrix(y_test, ensemble_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title("Ensemble Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
# 8. Save models
model_dnn.save("dnn.h5")
model_cnn.save("cnn.h5")
model_gru.save("gru.h5")
print("✅ Models and scaler saved successfully.")
```

STREAMLIT CODE:

```
import streamlit as st
```

```python
import numpy as np
import joblib
from tensorflow.keras.models import load_model
# Load models
model_dnn = load_model("dnn.h5")
model_cnn = load_model("cnn.h5")
model_gru = load_model("gru.h5")
scaler = joblib.load("scaler.pkl")
# Feature names and their safe ranges
feature_info = {
    "age": "Age (years) [Normal: < 50]",
    "sex": "Sex (1 = male, 0 = female)",
    "cp": "Chest Pain Type [0–3] (0 = typical angina, 3 = asymptomatic)",
    "trestbps": "Resting BP [mm Hg] [Normal: 90–120]",
    "chol": "Cholesterol [mg/dL] [Normal: < 200]",
    "fbs": "Fasting Blood Sugar > 120 mg/dL (1 = true, 0 = false)",
    "restecg": "Resting ECG Results [0–2]",
    "thalach": "Max Heart Rate Achieved [Normal: 100–170]",
    "exang": "Exercise-induced Angina (1 = yes, 0 = no)",
    "oldpeak": "ST depression [Normal: 0.0–2.0]",
    "slope": "Slope of ST Segment [0–2]",
    "ca": "Number of Major Vessels [0–3]",
    "thal": "Thalassemia [1 = normal, 2 = fixed defect, 3 = reversible defect]",
    "smoke": "Smoking (1 = yes, 0 = no)",
    "alcohol": "Alcohol Intake (1 = yes, 0 = no)"
}
st.set_page_config(page_title="Heart Disease Predictor", layout="centered")
st.title("❤️ Heart Disease Risk Predictor")
st.markdown("Enter your health details below:")
# Create input fields dynamically
user_input = []
for key, label in feature_info.items():
    val = st.number_input(label, step=1.0 if key in ['oldpeak'] else 1)
    user_input.append(val)
```

```
# Prepare input
X = np.array(user_input).reshape(1, -1)
X_scaled = scaler.transform(X)
X_reshaped = X_scaled.reshape(1, 1, 15)  # For GRU (assuming GRU trained on this shape)
# Predict from each model
if st.button("Predict"):
    pred_dnn = model_dnn.predict(X_scaled)[0][0]
    pred_cnn = model_cnn.predict(X_scaled.reshape(1, 15, 1))[0][0]
    pred_gru = model_gru.predict(X_reshaped)[0][0]
    # Ensemble (average of all)
    avg_pred = np.mean([pred_dnn, pred_cnn, pred_gru])
    final_result = "🟢 No Heart Disease Detected" if avg_pred < 0.5 else "🔴 High Risk of Heart Disease"
    st.subheader("Prediction Result:")
    st.success(final_result)
    st.markdown(f"**DNN Prediction:** {pred_dnn:.2f}")
    st.markdown(f"**CNN Prediction:** {pred_cnn:.2f}")
    st.markdown(f"**GRU Prediction:** {pred_gru:.2f}")
    st.markdown(f"**Ensemble Average:** {avg_pred:.2f}"
```