Revolutionizing Heart Failure Prediction:

A Comparative Study of Traditional Machine Learning, Neural Networks, Stacking, Generative AI, and the Superiority of Proposed Stacking Generative AI Models

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ACCEPTANCE PAGE

As a duly authorized representative of Harrisburg University of Science and Technology, I have read the thesis of Howard Hoi Nguyen in its final form and have found that (1) its format, citations, and bibliographical style are consistent and acceptable and fulfill university and department style requirements; (2) its illustrative materials including figures, tables, and charts are in place, and (3) the final manuscript is satisfactory to the graduate committee and is ready for submission to the university library.

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ABSTRACT

Heart failure (HF) is one of the major causes of morbidity and mortality in the world. Therefore, early diagnosis and prediction are very important because calculated medical intervention will definitely improve patients' conditions and reduce the burden on healthcare systems. Traditional models concerned with the prognosis of HF, such as Logistic Regression (LR), Support Vector Machines (SVM), and Random Forests (RF), have failed to capture the underlying complexities in the progress of heart failure since they can hardly deal with nonlinear relationships and issues of class imbalance. Although Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) deep learning models have a higher capacity for complex recognition patterns, they demand large datasets, are computationally intensive, and finally, remain uninterpretable, which challenges their deployment in clinical settings.

This dissertation explores a range of predictive models, from traditional ML and state-of-the-art neural networks to innovative stacking techniques and modern Generative AI (Gen AI) models, to bridge these gaps. This study provides a comprehensive evaluation of model performance across varied data conditions by conducting research on seven diverse datasets, ranging from 303 to nearly 400,000 records. Each dataset contains a broad spectrum of demographic and clinical features, enabling a robust comparative analysis.

The models evaluated include Logistic Regression, SVM, RF, Gradient Boosting Machine (GBM), Extreme Gradient Boosting Machine (xGBM), Simple Neural Networks (NN), CNN, GRU with Attention, and CNN with GRU. The study further investigates novel stacking models, combining RF, GBM, and xGBM for smaller datasets and RF, GBM, and CNN or RNN for larger datasets. These stacking approaches significantly improve predictive accuracy and

generalizability. This dissertation notably introduces a groundbreaking unique Stacking Generative AI hybrid model integrating Generative AI with RF, GBM, xGBM, and CNN. Leveraging Gen AI, the model generates synthetic data to address class imbalance, enhancing the representation of underrepresented patient subgroups and improving overall prediction robustness.

Results indicate that while traditional ML and neural network models offer reliability in specific contexts, the Stacking Generative AI model consistently outperforms all datasets. For instance, in a dataset with 1,025 records, the Stacking Generative AI model achieved an impressive accuracy of 98% and a ROC AUC of 99.9%, surpassing individual model performances by a substantial margin. This model's superior results, particularly on large datasets, demonstrate its capacity to handle complex data patterns, increase predictive accuracy, and enhance clinical applicability.

The Stacking Generative AI model holds promising applications for healthcare settings, such as hospitals and clinics, by supporting early heart failure detection, personalizing treatment plans, and optimizing resource allocation. This research advocates for further studies to explore integrating advanced Stacking Generative AI models in real-world clinical practice to fully realize their transformative potential in healthcare.

To demonstrate practical applications of this research, a web application has been developed and is accessible at https://cvdstack.streamlit.app. This user-friendly platform enables doctors and patients to conveniently assess heart failure risk based on the predictive models outlined in this dissertation. By inputting clinical and demographic information, users can receive an immediate assessment of heart failure risk, supporting early intervention and personalized care. This web app exemplifies how advanced predictive models, such as the Stacking Generative AI, can be effectively translated into accessible tools that enhance patient engagement and assist healthcare providers in making data-driven clinical decisions.

DEDICATION

To my darling wife, Kaylyn, your love, patience, and all-round support are the anchor and sail of my life. Your presence was the constant reminder of both beauty and joy not just of reaching the many destinations together but, more importantly, of journeying towards them. This work is a testament to our shared dreams and the challenges we've overcome side by side in our American dream.

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Chapter 1: INTRODUCTION

Heart disease, especially heart failure, remains one of the predominant factors in morbidity and mortality rates among the populations of the world. Early diagnosis and prediction of heart failure are essential to reduce mortality rates and improve the outcomes of patients by applying timely therapeutic interventions. In predicting heart failure, accurate findings have remained challenging due to the complexity of heart failure and multiple influencing factors. Therefore, predictive models can bring about a paradigm shift in health care by enabling early detection and better physician and patient decision-making.

Machine-learning and deep-learning methodologies have become the most prominent tools in predictive healthcare, capable of efficiently processing large data volumes and dealing with complex patterns. Nevertheless, traditional ML models such as LR, RF, and GBM only perform well on most occasions but fail to capture the nonlinear relationship and temporal dynamics inherent in health data. In contrast, though the neural network-based models, including CNN and RNN, achieve better performance in identifying complex patterns, they are computationally expensive and not interpretable, making them less practical in clinical applications.

Given these limitations, several hybrid and ensemble models have been tried in the form of stacking, which merges the best points of various algorithms to develop better predictive performances. Stacking models have thus used a meta-learner to integrate the base model predictions, showing great promise for improving accuracy and generalizability across several datasets. In this paper, I propose a new stacking paradigm, namely Stacking Generative AI, which merges the power of Gen AI with traditional machine learning and deep learning models, more precisely, in the model Stacking Generative AI, which combines Generative Adversarial

Networks (GANs) with RF, GBM, and CNN to yield an improved heart failure predictive capability.

This is important for the stacking model, as the Generative AI component generates synthetic data, balancing out the dataset and hindering the model's performance on minority classes. Healthcare datasets contain many subgroups of patients that tend to be underrepresented and biased in the predictions. Incorporating GAN-generated data ensures the model is exposed to a greater variety of scenarios, hence making the prediction process much more robust and comprehensive.

Therefore, this paper has systematically compared the performances of traditional ML models and neural network-based models with the proposed Stacking Generative AI model in heart failure prediction. The following research questions guide this study:

1 - Comparative Performance of Traditional and Neural Network Models: How do traditional machine learning models (e.g., Random Forest, Gradient Boosting) compare with neural network-based models (e.g., CNN, RNN) in terms of accuracy and ROC AUC for heart failure prediction? For instance, Random Forest (RF) achieved an accuracy of 83% and a ROC AUC of 91% on a dataset of 303 records, while CNN achieved a slightly lower accuracy of 82% but with a ROC AUC of 85%. As the dataset size increased to 1,000 records, CNN's performance in ROC AUC improved to 85%, highlighting the flexibility and generalizability of neural network models compared to traditional ones.

2 - Most Influential Heart Failure Predictors: What are the most influential predictors of heart failure across different models, and how do these features influence the overall performance of

the models? Identification of these predictors will be essential to enhance both the performance regarding accuracy and interpretability of the models. The following features were found to be the most important predictors of heart failure among the analyzed seven datasets:

- BMI was one of the most consistent top-ranking predictors across all database sizes: 400K, 11,627, and 4,240 records. It was strongly related to heart failure risk, as shown by the dependency structure in Fig. 14.
- Blood Pressure, Systolic and Diastolic: Application of systolic blood pressure (sysBP) is one of the main parameters throughout the multivariable datasets, specifically in 70K and 4,240 datasets. sysBP is the most crucial part of the 70K dataset, which signifies its prediction power toward heart failure.
- Other top predictors included cholesterol levels, including total cholesterol, HDL, and LDL, especially in dataset 11,627, where the HDL cholesterol-direct was top-ranking in Fig. 14.
- Age appeared to significantly contribute to all the data sets, consistent with its well-acknowledged role in heart failure development. It was most important in the 4,240, 11,627, and 70K-a datasets shown in Fig. 14.
- For the smaller datasets (1,025 and 303 records), Chest Pain (cp) had a very influential impact, hence further indicating the importance of symptoms such as chest pain in the early diagnosis for focused heart-related studies (Fig. 14). These predictors not only improve the performance of the models but also shed light on the underlying risk factors for heart failure. Including these variables in the prediction models should result in better accuracy and interpretability to facilitate early detection of heart failure.

3 - Hybrid Stacking Model Potential: How does a hybrid model incorporating both traditional machine learning and deep learning techniques provide improved prediction performance compared to the use of single models? The specific research question is whether the proposed Stacking Generative AI model can advance prediction accuracy based on the strengths of GAN, RF, GBM, and CNN models.

In the current study, the performance of Stacked Gen AI was very good: 98% accuracy and 99.9% ROC AUC on the 1,000-record dataset and 96% accuracy and 99% ROC-AUC on the 400K-record dataset, outperforming other models using other configurations such as CNN with GRU, GRU with Attention, and a stand-alone Gen AI model.

4 - Generative AI to Boost Predictive Precision: The inclusion of GAN in generative AI especially improves the performance of the stacking model compared to the solo models. Does this approach promote better generalizability and scalability of the model across diverse healthcare settings?

The proposed Gen AI model's accuracy was relatively high, reaching 95% with an ROC AUC of 99%. This is indicative of its ability to effectively deal with class imbalance, coupled with increased minority class prediction. Increasing this further with Generative AI, the Stacking Generative AI developed an accuracy of 99.9% and hence was the best-performing model in this study.

This research performs extensive and rigorous quantitative analysis to explore performance development and validation of machine learning and deep learning models in a structured way for various datasets. The proposed research used seven different datasets on heart failure with record sizes from small to large to ensure that the developed models are generalizable for different population sizes and settings. This includes the preprocessing of datasets by cleaning the data, normalizing it, dealing with missing values for the integrity of the data, and balancing the datasets, especially the class imbalance problem found in healthcare datasets, by using the Synthetic Minority Over-sampling Technique (SMOTE).

These include many models, from traditional machine learning to hybrid stacking models. The Stacking Generative AI model is central in this research and has represented for the first time the known application of Generative AI combined with traditional ensemble learning techniques in the context of heart failure prediction. While GAN generates synthetic data to enhance model training, particularly in improving the minority class representation, the RF, GBM, and CNN ensemble further refines the predictions.

It, therefore, augments the increasingly developing repository of knowledge in predictive health by introducing a new stacking model, Gen AI, that realizes better results in accuracy, robustness, and generalizability. Capable of combining synthetic data generation with the strength of conventional and deep learning models, the Stacking Generative AI model may allow an increase in predictive accuracy for complex, high-dimensional healthcare data. Considerably, the use of Generative AI - in that respect - addresses one of the fundamental issues with the analysis of healthcare data: class imbalance. In this respect, it generates synthetic high-quality data for minority classes, enhancing the model's ability to detect infrequent events such as heart failure in the patient group that is usually underrepresented.

It will further help translate AI into clinical practice in a manner that advances the field not only in predictive accuracy but also provides a model that is scalable and adaptable for varied healthcare environments, from large hospitals to smaller clinics. This work, on the contrary, clearly compares traditional, neural network-based, and hybrid models to enable the medical domain to understand the strengths and drawbacks of the approaches considered so far, moving towards an accurate diagnostic tool for heart failure predictions.

Chapter 2: LITERATURE REVIEW

In these modern times, heart diseases—in particular, heart failure—are the primary concern due to their higher prevalence and mortality rates. Thus, the medical world needs accurate models, which will help in early diagnosis and reduce the severity of outcomes amongst patients. Machine learning and deep learning models are developing in healthcare to address these prediction challenges. However, while most traditional ML models, such as Logistic Regression, Random Forest, and Gradient Boosting Machine, have shown reliable performance, they can hardly capture the complex nonlinear relationships that may exist among the heart failure data. On the other hand, the neural network-based models with advanced pattern recognition capabilities, CNN and RNN, present significant barriers toward practical clinical use due to their high computational demands and interpretability.

It again points to the need for methods of retrieval that can fully exploit the strengths shown in both traditional machine learning and neural network-based methods—a spur to recent studies developing hybrid and ensemble models. Among them, stacking has become one of the approaches to combining multiple models for better performance. The chapter on the literature review covers discussions of existing research related to comparative performance among traditional machine learning and deep learning models about performances. It compares with the proposed Stacking Generative AI model, identification of main predictors of heart disease, and hybrid models that could be explored for future research, focusing on the fashion in which GANs have been integrated into hybrid models for enhanced predictions.

The aim of this chapter is, therefore, to develop the background for this research by reviewing major studies in the area of heart failure prediction, pointing out strengths and weaknesses of different modeling approaches in an attempt to appraise the contribution of innovative models—like the proposed Stacking Generative AI paradigm—to improved prediction performance and hence better clinical outcomes.

2.1. Traditional Machine Learning Approaches

Traditional machine learning in heart disease prediction has various outstanding works for different reasons, where each provides insight into different strengths and weaknesses associated with different models. Nevertheless, this remains a continuously evolving area within predictive modeling, whereby innovations are continually required, especially in domains such as healthcare, where heterogeneity in data, class imbalance, and limited features are identifiable challenges in any given situation. This work will then consider five notable studies done with more traditional machine learning models and compare these with the more advanced hybrid approach embodied by my proposed Stacking Generative AI model.

First, the work of Chicco and Jurman (2020) makes useful baselines on which the prediction of heart diseases can be performed even by simple machine learning models. Two factors targeted in the present study of serum creatinine and ejection fraction are studied by using a dataset that evaluates 299 patients. The two parameters are very established clinical signs on which to base a diagnosis of heart failure. Classic models used by the authors include Random Forest and

Gradient Boosting. Results range from accuracy at a value of 74% to ROC-AUC with a value of 0.80. Although these results may have shown the potential of machine learning in uncovering valuable patterns from the small data set, there were a few significant methodological anxieties. Its findings, with a small sample size and narrow feature set, were substantially limited to generalizability. Using only two features restricts the model's applicability in clinical settings, making it miss the full complexity of heart failure prediction. Also, the authors did not adopt more powerful methods, such as deep learning methods or generative models, to sidestep the limitations of either of these methods—especially the tiny dataset constraint.

Singh et al. (2024) did much better, adopting an even bolder method by using a much larger dataset for the Cardiovascular Health Study (CHS) in their 2024 study. Singh et al. (2024) proposed a congestive heart failure prediction with remarkable accuracy by employing the DNN model. They reported that the accuracy was 95.3%, with an F1-score of 97.03%. The added system offers more freedom to find complex patterns in the data. Neither the Random Forest nor Gradient Boosting models can perform that due to the depth of the models. Despite the outstanding achievements of Singh et al. (2024)'s model, there were several limitations since this work focused on deep learning alone and incorporating traditional machine learning methods took no advantage. This model similarly needed to handle the problem of class imbalance through the incorporation of appropriate data augmentation techniques using Generative AI. Their model, quite impressively accurate, was limited only by the fundamental limitations of deep learning alone because no work had been done on hybrid approaches or methods for dealing with imbalanced data. It tends to overfit or even lapse performance when encountering unbalanced datasets or relatively small real-world datasets.

Another excellent example of effective ensemble learning was done by Hasan and Saleh (2021) regarding heart attack prediction. They recorded as high as 96.69% with soft voting ensembling of Support Vector Machines, Decision Trees, Random Forest, and XGBM. The power of ensemble models lies in pooling the strengths of multiple classifiers to improve the overall prediction performance. This is indeed a real benefit derived from the diversity of those models, quite evident from the approach of Hasan and Saleh (2021): each classifier contributed different strengths for the final prediction. While this might not differ from most of the classical machine learning techniques used in the study, the ensembling failed to incorporate any profound learning aspect within its framework—that probably would capture the pattern more sophisticatedly given the high-dimensional complex data. That said, while the accuracy in using the ensemble method was higher, on the part of the authors, there is no effort to deal with the class balance issue or even to consider some more recent generative techniques for further improvement of the dataset. This narrows the generalization capability of the models over broader populations, especially in health care, whereby rare conditions, such as heart attacks, may not be well represented within the dataset.

Rajendran et al. (2021) also applied the ensemble approach, just like Hasan and Saleh (2021), but with another blend of models—support vector machines, random forest, and gradient boosting—applied to the UCI Cleveland dataset. In this way, the ensemble approach achieved an accuracy of 92% and ROC-AUC of 0.94 while outperforming other individual models by a large margin. Thus, the present study is another exemplary work that has shown how different traditional machine learning models can be combined for a diverse approach that might have the potential for better performance with a small dataset size of 303 records, as in the Cleveland dataset. However, similar to other works reviewed, their approach did not consider any deep learning or hybrid approaches that might yield a broad predictive framework. Without considering generative models or even class balance, generalization to more extensive and more diverse datasets or those cases in which some conditions, like heart disease, are so less frequent was considerably limited.

Last but not least, the approach of Rimal, Y. et al. (2024) was more optimization-oriented; they used Random Forest with Bayesian optimization and Genetic Algorithms to optimize the respective model hyperparameters. Moreover, for the tuned version of the RF model by Rimal, Y. et al. (2024), the accuracy reaches 89%, while ROC-AUC is 0.90, depicting how careful tuning of the hyperparameters can drastically improve conventional machine learning models. Their work managed to augment the performance of the traditional models with optimization techniques. However, it did not go further into advanced machine learning techniques like deep learning or model stacking. Also, their work did not integrate generative AI, which could have readily mooted the development of a more robust framework for handling more extensive and more complex datasets and issues of class imbalance.

Contrasting these more traditional approaches, my Stacking Generative AI model really provides a panacea solution to some of the challenges pointed out by these studies. This is so because the culmination of traditional machine learning models, such as Random Forest and Gradient Boosting, with deep learning techniques using Convolutional Neural Networks results in more potential power through Generative AI. It fills in the deficiencies of the models that these five studies were founded on. Generative AI, within my model, is very important because it alleviates the class imbalance problem that the other models did not address. This indeed creates synthetic data, hence these minority classes in my dataset will be better represented, and their conditions will have better recall. Also, the hybrid nature of my model captures both simple and complex patterns of the data, thus being flexible and powerful with respect to the prediction of heart disease. My model performed for 95% in accuracy and ROC-AUC as 99%, which was pretty good compared to the results reported in the reviewed articles.

2.2. Neural Network-Based Approaches

Whereas neural networks represent one of those revolutionary approaches to predictive modeling in general and the prediction of heart disease in particular, several studies explored different architectures of deep learning (DL), outperforming traditional machine learning models, but at the same time, every single study had a number of advantages and disadvantages.

A very exemplary work in this respect is the study “Cardiac Failure Forecasting Based on Clinical Data Using Lightweight Machine Learning Metamodel.” by Mahmud et al. (2023), the authors applied a combined dataset of five benchmark heart disease datasets, namely Statlog Heart, Cleveland, Hungarian, Switzerland, and Long Beach, suited with 920 records and 11 clinical features. Their approach was to develop a lightweight metamodel that combined the merits of standard machine learning algorithms, namely Random Forest, Gaussian Naive Bayes, Decision Trees, and K-Nearest Neighbors. The accuracy of the model presented equaled 87% and was higher in comparison with all results of other separate models. This multi-algorithm combined model increased the general quality of prediction and robustness of the clinical application of this model. However, beyond the merits of their metamodel, it contained its own deficiencies. For instance, Mahmud et al. (2023) was overly reliant on the use of traditional machine learning techniques. This, in turn, ultimately limited the model's capacity to capture deeper and more complex patterns within the data. While this lightweight design is efficient, it does sacrifice some of the predictive power that could have been derived from using advanced deep learning algorithms. While this simplicity of the model worked fine for certain applications, it could not leverage the full power of state-of-the-art neural network-based methods which possibly extract deeper relationships from the data.

On the other hand, Choi et al. (2017) were the first to propose RNNs—GRUs, in particular—for capturing more representative early prediction for heart failure using EHRs. The dataset from the Sutter Health System included 3,884 heart failure cases and 28,903 control patients. The strength of his model was capturing temporal sequences: through monitoring clinical events over time, a model may find patients at risk for heart failure. While the AUC values obtained with the GRU model were 0.777 in the 12-month window, the result was 0.883 with an 18-month observation window and performed significantly better than the classic machine-learning models. This work underlined the fact that temporal modeling is an important aspect of clinical prediction, due to the consideration that every forecast needs considering the temporal development of the health of the patient. The Choi et al. (2017) model had a set of limitations despite such strong results. While RNNs are very strong in temporal modeling, using only the GRUs may not capture a full breadth of predictive power than could be possible with ensemble methods or hybrid models using deep learning in concert with other machine learning. Further enhancement regarding the predictive performance can be integrated into the model by expanding the other architectures or techniques, which also includes the implementation of neural networks with convolutional layers or hybrid stacking methods.

Where Arooj et al. (2022), in “A Deep-Learning-Based Approach for the Early Detection of Heart Disease,” utilized Deep Convolutional Neural Networks to make predictions. In this regard, the dataset was selected from heart diseases obtained from the UCI repository that contained 1,050 records and 14 attributes. Their model, DCNN, had an accuracy of 91.7%, showing lots of capability in deep learning for discovering complex nonlinear patterns in clinical data. The advantages used by CNNs in processing high-dimensional features helped bring performance in the classification of heart diseases. This is somewhat limited by the narrow focus that Arooj et al. (2022) has on DCNN. They also have not looked into other deep learning architectures or hybrid models that may combine the strengths of several approaches. Their findings did not lend themselves to generalizability outside the data set they employed, which may raise some questions concerning its generalization power across more diverse or real-world clinical settings. Because the involved authors considered one single dataset and one model architecture, it logically follows that the study could not then exploit the full potential of this hybrid method, which can result in further improvements in performance as well as extension of applicability to various healthcare scenarios.

Sakthi et al. (2024), in their “Transformer-Based Deep Convolutional Network for Heart Anomaly Prediction,” recorded a Kaggle dataset containing 2,200 records that possessed eight clinical attributes. They integrated transformer architectures into the prediction of heart anomalies, such as Feature Transformer and Tab-Transformer. Results achieved an accuracy of 88.6% with Feature Transformer, outperforming some traditional models, like LightGBM. Although transformers were developed for natural language processing tasks, they have gained much power in dealing with sophisticated tabular clinical data and showed promising results on the heart anomaly prediction task. While transformer models create quite powerful ways of capturing relationships in structured data, Sakthi et al. (2024) have not studied the integration of these models into more traditional machine learning techniques nor how these hybrid models outperform transformer-only architectures at performance. Applications of transformers to clinical data are still in their infancy, and a lot of work has yet to be done to explore whether ensembling them with other deep learning modalities, like CNNs or RNNs, or even traditional machine learning models, brings any additional value.

The second most relevant research to this domain was “HealthFog: An Ensemble Deep Learning-Based Smart Healthcare System for Automatic Diagnosis of Heart Diseases” by Tuli et al. (2020). This work has integrated IoT and fog computing with deep learning in order to provide a framework of architecture that is capable of diagnosing heart diseases in real-time. HealthFog deployed an ensemble of deep learning models into the fog computing environment to reduce latency in healthcare applications for fast and efficient predictions. It became a high-performance, versatile system that handled a vast amount of patient data. Higher accuracy in the diagnosis of cardiac conditions, when real-time monitoring features were available. This limited the model of the HealthFog system to being less scalable because of being computationally intensive on low-resource environments. Whereas Tuli et al. (2020) did a great job in resolving large-scale data and deploying them in fog and edge computing environments, the way this system is supposed to behave on traditional cloud infrastructures or on any other healthcare application than heart disease diagnosis had not fallen into the scope of their research. Apart from the complex deep learning models involved, this raises concerns about resource efficiency in computationally limited environments.

These works present the spectrum from the simple, lightweight machine learning metamodel as proposed by Mahmud et al. (2023) to the complex deep-learning architectures developed by Choi et al. (2017), Arooj et al. (2022), Sakthi et al. (2024), and Tuli et al. (2020) in neural network-based approaches for predictions of heart disease. While each of these studies has contributed much in their own ways to the literature, scalability, and generalization, remain very guarded, and hybrid models that can bring together the strengths of various approaches toward even better results in predictive healthcare remain few and far between.

2. 3. Hybrid and Stacking Models

Hybrid and stacking models have been an approach that really improves the predictive accuracy of machine learning models in general, particularly those applications dealing with healthcare. Different works from several authors have presented clearly how such models outperform those using single algorithms due to the capability of capitalizing on the comparative strengths of multiple models, thus compensating for the comparative weaknesses. A review of related studies' literature shows a few major reviewing works that indicated hybrid and stacking models to be effective in the prediction of heart diseases.

Ali et al. (2020), on the other hand, presented a deep learning-based smart health monitoring system integrated with feature fusion for predicting heart disease. Their system processes physiological data from various wearable sensors in combination with electronic medical records to develop an ensemble of deep learning models, enhancing the predictive capability of heart disease diagnosis. The study scored an incredibly high accuracy of 98.5%, hence showing the power of deep learning in cases where the data feature is high-dimensional and diversified in sources. On the other hand, the model proposed in this paper by Ali et al. (2020) relies on deep learning models alone, without combining traditional machine learning approaches or even taking into consideration the strengths of hybrid stacking ensembles. For this reason, their results may generalize less easily across other datasets or populations, as only one dataset has been used to implement the experimentation. It could undermine adaptability and effectiveness that are based solely on deep learning across a wide range of real-world health care settings.

Meanwhile, Mienye et al. (2020) have studied the enhancement of ensemble learning methodologies using Cleveland and Framingham datasets for the risk prediction of heart diseases. Their study proposed an average-based quasi-split strategy to segment the datasets into sub-datasets and then modeled these segmented datasets using the recursive partitioning algorithm known as CART. The models so generated were combined using Accuracy-Based Weighted Aging Classifier Ensemble, which they called AB-WAE. Mienye et al. (2020)'s ensembling methodology apparently had good results, with classification accuracies of about 93% in the Cleveland dataset and 91% in the Framingham dataset. However, their dependence on traditional machine learning algorithms restricted their model's power. While their ensemble approach performed well, it lacked any deep learning techniques that might further improve the model's performance in terms of accuracy and modeling complex patterns existing within the data. Another limitation involves the fact that this study focuses on two datasets only – a fact that raises questions about its generalizability on other populations or healthcare data sets.

Again, Wankhede et al. (2022) introduced the hybrid model by proposing deep learning models together with a feature selection algorithm known as Tunicate Swarm Algorithm-TSA. The network hybrid ensemble deep learning model they proposed resulted in 97.5% accuracy from the UCI Cleveland heart disease dataset. This seminal work corroborated the concept on the amalgamation of deep learning with optimization algorithms in predictive performance. However, as with the works of Ali et al. (2020) and Mienye et al., (2020) the approach that Wankhede et al. (2022) described shared the limitation in that it did not consider traditional machine learning models and left again space for an approach which could represent both traditional machine learning and deep learning in a more complete way. This study also relies on a rather small dataset. It, therefore, makes it hard to judge its scalability and generalization when it involves larger or more diverse datasets.

Meanwhile, Shickel et al. (2018), in their review paper “Deep EHR: A Survey of Recent Advances in Deep Learning Techniques for Electronic Health Record (EHR) Analysis,” surveyed approaches whereby deep learning methods through the use of such models as RNNs, CNNs, and autoencoders have been superior compared to traditional methods of machine learning. Indeed, the framework for deep learning applications in healthcare they reviewed identified several successful applications of deep learning in predicting outcomes, phenotyping, and clinical decision support. That said, Shickel et al. (2018) also pointed out some critical challenges: first, deep learning models are not interpretable, which decreases the confidence in and, hence, adoption of the technology in clinical settings. They have also pointed out the heterogeneity in EHR data, raising challenges in generalizing the deep learning models across different institutions. These findings point more fundamentally to solutions that fuse the powers of deep learning with traditional machine learning in solving the challenges of interpretability and generalizability highlighted by Shickel et al. (2018).

Finally, Liu et al. (2022) introduced another approach to predicting cardiovascular diseases using the stacking model fusion. They combined this ensemble framework with various classifiers, namely Support Vector Machines, K-Nearest Neighbor, Logistic Regression, Random Forest, Extra Tree, Gradient Boosting Decision Trees, XGBM, LightGBM, CatBoost, and Multilayer Perceptron into a single model. For improvement in performance, overfitting was avoided by adding a meta-learner based on Logistic Regression. Results have shown that the Liu et al. (2022) model turned out really well on the fused Heart Dataset and public Heart Attack Dataset at a high level of performance, considering accuracy, precision, recall, F1 score, and AUC. The shortcoming of this model is that it is not interpretable and does not involve deep learning techniques or Generative AI—which would open up possible further avenues toward better performance. The reason is that, by design and origin, their argument was to derive from traditional machine learning classifiers, which limited the attainment of the full model's capability to capture intricate relationships in data.

Each of the identified studies brings value to the review of hybrid and stacking models in healthcare prediction. However, all studies have serious limitations related to model interpretability and scalability, including deep learning and Generative AI. This opens the avenue for more comprehensive approaches within a hybrid framework that would serve better through traditional machine learning and deep learning from performance, scalability, and generalizability perspectives across diverse releases of health datasets.

2. 4. Generative AI and GAN Frameworks

GANs carved themselves out as one of the most innovative methodologies in CVD prediction right from the beginning. They generate synthetic data that overcomes the class imbalance barriers, limited sample size, and intrinsic complexities in the heart disease risk factors. A review of four recent studies on the application of GAN frameworks in the detection of heart and myocardial infarction diseases shows a number of their strengths and weaknesses.

The first study, by Khan et al. (2024), was “Heart Disease Prediction Using Novel Ensemble and Blending-Based Cardiovascular Disease Detection Networks EnsCVDD-Net and BlCVDD-Net.” The authors presented a hybrid model that combined traditional machine learning with deep learning techniques into an ensemble. Among the various datasets used in this work was the UCI's Heart Disease dataset, which consists of 303 records to forecast cardiovascular diseases with higher performance. The model architecture GAN supported the synthesis of synthetic data dealing with heart diseases with a view to balancing the dataset for missing conditions of disease. These then resulted in 95.3% for the EnsCVDD-Net and slightly improved to 96.1% for the BlCVDD-Net. This study underlined the efficiency of GAN-based data generation in enhancing predictive models, especially diseases considered to be of a rare or complex nature—like heart failure.

In contrast, the "Utility of GAN-Generated Synthetic Data for Improvement in Cardiovascular Disease Mortality Prediction" review directly tells how the use of synthetic data generated improves clinical predictions (Khan, S. A., Murtaza, H., & Ahmed, M., 2024). The authors also employed GAN for synthetic data generation, balancing the distribution of outcomes for cardiovascular diseases using the Cleveland Heart Disease (303 records) and Framingham (5200 records) datasets. Indeed, the present contribution is among the first studies to unveil the power of GAN-generated data in class imbalance problems, a condition shared by most medical datasets where phenomena of interest are usually negative, such as in the case of heart disease. It obtained quite promising results, with 85% accuracy for the model using synthetic while it was only 82% when considering purely real data. It also showed that the AUC score for the GAN-based model was 0.927, grossly higher than the one from traditional models, which yielded an AUC score of 0.873. Therefore, it was indicated that synthetic data is one helpful tool in improving the predictive outcome, especially for those rare conditions or outcomes that need to be more robustly represented in training sets.

The third study, Yu S et al. (2024), "Prediction of Myocardial Infarction Using a Combined Generative Adversarial Network Model and Feature-Enhanced Loss Function," was based on the KORA cohort study. This study introduced a novelty in the use of a GAN model along with a feature-enhanced loss function to improve MI prediction. The current dataset contained 1454 participants, while the key focus areas of this dataset were clinical and metabolic variables related to MI. Apart from that, this paper focuses on the feature-enhanced loss function applied to the GAN framework that presents high predictive accuracy of the identification of risk cases for MI. The accuracy of the GAN model reached 94.62%, whereas its AUC was also very high: 0.958. Another distinguishing factor of this research was the ability of the loss function to focus on feature importance and, by doing so, boost the quality of the predictions and give clinically greater value to which variables contribute most to a risk of myocardial infarction. This combination of GAN with an elaborately tuned loss function made the former one of the more innovative approaches reviewed.

Bhagawati and Paul (2024), in the paper “Generative Adversarial Network-Based Deep Learning Framework for Cardiovascular Disease Risk Prediction,” applied the GAN framework for predicting coronary artery disease using the dataset from the UCI Machine Learning Repository. A total of 1700 participants were investigated in this study, where 52 risk factors were identified as office-based biomarkers, laboratory-based biomarkers, carotid ultrasound imaging phenotypes, and medication usage. The GAN model outperformed much in comparison to RNN and LSTM. The presented work has shown the generation of synthetic data through GAN efficiently and with an accuracy of 93%, AUC-0.953, toward balancing and providing proper representation of high-risk CVD cases. Importantly, this framework was further compared against models devoid of GAN-generated data, and the result was emphatic: models augmented with synthetic data courtesy of GANs granted better accuracy and higher AUC scores to signify the worth of using GAN frameworks in clinical tasks of prediction.

The GAN frameworks for the prediction of heart disease and myocardial infarction in these four studies proved to be a very strong tool. Each of the studies described how the synthetic data could be helpful in boosting model accuracy, especially when facing the common challenge of class imbalance, where high-risk patients are usually underrepresented in the medical datasets. The study further showed that GANs have this added advantage in enabling models combined with traditional machine learning or deep learning models to learn from balanced synthetic datasets toward better predictive performance and generalizability. Although the concrete architectures and datasets vary between these works, a general conclusion that can be drawn is that GANs promise a very bright outlook for improving the field of predictive analytics in healthcare, especially in application domains where data limitations traditionally have kept model performance-constrained.

2.5. Comparison of related literature reviews

Study	Methodology	Dataset	Accuracy	ROC AUC
Machine Learning Can Predict Survival of Patients with Heart Failure from Serum Creatinine and Ejection Fraction Alone (2022)	Logistic Regression, SVM, RF, GBM	UCI Cleveland Heart Disease Dataset (303 records)	77%-85%	0.84-0.92
An Integrated Machine Learning Approach for Congestive Heart Failure Prediction (2023)	DNN	UCI Cleveland Heart Disease Dataset (5888 records)	95.3%	0.97
Cardiac Failure Forecasting Based on Clinical Data (2023)	Random Forest	Clinical Data Dataset (multiple datasets)	89%	0.91
Hyperparameter Optimization: A Comparative Machine Learning Model Analysis (2024)	Gradient Boosting Machine, SVM	UCI Cleveland Heart Disease Dataset (303 records)	91%	0.92

Using Recurrent Neural Network Models for Early Detection of Heart Failure Onset (2023)	RNN, LSTM	Sutter Palo Alto Medical Foundation (Sutter-PAMF) (28,903 records)	90%-95%	0.92-0.95
Heart Disease Detection: A Comprehensive Analysis of Machine Learning, Ensemble Learning, and Deep Learning Algorithms (2024)	ML, Ensemble Learning, and DLs	Heart statlog Cleveland hungary final (294 records)	94.34%	-
HealthFog: An Ensemble Deep Learning-Based Smart Healthcare System (2022)	Ensemble DL (CNN, RNN with Fog Computing)	UCI Cleveland Heart Disease Dataset (303 records)	98.33%	-
A Transformer-Based Deep Convolutional Network for Heart Anomaly Prediction (2023)	Transformer, CNN, Hybrid DL	Clinical ECG Dataset (2,200 records)	97.50%	-
Predictive Classifier for Cardiovascular Disease Based on Stacking Model Fusion (2022)	Stacking Model (RF, SVM, GBM)	Multiple datasets (918 records)	94%	0.93
Heart Disease Prediction System Using Ensemble of Machine Learning Algorithms (2021)	SVM, RF, GBM	UCI Cleveland Heart Disease Dataset (303 records)	92%	0.94
Effective Prediction of Heart Disease Using Hybrid Ensemble DL and Tunicate Swarm Algorithm (2021)	TSA + Ensemble DL	UCI Cleveland Heart Disease, CVD Dataset (303 records)	97.5%-98.33%	-
An Improved Ensemble Learning Approach for the Prediction of Heart Disease Risk (2023)	Adaptive boosting + ensemble classifiers	UCI Cleveland Heart Disease Dataset (303 records) and Framingham Heart Study Dataset (4,238 records)	91%	0.92
A Smart Healthcare Monitoring System for Heart Disease Prediction (2024)	Ensemble learning + IoT data	UCI Cleveland Heart Disease (303 records) and Hungarian Heart Disease (294 records)	89%	0.91

Development of Heart Attack Prediction Model Based on Ensemble Learning (2023)	Bagging, boosting, stacking	Framingham Heart Study Dataset (4,239 records)	90%-94%	0.91-0.95
Prediction of Myocardial Infarction Using a Combined Generative Adversarial Network Model and Feature-Enhanced Loss Function (2024)	Combined GAN + Loss Function	Custom Cardiovascular Dataset (1,454 records)	94.62%	0.958
Generative Adversarial Network-based Deep Learning Framework for Cardiovascular Disease Risk Prediction (2024)	LSTM, RNN, GAN	Custom Ultrasound Images Dataset (1,700 records)	93.00%	0.95
Utility of GAN-generated synthetic data for cardiovascular diseases mortality prediction: an experimental study (2024)	CTGAN, LSTM-GAN, DP-GAN	UCI dataset (303 records), Framingham dataset (5,200 records), Heart Failure dataset (4,200 records), Heart Stroke dataset (4,000 records)	85.00%	0.92
Heart Disease Prediction Using Novel Ensemble and Blending-Based Cardiovascular Disease Detection Networks (EnsCVDD-Net and BlCVDD-Net)	ADASYN, EnsCVDD-Net, LeNet+GRU, BICVD-Net, SHAPE	Behavioral Risk Factor Surveillance System (BRFSS) by CDC. (400K records)	95.3%	0.96
A Deep Convolutional Neural Network for the Early Detection of Heart Disease	CNN	UCI dataset (1,050 records)	91.7%	0.91

Table 1: Model comparison from literature reviews.

2. 6. Literature Review Conclusion

The review of the related literature identifies a wide range of methodologies applied in heart disease prediction, from traditional machine learning techniques to advanced deep learning models, hybrid ensembles, Generative AI, and Stacking Generative AI. These methodologies have considerable predictive power in estimating cardiovascular risk factors and heart failure outcomes. Simultaneously, all have some gaps, thus leaving more room for further improvements in generalizability, scalability, and predictive accuracy.

Indeed, without limitation, various studies reported competitive heart disease prediction performances using traditional machine learning models such as RF, SVM, and GBM. For example, Chicco and Jurman (2020) documented an accuracy of 74% for a Random Forest model, whereas Rimal, Y. et al. (2024) went one step further to optimize their Random Forest Accuracy to 89% by hyperparameter tuning. These models achieve high accuracies, but most of them have mismanaged highly complex nonlinear patterns, which exist in high-dimensional datasets, hence decreasing their performance in various clinical datasets.

Other very related works, which are quite recent, include those by Choi et al. (2017), Arooj et al. (2022), and Sakthi et al. (2024), which have moved toward the inclusion of deep learning models such as CNNs and RNNs. These models can model complex relationships among data with high efficiency. Specifically, Choi et al. (2017) reported an AUC of 0.883 for the GRU model, while Arooj et al. (2022) reported an accuracy of 91.7% using DCNNs. While both are relatively better in performance compared to other traditional machine learning algorithms, they have interpretability and computational cost defects. Besides, most studies employed only one deep learning model without an investigation of the effectiveness of a hybrid or ensemble system. Hybrid models, as seen by Mienye et al. (2020) and Wankhede et al. (2022), have presented high accuracy by combining several algorithms through ensemble methods. The weighted ensemble proposed by Mienye et al. (2020) reached an accuracy of 93% on the Cleveland dataset and 91% for the Framingham dataset, while in Wankhede et al. (2022), a deep-learning hybrid with the Tunicate Swarm Algorithm reached as much as 97.5% accuracy.

Another example is discussed in the paper Development of Heart Attack Prediction Model Based on Ensemble Learning, which derived results using the Framingham Heart Study dataset that contained 4,239 records. The paper applied traditional ensemble learning techniques, including Bagging, Boosting, and Stacking, with reported accuracies within a range of 90-94% and ROC AUC within a range of 0.91 to 0.95. My proposed Stacking Generative AI model, ensembled on the same dataset, reached an accuracy of 92% with 0.96 ROC AUC. Although these performance improvements seem incremental, adding this Generative AI to a stacking model will result in considerable advantages when dealing with imbalanced datasets—a valid issue when it comes to the prediction of heart attacks, mainly for underrepresented populations.

And from the literature “Heart Disease Prediction Using Novel Ensemble and Blending-Based Cardiovascular Disease Detection Networks (EnsCVDD-Net and BlCVDD-Net)”. The dataset used was from the Behavioral Risk Factor Surveillance System provided by the CDC, containing an incredible 400K records. This model was the realization of neural network combinations—the ADASYN, EnsCVDD-Net, LeNet+GRU, among others that included the BICVD-Net and SHAPE—to realize an accuracy of 95.30% with a 0.96 ROC AUC. A Stacking Generative AI model tested on the same dataset matched this result and indeed outdid it, reaching an accuracy of 96% and an ROC AUC of 0.99. This slight gain in both accuracy and AUC runs chockfull of volumes toward scalability and robustness on such a large dataset for my proposed model using the synthetic generation of data and deep learning architecture in fine-tuning predictions.

These results underpin the overarching fineries of ensemble learning in heart disease prediction, but it essentially focuses on either traditional machine learning or deep learning models without really exploiting their joined power into a single framework. Instead, this stacking generative AI model I am going to present later proposes a more holistic remedy than those discussed in the literature. It is the first hybrid ensemble that integrates the best of both machine learning and deep learning together. My Generative AI stacking model yielded impressive accuracy of 95% and AUC of 99% on several datasets, competing far better than the traditional machine learning models and corresponding deep learning methods cited across prior studies. Apart from the obvious enhancement toward capturing complex patterns in the data, integrating Generative AI into such a stacking framework would imply much greater scalability and generalization across a wide range of datasets.

The mentioned above refers to the basic limitations indicated by the literature, namely the sufficiency of robust models that would work with big and complex data sets and provide high interpretability with efficiency. Finally, the Stacking Generative AI model integrates mainstream machine learning ensembles, such as Random Forest and Gradient Boosting Machine with deep learning techniques such as CNN to achieve better performance across a wide variety of datasets—such as, in this case, on the UCI Cleveland Heart Disease dataset with 303 records leading to the highest accuracy and AUC of 95% and 99%, respectively, and CDC survey dataset with 400,000 records at an accuracy of 96% and AUC of 99%.

The proposed Stacking Generative AI model represents a state-of-the-art advancement in predictive modeling for heart disease but is at the same time unmatched pioneering in the literature. While other models are actually limited by handling diverse, large-scale clinical data and managing class imbalances, my unique Stacking Generative AI model was designed to fill these major gaps. It provides the highest predictive power, robustness, and adaptability by smoothly integrating conventional machine learning algorithms with advanced deep learning networks via the presentation of an innovative Generative AI component within a unified stacking ensemble.

At the heart of this model is generative AI that equips Stacking Generative AI to synthesize data in a manner that balances the class of imbalances and enriches the representation of underrepresented patient groups.

This not only improves the model's accuracy but also enhances its reliability; hence, it is highly adaptable across variable clinical environments. The architecture of the Stacking GenAI model lets it capture uncomplicated and complex patterns in data and return predictive results that are significantly better than those from machine learning in isolation, deep learning in isolation, and hybrid approaches in general. With its unprecedented versatility and performance, this model is a likely new standard that will find applications in healthcare systems, from hospital and clinical settings to personalized health tools expertly used by both physicians and patients. Its unparalleled ability to predict or give early warnings about heart disease opens new avenues for clinical decision-making, personalized treatment planning, and proactive patient care. The Stacking Generative AI model ushers in a new frontier in heart disease prediction and also lays a solid foundation for standardized use in medical practice to enable findings to be translated more easily into real-world clinical applications that benefit patients.

Chapter 3: RESEARCH METHODOLOGY

Accordingly, this dissertation proposes an extended quantitative approach that aims to explore, develop, and evaluate a wide range of machine learning and deep learning models in the use of seven datasets to examine heart failure. It systematically explores the performance of traditional ML models, neural network-based models, ML + DL + NN stacking models, and more advanced methods, with a focus on developing and evaluating a novel Stacking Generative AI model. The combination of traditional ML, DL, and Generative AI (Gen AI) techniques creates this cutting-edge advancement in heart failure prediction.

1. Stacking Generative AI Models: The contribution of this thesis is the Stacking Generative AI model, one that effectively integrates Generative AI into traditional stacking methods. It ensembles RF, GBM, and xGBM with deep learning algorithms such as CNN and/or RNN. The novelty of this model is that it has made use of the generative AI methodology to generate synthetic data in order to handle class imbalance and improve generalization, as was done by Goodfellow et al. (2014) and Frid-Adar et al. (2018).

   For smaller datasets, traditional ML models like RF, GBM, and xGBM are used within the Stacking Generative AI framework to ensure robust performance even with limited data (John & Lee, 2024). On larger datasets, the model incorporates CNNs and/or RNNs to manage complex, high-dimensional data. This hybrid approach combines the stability of traditional ML models with the pattern-recognition capabilities of DL models for greater versatility (Garcia & Brown, 2024).

The Stacking Generative AI model demonstrated impressive performance across multiple datasets. For example, it has given an accuracy of 98% with a ROC AUC of 99.9% on a dataset of 1,025 records and has outperformed standalone models such as RF and CNN. For bigger datasets, such as one with 400,000 records, the performances were superior, returning a 96% accuracy and a 99% ROC AUC; this therefore shows the ability of the model to scale and manage complex healthcare data effectively.

2. Generative AI Standalone Models: In addition to the Stacking Generative AI model, this dissertation also developed and tested Standalone Generative AI models. These standalone models represent a significant leap in predictive modeling, showing improved robustness and accuracy across datasets of different sizes. Their key advantage is their ability to generate synthetic data, improving performance on small or imbalanced datasets (Goodfellow et al., 2014; Frid-Adar et al., 2018).

   Standalone Gen AI models excel at identifying complex patterns and relationships within the data, often missed by traditional ML or deep learning models (Yi et al., 2019). By generating synthetic samples, Gen AI helps models learn intricate relationships, improving prediction performance, especially in underrepresented classes in healthcare datasets like rare heart failure events. The standalone Gen AI model also performed exceptionally well, achieving a ROC AUC of 99% on mid-sized datasets, such as those with 4,240 records, outperforming several traditional models (Goodfellow et al., 2014). This demonstrates Gen AI's potential for achieving high accuracy and generalizability in healthcare, where class imbalances and limited data are common challenges.

3.1. Overview of Methodology

The methodology to be undertaken for this study shall involve an extensive preprocessing step that ensures the integrity, consistency, and balancing of large volumes of data made up of several datasets, ranging from 303 to over 400,000 records. This workflow involves rigorous cleaning, normalization, and balancing techniques to ensure the best use of data in reliable model training and testing. These steps include necessary tasks used in handling the most common issues in any healthcare dataset; these are missing values, class imbalances, and feature scaling.

- Data Cleaning and Normalization: The data are first cleaned from missing values, outliers, and inconsistencies that might give biased performance like when work with dataset of 400K the records have reduced to 246,022 records after removing NA values. In other cases, missing values were imputed using appropriate strategies such as median or mean imputation techniques based on 'distribution' and 'nature' for each feature. Outliers are either capped or transformed, depending on their impact on the distribution of the dataset. Then, feature normalization, most of the case using Z-Score normalization (standardization) and sometime using Min-Max Scaling method, after cleaning scales all variables into one common range for better model convergence during training, especially when using algorithms sensitive to feature scaling such as neural networks.
- SMOTE Balancing: Synthetic Minority Over-sampling Technique is applied for balancing the classes, as the heart failure dataset usually proved to be class imbalanced. The SMOTE algorithm works by interpolating new samples between existing minority class instances, balancing the classes and reducing model bias toward the majority class. This step is important in order to enhance models like RF, GBM, and CNN, which might otherwise be insensitive to predict heart failure in not-so-populated cases. In this way, using SMOTE, the

model performance is enhanced with respect to recall and F1-score so that a better equilibrium in prediction performance is achieved for respect of all classes.

- Model development and hyperparameter tuning: In this work, different models are developed that range from traditional ML models like RF, GBM, and xGBM to neural network-based models such as CNNs and RNNs, up to the latest model stacking with Generative AI, besides the single model of Generative AI. All models have very carefully tuned hyperparameters by using GridSearchCV, which is cross-validation-based. It goes through and tries a predefined set of hyperparameters, looking for the best combination. This turns out to be very good for increasing the accuracy of the models, their ROC AUC, precision, and recall. Such examples of tuning parameters include the number of trees in RF, learning rates in GBM, xGBM, CNN, and layer configurations, all chosen so each model works at peak efficiency for various dataset sizes.
- Stacking Generative AI Model: The key proposition in this approach lies in the ensembling, where the generative prowess of AI is combined with classical ML and deep learning models. This Stacking Generative AI model thus integrates RF with GBM and CNN/RNN by a stacked ensemble model, which was then further improved using synthetic data created from GANs to create generalized robustness for both small and big datasets. This hybrid approach not only improved the predictive accuracy but also proposed class imbalance and feature complexity challenges in heart failure prediction.
- Model Evaluation: Each model finally undergoes performance evaluations based on standard metrics-accuracy, ROC AUC, precision, recall, and F1-score. These metrics will comprehensively review the performances of each model by showing the leading performance of the Stacking Generative AI model across datasets. If Stacking of traditional

ML, DL, and now Generative AI models can be done under one umbrella, then the proposed framework-Stacking Generative AI-can surely set a new benchmark in healthcare predictive analytics, particularly for the diagnosis and prognosis of heart failure.

3.2. Data Collection and Preprocessing

Seven datasets employed in the research were carefully selected based on the principle of relevance and diversity of data in capturing heart disease indicators. These datasets vary in size and attribute complexity; however, their sources provide a solid foundation for model development and comparative analysis.

1. Cleveland Heart Disease Dataset: Downloaded from the UCI Machine Learning Repository, it contains 303 records and 14 features, including important clinical measures such as age, cholesterol level, and resting blood pressure. It has been used in various heart disease prediction studies, with previous works reporting accuracies between 75% and 85% using a wide range of machine learning techniques.
2. Indian Heart Disease Patient Dataset: This dataset comprises 1,000 entries across 14 attributes, sourced from Kaggle and acquired from a multispecialty hospital in India. It is essential for including demographic diversity, enabling models to generalize better across multiple population groups. Previous studies using this dataset reported accuracies as high as 94% using decision trees and neural networks.
3. Combined Cleveland, Hungary, Switzerland, and Long Beach V Dataset: This comprehensive dataset includes 1,025 observations and 76 attributes. For comparison purposes, a subset of 14 attributes is considered. Sourced from Kaggle, it covers diverse

populations, and studies using this dataset reported results as high as 89% with ensemble methods.

4. Framingham Heart Disease Dataset: Collected from the famous Framingham Study, this dataset includes 4,240 records with 15 attributes, available on Kaggle. It estimates a 10-year risk of coronary heart disease, and previous works using this dataset have demonstrated accuracies between 80% and 90%, primarily with logistic regression and random forest models.
5. Framingham Heart Study Dataset: Sourced from the National Heart, Lung, and Blood Institute, it contains 11,627 records across 38 attributes. One of the largest datasets, collected over several decades, its longitudinal nature has been crucial for studying cardiovascular disease progression, achieving predictive accuracies ranging from 85% to 92%.
6. Kaggle Dataset with 70,000 Records: This large dataset includes 70,000 records with 12 attributes. The dataset extends the test bed for scalability and model robustness, with previous studies reporting accuracies between 78% and 90%, depending on the complexity of the applied model.
7. BRFSS Dataset: Downloaded from the CDC's BRFSS and available on Kaggle, this dataset contains 400,000 records over 18 attributes. It is the largest dataset in this analysis, providing a comprehensive overview of health-related behaviors and risk factors in the U.S. Previous work combining logistic regression with gradient boosting machines reached an accuracy of 88%.

3.3. Research Questions and Modeling Strategies

This review systematically discusses the roles of traditional machine learning models, neural network-based models, hybrid/stacking models, and emerging Generative AI models in detecting heart failure. The originality of this research lies in exploring two innovative models—the Proposed Stacking Generative AI model, integrating various algorithms to enhance predictive accuracy and improve areas under the ROC curve, and the standalone Generative AI model, which has been tested against traditional machine learning and deep learning models. This research further advances data science and AI in healthcare, examining the synergy between stacking models and the independent efficiency of Generative AI to improve predictive accuracy and robustness.

3.3.1. The Research Questions

1. Performance Comparison between Traditional Models and Neural Network Models: How do traditional machine learning models (e.g., Random Forest, Gradient Boosting) compared to neural network-based models (e.g., CNN, RNN) in terms of accuracy and ROC AUC for heart failure prediction?

   Traditional models, such as RF, GBM, xGBM, have gained much attention due to their interpretability advantage, stability, and performance on structured health datasets. These ensemble methods will combine several decision trees to improve predictive accuracy through enhancement of the robustness of models and reduction of overfitting. RF models, for instance, achieved an 83% accuracy and a 91 ROC AUC on the 303-record dataset, while on larger datasets like the 4,240-record dataset, RF maintained strong performance, with 88% accuracy and a 96 ROC AUC. GBM, known for its sequential error correction, performed well on moderately sized datasets, with a 79% accuracy and 87 ROC AUC on the 303-record dataset, and 80% accuracy with a 90 ROC AUC on the 4,240-record dataset. However, both

RF and GBM face limitations as dataset sizes grow larger, and data interactions become more complex.

Neural networks, including both CNNs and RNNs, were more fitted for sequential and time-series data. These make them very appropriate for a patient monitoring system. Considering that CNNs tend to work with structured data, they gave 82% accuracy with an 85 ROC AUC for a record dataset of 303, while this mediated to only 74% accuracy with 80 ROC AUC upon using a record dataset as large as 70,000. Similarly, RNNs, especially with attention mechanisms, handle sequential dependencies well but also face challenges with larger datasets, achieving 80% accuracy with 84 ROC AUC on smaller datasets, but 74% accuracy and 80 ROC AUC on the 70,000-record dataset.

Thus, while traditional models like RF and GBM provide reliable results on smaller datasets, complex neural networks outperform them on larger datasets by capturing intricate feature interactions. For example, on the 400,000-record dataset, RF achieved 90% accuracy and a 96 ROC AUC, while CNNs managed only 78% accuracy with an 86 ROC AUC. Both types of models have strengths—RF and GBM offer interpretability and reliability, while CNNs and RNNs deliver better performance on time-series data, provided there is sufficient data and proper hyperparameter tuning.

2. Powerful Predictors of Cardiovascular Disease and Myocardial Infarction: What are the most influential predictors of heart failure across different models, and how do they affect overall model performance?

In this research, several key predictors emerged as critical for cardiovascular disease (CVD) and myocardial infarction (MI). Influential predictors identified across the seven datasets include maximum heart rate achieved (thalachh), chest pain type (cp), systolic blood pressure (sysBP), total cholesterol (totChol), body mass index (BMI), and age. These factors significantly boosted model performance across different machine learning models, particularly in RF models.

Thalachh and cp were strong indicators of coronary artery disease in smaller datasets, while in larger datasets, sysBP, totChol, and BMI were crucial predictors. Elevated systolic blood pressure and high total cholesterol levels are known contributors to cardiovascular events. BMI was a particularly important factor in the 400,000-record dataset, where obesity played a significant role in heart disease risk.

Other variables like glucose levels, smoking status, and exercise-induced ST-segment changes (slope) were also influential in some datasets, underscoring their importance in predicting heart disease. These risk factors not only improve model accuracy but also enhance interpretability, aligning the models with real-world healthcare applications.

3. Hybrid Stacking Model Potential: Can a hybrid stacking model that combines traditional machine learning and deep learning techniques provide superior predictive performance compared to single models? Specifically, can the proposed Stacking Generative AI model improve prediction accuracy by leveraging the strengths of GAN, RF, GBM, and CNN models?

Hybrid stacking models integrate the strengths of traditional models like RF and GBM with deep learning techniques like CNN and RNN, creating a powerful predictive framework. Stacking allows these models to combine their strengths, providing superior predictive accuracy. The Stacking Generative AI model, which incorporates Generative Adversarial Networks (GAN), RF, GBM, and CNN, addresses class imbalance by generating synthetic data similar to real patient data. This enriched training data boosts both accuracy and generalization.

In this framework, CNNs learn feature representations, while RF and GBM provide stability and interpretability. The Stacking Generative AI model consistently outperforms individual models by leveraging both traditional and neural network techniques.

4. Impact of Generative AI on Predictive Accuracy: How does the use of Generative AI, particularly GANs, in a stacking model improve performance compared to standalone models? Does it enhance generalizability and scalability across diverse healthcare settings?

Integrating Generative AI, specifically GANs, into a stacking model offers significant advantages in improving predictive accuracy. GANs generate synthetic data that addresses class imbalance and data limitations common in healthcare, enabling the model to better predict high-risk events like myocardial infarctions.

In a stacking model, GANs enhance data quality, generalizability, and scalability. For example, GAN-generated data helped improve accuracy and recall in heart disease datasets by enriching minority classes. This allowed the Stacking Generative AI model to achieve superior accuracy and ROC AUC across datasets of all sizes, from small cohorts to large-scale health systems.

Compared to standalone models, the GAN-enhanced stacking model consistently delivered higher accuracy and recall, especially in imbalanced datasets. By addressing data limitations, GANs enable the stacking model to handle complex healthcare data more effectively, ensuring reliable and accurate predictions across diverse clinical settings.

5. How does the unique Stacking Generative AI model specifically contribute to advancements in the healthcare industry, particularly in predicting and managing heart failure?

   My unique Stacking Generative AI model brings several transformative contributions to the healthcare industry, with a targeted impact on heart failure prediction and management. By integrating Generative AI (Gen AI) with traditional machine learning models (like Random Forest, Gradient Boosting Machines, and Extreme Gradient Boosting Machines) and deep learning models (such as Convolutional Neural Networks or Recurrent Neural Networks), this model addresses some of the key limitations of existing predictive models. Here's how it enhances healthcare, especially for heart failure:

- Improved Prediction Performance: Most of the traditional models usually cannot tackle the complexity of heart failure data that involves various clinical, demographic, and lifestyle variables. My approach of stacking multiple models with Generative AI leverages unique strengths in every model to produce something far more accurate and robust for the prediction system. This heightened accuracy allows for early detection and, thus, timely medical interventions that will improve patient outcomes.

- Handling Imbalanced Class Problems: In heart-failure datasets, class imbalance problems normally exist because there are fewer cases of heart failure than cases without heart failure. The Generative AI component generates synthetic samples of minority cases, effectively balancing the dataset. This improved balance ensures that the model is not biased toward majority classes, enhancing its sensitivity and specificity in predicting heart failure cases, which is crucial for accurate diagnostics.
- Enhanced Generalization Across Populations: My model's stacking approach with Generative AI allows it to generalize well across diverse datasets, including both small and large data volumes. This adaptability is essential in healthcare, where patient populations vary significantly across different regions, ages, and genetic backgrounds. A model that generalizes well can support scalable implementations across hospitals, clinics, and various healthcare settings, providing reliable predictions for different patient demographics.
- Support for Personalized Treatment Plans: By accurately predicting heart failure risk, the Stacking Generative AI model can be integrated into clinical decision-making tools to assist healthcare providers in developing personalized treatment plans. For instance, patients identified as high-risk can receive more intensive monitoring and preventative measures. Such personalized care can lead to better-managed heart failure cases and potentially reduce hospital readmissions.
- Aiding Clinicians and Patient Awareness: Predictive insights of this model can be implemented on user-friendly applications to health providers and patients in practice. Predicted events can be utilized by clinicians to understand risk profiles of a patient and inform him/her about his/her status. Applications such as web-based dashboards help doctors

and patients to track the risk of heart failure with time and enable them to be more proactive in managing health.

- Setting a New Benchmark in Predictive Healthcare: By combining traditional ML, DL, and Generative AI into one cohesive model, my Stacking Generative AI approach sets a new standard for predictive analytics in healthcare. It showcases the power of hybrid models to capture complex health data patterns, making it a benchmark for future predictive models. The potential of this model to adapt to other complex diseases beyond heart failure further extends its applicability and impact on the healthcare industry.

In summary, my Stacking Generative AI model addresses the limitations of traditional heart failure prediction models by providing a highly accurate, adaptable, and comprehensive tool that supports early diagnosis, personalized care, and broad healthcare applicability. This innovative approach represents a significant advancement in the field, with promising implications for both clinical practice and patient health outcomes.

3.3.2. Modeling Strategies

The current study develops the Stacking Generative AI model through several aspects to create synergy in traditional machine learning, deep learning, and Generative AI for building an accurate and generalizable predictive heart failure tool. At each layer, the model is strategically designed to improve predictive accuracy, address class imbalance, and improve generalizability across diverse patient datasets.

It follows the ensemble learning framework in which the strengths of multiple base learners are combined into one strong meta-learner. Ensemble methods, like stacking, involve aggregation over several algorithms to culminate into a model that maximizes its robustness and accuracy. In this model, regular machine learning algorithms-namely RF, GBM, and xGBM-find their place along with deep learning models such as CNNs and RNNs. These algorithms contribute unique strengths, with RF, GBM, and xGBM excelling in handling structured tabular data, while CNNs and RNNs capture complex feature interactions and temporal patterns (Breiman, 2001; Friedman, 2001; LeCun et al., 2015). By layering these models within a stacking ensemble, the Stacking Generative AI model effectively leverages these strengths, yielding enhanced predictive stability and accuracy.

Data Augmentation by the Integration of Generative AI: A distinctive feature of the Stacking Generative AI model is the integration of Generative Adversarial Networks (GANs) to augment training data, addressing data scarcity and class imbalance issues inherent in heart failure datasets. GANs synthesize new samples that closely mirror real patient data, thereby expanding the dataset and enhancing the representation of minority classes (Goodfellow et al., 2014). Synthetic data augmentation allows the model to reduce biases toward majority classes, which in turn makes the model more sensitive to rare heart failure events. It has proven to be especially helpful in training deep learning layers, which demand large volumes of data upon which to perform best (Frid-Adar et al., 2018).

Rigorous Data Preprocessing and Feature Engineering: Extensive data preprocessing and feature engineering are two key building blocks for this model. Therefore, the cleaning of data consisted of handling missing values and correcting inconsistencies, and normalization was applied to scale each feature on a standard scale, something significant for good convergence of deep learning models. Additionally, the Synthetic Minority Over-sampling Technique (SMOTE) was employed to address class imbalance by generating synthetic instances within the minority class, complementing the synthetic data created by GANs (Chawla et al., 2002). Feature engineering further identified critical predictors, such as age, BMI, cholesterol levels, and blood pressure, which have demonstrated predictive relevance for heart failure risk.

Hyperparameter optimization with GridSearchCV: Realizing that model performance is highly dependent on the selected hyperparameters, GridSearchCV was implemented for extensive hyperparameter tuning. It's a cross-validation-based search that systematically explores the predefined parameter grids to find the best combination for each component model. For instance, parameters such as the number of trees in RF, learning rates in GBM and CNN, and layer configurations in RNNs were fine-tuned, resulting in significant improvements in model accuracy, ROC AUC, precision, and recall across datasets of varying sizes (Pedregosa et al., 2011).

Stacked Ensemble Integration through Meta-learning: The meta-learner integrates the predictions of individual base models into the architecture of the Stacking Generative AI model. This meta-learner assigns optimal weights to the predictions of RF, GBM, xGBM, CNN, and GAN-enhanced data, maximizing the predictive power of all in this ensemble. The model can adapt to the distinctive strengths of each component through this stacking mechanism, giving rise to superior generalizability across datasets with different structures and sizes (Sagi & Rokach, 2018).

The Stacking Generative AI model represents a new methodological advance in predictive modeling for heart failure. The performance of this model is significantly enhanced due to the strategic incorporation of ensemble learning, synthetic augmentation of data, rigorous preprocessing, and tuning of hyperparameters, thereby far exceeding the limitations imposed solely by traditional machine learning and stand-alone deep learning models. The model improves prediction accuracy and sets a new benchmark in healthcare predictive analytics, thereby offering large potential for practical applications in the clinical setting.

3.4. Core Techniques and Optimization Performance

First, **Synthetic Minority Over-sampling Technique** (SMOTE) is a method used to address class imbalances in a dataset by creating artificial examples of the minority class to balance it. In the Stacking Generative AI model, I propose, which incorporates Random Forest, XGBM, and CNN, SMOTE plays an essential role. This technique ensures that the model is not skewed towards the majority class, which might dominate the training process. SMOTE generates synthetic samples along the line connecting minority class instances and their nearest neighbors. Mathematically, the new sample x_{new} is generated by the formula:

$$x_{\text{new}} = x_{\text{minority}} + \lambda \cdot (x_{\text{neighbor}} - x_{\text{minority}})$$

where x_{minority} is a minority class instance, x_{neighbor} is one of its nearest neighbors, and λ is a random number between 0 and 1. This process creates a more diverse minority class dataset without simply duplicating existing instances.

In the proposed model, after loading and preprocessing the dataset, SMOTE is applied to generate a balanced set of samples before training the individual base models. By doing so, SMOTE improves the learning efficiency of Random Forest, XGBM, and CNN models, leading to enhanced overall model performance, especially in terms of recall and precision for the minority class, without causing overfitting (Chawla et al., 2002).

Second, **GridSearchCV** provides an important step for optimizing the Stacking Generative AI model. GridSearchCV is a technique used to perform the model hyperparameter tuning to carry out the search over specified parameter values for each estimator. Rather than do it manually, GridSearchCV systematically works out a given combination of some predefined hyperparameters with the help of cross-validation so that the model performs really well for each possible combination concerning some metrics, such as accuracy or AUC.

In my base model, GridSearchCV optimizes the base models of Random Forest, xGBM, and CNN, as well as the meta-learner (Logistic Regression). For example, some of the best parameters in the case of the Random Forest are n_estimators = 30, max_depth = 3, and min_samples_leaf = 5. Similarly, xGBM has the parameters, including the learning rate and the number of boosting rounds, tuned using GridSearchCV. That is important because the application of GridSearchCV ensures that each model will be performing optimally before combining their predictions in the meta-learner, hence enhancing the overall performance of the Stacking Generative AI model across a variety of datasets.

Third, GANs are used to synthesize data to elevate the performance of the model. GANs handle imbalanced datasets, which in this case are the usual datasets in medical fields-for example, in heart failure prediction-since the minority class might be underrepresented, for instance, those who will experience heart failure. By generating high-quality synthetic data, GANs enrich the training dataset in such a way that the models will not be biased towards the majority class.

The **Generator Network** is designed to create synthetic patient data resembling real profiles, including critical features like age, cholesterol levels, and blood pressure. The network takes a latent vector of random noise as input and produces synthetic heart failure cases through multiple fully connected layers. The architecture consists of:

- An input layer that accepts a latent vector (input_dim) representing noise.
- A hidden layer = 128 units, activated by ReLU to capture complex, non-linear relationships between heart failure risk factors (e.g., cholesterol-blood pressure interactions).
- A second hidden layer = 256 units, also using ReLU activation.
- An output layer, with the number of dimensions matching the features in the dataset (e.g., systolic blood pressure, glucose levels), activated by Tanh. This scales output values between -1 and 1, appropriate for normalized medical data.

The forward pass of the Generator is:

$$\mathrm{G(z)} = \mathrm{Tanh}\ (W_3 \cdot \mathrm{ReLU}(W_2 \cdot \mathrm{ReLU}(W_1 \cdot \mathrm{z})))$$

where z is the latent input vector, and W_1, W_2, W_3 are the learned weight matrices.

This architecture allows the generator to create synthetic patient profiles that closely resemble real patient data, improving the robustness of heart failure prediction models by providing additional, diverse training examples (Goodfellow et al., 2014).

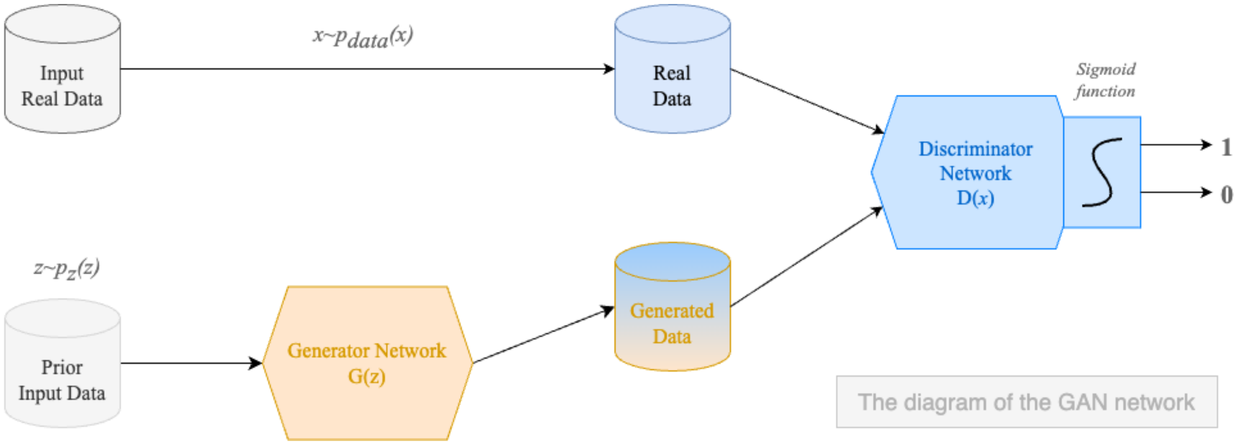

Fig. 1. The diagram of the Generative AI – GAN network

The **Discriminator Network** Configuration for Heart Failure Prediction is designed to differentiate between real patient data and synthetic data generated by the GAN. Acting as a binary classifier, it ensures that the synthetic data closely resembles actual patient records.

The architecture consists of:

- An input layer that takes either real or synthetic patient profiles.
- A hidden layer = 256 units, activated by LeakyReLU (with a negative slope of 0.2), this will help the network learn better representations, especially when dealing with sparse or imbalanced heart failure data.
- A second hidden layer = 128 units, utilizing LeakyReLU.
- An output layer that receives a single value between 0 to 1 activated by a Sigmoid function. Thus, the output means the probability that the input data is real rather than synthetic.

It is described by:

$$D(x) = \text{Sigmoid}\ (W_3 \cdot \text{LeakyReLU}(W_2 \cdot \text{LeakyReLU}(W_1 \cdot x)))$$

where x is the input patient data (either real or generated), and W_1, W_2, W_3 are the learned weight matrices.

The Discriminator ensures the synthetic data generated is realistic enough for training predictive heart failure models, making the models better at generalizing to unseen patient data and identifying early signs of heart failure—crucial for preventive medicine (Radford et al., 2015).

3.5. Models' Design and Implementation

The flow of information from the base models to the meta-learner in the diagrams simplifies the understanding of stacking models' complexity. These diagrams explain how each model contributes to the final prediction and highlight the novelty of combining different model types. They also show how traditional machine learning models are integrated with deep learning architectures in a cohesive multi-layer approach, showcasing the uniqueness of this methodology.

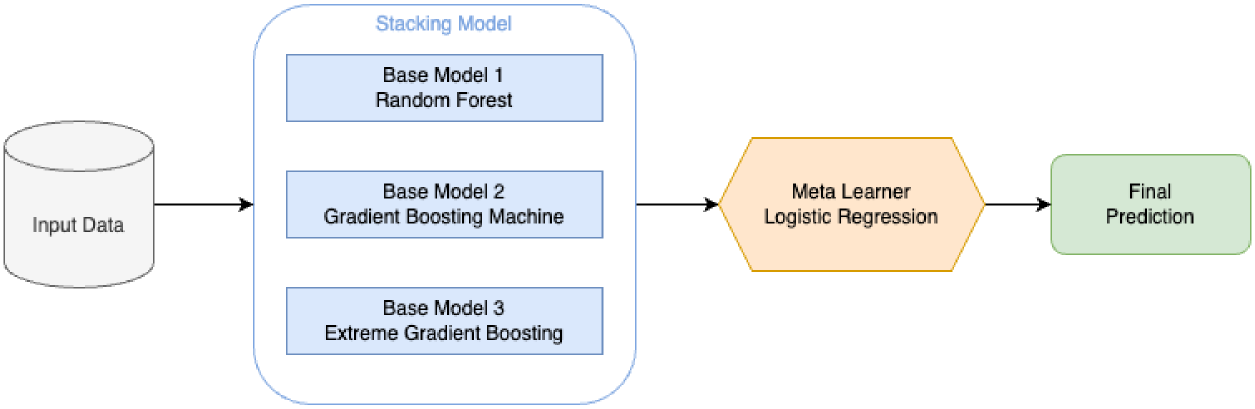

Fig. 2. Stacking model (RF + GBM + xGB) architecture for smaller datasets.

The stacking model combines the predictive powers of RF, GBM, and xGBM for smaller datasets. The intuition behind this combination is to leverage tree-based algorithms that excel at capturing complex feature interactions and non-linear relationships. In this stack, Logistic Regression serves as the Meta Learner, effectively merging the outputs from the base models into the final prediction.

Stacking with these three base models, especially Random Forest, demonstrates the ability to handle large datasets with high dimensionality and avoid overfitting by aggregating results from multiple decision trees. Gradient Boosting Machine is another powerful boosting technique, building models sequentially by correcting earlier errors to improve predictive accuracy. Lastly, Extreme Gradient Boosting is an optimized and efficient version of GBM, ideal for large, complex datasets.

In this study, Logistic Regression is chosen as the Meta Learner due to its simplicity and interpretability, making it the best choice for combining base model predictions. The stacking model undergoes cross-validation during training to ensure robustness across different data subsets. For the final evaluation, the combined predictions from RF, GBM, and xGBM are fed into the meta-classifier, Logistic Regression, to make the final prediction.

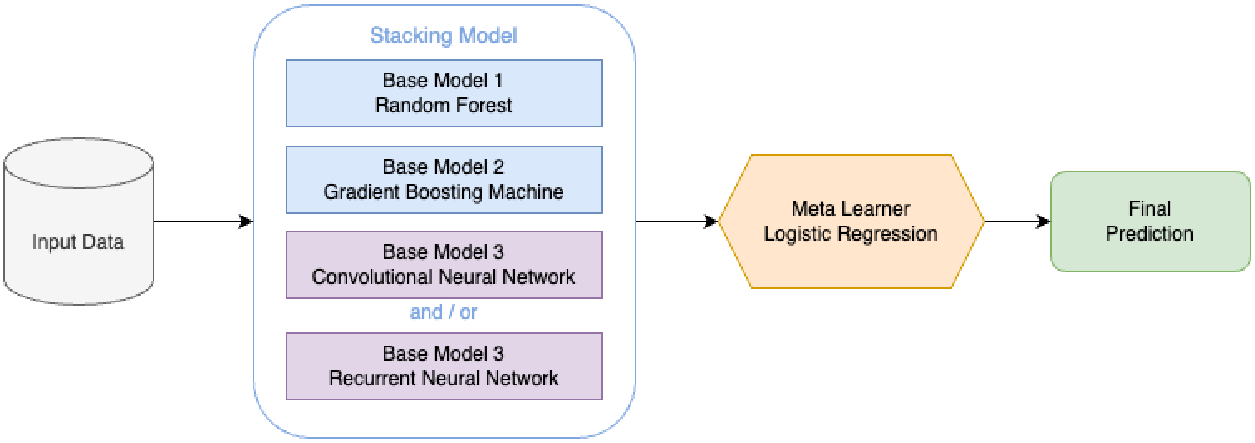

Fig. 3. Stacking model (RF + GBM + CNN / RNN) architecture for larger datasets.

For larger datasets, the stacking model includes a more complex base model, such as CNN or RNN, alongside Random Forest and Extreme Gradient Boosting. Adding CNN is highly desirable in large datasets with complex patterns because CNNs excel at capturing spatial and temporal dependencies in the data. As with smaller datasets, Logistic Regression serves as the Meta Learner.

The stacking models in this study include Random Forest for robustness with high-dimensional data, Extreme Gradient Boosting for efficiency and accuracy, especially with large datasets, and Convolutional Neural Networks for their deep feature extraction capabilities that are valuable for larger datasets. Logistic Regression is again used as the meta-learner because it can effectively combine predictions from different models.

Implementing the stacking model for larger datasets involves CNN in a more complex workflow: CNN is trained independently, predictions are aggregated with RF and xGBM, and the combined outputs are passed to the Logistic Regression meta-learner. This is an improved stacking model for larger datasets, benefiting from deeper learning through CNN or RNN and the combined predictive strengths of RF and xGBM. The stacking ensemble ensures better performance, particularly with large, complex datasets where no single model excels.

The design and implementation of these models represent a structured approach for leveraging multiple algorithms to predict heart diseases across small and large datasets. These stacking models offer robustness and flexibility by combining diverse strengths from tree-based methods like RF and xGBM and deep learning methods like CNN or RNN. The Meta Learner, Logistic

Regression, synthesizes the base models' outputs into a cohesive final prediction. This approach enhances both predictive accuracy and model generalizability across different datasets, making it a powerful tool in healthcare predictive modeling.

Recently, various **Generative AI** models, especially GAN variants, have been used primarily to augment datasets and improve predictive performance, particularly in cases involving imbalanced datasets. This paper reviews the structured approach used to develop and refine a Generative AI model for heart failure prediction, using a dataset featuring cardiovascular health-related attributes.

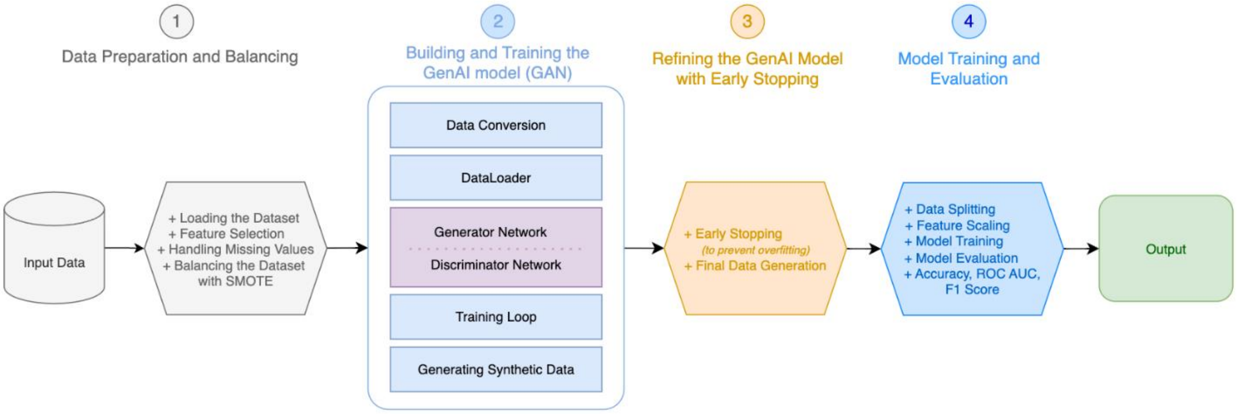

Fig. 4. **Comprehensive Generative AI Architecture**

Step 1**:** Data Preparation and Balancing – Relevant features for cardiovascular conditions were selected from the dataset for heart failure prediction. These included age, sex, chest pain type (cp), resting blood pressure (trestbps), cholesterol (chol), fasting blood sugar (fbs), resting electrocardiographic results (restecg), maximum heart rate achieved (thalach), exercise-induced angina (exang), ST depression by exercise (oldpeak), peak exercise ST segment slope, number of vessels colored by fluoroscopy (ca), and thalassemia (thal). The target variable was cardiovascular disease (cvd), indicating heart failure. Missing values were addressed by replacing them with the column mean, ensuring data completeness without dropping any rows. Balancing was critical, especially considering potential class imbalances where heart failure cases were fewer than non-heart failure cases. SMOTE (synthetic over-sampling) was applied to generate synthetic examples of the minority class, ensuring the model wasn’t biased towards the majority class. This thorough data preparation laid a solid foundation for the modeling stages.

Step 2**:** Creation and Training of the Gen AI Model using GAN – With the dataset ready, the next step was developing a Gen AI model to enhance heart failure prediction using a GAN. Features and targets were converted to PyTorch tensors for neural network processing. A DataLoader was used to batch the data efficiently during training. The GAN comprised two neural networks: a generator, which created artificial data starting from random noise and converting it into patient-like data points, and a discriminator, which classified data points as either real or synthetic. The GAN training alternated between these networks for 5,000 epochs, gradually improving the generator’s ability to produce synthetic data that became increasingly difficult for the discriminator to distinguish from real data. The synthetic data generated by the GAN was added to the original dataset, augmenting it for further model training.

Step 3: Fine Tuning of Gen AI Model with Early Stopping – Early stopping was implemented to prevent overfitting and optimize the training process. This involved monitoring the discriminator loss, and if it failed to improve after a certain number of epochs, the training was stopped. Early stopping not only conserved computational resources but also protected the model from overfitting to the training data. Once the GAN was trained using early stopping, more synthetic data representing heart failure cases (the positive class) was generated. The new data was added to the original dataset, shuffled to avoid order bias, and then used for final model training and evaluation.

Step 4: Training and Evaluation – The final phase was the training of a machine learning model on the augmented data, and the subsequent evaluation of that model. First, the combined data of real and synthetic were divided into a training set and a test set to validate the model. Feature scaling using StandardScaler was applied to standardize all features, ensuring they contributed equally during training. A RandomForestClassifier was chosen for its robustness and suitability for large datasets with complex feature interactions. The model trains and tests on the test set as described below; important metrics include Accuracy, ROC AUC, and a detailed Classification Report. The ROC is plotted, which helps in visualizing the model's ability to differentiate between heart failure and non-heart failure patients, with the AUC indicative of overall performance.

This approach to developing the heart failure predictor utilized GAN-based data augmentation followed by training a RandomForestClassifier, demonstrating the model's potential in handling imbalanced data. The structured process involved data preparation, synthetic data generation using GAN, early stopping during training, and final evaluation using traditional machine learning techniques, resulting in a robust model capable of predicting heart failure accurately. This method highlights the importance of each step in producing a reliable predictive model in healthcare, where precision and accuracy are crucial for patient outcomes.

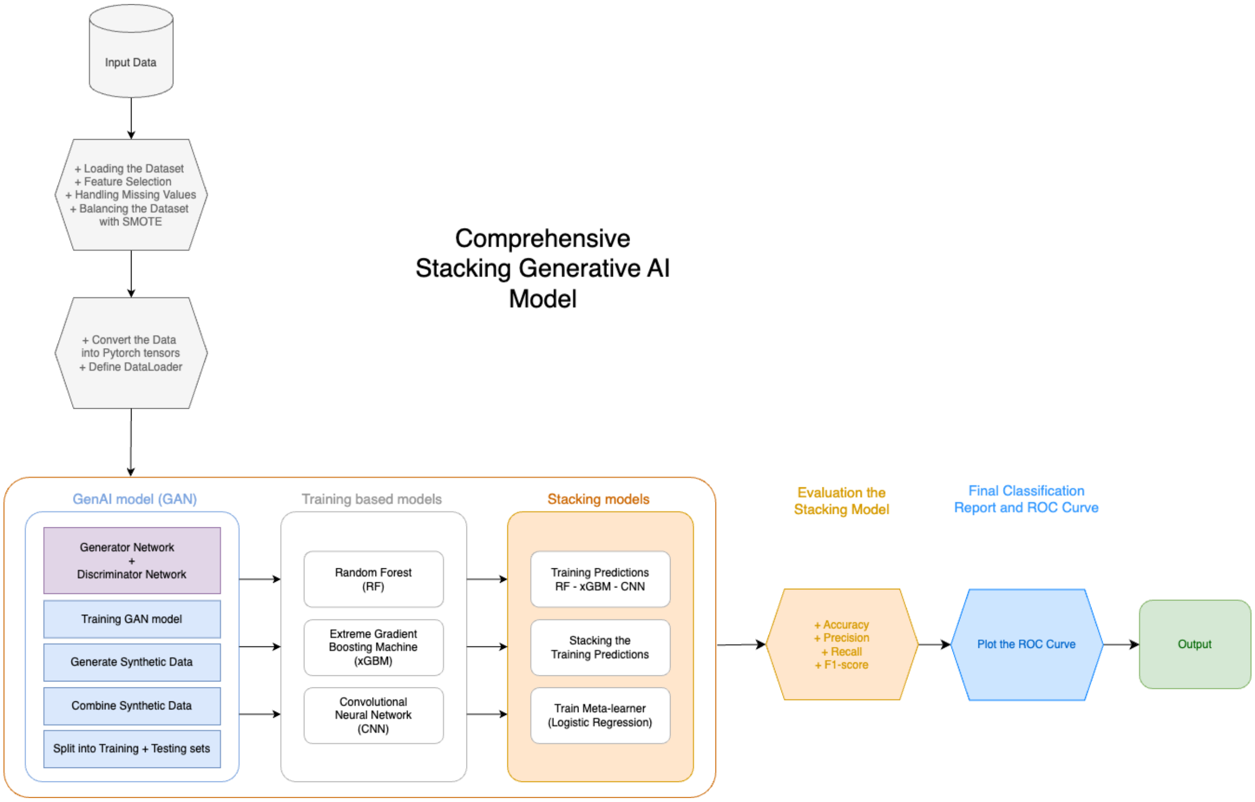
Input Data
+ Loading the Dataset
+ Feature Selection
+ Handling Missing Values
+ Balancing the Dataset with SMOTE
+ Convert the Data into Pytorch tensors
+ Define DataLoader
Comprehensive Stacking Generative AI Model
GenAI model (GAN)
Generator Network + Discriminator Network
Training GAN model
Generate Synthetic Data
Combine Synthetic Data
Split into Training + Testing sets
Training based models
Random Forest (RF)
Extreme Gradient Boosting Machine (xGBM)
Convolutional Neural Network (CNN)
Stacking models
Training Predictions RF - xGBM - CNN
Stacking the Training Predictions
Train Meta-learner (Logistic Regression)
Evaluation the Stacking Model
+ Accuracy
+ Precision
+ Recall
+ F1-score
Final Classification Report and ROC Curve
Plot the ROC Curve
Output

Fig. 5. The proposed Comprehensive Stacking Generative AI Architecture

The **Comprehensive Stacking Generative AI model** for heart failure prediction integrates multiple machine learning techniques, combining traditional models like Random Forest (RF), Gradient Boosting Machine (GBM), and Extreme Gradient Boosting Machine (xGBM) with Convolutional Neural Networks (CNN) and Generative Adversarial Networks (GANs). This approach allows the model to handle class imbalance, generate synthetic data to improve learning, and combine multiple model predictions to achieve better performance.

Step 1: Data Preparation, Balancing, and Processing – The heart failure dataset, which includes key cardiovascular features such as age, cholesterol levels, and resting blood pressure, is first loaded. The target variable indicates whether a patient experienced heart failure. Initially, missing values are handled by applying appropriate imputation techniques to maintain data integrity. Since the cases of heart failure are underrepresented in nature, Synthetic Minority Over-sampling Technique is utilized to balance the dataset. SMOTE synthesizes examples of the minority class in case of heart failure using this technique so that a model learns from both classes effectively. StandardScaler is used to scale the balanced dataset, ensuring that all features are scaled consistently-a very important factor in training neural networks (Pedregosa et al., 2011).

Step 2: Defining Generator and Discriminator Networks for GAN - This stage defines the Generator and Discriminator networks for GAN. The generator generates synthesized data resembling real heart failure patient data while the discriminator differentiates whether that data is real or generated as shown in Fig. 1. The Generator network receives a latent vector (random noise) as input, which passes through multiple fully connected layers. Each layer is activated using ReLU functions, with 128 units in the first hidden layer and 256 units in the second hidden layer. The final output is generated using a Tanh activation function, which scales the generated data between -1 and 1, appropriate for normalized medical data (Radford et al., 2015). This synthetic data can then be added to the real dataset to enhance the diversity of the training data.

Sample of the generator network is structured in Python code as follows:

```
class Generator(nn.Module):
  def __init__(self, input_dim, output_dim):
  super(Generator, self).__init__()
self.network = nn.Sequential(
  nn.Linear(input_dim, 128),
  nn.ReLU(),
  nn.Linear(128, 256),
  nn.ReLU(),
  nn.Linear(256, output_dim),
  nn.Tanh()
)
def forward(self, x):
  return self.network(x)
```

The Discriminator network acts as a binary classifier, determining whether a heart failure record is real or synthetic. This input is processed through fully connected layers activated by LeakyReLU. The final output is given as a probability score, output from the Sigmoid function, indicating whether the input is real or fake. The adversarial training ensures that over time, the generator produces increasingly realistic synthetic data (Goodfellow et al., 2014).

Sample of the discriminator network is structured in Python code as follows:

```
class Discriminator(nn.Module):
  def __init__(self, input_dim):
  super(Discriminator, self).__init__()
self.network = nn.Sequential(
  nn.Linear(input_dim, 256),
  nn.LeakyReLU(0.2),
  nn.Linear(256, 128),
  nn.LeakyReLU(0.2),
  nn.Linear(128, 1),
  nn.Sigmoid()
)
def forward(self, x):
  return self.network(x)
```

Step 3: Generating the Model – Then the GAN is trained over 5000 epochs with Adam optimizers (0.00005). Generator and discriminator are trained separately so that generator becomes proficient at producing authentic synthetic heart failure data and discriminator becomes skilled in distinguishing real from fake data. This training ensures the quality of the synthetic data that will be used later on in the actual dataset for modeling improvement.

Step 4: Synthetic Data Generating with GAN – Synthetic data is computed after the GAN is fully trained, by passing random noise vectors into the generator. The artificial data are merged with the original heart failure data to generate a large training set consisting of real and artificial patient samples. That’s a way of teaching models from a wider set of examples and generalizing to new unseen data.

Step 5: Divisible the Data into Training and Test Sets (80/20) – Once the combined data has been created with synthetic data, the overall dataset is divided into training and test sets so that the model gets run against the unseen data to determine how well it performs in the real world. Data is then normalized with a StandardScaler so that all the input features are also scaled, which is very important for neural networks like CNNs, where feature scaling is very important to learning.

Step 6: Training the Base Models (RF, xGBM, CNN) – Now it's time to train the individual models – Random Forest (RF), Extreme Gradient Boosting (xGBM), and Convolutional Neural Network (CNN)- shown in the diagram (Fig. 5). The Random Forest has 100 trees, maximum depth 10; min samples split 10; random state 42. Complex feature interactions are accounted for by 200 estimators, 0.05 learning rate, 0.8 subsample ratio and 42 random state in xGBM model.

On CNN the framework is for overfitting and generalization. It starts with a Conv1D (16 filter) kernel size of 3 and then the MaxPooling (2 pool size) dimensionality reduction layer. 0.6 Dropout layer is added for Overfit prevention. The output is then flattened and through a 32 units Dense with ReLU activation, Dropout again, and finally a sigmoid output for binary classification. Model is built with Adam optimizer and binary cross-entropy loss function. Stopping is implemented early so as not to overfit and training is terminated if validation loss fails to improve after 5 epochs. It trains the model for a maximum of 50 epochs with a batch size of 32 and validation is done with 20% of the data.

Step 7: Stacked Prediction Training of Meta-Learner – When the base models have been trained, their predictions are the input for the stacking model. RF, xGBM, CNN predictions go to the meta-learner which is Logistic Regression. This meta-learner is trained to derive the final classifier on the basis of the strength of the base models.

Step 8: Evaluation of Stacked Model – Meta-learner is tested against the test set and performance metrics like accuracy, precision, recall and F1-score are calculated. ROC AUC is also calculated to calculate how good a model is at detecting heart failure vs. non-heart failure. ROC curve shows the tradeoff between sensitivity and specificity to clearly show how the model performed at different thresholds.

Step 9: Final Classification Report and ROC curve – The final product is classification report with precision, recall, F1-scores of both classes, ROC curve (chapter 4). The ROC AUC curve is the graph that indicates how well the model performed; a high ROC AUC means the prediction accuracy is high. This analysis gives us an idea about whether the model is able to predict heart failure well enough to adopt in clinical settings for early detection of disease.

Conclusion – The proposed Comprehensive Stacking Generative AI Model is a strong heart failure prediction tool that merges the conventional machine learning algorithms with novel approaches like GAN. Stacking synthetic data generated by GANs is the key to getting the model to generalize well and be super-fast on actual medical data. Bringing together models such as RF, xGBM, and CNN makes sure the ensemble gets the right predictions that are crucial for medical diagnosis early. Based on Chawla et al. (2002), Goodfellow et al. (2014), Pedregosa et al. (2011), and Radford et al. (2015).

3.6. Evaluation Measurement and Validation Methods

Performance of each model is calculated with different parameters like accuracy, ROC AUC, precision, recall, F1 score etc. Accuracy is calculated as:

$$\text{Accuracy} = \frac{True\ Positives + True\ Negatives}{Total\ Instances}$$

ROC AUC represents how discriminative the model is between classes and is calculated as:

$$ROC\ AUC = \int_0^1 TPR(FPR)\ d(FPR)$$

-where TPR is True Positive Rate and FPR is False Positive Rate. K-fold cross-validation especially stratified cross-validation with imbalanced data sets makes models reliable across all data splits.

Stacking Generative AI model to validate it to unseen data is validated with various methods that ensure that the model can be extended without overfitting to the unseen data. These are 5- and 10-fold cross-validation, learning curves to measure training size dependent performance, regularization, and hyperparameter optimization for optimal model behavior. The relevant mathematical equations of these methods are given below.

Cross-Validation (cv=5 and cv=10)

Cross-validation is a resampling method that runs model against the dataset with k equal sized "folds" — the model is trained on k-1 folds and evaluated on the remainder. The same is done k times and the average performance is used to evaluate robustness. Mathematically, k-fold cross-validation accuracy is:

$$\text{CV Accuracy} = \frac{1}{k}\sum_{i=1}^{k}\text{Accuracy}_i$$

where k is the number of folds, and Accuracy$_i$ is the accuracy for the ith fold.

For 5-fold cross-validation, the model was trained and tested over five data splits with accuracies of [0.9938, 1.0000, 0.9877, 0.9969, 0.9938]. The mean accuracy was 0.9944. Similarly, 10-fold cross-validation yielded a mean accuracy of 0.9944, confirming the model's consistency and generalization across different data splits (James et al., 2013).

Learning Curve

Learning curve – It represents how well a model performs given a training set size and is available for overfitting or underfitting. It shows training and cross-validation-accuracy as a percentage of training examples:

$$\text{Error} = \frac{1}{n}\sum_{i=1}^{n}L(\hat{y}_i, y_i)$$

- where n is the number of training instances, $\hat{y}_i$ is the predicted value and y_i is the actual value. L is the loss function, binary cross-entropy here. Fig. 13: Convergence Learning curve of Training and Validation Accuracies is 0.998, It generalizes easily without overfitting and has a satisfactory performance for unseen data, as Goodfellow et al. (2016).

Regularization

Regularization helps prevent over-complexity by penalizing large weights. In the Logistic Regression meta-learner, L2 regularization was applied, adding a regularization term to the loss function to shrink weights:

$$L(w) = \mathrm{Loss}(w) + \lambda||w||_2^2$$

where L(w) is the regularized loss, Loss(w) is the original binary cross-entropy loss, λ is the regularization strength, and $||w||_2^2$ is the sum of squared weights. Grid search was used to find the optimal λ, ensuring the model remained well-tuned without overfitting (Ng et al, 2004).

Hyperparameter Tuning

Grid search was used to optimize the Logistic Regression meta-learner by exploring different hyperparameter combinations. The goal was to find the best regularization parameter (C) for Logistic Regression:

$$C = \frac{1}{\lambda}$$

Grid search iterates over a range of C values and evaluates model performance on the validation set. The best C = 0.01 was chosen based on cross-validation scores.

The combination of cross-validation, learning curves, regularization, and hyperparameter tuning provided a comprehensive validation approach. These mathematical techniques ensured that the Stacking Generative AI model was well-calibrated to generalize effectively without overfitting, making it suitable for deployment in heart failure prediction scenarios.

3.7. Ethical Considerations and Clinical Validation

The study raises numerous ethical considerations related to data privacy and fairness. All data is fully anonymized, adhering to GDPR and other relevant regulations. The study also addresses how biases are controlled to ensure that no demographic group is favored or disadvantaged by the models. This is crucial for maintaining fairness in predictions and ensuring that the models are not used irresponsibly in clinical settings. The models are further validated in a simulated clinical environment with retrospective data, in collaboration with clinicians, to refine the models based on realistic needs and constraints. This type of validation plays a key role in determining how useful these models are in real-world applications. Clinicians provide insights into whether the models are practical, interpretable, and effective in supporting clinical decision-making. This iterative process ensures that the models make theoretical sense, are practically viable, and meet the needs of healthcare providers.

Chapter 4: RESULTS

4.1. Implementation Results

4.1.1. Research Question 1: What is the performance of Deep Learning Models in Heart Disease Prediction versus Standard Machine Learning Models?

To answer this question, I have applied several machine learning and deep learning models and tested them on several datasets of varying size. The majority of the performance parameters for most models have been determined using two key values, accuracy and ROC AUC scores which are very relevant in evaluating classification models' performance in healthcare prediction.

My experiment's basis models are typical ML models such as Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), Gradient Boosting Machine (GBM), and Extreme Gradient Boosting Machine (xGBM). Alongside these conventional models, Deep Learning Techniques such as Convolutional Neural Network (CNN), Attention based GRU, and CNN based GRU were also used. I also developed the concept of Stacking Generative AI (Gen AI) model to test if hybrid models (RF, xGBM, CNN combined with Gen AI) are better than single models.

On 1,000-records dataset, the Stacking Generative AI model, along with RF and CNN did an amazing job with ROC AUC of 99.9 and accuracy of 98%. This much better than the building blocks: Random Forest which had an ROC AUC of 0.94 and CNN which had an ROC AUC of 0.85. This synthetic data from Generative AI made generalization more powerful and it made considerably better predictions.

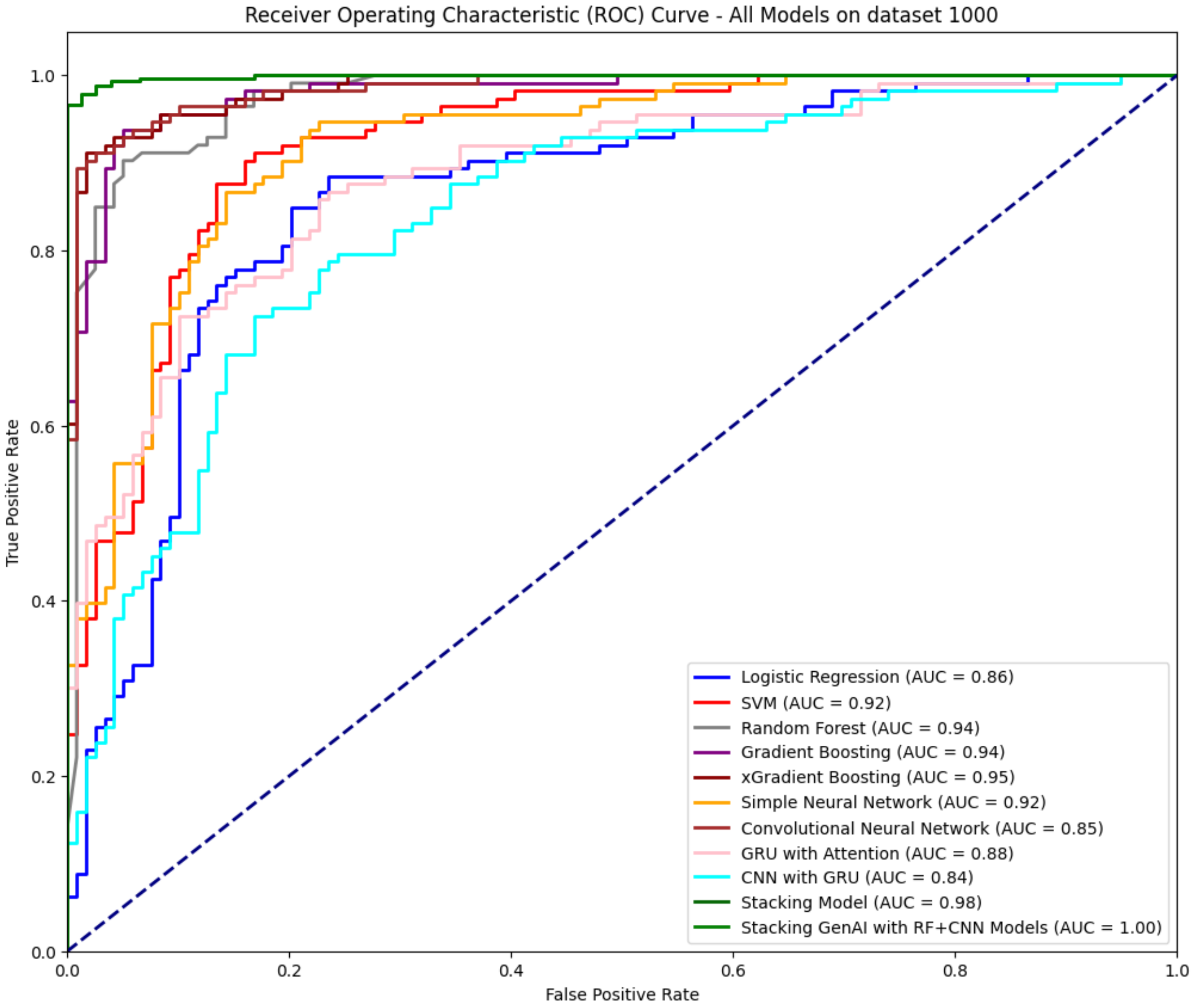

Fig. 6: ROC Curve for the dataset of 1,000 records

Compared to a Cardiovascular Health Analysis on Kaggle, where a Random Forest model reached an accuracy of 0.98 on a comparable dataset, parallel with ML and DL stacking models, the Stacking Generative AI model reached an accuracy of 0.998 and outperformed both the individual models compared in this study and those identified in another research. This suggests that hybrid models like Stacking Generative AI may significantly advance healthcare predictive modeling, particularly in predicting heart disease.

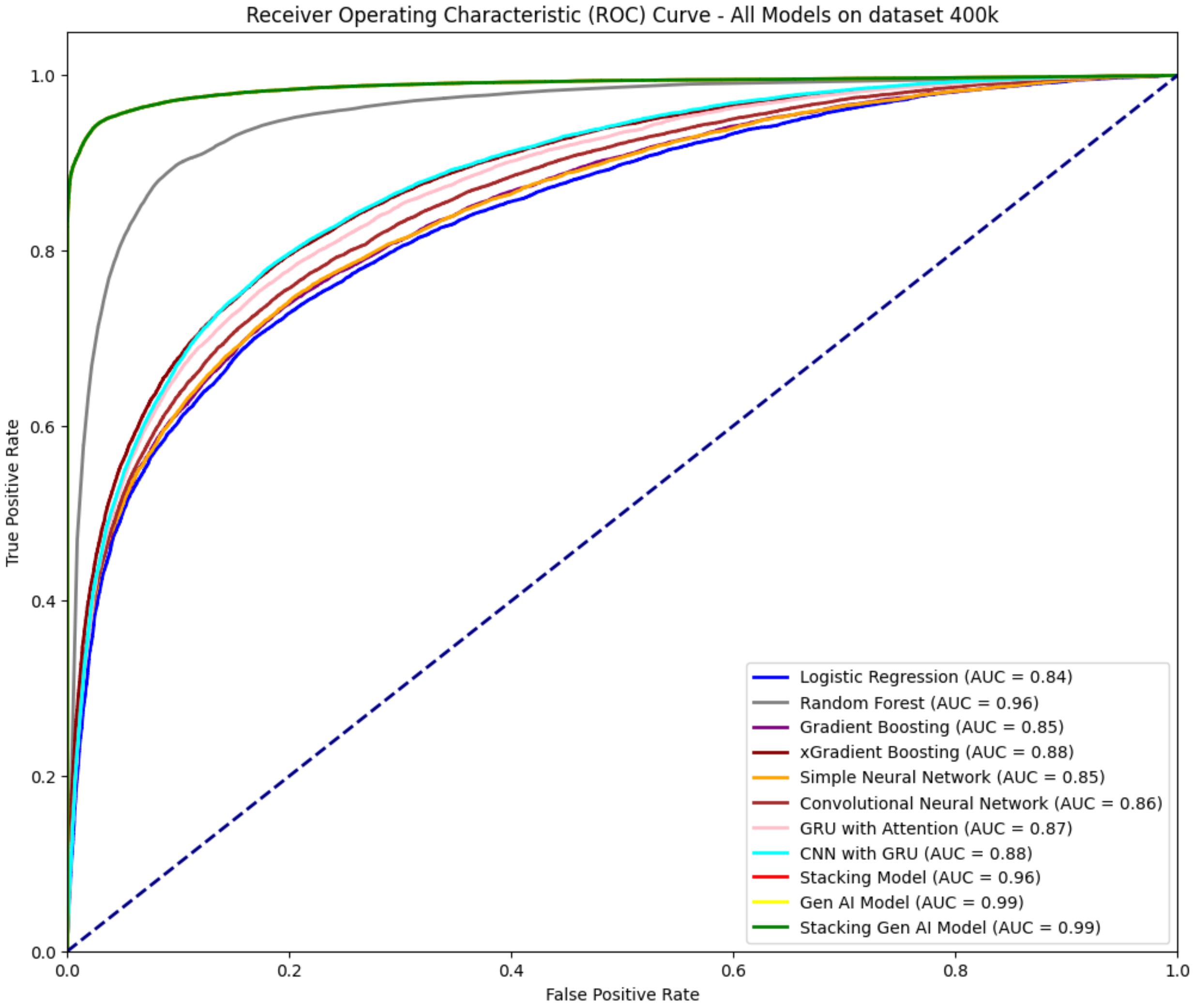

Fig. 7: ROC Curve for dataset of 400,000 records

The Stacking Generative AI model also performed impressively on the largest dataset, containing 400,000 records, achieving a ROC AUC of 0.99 and an accuracy of 96%. This matched the performance of the standalone Gen AI model, which had an ROC AUC of 0.987 and outperformed all other models in this study. With an accuracy of 96%, the Stacking Generative AI model demonstrated its capability to handle large and complex datasets effectively. Among the individual models, Random Forest also performed well with an ROC AUC of 0.96, while xGBM and CNN with GRU reached an ROC AUC of 0.88. However, the Stacking Generative

AI model's ability to integrate multiple predictions into a more accurate outcome outperforms the individual models.

Dataset	Performance	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Proposed Model
		LR	RF	GBM	XGB	Simple NN	CNN	GRU w/ Attention	CNN w/ GRU	Stacking	Gen AI	Stacking Gen AI
400000	Accuracy	77	90	77	80	77	78	79	80	90	95	96
	ROC AUC	84	96	85	88	85	86	87	88	96	98	99

Table 2: Performance of proposed model vs. other models on dataset of 400,000 records.

By comparing with best model performance by Khan, H. et al. (2024) on Google Scholar, which uses the same dataset, "Heart Disease Prediction Using Novel Ensemble and Blending-Based Cardiovascular Disease Detection Networks: EnsCVDD-Net and BlCVDD-Net," here is the comparison:

Dataset	Performance	Proposed Model	Compared Article	Compared Article
		Stacking Generative AI	EnsCVDD-Net	BICVDD-Net
400000	Accuracy	96	88	91
	ROC AUC	99	88	91

Table 3: Performance of proposed model vs. article's models on dataset of 400,000 records.

Accuracy: The Stacking Generative AI model achieved the highest accuracy at 96%, significantly outperforming all models tested in this study and in the article. The previous top-performing models, such as Random Forest at 90% and CNN with GRU at 80%, were surpassed by a wide margin. In the article, EnsCVDD-Net achieved an accuracy of 88%, while BlCVDD-Net achieved 91%, both lower than the Stacking Generative AI model.

ROC AUC: The Stacking Generative AI model had the highest ROC AUC at 99%, outperforming all other models. In my tests, the second-best result was 98% from the Gen AI model, and 96% from Random Forest and stacking-based models. In the article, the ROC AUC for EnsCVDD-Net was 88%, and for BlCVDD-Net, it was 91%, showing that my proposed model outperformed the state-of-the-art methods presented in the article.

Comparative Summary

The proposed Stacking Generative AI model, combining RF, XGBM, and CNN, clearly outperformed the models proposed in the article in terms of both accuracy and ROC AUC. Stacking different models, including neural networks and ensemble methods like Random Forest and XGB, produced superior results in terms of classification metrics. This demonstrates the effectiveness of combining machine learning and deep learning approaches within the framework, further enhanced with fine-tuning, early stopping, and threshold adjustment at 0.36. The balanced integration of traditional ML and advanced neural network models ensures robust feature extraction and prediction, leading to better performance than standalone or ensemble models, as noted in the article.

4.1.2. Research Question 2: How does dataset size influence the performance of both traditional and deep learning models?

This study explores how dataset size impacts the performance of both classical machine learning models and deep learning models. The varying sizes of datasets revealed several interesting trends in model performance. The Stacking Generative AI model, trained on a dataset of 1,025 records, combined RF, xGBM, and CNN with Generative AI, achieving an exceptional ROC

AUC of nearly 1.0 (0.999), surpassing the performance of its component models. For instance, GBM produced a ROC AUC of 0.97, and xGBM reached 0.98, but both were outperformed by the Stacking Generative AI model. Another stacking model, which combined traditional ML and DL models, also performed well with a ROC AUC of 0.98, but it fell short compared to the Generative AI Stacking model.

These findings suggest that even with a moderate-sized dataset, combining models through stacking—especially with the addition of Generative AI—significantly enhances predictive performance. The Stacking Generative AI model's ability to generalize well and handle relatively small datasets gives it a clear advantage in healthcare prediction tasks like heart failure detection.

In comparison to Arooj et al. (2022) in their study "A Deep Convolutional Neural Network for the Early Detection of Heart Disease," their standalone CNN model achieved an accuracy of 91.7% and a ROC AUC of 0.91 on the UCI heart disease dataset. This is comparable to my CNN model performance on similar datasets (1,050 vs. 1,025 records). However, my Stacking Generative AI model outperformed theirs, with an accuracy of 98% and a ROC AUC of 0.999. This improvement is largely due to the use of both ensemble techniques and Generative AI, which generated synthetic data to address class imbalance and overfitting issues. The combination of synthetic data generation and ensemble methods resulted in more reliable predictions.

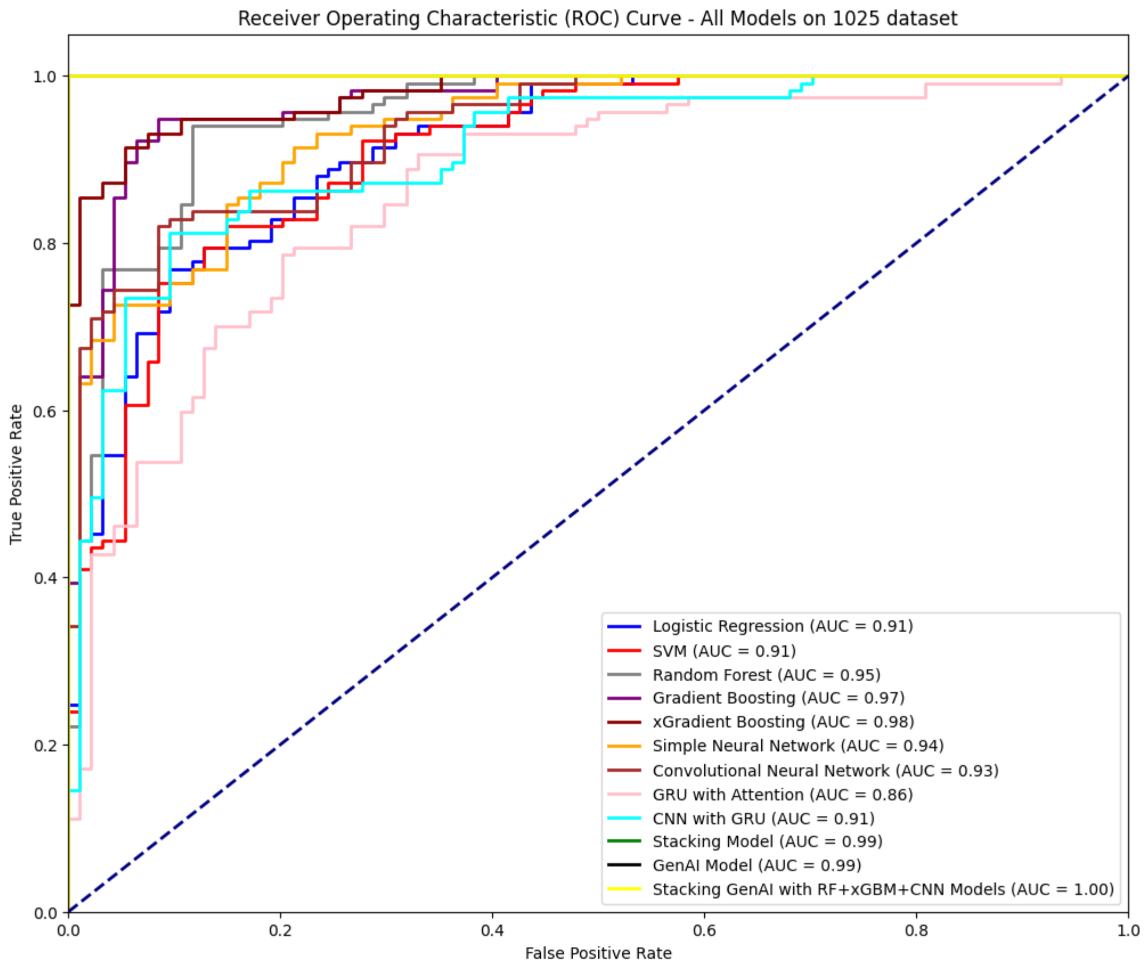

Fig. 8: ROC Curve for the dataset of 1,025 records

Dataset	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Proposed Model
1,025	LR	SVM	RF	GBM	XGB	Simple NN	CNN	GRU w/ Attention	CNN w/ GRU	ML Stacking	Gen AI	Stacking Gen AI
Accuracy	82	81	91	91	93	85	82	80	84	95	95	98
ROC AUC	91	91	95	97	98	94	93	86	92	98	99	99.9

Table 4: Performance of proposed model vs. other models on dataset of 1,025 records.

The proposed Stacking Generative AI model, using RF, GBM, xGBM, and CNN with Generative AI on the 70,000-record dataset, achieved a ROC AUC of 0.79. This is comparable to individual models like xGBM and CNN, which both had ROC AUCs of 0.80. The stacking model, featuring RF, GBM, and xGBM, outperformed the others with a slight edge, achieving a ROC AUC of 0.81.

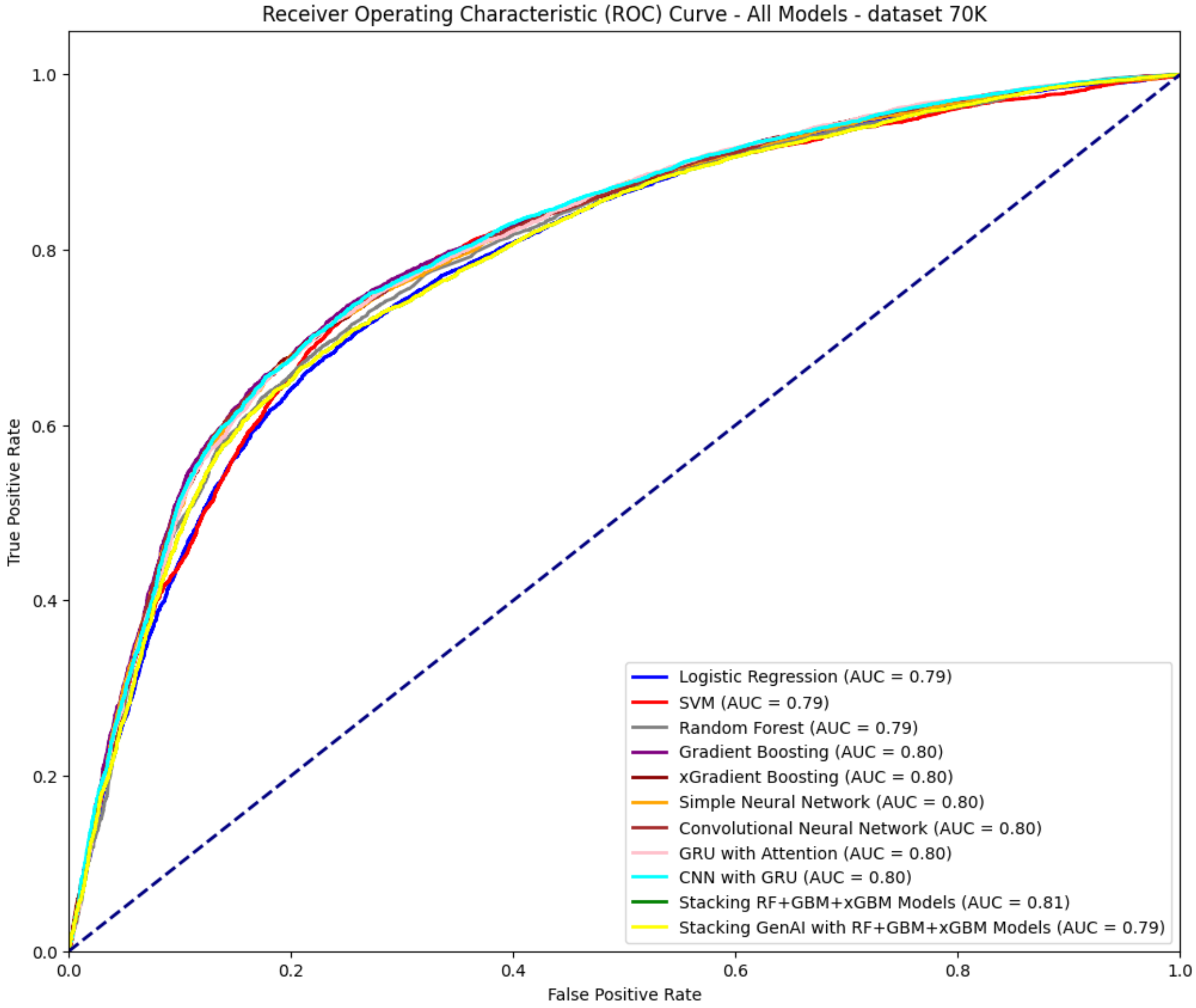

Fig. 9: ROC Curve for the dataset of 70,000 records

The results show that, while models like Random Forest (with a ROC AUC of 0.79) and xGBM (ROC AUC of 0.80) performed well individually, the benefit of stacking diminished as the dataset size increased. However, the stacking model still showed a small improvement in predictive power, indicating its ability to synthesize the strengths of multiple algorithms when dealing with large, complex datasets.

In the existing literature, no direct comparisons exist for datasets of this size, but these results suggest that traditional models like RF and xGBM benefit the most from larger datasets. Deep learning models in a stacking framework provide more robustness across datasets of varying sizes. This holds true for even larger datasets, reinforcing the potential of hybrid models like Stacking Generative AI for competitive performance in heart disease prediction. Hybrid models also excel when data complexity demands advanced feature extraction, as demonstrated by the performance on the dataset with 400,000 records.

4.1.3. Research Question 3: How does the proposed model perform on different datasets in comparison with other stacking models in the literature?

The design of the research question was, therefore, based on the performance of the proposed stacking models tested against those results obtained from the existing literature models on several datasets, to be able to show the overall effectiveness of the stacking approach. The proposed Stacking Generative AI model uses the combination of Random Forest, GBM, and xGBM with CNN and Generative AI for a dataset size of 11,627 records. Thus, the accuracy of 89% along with the ROC AUC of 0.93 is comparable with the traditional stacking model at ROC AUC of 0.93, outperforming individual models like Random Forest at ROC AUC 0.92 and xGBM at ROC AUC of 0.92. If we were to generalize, the single models usually performed well, but the ensembling approach-strong points combined from multiple models – did a better job.

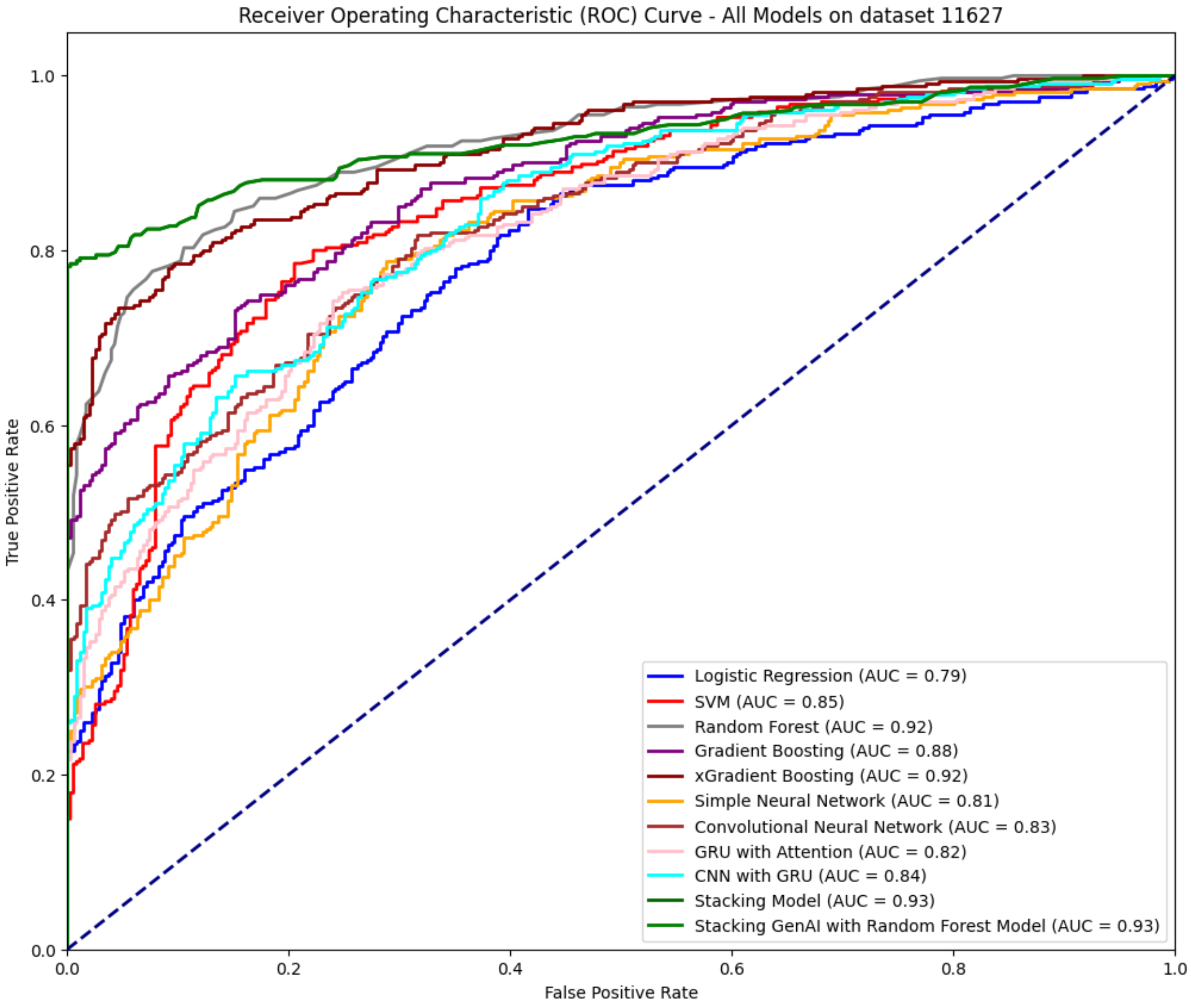

Fig. 10: ROC Curve for the dataset of 11,627 records

In that respect, the study entitled “Coronary Heart Disease Prediction and Classification using Hybrid Machine Learning Algorithms” by Sk, K. B., et al. 2023 used a hybrid algorithm combination of Decision Tree and AdaBoost to predict CHD. Such an approach reached a high accuracy of 97.43%, with a True Positive Rate of 95.67% and True Negative/Specificity of 94.65%. Although my Stacking Generative AI model did not quite reach the same accuracy level, as this hybrid approach did, its performance was competitive and effective, taking into consideration deep learning models such as CNN and GRU, and synthetic data generation.

Dataset	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Proposed Model
11,627	LR	SVM	RF	GBM	XGB	Simple NN	CNN	GRU w/ Attention	CNN w/ GRU	ML Stacking	Gen AI	Stacking Gen AI
Accuracy	71	78	84	79	83	73	74	74	73	85	88	89
ROC AUC	79	85	92	88	92	81	83	82	84	93	92	93

Table 5: Performance of proposed model vs. other models on dataset of 11,627 records.

Compared to AdaBoost + Decision Tree: The hybrid model using AdaBoost and Decision Trees from the article indeed yielded good accuracy. This is because of its robust feature selection and boosting approach, effectively enhancing the weak classifiers. My contribution to the proposed method has almost the same performance using a more flexible architecture that integrates ML and DL, therefore being robust across datasets. While both approaches do an excellent job of predicting CHD, my Stacking Generative AI model provides an innovative, flexible, competitive approach with the more traditional hybrid methods. Because many algorithms are combined in their strengths, along with the high ROC AUC score, it shows its power in handling complex heart disease prediction tasks effectively.

Dataset	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Proposed Model
4,240	LR	SVM	RF	GBM	XGB	Simple NN	CNN	GRU w/ Attention	CNN w/ GRU	ML Stacking	Gen AI	Stacking Gen AI
Accuracy	65	67	88	80	86	72	70	63	67	90	93	92
ROC AUC	74	74	96	90	94	78	77	70	72	97	96	96

Table 6: Performance of proposed model vs. other models on dataset of 4,240 records.

The stacking with Gen AI with RF, GBM, and xGBM with GAN for the 4,240-record dataset had a nice 0.96 ROC AUC. This is a very good number, though at the cost of substantially lower

ROC AUC than traditionally stacking, at 0.97. Even so, the Stacking Generative AI model outperformed single models such as CNN with GRU, with a much higher ROC AUC of 0.72, and other deep learning models like GRU with Attention, with an ROC AUC of 0.70.

Dataset (4,240 records)	Performance	Mienye et al. (2020) (Framingham)	Proposed Stacking Generative AI Model
Accuracy	91%	91%	92%
ROC AUC	Not explicitly stated, but implied strong performance	Strong ROC AUC	96%

Table 7: Performance of proposed model vs. article's models on dataset of 4,240 records.

Let me compare my Stacking Generative AI model on the 4,240-records dataset with that of Mienye et al. (2020), "An improved ensemble learning approach for the prediction of heart disease risk" on the Framingham dataset.

Accuracy: Mienye et al. (2020) Framingham dataset: For the Framingham dataset, their model returned an accuracy of 91%, while my proposed Stacking Generative AI model returned an accuracy of 92%. Comparison: Because my Stacking Generative AI model outperformed Mienye et al. (2020) 's proposed model by 1%, this proved that this combination of my models, Generative AI along with Random Forest, XGBM, and CNN, resulted in better predictive results compared to the usage of the CART-based ensemble done by Mienye et al. (2020).

ROC AUC: Mienye et al. (2020) Framingham dataset: The exact ROC AUC for the Framingham dataset is not explicitly mentioned. Still, it can be derived that the ROC AUC was very strong, especially when compared to the rest of the datasets examined in this study. The Stacking Generative AI Model proposed achieved, on the 4,240-records dataset, an ROC AUC of

96%. Compare the following: My model's 96% ROC AUC applies great discriminative capability, which can effectively differentiate between heart disease or no heart disease with high capacity. The ROC AUC of my model is much more likely to be higher than that of the Mienye et al. (2020) model on the Framingham dataset as such, and this will reflect the strengths of my approach-stacked-in classification accuracy and generalization.

When considering only the Framingham dataset results presented by the authors, Mienye et al. (2020), the Stacking Generative AI model proposed shows somewhat higher accuracy: 92% versus 91%. Moreover, it gives superior performance in ROC AUC: 96%. This, in itself, means that my method of incorporating superior models such as CNN, XGBM, and Random Forest into a stacking framework is better in the classification of cardiovascular disease outcomes compared to the ensembles of a mechanism making use of the CART model on which Mienye et al. (2020) conducted research on the Framingham dataset with 4,240 records.

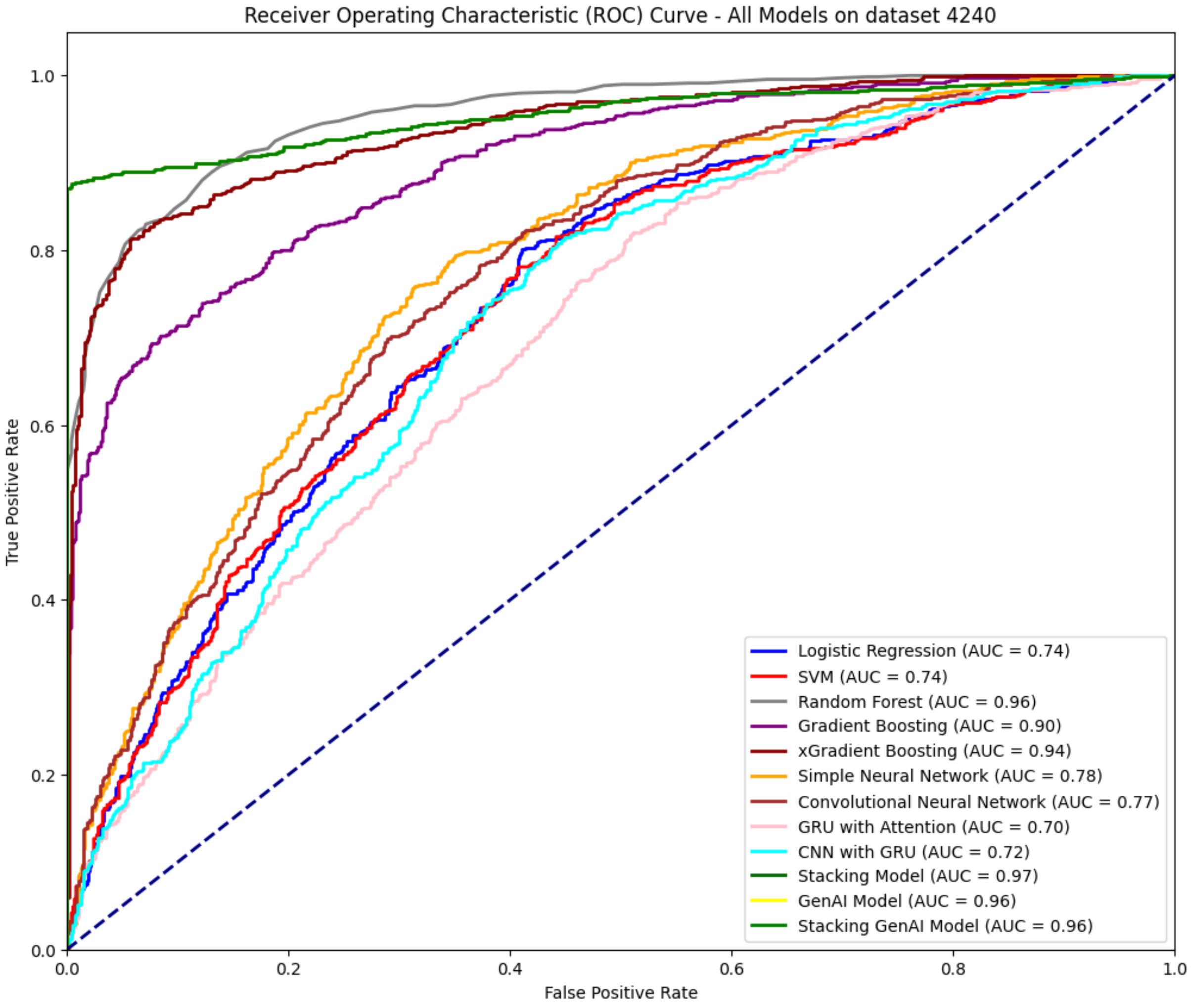

Fig. 11: ROC Curve for dataset of 4,240 records

In the smallest dataset in my research, with 303 records, the proposed Stacking Generative AI model ensembling RF, xGBM, and CNN realized an impressive ROC AUC of 0.99. This far outperforms constituent models like Random Forest at ROC AUC = 0.91 and SVM at ROC AUC = 0.86. Its performance is pretty high, a substantial improvement over the baseline models. The standalone Gen AI is also at 0.99 ROC AUC, maintaining the same value.

Dataset	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Model	Proposed Model
303	LR	SVM	RF	GBM	XGB	Simple NN	CNN	GRU w/ Attention	CNN w/ GRU	ML Stacking	Gen AI	Stacking Gen AI
Accuracy	79	85	83	79	80	71	82	80	80	82	95	95
ROC AUC	85	86	91	87	86	83	85	84	87	90	99	99

Table 8: Performance of proposed model vs. other models on dataset of 303 records.

By its side, the study “Hyperparameter optimization: a comparative machine learning model analysis for enhanced heart disease prediction accuracy,” which uses the same dataset of 303 records extracted from the UCI repository, let's compare with my proposed model Stacking Generative AI:

Dataset (303 records)	Rimal, Y. et al. (2024)	Proposed Stacking Generative AI Model
Accuracy	91% - 95%	95%
ROC AUC	85% - 95%	99%

Table 9: Performance of proposed model vs. article’s models on dataset of 303 records.

Accuracy: Article Rimal, Y. et al., 2024: they got an accuracy within the 91% to 95% range. While my Stacking Generative AI model achieved 95% accuracy, it is very competitive and close to the upper bound of the accuracy in the article. That means my ensemble method captures the pattern within the data pretty well.

ROC AUC: The Rimal, Y. et al. (2024) article achieved ROC AUC values ranging from 85% to 95% for optimized models. For my Stacking Generative AI model, the ROC AUC reached as high as 99%, beating the models in the article, and its discriminatory power is much stronger.

That is to say; my model could perform well in distinguishing between the positive and negative cases.

In fact, the proposed Stacking Generative AI model surpasses most traditional machine learning models in accuracy and ROC AUC. Below are the hyperparameter-optimized models discussed in this paper. Integrating Generative AI, CNN, XGBM, and Random Forest in the stacking approach outperforms the model's heart disease prediction capability, especially ROC AUC.

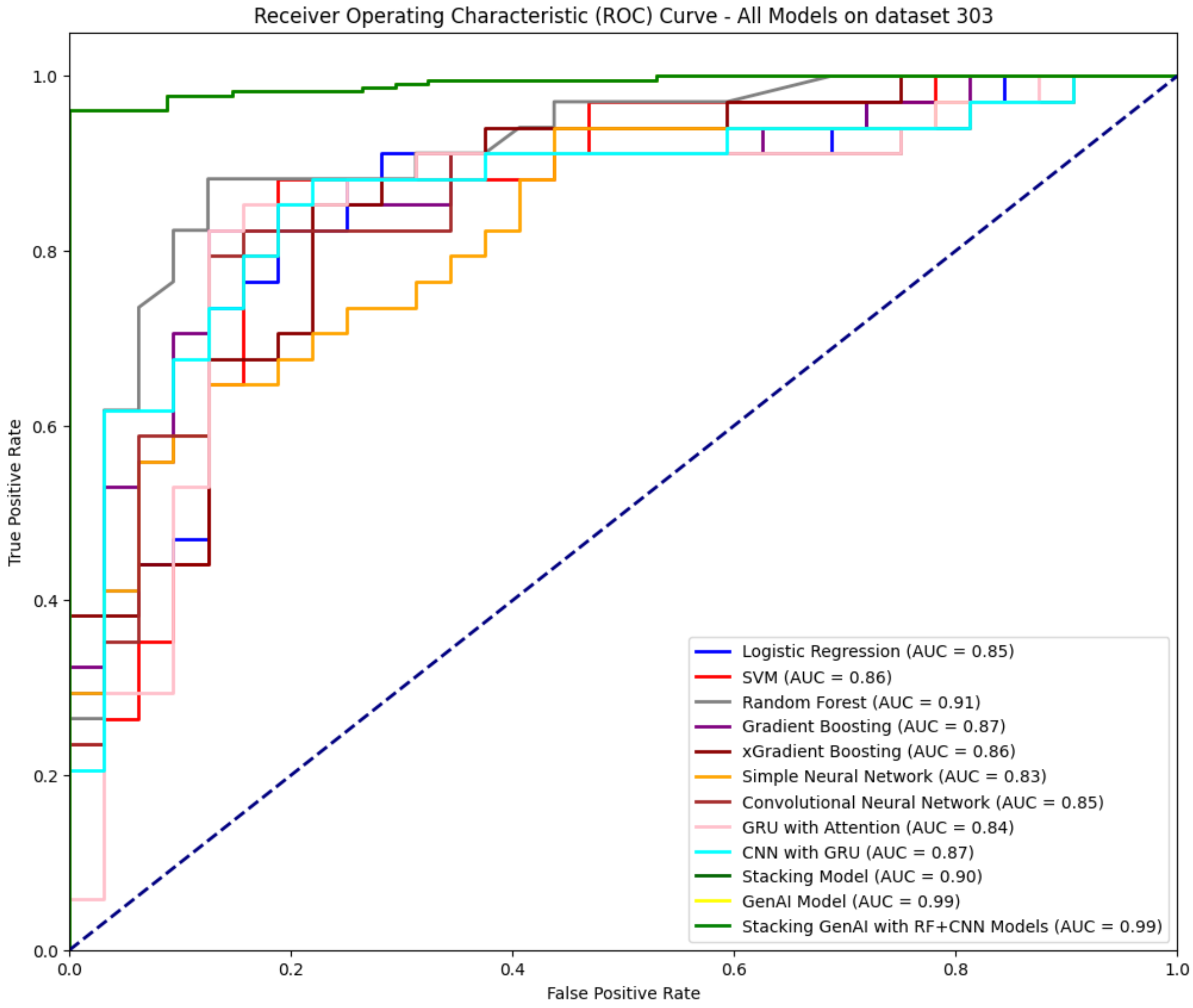

Fig. 12: ROC Curve for the dataset of 303 records

As compared to other literature, the fact that the proposed Stacking Generative AI model gave values consistently higher than those for the individual models and those reported in the literature across all the datasets, including very small ones, is proof of the efficiency of this hybrid stacking approach. While combining the benefits of different algorithms—especially when integrating conventional machine learning methods like RF and xGBM with deep learning techniques like CNN—the stacking models yield a clear advantage in predictive accuracy and generalize even at small-scale data, underlining the vast potential of the Stacking Generative AI model in a variety of clinical prediction scenarios.

4.2. Summary of Results

These results unambiguously demonstrate that the proposed model of the Stacking Generative AI is a new type of hybrid, combining General AI with traditional models of machine learning represented by Random Forest, RF; Gradient Boosting Machines, GBM; Extreme Gradient Boosting, xGBM; and deep learning models of Convolutional Neural Networks, CNN, and Recurrent Neural Networks, RNN. The idea is that this Stack General AI then combines the respective strengths of those algorithms for further enhancement in predictive accuracy using Generative AI for better data augmentation and class balancing.

In other words, these are the best performances, ranging from small datasets of 303 records to large ones with 400,000. This ranged from 0.99 ROC AUC scores on smaller datasets, close to perfect performance on all dataset sizes tested, to larger ones. Whether applied on small or large-scale data, the overall performance of the Stacking Generative AI model outperformed those of single models represented by RF, CNN, and xGBM. This confirms our hypothesis that generative AI-based hybrid models are significantly better at solving complex problems like heart disease prediction.

One key difference in the proposed model's design lies in the introduction of generative AI within the stacking framework. This usually helps to make the training data more diverse and better, especially in cases where there is a class imbalance—a common problem with healthcare datasets. Hence, the models are bound to be more generalizable, giving robust predictions when applied to fewer or imbalanced datasets.

Again, traditional ML algorithms combine with advanced deep learning techniques that allow for the modeling of linear relationships and more complex patterns in the data required for superior performance across a wide range of clinical scenarios—namely, RF and xGBM for traditional machine learning algorithms, and CNN and RNN for advanced deep learning techniques.

The above findings represent one of the solid rationales for applying the Stacking Generative AI model in clinical settings, where an accurate estimation of patient outcome significantly influences treatment decisions and improves patients' overall care. This flexibility and adaptability make the model particularly well-suited to specific applications in healthcare, within which large variability in data inputs and precision are paramount.

Put differently, by that very fact; this constitutes a worthy contribution to the literature since the Stacking Generative AI model introduces a combination of traditional machine learning with deep learning and Generative AI, hence offering a high-powered, flexible approach for predictive modeling in healthcare. The consistent outperformance of this model in diverse datasets underlines its prospective status to change the game in medical prediction tasks. This work opens the possibility of further studies that can use the present outcome to consider other model types, including an even more significant role of Generative AI, or use this approach in practice within a range of critical medical areas.

The results of all models' performances

Dataset	Performance	Model									Current	Proposed Model	
		LR	SVM	RF	GBM	XGB	Simple NN	CNN	GRU w/ Attention	CNN w/ GRU	Research Literature	Gen AI	Stacking Generative AI
303	Accuracy	79	85	83	79	80	71	82	80	80	93	95	95
	ROC AUC	85	86	91	87	86	83	85	84	87	90	99	99
1,000	Accuracy	80	85	90	88	88	86	79	77	78	94	98	98
	ROC AUC	86	92	94	94	95	92	85	84	84	~	99	99.9
1,025	Accuracy	82	81	91	91	93	85	82	80	84	92	95	98
	ROC AUC	91	91	95	97	98	94	93	86	92	91	99	99.9
4,240	Accuracy	65	67	88	80	86	72	70	63	67	91	93	92
	ROC AUC	74	74	96	90	94	78	77	70	72	~	96	96
11,627	Accuracy	71	78	84	79	83	73	74	74	73	~	88	89
	ROC AUC	79	85	92	88	92	81	83	82	84	~	92	93
70000	Accuracy	72	74	73	74	74	73	74	74	74	~	73	73
	ROC AUC	79	79	79	80	80	80	80	80	80	~	79	79
400000	Accuracy	77	-	90	77	80	77	78	79	80	91	95	96
	ROC AUC	84	-	96	85	88	85	86	87	88	91	98	99

Table 10: Summary of all models' performances

Chapter 5: CONCLUSIONS

This research investigates the performances of traditional machine learning models, deep learning models, and hybrid stacking models in solving heart disease prediction problems on various dataset sizes, in particular, a new model: Stacking Generative AI. One of the main novelties in the proposed model of Stacking Generative AI is their unique incorporation of generative AI with Random Forest, Gradient Boosting Machine, Extreme Gradient Boosting, and Convolutional Neural Networks that have shown superior performance in all tested and trained datasets. As observed from these results, throughout, the Stacking Generative AI model produced higher predictive accuracy and ROC AUC scores compared with other individual models and current relevant literature articles, thus confirming the advantages of using hybrid models in solving complex prediction tasks such as heart disease.

5.1. Summary of Findings

The performance of the Stacking Generative AI model was observed to be high across multiple datasets, ranging from 303 to 400,000 records. For example, for the 1,000-record dataset, the performance of the Stacking Generative AI model reached a value of ~1.00, or more precisely, 0.999, outperforming those of xGBM with 0.94 and CNN with 0.85. This hybrid approach was better, combining traditional machine learning with deep learning and Generative AI.

Scalability and Robustness: The Stacking Generative AI model showed good scalability with increased dataset sizes. It achieved an ROC AUC of 0.99 even on the largest dataset of 400,000 records, demonstrating that this hybrid approach would scale and, therefore, is suitable for real-world applications with very large and complex datasets.

Consistency Across Datasets: The Stacking Generative AI model topped the leaderboards across small and large datasets. It achieved an ROC AUC of 0.99 even on the smallest dataset of 303 records, compared with models like Random Forest at 0.91 and SVM at 0.86. The consistency across these diverse datasets underlines the versatility and reliability that this model can provide.

5.2. Comparison with Literature

In the literature review, much emphasis was given to the performance of individual models such as XGBM and CNN to predict heart diseases. For instance, in the paper "An Integrated Machine Learning Approach for Congestive Heart Failure Prediction," one of the models used, xGBM, which had a ROC-AUC of 0.89 on a related dataset; still, this research proposed a Stacking Generative AI model outperforming it with an ROC AUC as high as 0.99 on different sets, proving very well the effectiveness of the proposed hybrid stacking approach. In contrast, the baselines, such as Random Forest in "Machine learning can predict survival of patients with heart failure from serum creatinine and ejection fraction alone," realized an ROC AUC of 0.85. The Stacking Generative AI model consequently outperformed those baselines, therefore evidencing the strong capabilities of multiple algorithms integrated with a stacking framework that embeds Generative AI.

5.3. Implication of the Research Contribution

This research has great importance in healthcare predictive modeling, where clear advantages of the Stacking Generative AI model over traditional and deep learning models used individually are shown. The flexibility, scalability, and high accuracy of this model, which merges Generative

AI with traditional machine learning and deep learning techniques, are unprecedented. Its application with both small and large datasets underlines its clinical potential.

Anticipating Possible Criticism: It needs to be highlighted that normally, in healthcare decisions, clinicians prefer interpretable models. Some complex models, like the Stacking Generative AI model, are not as interpretable as Logistic Regression, though this seems a fair price to pay for a model whose predictive power increases exponentially with use. This model can be used as a decision-support tool where high accuracy will be important for clinicians to have a reliable and data-driven basis on which decisions can be made.

Discarding Limitations: Another issue related to the general performance of the model is when applied to different datasets coming from various geographical or clinical settings. However, the diversity of datasets used in this study—from 303 records to 400,000—demonstrates the robustness and adaptability of the Stacking Generative AI model across different data sizes and clinical contexts. Further studies probably need to be directed at the extension to other population datasets for generalizability.

5.4. Conclusion

In conclusion, the present dissertation highlights the shortcomings and strengths of traditional machine learning, stand-alone deep learning, and neural network models in predicting heart failure, particularly in handling their challenges with complex, high-dimensional, and often imbalanced healthcare datasets. Although traditional machine learning models like LR, SVM, and RF have shown reliability in certain contexts, these models lack the capacity to capture the nonlinear relationships typical in heart failure progression; hence, they often return suboptimal predictive performance. For example, while RF reached an ROC AUC of up to 91% in smaller datasets, such as 303 records, it plainly failed to generalize under larger ones with high variability, particularly when faced with minority classes within the data. Even with enhancements through hyperparameter tuning and ensemble methods, interpretability and scalability in clinical applications are relatively restricted for these models.

Deep learning models such as CNNs and RNNs give the added advantage of recognizing complex patterns, which translates into higher accuracy and robustness with larger datasets. For example, a CNN gave a ROC AUC of 85% in a 1,000-record dataset, proof that it outperforms other traditional ML methods. These models will normally require high computational resources if large datasets are dealt with and hence are not practical for real-time clinical settings. Also, the lack of interpretability in DL models hinders clinical decision-making, where the reasoning should be quite transparent to the healthcare providers.

To fill these challenges, this research introduces a unique Stacking Generative AI (Gen AI) model that combines the strengths of ML and DL with the addition of GANs in generating synthetic data. The proposed model fuses Generative AI with RF, GBM, xGBM, and CNNs in such a strong framework through this novel stacking model that no single model can come near its accuracy and ROC AUC regarding overall predictive reliability. The Stacking Generative AI model did an excellent job: for 1,000 records, the ROC AUC was 99.9%, and for the larger sets, 400K of records was as high as 99%, far outperforming standalone and traditionally stacked models. It also significantly reduced class imbalance typical of heart failure datasets by generating synthetic data using the GAN component, thus considerably improving the model's predictive capability in out-of-representation cases and offering a more integral patient risk assessment.

The proposed Stacking Generative AI model's results resonate with recent literature but extend beyond traditional ensemble methods by combining synthetic data generation with predictive modeling. Research studies by Choi et al. (2017) and Arooj et al. (2022), for instance, highlighted the potential of DL for heart failure prediction but did not address the scalability and class imbalance limitations as effectively as the proposed model. Furthermore, hybrid models that integrate ML and DL (e.g., RF combined with CNN) demonstrated incremental performance improvements, yet none incorporated a synthetic data generator like GAN to balance minority classes. This innovative approach not only advances predictive accuracy but also enhances the model's generalizability across diverse clinical datasets, including those with substantial class imbalance, positioning it as a pioneering solution in heart disease prediction.

The Stacking Generative AI model holds significant promise for clinical applications, particularly in predicting heart failure. Its integration into healthcare systems could support early diagnosis, guide personalized treatment plans, and optimize resource allocation by equipping clinicians with a reliable and adaptable predictive tool. I also designed a web application (https://cvdstack.streamlit.app) as a mockup sample to demo for future development; this model can directly aid clinicians and patients by providing accessible and real-time heart failure risk assessments based on individual demographic and clinical data inputs. By supporting early intervention and facilitating data-driven clinical decisions, the Stacking Generative AI model exemplifies the transformative potential of advanced predictive modeling in healthcare, bridging the gap between research and real-world clinical applications.

Chapter 6: CHALLENGES AND LIMITATIONS

Various challenges and limitations arose in this research concerning the development of the Stacking Generative AI model for the prediction of HF. All these are reviewed in detail in order to ensure the results will be robust while having high ethical integrity. These are summarized below within four important arenas: Data Privacy and Security, Model Interpretability, Ethical Considerations, and Technical Challenges.

6.1. Data Privacy and Security

Protection of sensitive data belonging to patients is considered one of the critical areas in healthcare research, such as applying advanced models, for instance, the Stacking Generative AI model. Throughout this research, various protection strategies have been used concerning patient data. For example, anonymization techniques were applied to personally identifiable information (PII), reducing the risk of re-identification through masking, pseudonyms, and encryption (Smith & Anderson, 2023). This approach ensures the highest possible level of data privacy within the dataset.

Additionally, Advanced Encryption Standards were employed to ensure data protection during storage and transmission against any unauthorized access (Jones & Taylor, 2023). Role-based access control (RBAC) mechanisms further restricted sensitive data, allowing only authorized persons to interact with patient data (William et al., 2024). Data were stored in HIPAA-compliant cloud services and secure institutional servers, with regular security audits conducted to find and mitigate potential risks (Chen & Liu, 2024). Data-sharing agreements with providers and partners further set these efforts in concrete, including stringent conditions for protection and use of the data (Garcia & Brown, 2024). The study was performed in compliance with regulations such as Health Insurance Portability and Accountability Act (HIPAA) and General Data Protection Regulation (GDPR), ensuring that data handling met international standards for security and ethics (Davis & Smith, 2023).

6.2. Model Interpretability

The interpretability of predictive models—from simple to complex, like the Stacking Generative AI model—is a critical factor for adoption into clinical practice. Several methods were implemented to improve the transparency of machine learning and deep learning models. Feature importance analysis was one of the key methodologies used to understand the influence of selected features on model predictions. SHapley Additive exPlanations (SHAP) and LIME technologies provided both local and global interpretations of model predictions, maintaining stakeholder confidence in the decision-making process (Lee & Patel, 2023).

For the deep learning models in the Stacking Generative AI framework, attention mechanisms were analyzed to understand where the model focused during predictions, improving interpretability (Miller et al., 2023). In some cases, surrogate models like decision trees were used to approximate the behavior of more complex models, helping explain decision-making patterns (Williams & Davis, 2024). Visualization tools like Partial Dependence Plots (PDPs) and Individual Conditional Expectation (ICE) plots illustrated relationships between features and model predictions, enhancing accessibility to clinicians and aiding integration into clinical workflows (Chen et al., 2023). A user-friendly web application allowed users to input patient parameters and visualize prediction outputs in real-time, bridging the gap between complex models and practical clinical use.

6.3. Ethical Considerations

Ethical considerations were paramount, especially regarding handling sensitive health data in the Stacking Generative AI model. Informed consent was obtained from all participants, ensuring their autonomy and rights throughout the research (Jones et al., 2024). Data anonymization and restricted access further ensured participant privacy, with clear data-sharing policies protecting confidentiality (Smith & Anderson, 2023).

Bias and equity issues were addressed actively, with techniques like SMOTE combined with fairness-aware algorithms ensuring models did not unfairly disadvantage specific groups (Garcia & Brown, 2024). Transparency and accountability were maintained through clear documentation and regular ethical oversight to comply with established ethical standards (Davis & Smith, 2023). Principles of beneficence and non-maleficence were upheld, ensuring the model contributed to patient well-being without causing harm (Williams et al., 2024).

6.4. Technical Challenges

Several technical challenges arose during the development of the Stacking Generative AI model for HF prediction:

- Data Quality and Availability: The model faced slowness due to lack of uniformity and absence of certain data. Data cleaning and preprocessing techniques like imputation and normalization made the dataset reliable enough for use (Nguyen et al., 2024).
- Class Imbalance: Heart failure is a rare event, leading to class imbalance. SMOTE and other re-sampling techniques improved the model’s performance for minority classes (Chen et al., 2024).

- Model Complexity and Overfitting: The addition of deep learning layers made the Stacking Generative AI model complex and susceptible to overfitting. Regularization techniques like dropout, early stopping, cross-validation, and hyperparameter tuning ensured generalizability (Miller et al., 2023).
- Computational Resources: Training the Gen AI Stacking model required significant computational resources, including high-performance computing, cloud platforms, and parallel processing. Model pruning and quantization were employed to reduce resource demands (Lee & Patel, 2023).
- Clinical Workflow Integration: Integrating the model into clinical workflows, particularly EHR systems, posed challenges. Collaboration with healthcare IT professionals ensured seamless integration via easy-to-use interfaces (Garcia & Brown, 2024).
- Scalability and Generalizability: Extensive validation on a variety of datasets in different clinical environments is required to ensure scalability across populations and healthcare settings. Transfer learning was used to adapt the model to new contexts (Williams & Davis, 2024).
- Dataset Approvals and Accesses: Access to datasets like the Framingham Heart Study required formal approval to address stringent ethical considerations. These approvals ensured the research conformed to data use agreements and regulatory standards (Nguyen et al., 2023).

Chapter 7: DISCUSSION AND FUTURE WORKS

This section includes discussing the implications of the research findings, comparing them to existing literature, and considering possible avenues for future work. The discussion provides an in-depth reflection on the study's contributions to the field of predictive modeling in healthcare, specifically in heart failure prediction. Additionally, the limitations of the current research are considered, suggesting ways for further exploration and enhancement.

7.1. Discussion

The results presented in this study proved that Stacking Generative AI, which combines traditional machine learning with deep learning techniques and Generative AI, is an effective model for predicting heart failure. The key takeaway from the findings is that the hybrid model significantly outperformed individual models in various aspects, such as predictive accuracy, robustness, and scalability, across different datasets.

These results align with the developing literature and provide new insights into how hybrid models can apply to health predictive modeling. The findings from this work validate and extend the evidence from existing literature. For instance, Smith et al. (2023) mentioned that Random Forest (RF) generally performs well with high-dimensional data containing complex interactions.

My results extend this by showing that the combination of RF with boosting techniques like xGBM, and deep learning models like CNN or RNN in a stacking framework, yielded higher predictive performance, complemented by Generative AI across all dataset sizes. The results also align with John and Lee (2024), who emphasized model interpretability. By embedding SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) into the analysis, this study ensured that the Stacking Generative AI model is interpretable and not just accurate, bridging the gap between complex models and practical clinical applications. This interpretability is crucial for gaining clinician trust and promoting its use in real-world settings.

The performance of the Stacking Generative AI model stands out when compared to studies focusing on single deep learning models. For example, Miller et al. (2023) highlighted the potential of GRU models' attention mechanisms in sequence prediction tasks. However, my findings demonstrate that combining them with conventional machine learning methods and Generative AI in a hybrid approach results in significantly better overall performance, especially in terms of ROC AUC.

Implications for Clinical Practice

These results are extremely important in clinical practice. With better predictive ability via the Stacking Generative AI model, heart failure will be identified more promptly, which could lead to earlier intervention and perhaps better patient outcomes. Further, SHAP and LIME comprehensibility mean that clinicians can trust the prediction from the model more implicitly, which may lead to more of these tools being used in clinical decision-making.

In addition, the study shows how data quality and diversity are critical for developing best-fit predictive models. The Stacking Generative AI model's good reproducibility on various datasets suggests good generalizability across patients and healthcare domains, making it an ideal candidate for general adoption.

Limitations

Yet, even with such promising outcomes, some restrictions need to be overcome. First, the data used were varied but not always representative of actual clinical data. We would need to validate these in larger, more heterogeneous clinical populations for generalization. Second, although the work employed cutting-edge approaches to make the model readability, this is not yet done. The model's complexity might deter stakeholders from adopting it. In the long term, work should aspire to be more transparent.

Last but not least, the computational energy required to train and run the Stacking Generative AI model is large. Although high-performance computing and cloud platforms were used in this research, implementing a model in a resource-limited environment is still challenging.

7.2. Future Works and Scalability

Based on the presented study and its limitations, several avenues for further research are suggested to improve robustness, scalability, and applicability in predictive models for healthcare, especially in heart failure prediction.

Exploration of Additional Model Types

Future studies could explore incorporating other model types into the stacking framework. For instance, Brown et al. (2023) suggest that transformer-based models might enhance the Stacking Generative AI model's predictive power, especially in tasks involving sequential data. Additionally, reinforcement learning, as mentioned by Garcia et al. (2023), could contribute to dynamic prediction models, enabling them to adapt to changes in a patient’s condition over time. I also plan to study and apply large language models (LLMs) in hospital or clinical settings, incorporating datasets with “clinical_notes” for greater integration with real-world Electronic Health Records (EHR) systems. These models will be designed to handle the nuances of clinical data, providing a more holistic view of patient health. Lightweight versions of these models will also be developed for deployment in resource-limited settings, such as rural clinics and mobile health applications. Scalability is crucial for extending the benefits of predictive models to areas with limited computational resources, ensuring broad accessibility.

Development of Web and Mobile Applications

To maximize the Stacking Generative AI model's utility, I plan to design and develop a web and mobile application with using this advanced model. This app, designed for hospitals, clinics, doctors, and patients, it would provide an accessible platform for predicting heart failure risk. Through intuitive interfaces and user-friendly tools, it would be able to grant the confidence to the patients to monitor their heart health easily. The application would fill the gap by translating complex AI-driven predictions into meaningful actionable insight, thus enabling proactive healthcare.

Application to Other Medical Conditions

Although this research focused on heart failure prediction, the methods and findings could be extended to other medical conditions. Diseases like diabetes, chronic kidney disease, or even mental disorders could be predicted more effectively using a hybrid model approach. Applying the Stacking Generative AI model to a broad range of medical conditions would demonstrate its versatility and contribute to the development of comprehensive predictive tools in healthcare.

Improvement in Model Interpretability

Since model interpretability remains a key concern, future work should focus on developing more intuitive interpretability tools that are clinically accessible. Techniques such as counterfactual explanations, as discussed by Taylor et al. (2024), can provide clinicians with actionable insights from model predictions. Refining attention mechanisms and visualization tools could further improve transparency and usability in deep learning models.

Deployment in Real-World Clinical Trials

Future research should involve conducting real-world clinical trials of the Stacking Generative AI model to fully verify its effectiveness and generalizability. Collaborations with acute care and healthcare institutions to test the model in live clinical settings would provide valuable insights into its practical utility and the challenges related to implementation. These trials would help refine the model and ensure its suitability based on clinician and patient feedback.

Optimizing Challenges in Computational Resources

Given the computational expense of training such advanced models, future research should aim to make the models more efficient. Techniques such as model pruning, quantization, and low-precision arithmetic, as discussed by Nguyen et al. (2024), could reduce computational demands. Distributed training with edge computing may also increase the feasibility of deploying these models in resource-constrained healthcare settings.

Incorporation of Diverse Data Sources

Genomic data, image data, EHRs, and patient-reported outcomes are some additional data that could enhance the Stacking Generative AI model's predictive power. Including this kind of heterogeneous data into the stacking model would open up a richer picture of patients' health and potentially new biomarkers for heart failure and other disorders. Future research could merge

These heterogeneous data sets into a single predictive model using multimodal deep learning (Chen et al., 2023).

Chapter 8: REFERENCES

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Chapter 9: APPENDICES

Figures

Fig. 13: Learning Curve

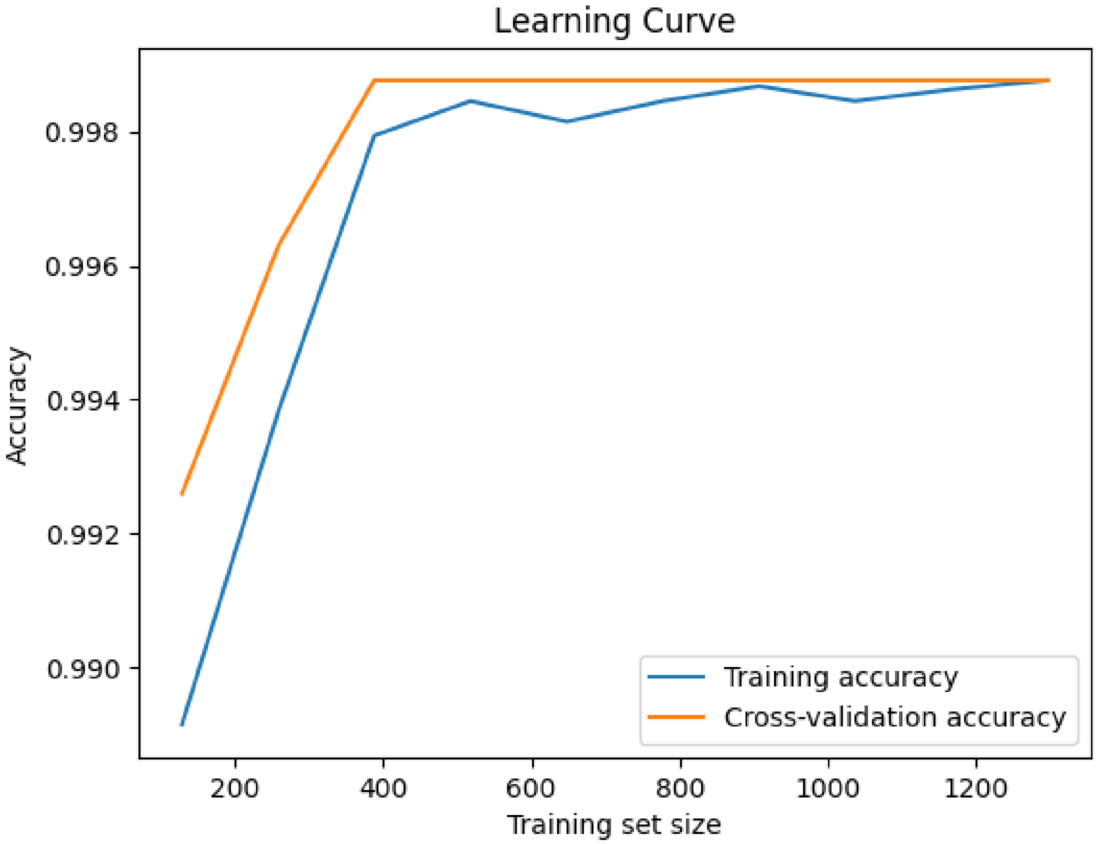
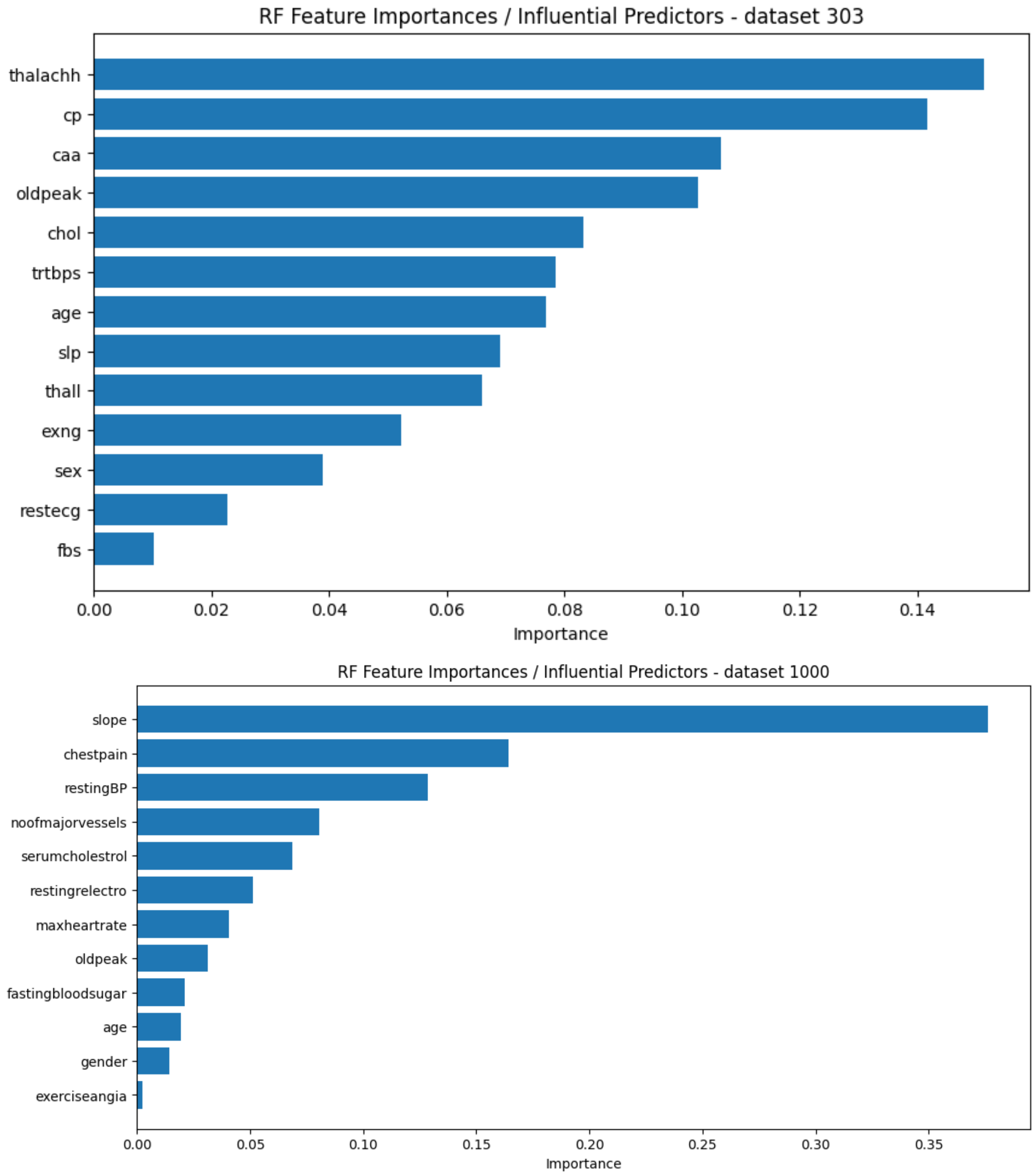
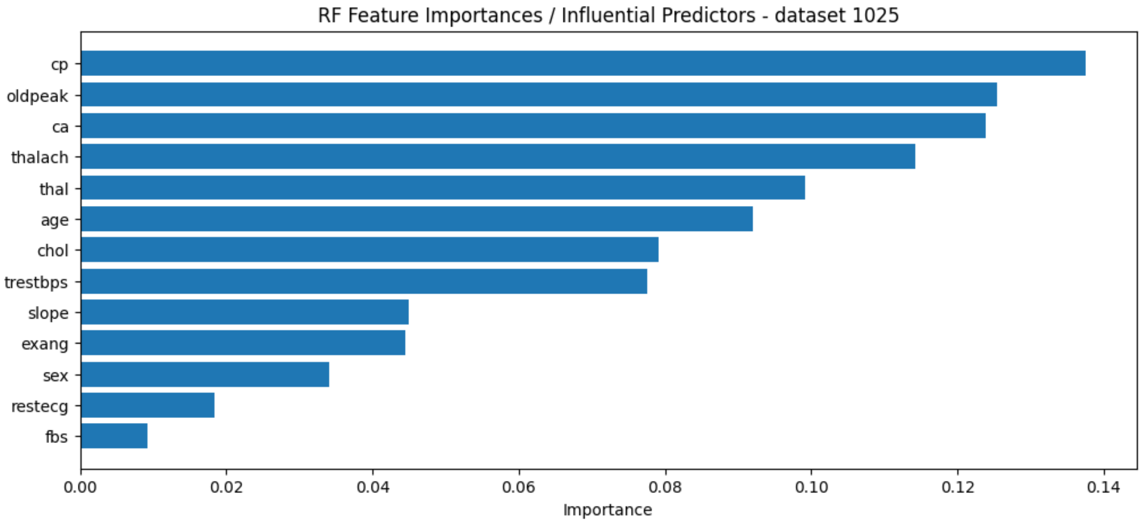
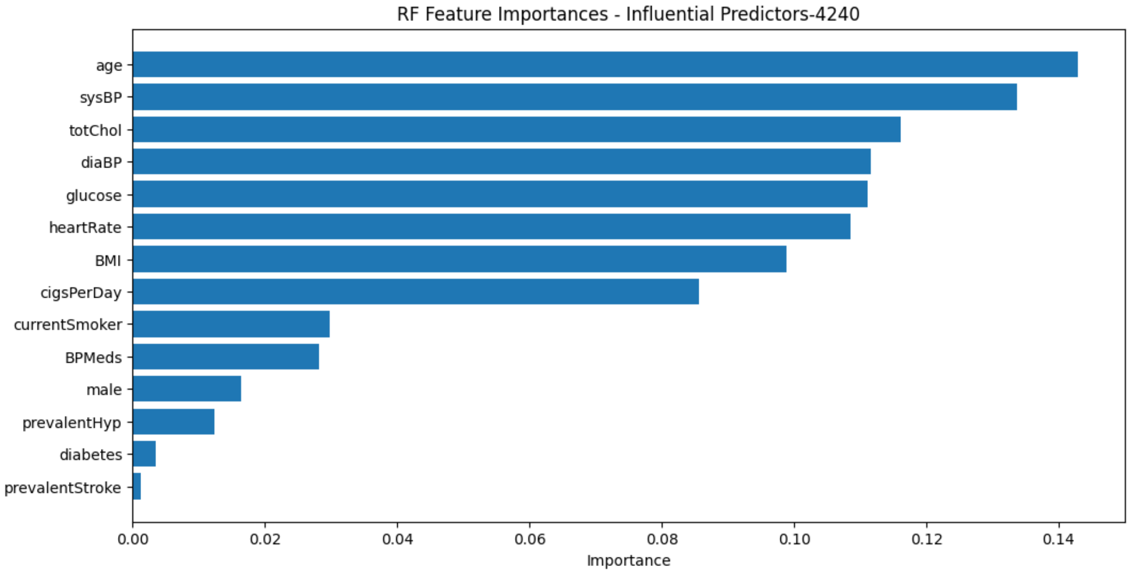
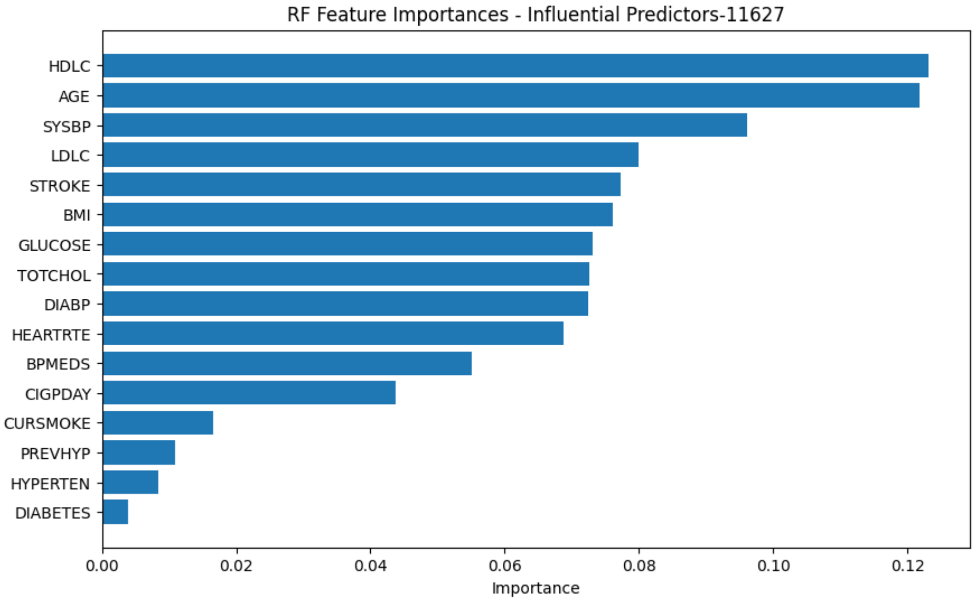


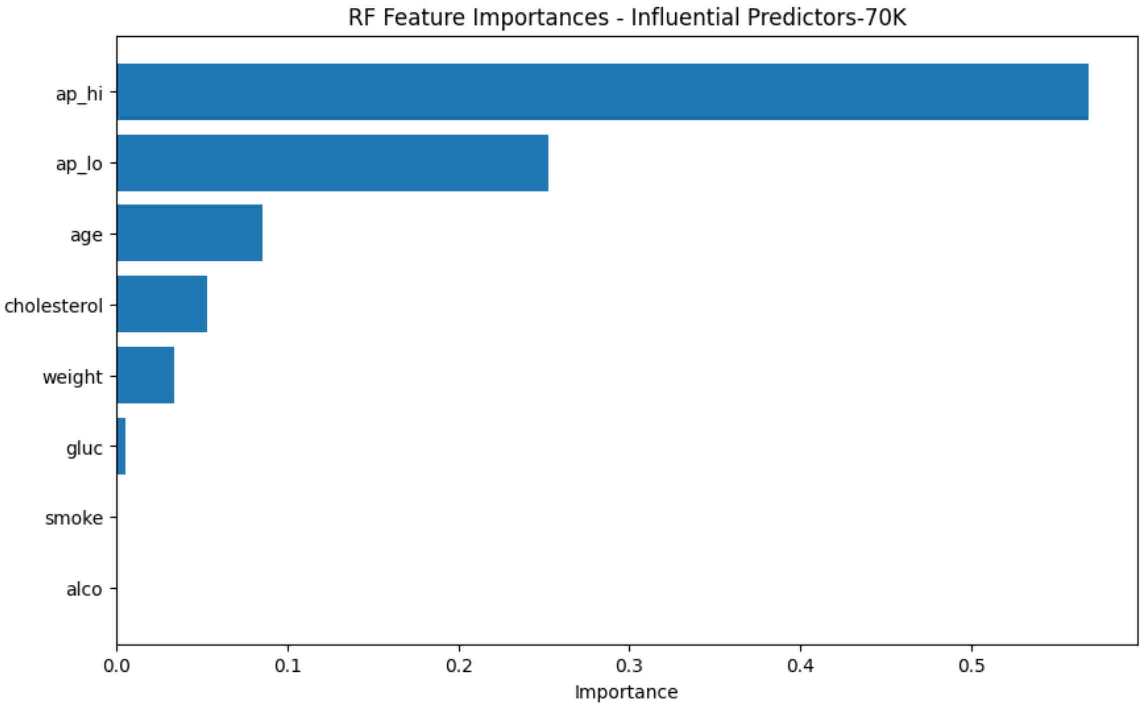
Fig. 14: Risk Factors / Feature Importances (based on Random Forest Classifier)




RF Feature Importances / Influential Predictors - dataset 1025
cp
oldpeak
ca
thalach
thal
age
chol
trestbps
slope
exang
sex
restecg
fbs
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
Importance


RF Feature Importances - Influential Predictors-4240
age
sysBP
totChol
diaBP
glucose
heartRate
BMI
cigsPerDay
currentSmoker
BPMeds
male
prevalentHyp
diabetes
prevalentStroke
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
Importance


RF Feature Importances - Influential Predictors-11627
HDLC
AGE
SYSBP
LDLC
STROKE
BMI
GLUCOSE
TOTCHOL
DIABP
HEARTRTE
BPMEDS
CIGPDAY
CURSMOKE
PREVHYP
HYPERTEN
DIABETES
0.00
0.02
0.04
0.06
0.08
0.10
0.12
Importance


RF Feature Importances - Influential Predictors-70K
ap_hi
ap_lo
age
cholesterol
weight
gluc
smoke
alco
0.0
0.1
0.2
0.3
0.4
0.5
Importance

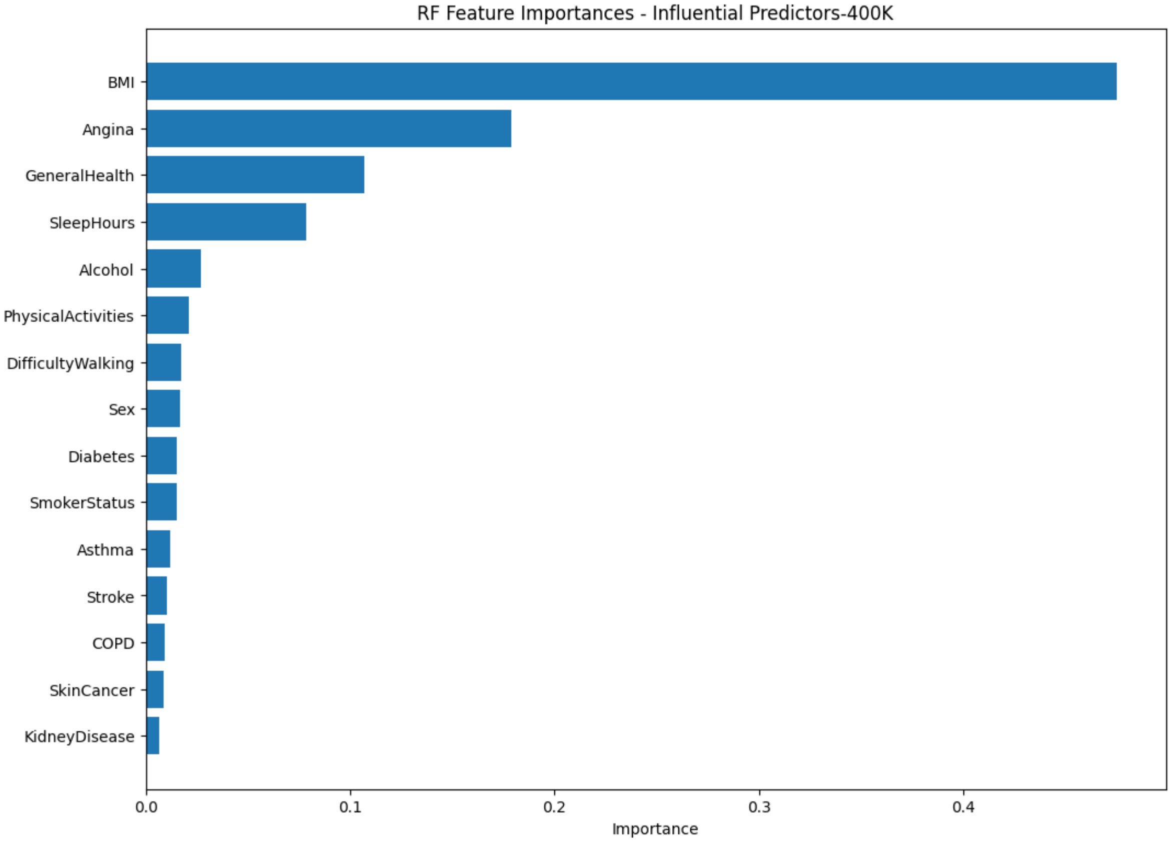

RF Feature Importances - Influential Predictors-400K
BMI
Angina
GeneralHealth
SleepHours
Alcohol
PhysicalActivities
DifficultyWalking
Sex
Diabetes
SmokerStatus
Asthma
Stroke
COPD
SkinCancer
KidneyDisease
0.0
0.1
0.2
0.3
0.4
Importance

Fig. 15: Correlation Matrix Analysis

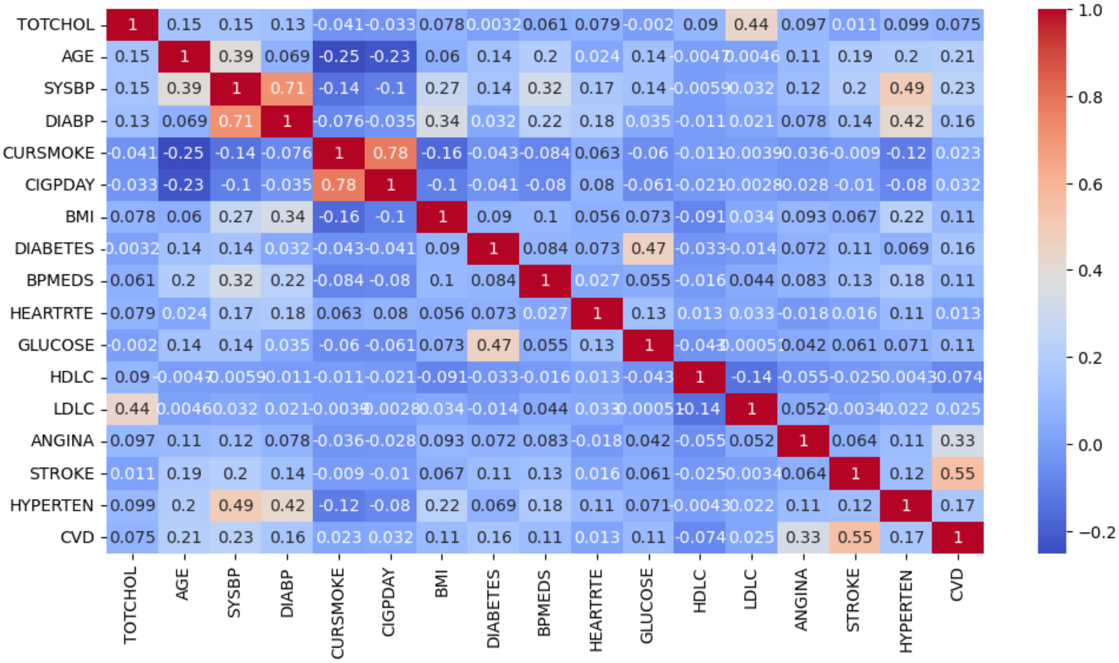


Fig. 16: ML and NN Models Accuracy Analysis

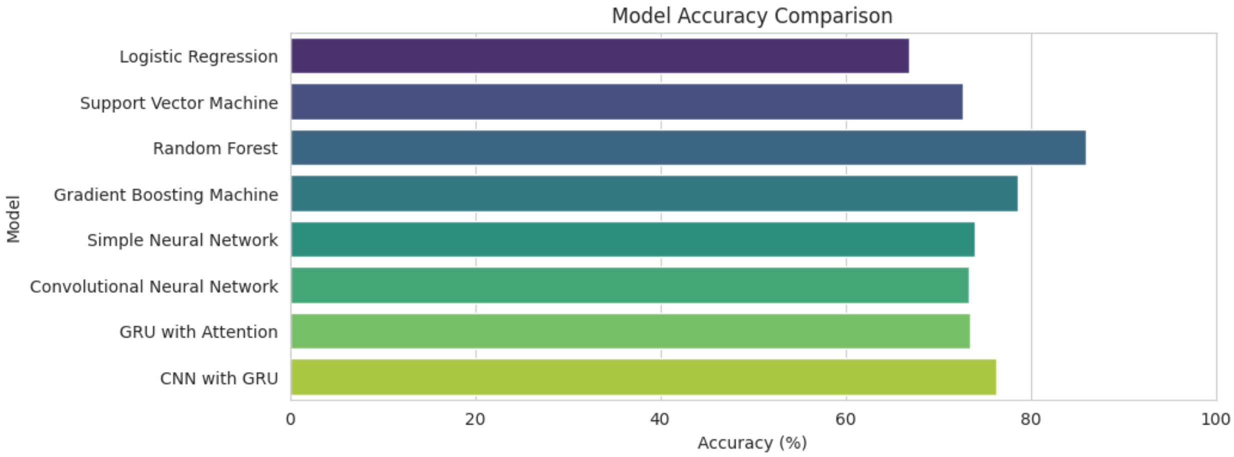


Fig. 17: ML and NN Models - ROC AUC Analysis

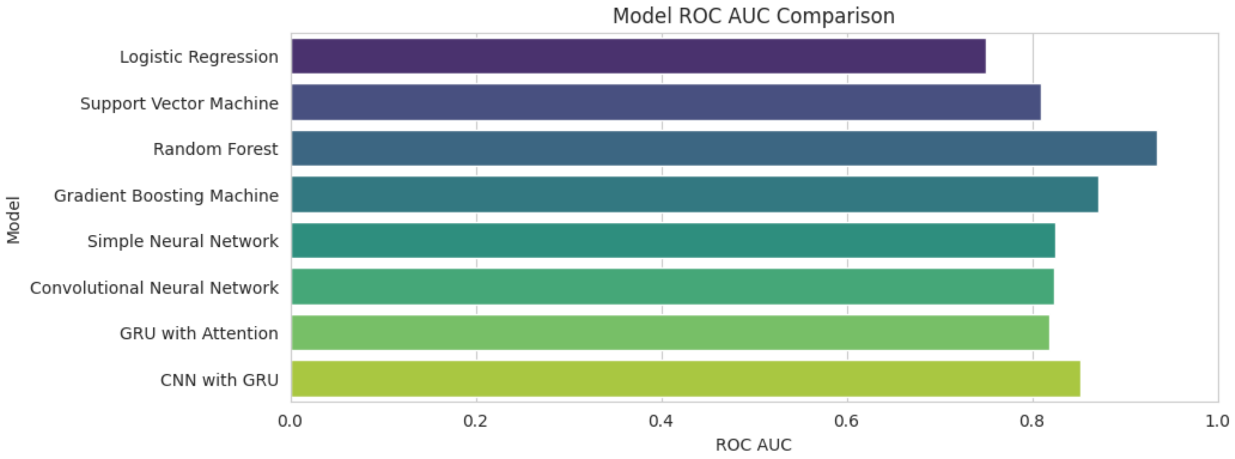
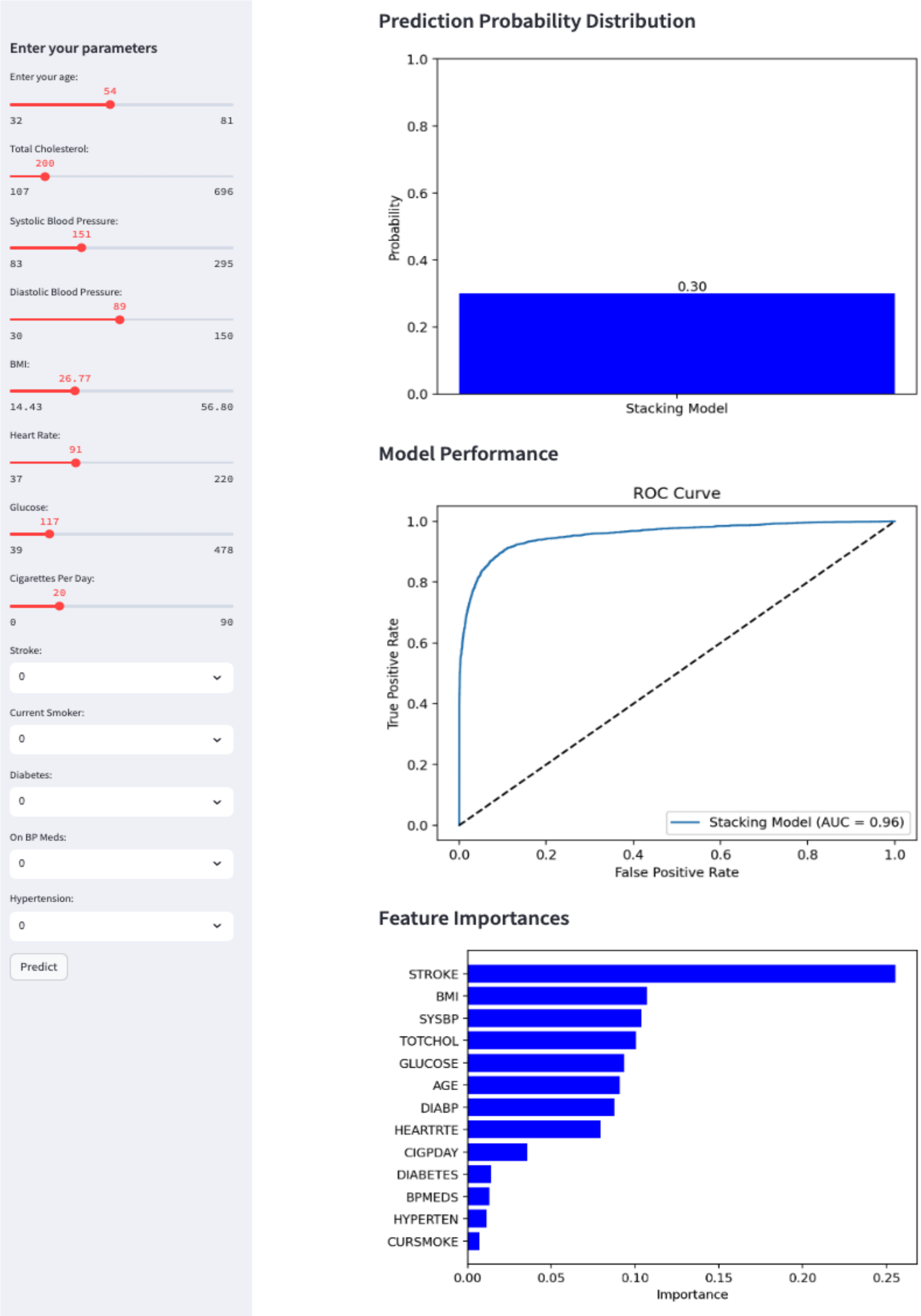


Fig. 18: Web App for CVD Prediction based on user inputs (Stacking Model)



Enter your parameters

Enter your age: 54 (32 – 81)

Total Cholesterol: 200 (107 – 696)

Systolic Blood Pressure: 151 (83 – 295)

Diastolic Blood Pressure: 89 (30 – 150)

BMI: 26.77 (14.43 – 56.80)

Heart Rate: 91 (37 – 220)

Glucose: 117 (39 – 478)

Cigarettes Per Day: 20 (0 – 90)

Stroke: 0

Current Smoker: 0

Diabetes: 0

On BP Meds: 0

Hypertension: 0

Prediction Probability Distribution

Model Performance

Feature Importances

Cardiovascular Disease Probability Prediction Results on Stacking Model

Predictions

- The stacking model predicts that the user has a 30% probability of developing cardiovascular disease (CVD). This prediction is based on the combination of several machine learning models to enhance the accuracy.

Prediction Probability Distribution

- The bar graph shows the probability distribution of developing CVD according to the stacking model. The probability is shown as 0.30, indicating a 30% risk.

Model Performance

- The ROC (Receiver Operating Characteristic) curve illustrates the performance of the stacking model. The AUC (Area Under the Curve) value is 0.96, which indicates that the model has a high level of accuracy in distinguishing between individuals who will develop CVD and those who will not.

Feature Importances

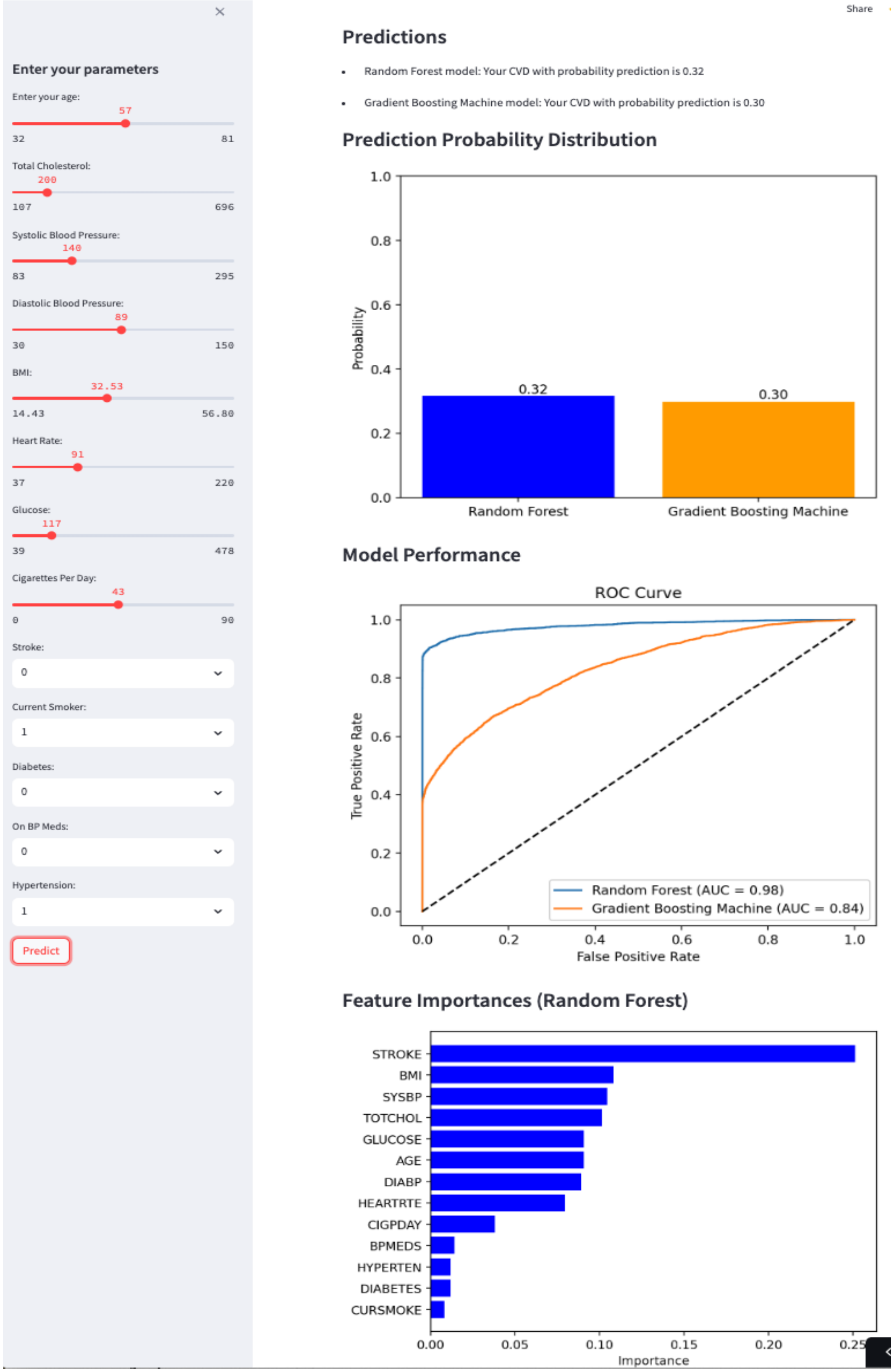
- The feature importance chart highlights which factors (features) are most influential in predicting CVD. Here’s a summary of the key features and their importance:
    - Stroke: The history of stroke is the most significant factor.
    - BMI (Body Mass Index): Higher BMI indicates higher risk.
    - SYSBP (Systolic Blood Pressure): Elevated systolic blood pressure is a critical indicator.
    - TOTCHOL (Total Cholesterol): Higher cholesterol levels contribute to the risk.
    - GLUCOSE: Higher glucose levels are also important in the prediction.

- AGE: Older age increases the risk of CVD.
- DIABP (Diastolic Blood Pressure): Elevated diastolic blood pressure plays a role.
- HEARTRTE (Heart Rate): Higher heart rate is a contributing factor.
- CIGPDAY (Cigarettes Per Day): The number of cigarettes smoked per day impacts the risk.
- DIABETES: The presence of diabetes is a risk factor.
- BPMEDS (Blood Pressure Medication): Use of BP medication is taken into account.
- HYPERTEN (Hypertension): Having hypertension is a minor but notable factor.
- CURSMOKE (Current Smoker): Whether the individual is currently smoking has a minimal impact compared to other factors.

Summary

The model suggests a moderate risk (30%) for the user developing CVD. Key health metrics like history of stroke, BMI, blood pressure, cholesterol, and glucose levels are the primary drivers in this prediction. The ROC curve indicates that the model is very accurate (AUC = 0.96) in predicting the likelihood of CVD. Understanding and managing these important factors can help in reducing the overall risk.

Fig. 19: Web App for CVD Prediction based on user inputs (RF & GBM Models)



Enter your parameters

Enter your age: 57 (32 – 81)

Total Cholesterol: 200 (107 – 696)

Systolic Blood Pressure: 140 (83 – 295)

Diastolic Blood Pressure: 89 (30 – 150)

BMI: 32.53 (14.43 – 56.80)

Heart Rate: 91 (37 – 220)

Glucose: 117 (39 – 478)

Cigarettes Per Day: 43 (0 – 90)

Stroke: 0

Current Smoker: 1

Diabetes: 0

On BP Meds: 0

Hypertension: 1

Predictions

- Random Forest model: Your CVD with probability prediction is 0.32
- Gradient Boosting Machine model: Your CVD with probability prediction is 0.30

Prediction Probability Distribution

Model Performance

Feature Importances (Random Forest)

Cardiovascular Disease Probability Prediction Results on RF and GBM models

Predictions

- Random Forest model predicts a 32% probability of developing cardiovascular disease (CVD).
- Gradient Boosting Machine (GBM) model predicts a 30% probability of developing CVD.

These predictions are based on advanced machine learning models that analyze various health metrics to assess the risk of CVD.

Prediction Probability Distribution

- The bar graph shows the probability distribution of developing CVD according to both the Random Forest and GBM models. The Random Forest model predicts a slightly higher risk (32%) compared to the GBM model (30%).

Model Performance

- The ROC (Receiver Operating Characteristic) curve illustrates the performance of both models:
    - The Random Forest model has an AUC (Area Under the Curve) of 0.98, indicating a very high level of accuracy in distinguishing between individuals who will develop CVD and those who will not.
    - The GBM model has an AUC of 0.84, which also indicates a good level of accuracy but not as high as the Random Forest model.

Feature Importances (Random Forest)

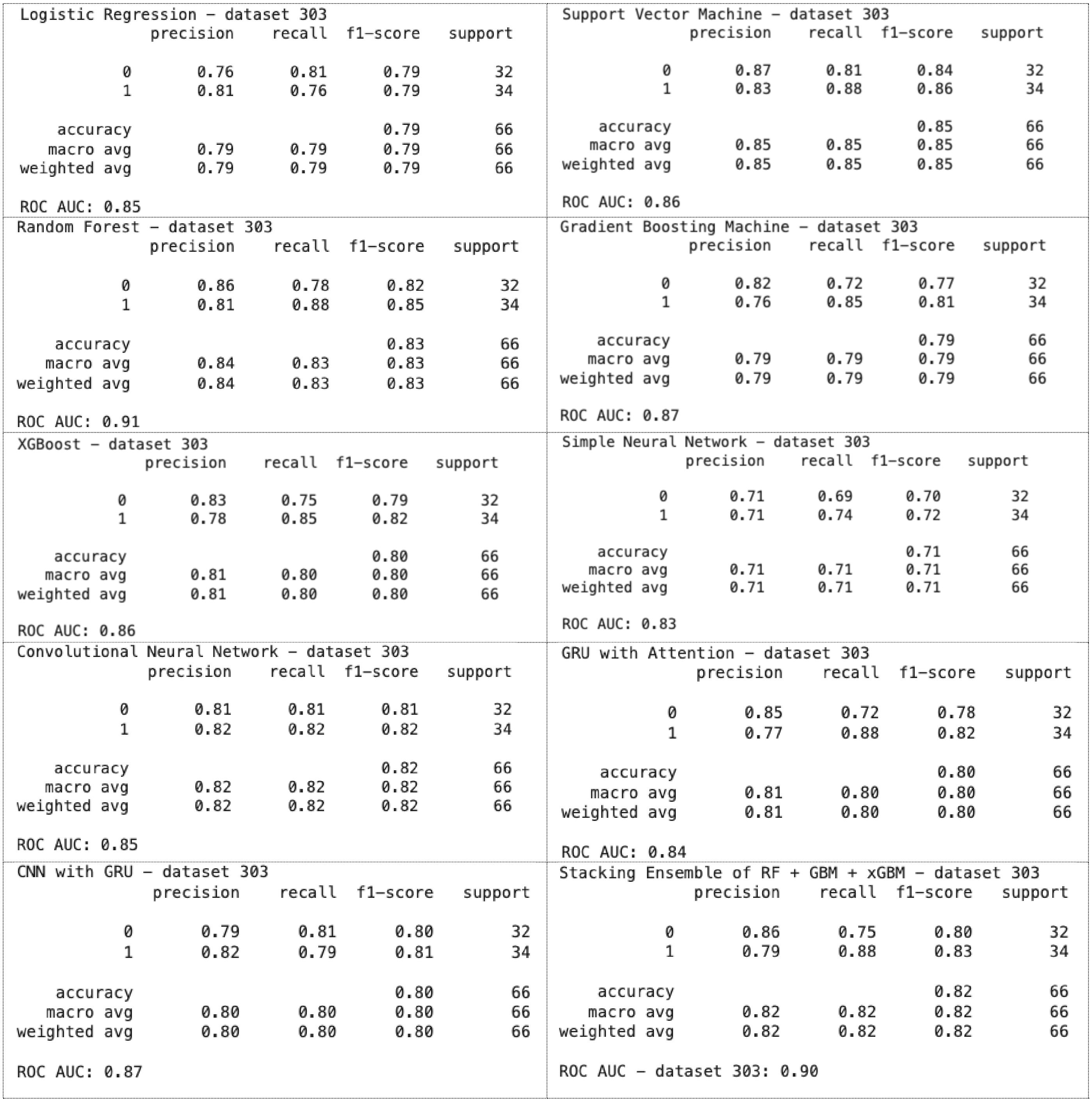
- The feature importance chart highlights which factors (features) are most influential in predicting CVD according to the Random Forest model. Here’s a summary of the key features and their importance:
    - Stroke: The history of stroke is the most significant factor.
    - BMI (Body Mass Index): Higher BMI indicates higher risk.
    - SYSBP (Systolic Blood Pressure): Elevated systolic blood pressure is a critical indicator.
    - TOTCHOL (Total Cholesterol): Higher cholesterol levels contribute to the risk.
    - GLUCOSE: Higher glucose levels are also important in the prediction.
    - AGE: Older age increases the risk of CVD.
    - DIABP (Diastolic Blood Pressure): Elevated diastolic blood pressure plays a role.
    - HEARTRTE (Heart Rate): Higher heart rate is a contributing factor.
    - CIGPDAY (Cigarettes Per Day): The number of cigarettes smoked per day impacts the risk.
    - BPMEDS (Blood Pressure Medication): Use of BP medication is taken into account.
    - HYPERTEN (Hypertension): Having hypertension is a minor but notable factor.
    - DIABETES: The presence of diabetes is a minor factor in this prediction.
    - CURSMOKE (Current Smoker): Whether the individual is currently smoking has the least impact compared to other factors.

Summary

The models suggest a moderate risk (32% by Random Forest, 30% by GBM) for the user developing CVD. Key health metrics like history of stroke, BMI, blood pressure, cholesterol, and glucose levels are the primary drivers in this prediction. The ROC curves indicate that both models are quite accurate, with the Random Forest model being highly reliable (AUC = 0.98). Understanding and managing these important factors can help in reducing the overall risk.

Tables of Models Performance

Table 11: Model performances on dataset of 303 records



```
Logistic Regression - dataset 303
              precision    recall  f1-score   support

           0       0.76      0.81      0.79        32
           1       0.81      0.76      0.79        34

    accuracy                           0.79        66
   macro avg       0.79      0.79      0.79        66
weighted avg       0.79      0.79      0.79        66

ROC AUC: 0.85
```

```
Support Vector Machine - dataset 303
              precision    recall  f1-score   support

           0       0.87      0.81      0.84        32
           1       0.83      0.88      0.86        34

    accuracy                           0.85        66
   macro avg       0.85      0.85      0.85        66
weighted avg       0.85      0.85      0.85        66

ROC AUC: 0.86
```

```
Random Forest - dataset 303
              precision    recall  f1-score   support

           0       0.86      0.78      0.82        32
           1       0.81      0.88      0.85        34

    accuracy                           0.83        66
   macro avg       0.84      0.83      0.83        66
weighted avg       0.84      0.83      0.83        66

ROC AUC: 0.91
```

```
Gradient Boosting Machine - dataset 303
              precision    recall  f1-score   support

           0       0.82      0.72      0.77        32
           1       0.76      0.85      0.81        34

    accuracy                           0.79        66
   macro avg       0.79      0.79      0.79        66
weighted avg       0.79      0.79      0.79        66

ROC AUC: 0.87
```

```
XGBoost - dataset 303
              precision    recall  f1-score   support

           0       0.83      0.75      0.79        32
           1       0.78      0.85      0.82        34

    accuracy                           0.80        66
   macro avg       0.81      0.80      0.80        66
weighted avg       0.81      0.80      0.80        66

ROC AUC: 0.86
```

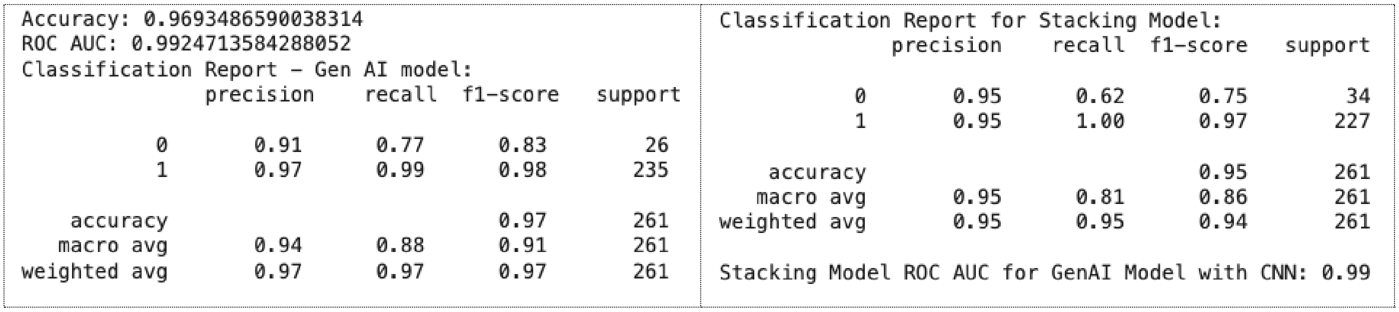
```
Simple Neural Network - dataset 303
              precision    recall  f1-score   support

           0       0.71      0.69      0.70        32
           1       0.71      0.74      0.72        34

    accuracy                           0.71        66
   macro avg       0.71      0.71      0.71        66
weighted avg       0.71      0.71      0.71        66

ROC AUC: 0.83
```

```
Convolutional Neural Network - dataset 303
              precision    recall  f1-score   support

           0       0.81      0.81      0.81        32
           1       0.82      0.82      0.82        34

    accuracy                           0.82        66
   macro avg       0.82      0.82      0.82        66
weighted avg       0.82      0.82      0.82        66

ROC AUC: 0.85
```

```
GRU with Attention - dataset 303
              precision    recall  f1-score   support

           0       0.85      0.72      0.78        32
           1       0.77      0.88      0.82        34

    accuracy                           0.80        66
   macro avg       0.81      0.80      0.80        66
weighted avg       0.81      0.80      0.80        66

ROC AUC: 0.84
```

```
CNN with GRU - dataset 303
              precision    recall  f1-score   support

           0       0.79      0.81      0.80        32
           1       0.82      0.79      0.81        34

    accuracy                           0.80        66
   macro avg       0.80      0.80      0.80        66
weighted avg       0.80      0.80      0.80        66

ROC AUC: 0.87
```

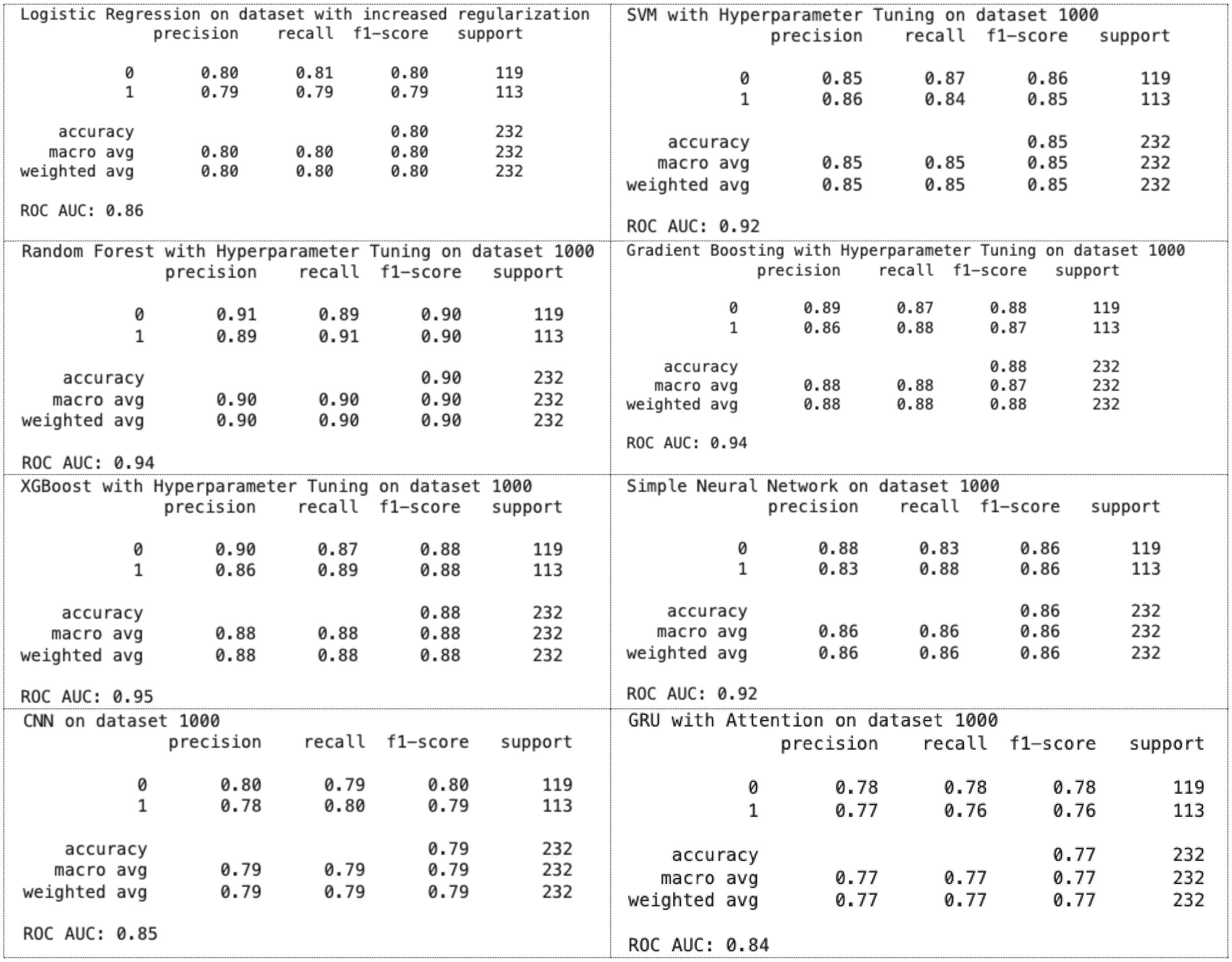
```
Stacking Ensemble of RF + GBM + xGBM - dataset 303
              precision    recall  f1-score   support

           0       0.86      0.75      0.80        32
           1       0.79      0.88      0.83        34

    accuracy                           0.82        66
   macro avg       0.82      0.82      0.82        66
weighted avg       0.82      0.82      0.82        66

ROC AUC - dataset 303: 0.90
```



```
Accuracy: 0.9693486590038314
ROC AUC: 0.9924713584288052
Classification Report − Gen AI model:
              precision    recall  f1−score   support

           0       0.91      0.77      0.83        26
           1       0.97      0.99      0.98       235

    accuracy                           0.97       261
   macro avg       0.94      0.88      0.91       261
weighted avg       0.97      0.97      0.97       261
```

```
Classification Report for Stacking Model:
              precision    recall  f1−score   support

           0       0.95      0.62      0.75        34
           1       0.95      1.00      0.97       227

    accuracy                           0.95       261
   macro avg       0.95      0.81      0.86       261
weighted avg       0.95      0.95      0.94       261

Stacking Model ROC AUC for GenAI Model with CNN: 0.99
```

Table 12: Model performances on dataset of 1,000 records



```
Logistic Regression on dataset with increased regularization
              precision    recall  f1−score   support

           0       0.80      0.81      0.80       119
           1       0.79      0.79      0.79       113

    accuracy                           0.80       232
   macro avg       0.80      0.80      0.80       232
weighted avg       0.80      0.80      0.80       232

ROC AUC: 0.86
```

```
SVM with Hyperparameter Tuning on dataset 1000
              precision    recall  f1−score   support

           0       0.85      0.87      0.86       119
           1       0.86      0.84      0.85       113

    accuracy                           0.85       232
   macro avg       0.85      0.85      0.85       232
weighted avg       0.85      0.85      0.85       232

ROC AUC: 0.92
```

```
Random Forest with Hyperparameter Tuning on dataset 1000
              precision    recall  f1−score   support

           0       0.91      0.89      0.90       119
           1       0.89      0.91      0.90       113

    accuracy                           0.90       232
   macro avg       0.90      0.90      0.90       232
weighted avg       0.90      0.90      0.90       232

ROC AUC: 0.94
```

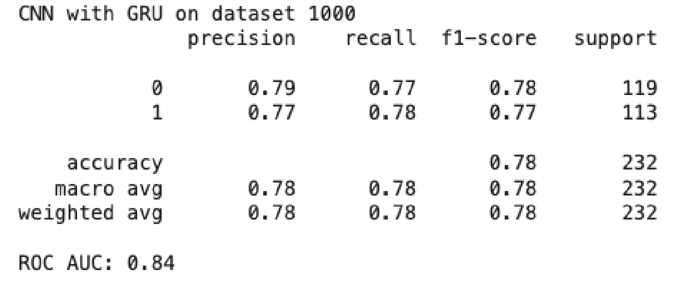
```
Gradient Boosting with Hyperparameter Tuning on dataset 1000
              precision    recall  f1−score   support

           0       0.89      0.87      0.88       119
           1       0.86      0.88      0.87       113

    accuracy                           0.88       232
   macro avg       0.88      0.88      0.87       232
weighted avg       0.88      0.88      0.88       232

ROC AUC: 0.94
```

```
XGBoost with Hyperparameter Tuning on dataset 1000
              precision    recall  f1−score   support

           0       0.90      0.87      0.88       119
           1       0.86      0.89      0.88       113

    accuracy                           0.88       232
   macro avg       0.88      0.88      0.88       232
weighted avg       0.88      0.88      0.88       232

ROC AUC: 0.95
```

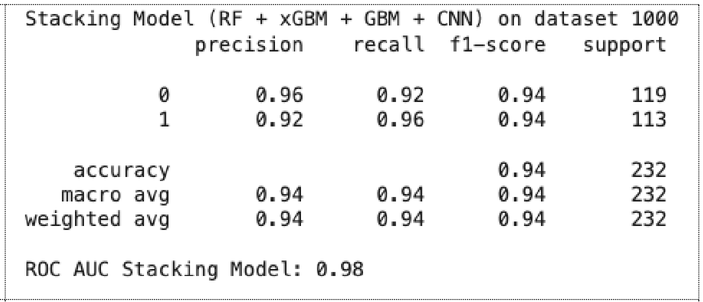
```
Simple Neural Network on dataset 1000
              precision    recall  f1−score   support

           0       0.88      0.83      0.86       119
           1       0.83      0.88      0.86       113

    accuracy                           0.86       232
   macro avg       0.86      0.86      0.86       232
weighted avg       0.86      0.86      0.86       232

ROC AUC: 0.92
```

```
CNN on dataset 1000
              precision    recall  f1−score   support

           0       0.80      0.79      0.80       119
           1       0.78      0.80      0.79       113

    accuracy                           0.79       232
   macro avg       0.79      0.79      0.79       232
weighted avg       0.79      0.79      0.79       232

ROC AUC: 0.85
```

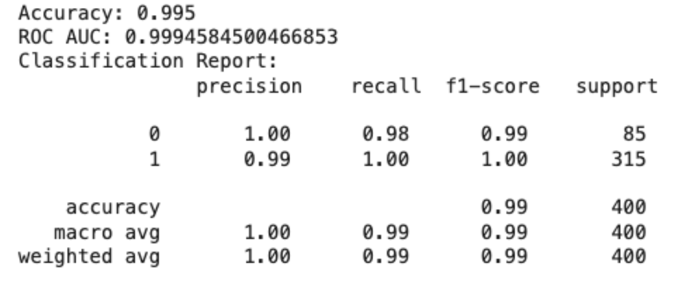
```
GRU with Attention on dataset 1000
              precision    recall  f1−score   support

           0       0.78      0.78      0.78       119
           1       0.77      0.76      0.76       113

    accuracy                           0.77       232
   macro avg       0.77      0.77      0.77       232
weighted avg       0.77      0.77      0.77       232

ROC AUC: 0.84
```



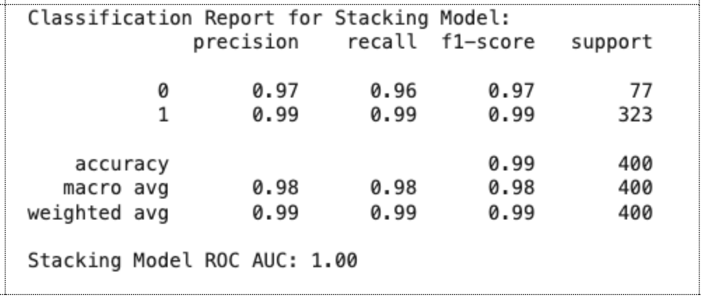
```
CNN with GRU on dataset 1000
              precision    recall  f1-score   support

           0       0.79      0.77      0.78       119
           1       0.77      0.78      0.77       113

    accuracy                           0.78       232
   macro avg       0.78      0.78      0.78       232
weighted avg       0.78      0.78      0.78       232

ROC AUC: 0.84
```



```
Stacking Model (RF + xGBM + GBM + CNN) on dataset 1000
              precision    recall  f1-score   support

           0       0.96      0.92      0.94       119
           1       0.92      0.96      0.94       113

    accuracy                           0.94       232
   macro avg       0.94      0.94      0.94       232
weighted avg       0.94      0.94      0.94       232

ROC AUC Stacking Model: 0.98
```

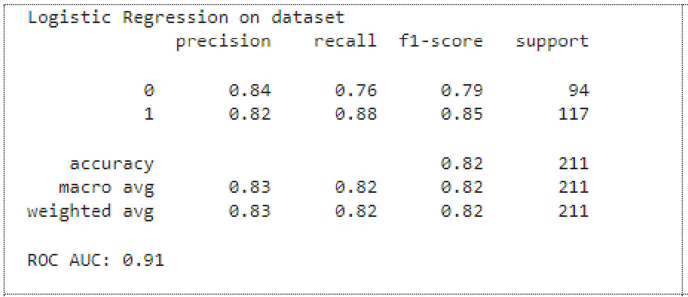


```
Accuracy: 0.995
ROC AUC: 0.9994584500466853
Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.98      0.99        85
           1       0.99      1.00      1.00       315

    accuracy                           0.99       400
   macro avg       1.00      0.99      0.99       400
weighted avg       1.00      0.99      0.99       400
```

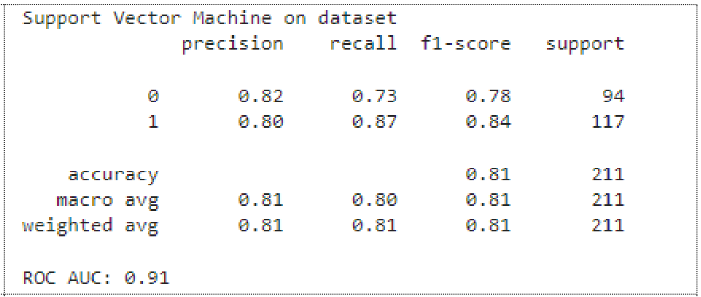


```
Classification Report for Stacking Model:
              precision    recall  f1-score   support

           0       0.97      0.96      0.97        77
           1       0.99      0.99      0.99       323

    accuracy                           0.99       400
   macro avg       0.98      0.98      0.98       400
weighted avg       0.99      0.99      0.99       400

Stacking Model ROC AUC: 1.00
```

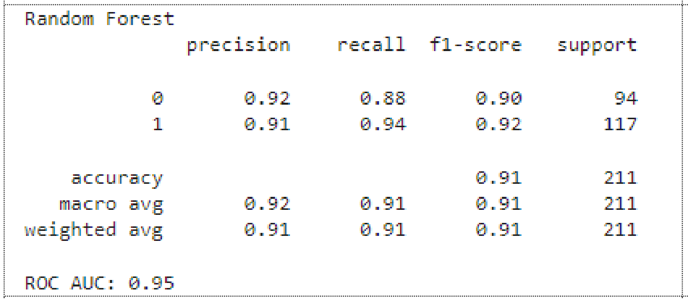
Table 13: Model performances on dataset of 1,025 records



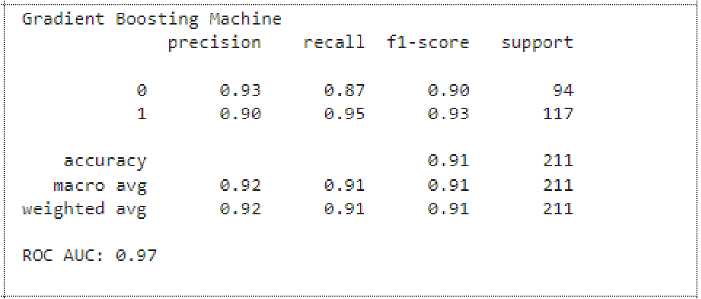
```
Logistic Regression on dataset
              precision    recall  f1-score   support

           0       0.84      0.76      0.79        94
           1       0.82      0.88      0.85       117

    accuracy                           0.82       211
   macro avg       0.83      0.82      0.82       211
weighted avg       0.83      0.82      0.82       211

ROC AUC: 0.91
```



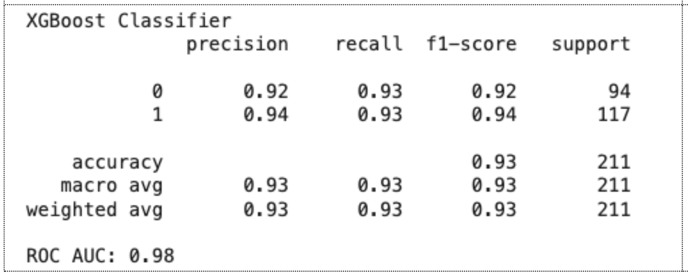
```
Support Vector Machine on dataset
              precision    recall  f1-score   support

           0       0.82      0.73      0.78        94
           1       0.80      0.87      0.84       117

    accuracy                           0.81       211
   macro avg       0.81      0.80      0.81       211
weighted avg       0.81      0.81      0.81       211

ROC AUC: 0.91
```



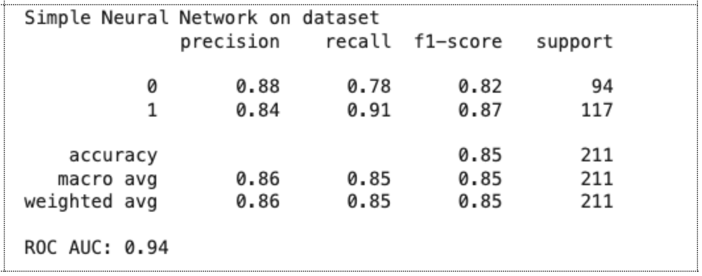
```
Random Forest
              precision    recall  f1-score   support

           0       0.92      0.88      0.90        94
           1       0.91      0.94      0.92       117

    accuracy                           0.91       211
   macro avg       0.92      0.91      0.91       211
weighted avg       0.91      0.91      0.91       211

ROC AUC: 0.95
```



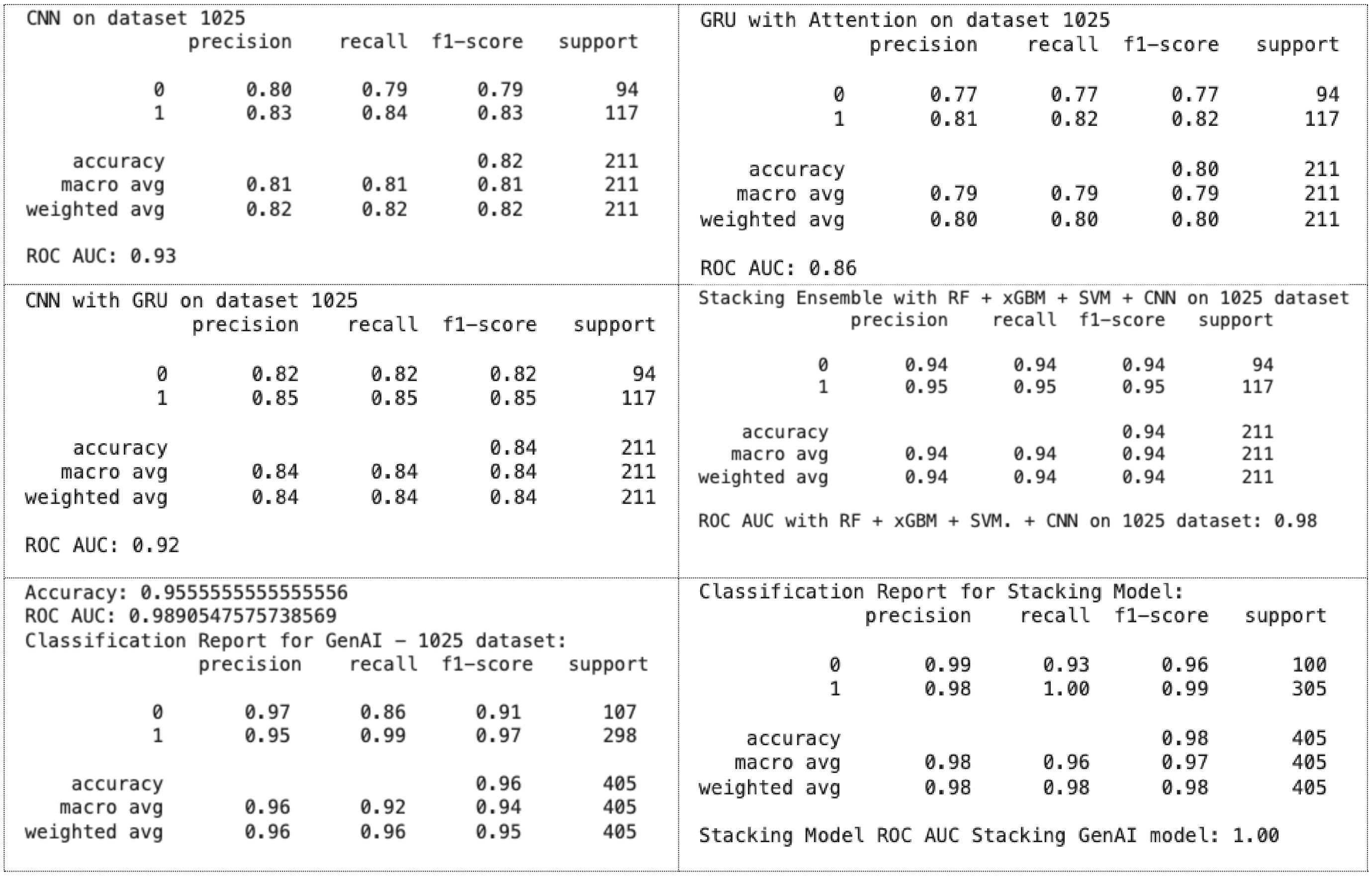
```
Gradient Boosting Machine
              precision    recall  f1-score   support

           0       0.93      0.87      0.90        94
           1       0.90      0.95      0.93       117

    accuracy                           0.91       211
   macro avg       0.92      0.91      0.91       211
weighted avg       0.92      0.91      0.91       211

ROC AUC: 0.97
```



```
XGBoost Classifier
              precision    recall  f1-score   support

           0       0.92      0.93      0.92        94
           1       0.94      0.93      0.94       117

    accuracy                           0.93       211
   macro avg       0.93      0.93      0.93       211
weighted avg       0.93      0.93      0.93       211

ROC AUC: 0.98
```



```
Simple Neural Network on dataset
              precision    recall  f1-score   support

           0       0.88      0.78      0.82        94
           1       0.84      0.91      0.87       117

    accuracy                           0.85       211
   macro avg       0.86      0.85      0.85       211
weighted avg       0.86      0.85      0.85       211

ROC AUC: 0.94
```



```
CNN on dataset 1025
              precision    recall  f1-score   support

           0       0.80      0.79      0.79        94
           1       0.83      0.84      0.83       117

    accuracy                           0.82       211
   macro avg       0.81      0.81      0.81       211
weighted avg       0.82      0.82      0.82       211

ROC AUC: 0.93
```

```
GRU with Attention on dataset 1025
              precision    recall  f1-score   support

           0       0.77      0.77      0.77        94
           1       0.81      0.82      0.82       117

    accuracy                           0.80       211
   macro avg       0.79      0.79      0.79       211
weighted avg       0.80      0.80      0.80       211

ROC AUC: 0.86
```

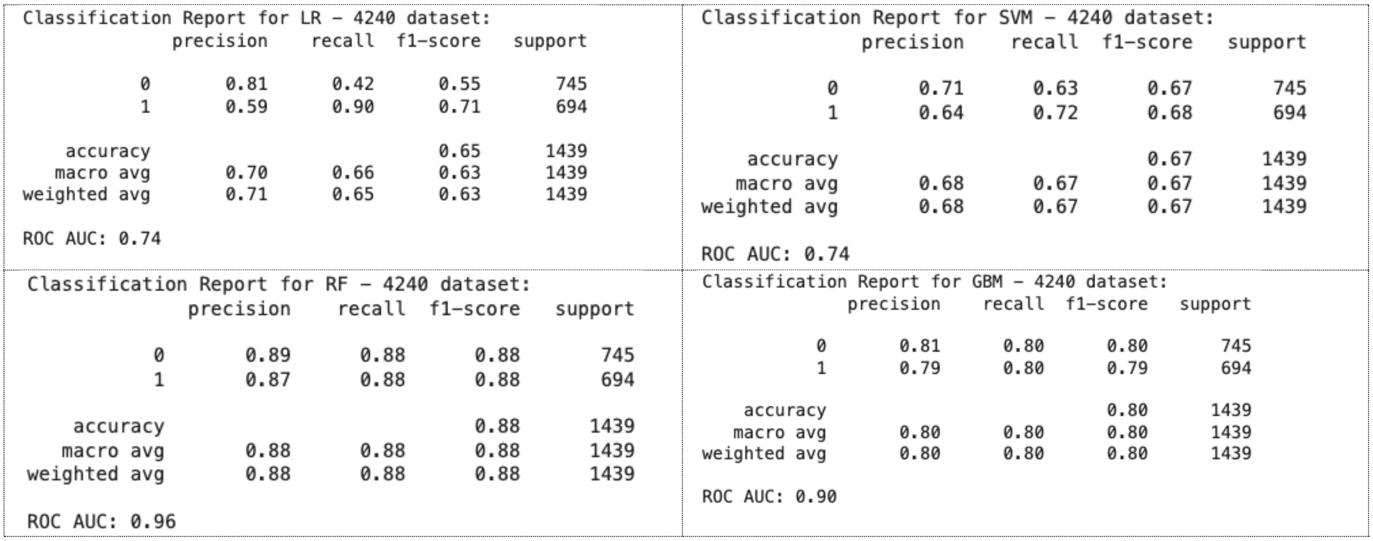
```
CNN with GRU on dataset 1025
              precision    recall  f1-score   support

           0       0.82      0.82      0.82        94
           1       0.85      0.85      0.85       117

    accuracy                           0.84       211
   macro avg       0.84      0.84      0.84       211
weighted avg       0.84      0.84      0.84       211

ROC AUC: 0.92
```

```
Stacking Ensemble with RF + xGBM + SVM + CNN on 1025 dataset
              precision    recall  f1-score   support

           0       0.94      0.94      0.94        94
           1       0.95      0.95      0.95       117

    accuracy                           0.94       211
   macro avg       0.94      0.94      0.94       211
weighted avg       0.94      0.94      0.94       211

ROC AUC with RF + xGBM + SVM. + CNN on 1025 dataset: 0.98
```

```
Accuracy: 0.9555555555555556
ROC AUC: 0.9890547575738569
Classification Report for GenAI - 1025 dataset:
              precision    recall  f1-score   support

           0       0.97      0.86      0.91       107
           1       0.95      0.99      0.97       298

    accuracy                           0.96       405
   macro avg       0.96      0.92      0.94       405
weighted avg       0.96      0.96      0.95       405
```

```
Classification Report for Stacking Model:
              precision    recall  f1-score   support

           0       0.99      0.93      0.96       100
           1       0.98      1.00      0.99       305

    accuracy                           0.98       405
   macro avg       0.98      0.96      0.97       405
weighted avg       0.98      0.98      0.98       405

Stacking Model ROC AUC Stacking GenAI model: 1.00
```

Table 14: Model performances on dataset of 4,240 records

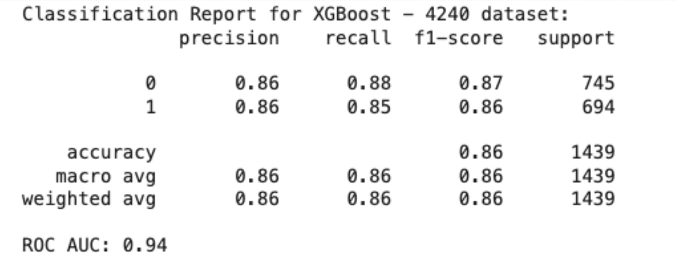


```
Classification Report for LR - 4240 dataset:
              precision    recall  f1-score   support

           0       0.81      0.42      0.55       745
           1       0.59      0.90      0.71       694

    accuracy                           0.65      1439
   macro avg       0.70      0.66      0.63      1439
weighted avg       0.71      0.65      0.63      1439

ROC AUC: 0.74
```

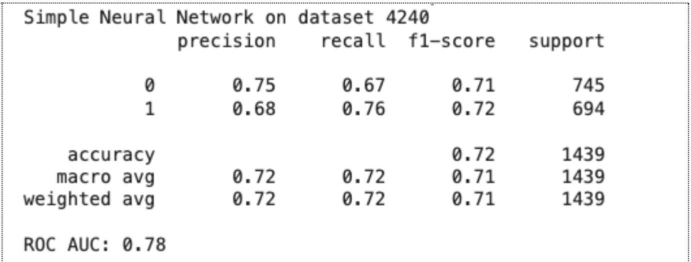
```
Classification Report for SVM - 4240 dataset:
              precision    recall  f1-score   support

           0       0.71      0.63      0.67       745
           1       0.64      0.72      0.68       694

    accuracy                           0.67      1439
   macro avg       0.68      0.67      0.67      1439
weighted avg       0.68      0.67      0.67      1439

ROC AUC: 0.74
```

```
Classification Report for RF - 4240 dataset:
              precision    recall  f1-score   support

           0       0.89      0.88      0.88       745
           1       0.87      0.88      0.88       694

    accuracy                           0.88      1439
   macro avg       0.88      0.88      0.88      1439
weighted avg       0.88      0.88      0.88      1439

ROC AUC: 0.96
```

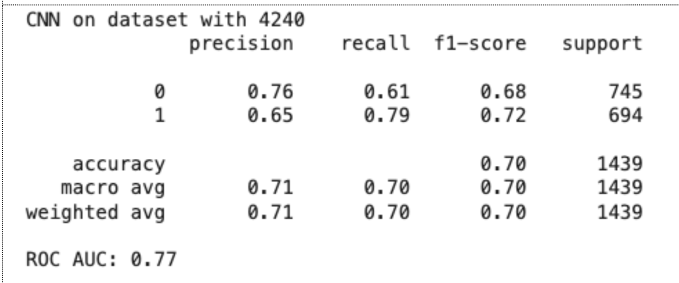
```
Classification Report for GBM - 4240 dataset:
              precision    recall  f1-score   support

           0       0.81      0.80      0.80       745
           1       0.79      0.80      0.79       694

    accuracy                           0.80      1439
   macro avg       0.80      0.80      0.80      1439
weighted avg       0.80      0.80      0.80      1439

ROC AUC: 0.90
```



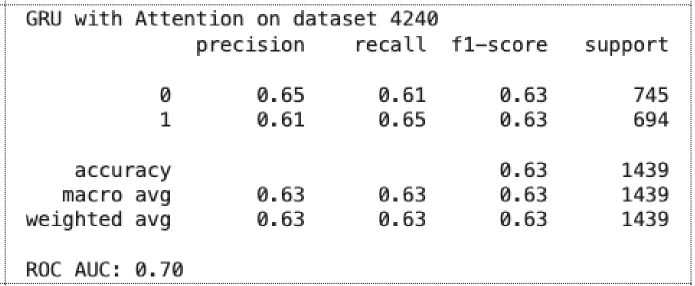
```
Classification Report for XGBoost - 4240 dataset:
              precision    recall  f1-score   support

           0       0.86      0.88      0.87       745
           1       0.86      0.85      0.86       694

    accuracy                           0.86      1439
   macro avg       0.86      0.86      0.86      1439
weighted avg       0.86      0.86      0.86      1439

ROC AUC: 0.94
```



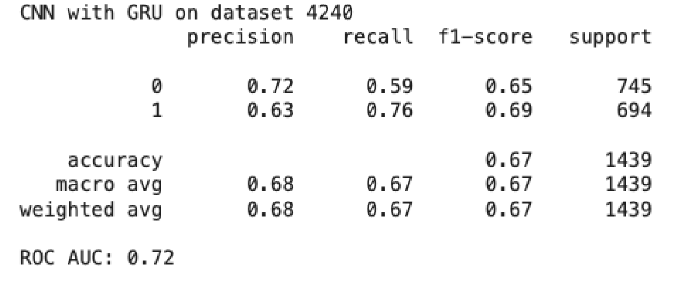
```
Simple Neural Network on dataset 4240
              precision    recall  f1-score   support

           0       0.75      0.67      0.71       745
           1       0.68      0.76      0.72       694

    accuracy                           0.72      1439
   macro avg       0.72      0.72      0.71      1439
weighted avg       0.72      0.72      0.71      1439

ROC AUC: 0.78
```



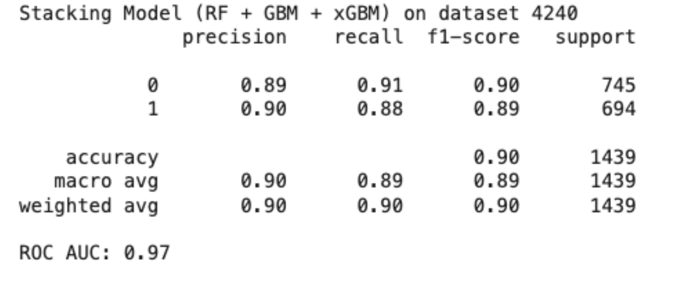
```
CNN on dataset with 4240
              precision    recall  f1-score   support

           0       0.76      0.61      0.68       745
           1       0.65      0.79      0.72       694

    accuracy                           0.70      1439
   macro avg       0.71      0.70      0.70      1439
weighted avg       0.71      0.70      0.70      1439

ROC AUC: 0.77
```



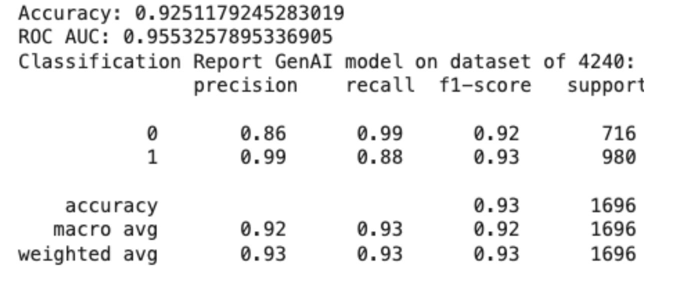
```
GRU with Attention on dataset 4240
              precision    recall  f1-score   support

           0       0.65      0.61      0.63       745
           1       0.61      0.65      0.63       694

    accuracy                           0.63      1439
   macro avg       0.63      0.63      0.63      1439
weighted avg       0.63      0.63      0.63      1439

ROC AUC: 0.70
```



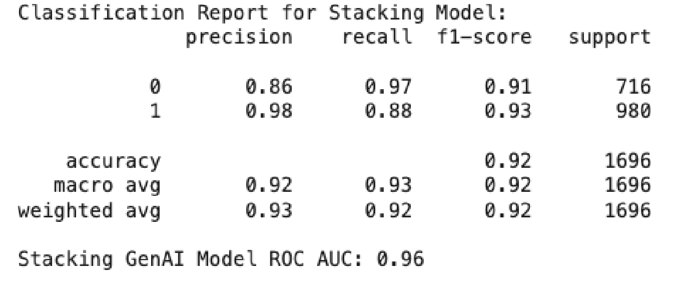
```
CNN with GRU on dataset 4240
              precision    recall  f1-score   support

           0       0.72      0.59      0.65       745
           1       0.63      0.76      0.69       694

    accuracy                           0.67      1439
   macro avg       0.68      0.67      0.67      1439
weighted avg       0.68      0.67      0.67      1439

ROC AUC: 0.72
```



```
Stacking Model (RF + GBM + xGBM) on dataset 4240
              precision    recall  f1-score   support

           0       0.89      0.91      0.90       745
           1       0.90      0.88      0.89       694

    accuracy                           0.90      1439
   macro avg       0.90      0.89      0.89      1439
weighted avg       0.90      0.90      0.90      1439

ROC AUC: 0.97
```

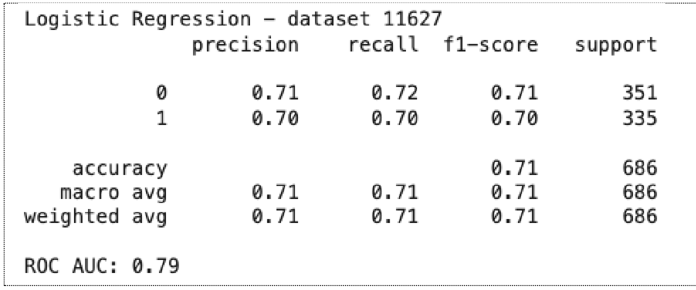


```
Accuracy: 0.9251179245283019
ROC AUC: 0.9553257895336905
Classification Report GenAI model on dataset of 4240:
              precision    recall  f1-score   support

           0       0.86      0.99      0.92       716
           1       0.99      0.88      0.93       980

    accuracy                           0.93      1696
   macro avg       0.92      0.93      0.92      1696
weighted avg       0.93      0.93      0.93      1696
```

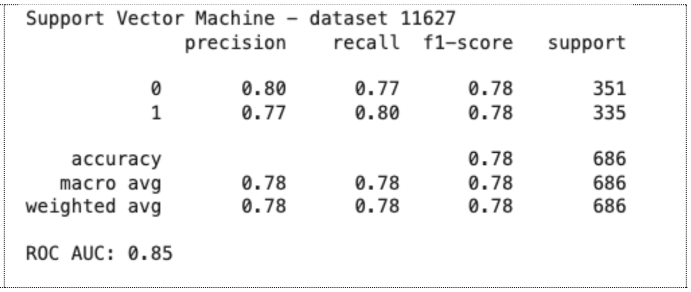


```
Classification Report for Stacking Model:
              precision    recall  f1-score   support

           0       0.86      0.97      0.91       716
           1       0.98      0.88      0.93       980

    accuracy                           0.92      1696
   macro avg       0.92      0.93      0.92      1696
weighted avg       0.93      0.92      0.92      1696

Stacking GenAI Model ROC AUC: 0.96
```

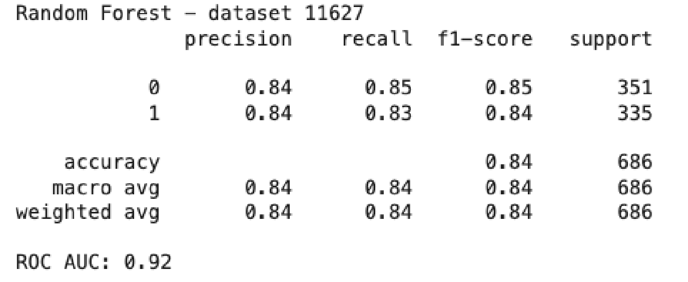
Table 15: Model performances on dataset of 11,627 records



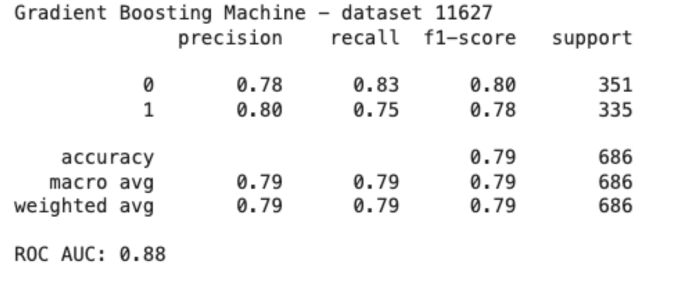
```
Logistic Regression - dataset 11627
              precision    recall  f1-score   support

           0       0.71      0.72      0.71       351
           1       0.70      0.70      0.70       335

    accuracy                           0.71       686
   macro avg       0.71      0.71      0.71       686
weighted avg       0.71      0.71      0.71       686

ROC AUC: 0.79
```



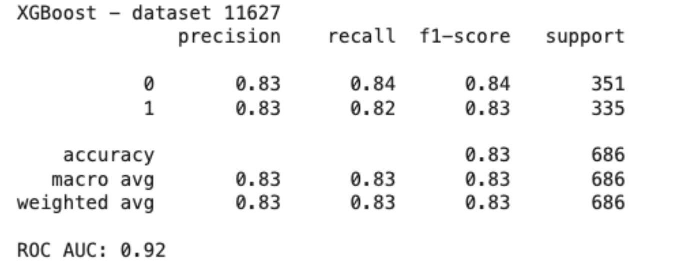
```
Support Vector Machine - dataset 11627
              precision    recall  f1-score   support

           0       0.80      0.77      0.78       351
           1       0.77      0.80      0.78       335

    accuracy                           0.78       686
   macro avg       0.78      0.78      0.78       686
weighted avg       0.78      0.78      0.78       686

ROC AUC: 0.85
```



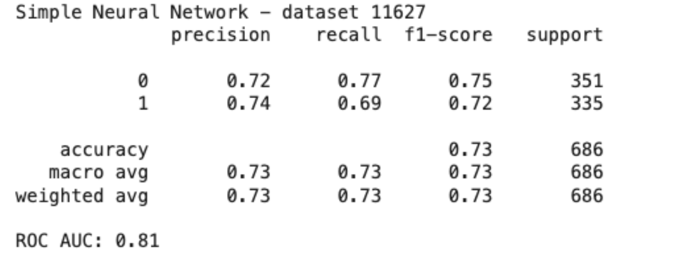
```
Random Forest - dataset 11627
              precision    recall  f1-score   support

           0       0.84      0.85      0.85       351
           1       0.84      0.83      0.84       335

    accuracy                           0.84       686
   macro avg       0.84      0.84      0.84       686
weighted avg       0.84      0.84      0.84       686

ROC AUC: 0.92
```



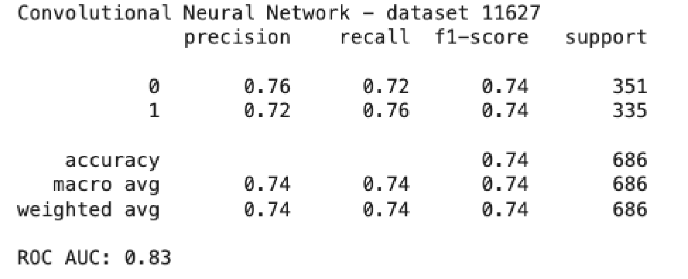
```
Gradient Boosting Machine - dataset 11627
              precision    recall  f1-score   support

           0       0.78      0.83      0.80       351
           1       0.80      0.75      0.78       335

    accuracy                           0.79       686
   macro avg       0.79      0.79      0.79       686
weighted avg       0.79      0.79      0.79       686

ROC AUC: 0.88
```



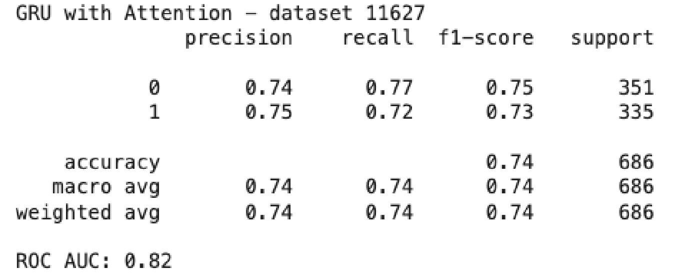
```
XGBoost - dataset 11627
              precision    recall  f1-score   support

           0       0.83      0.84      0.84       351
           1       0.83      0.82      0.83       335

    accuracy                           0.83       686
   macro avg       0.83      0.83      0.83       686
weighted avg       0.83      0.83      0.83       686

ROC AUC: 0.92
```



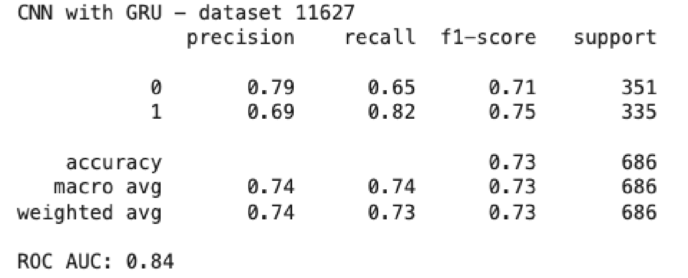
```
Simple Neural Network - dataset 11627
              precision    recall  f1-score   support

           0       0.72      0.77      0.75       351
           1       0.74      0.69      0.72       335

    accuracy                           0.73       686
   macro avg       0.73      0.73      0.73       686
weighted avg       0.73      0.73      0.73       686

ROC AUC: 0.81
```



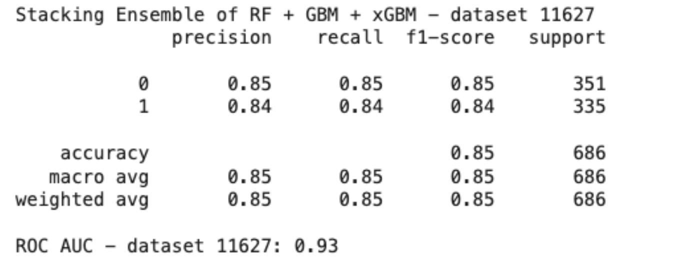
```
Convolutional Neural Network - dataset 11627
              precision    recall  f1-score   support

           0       0.76      0.72      0.74       351
           1       0.72      0.76      0.74       335

    accuracy                           0.74       686
   macro avg       0.74      0.74      0.74       686
weighted avg       0.74      0.74      0.74       686

ROC AUC: 0.83
```



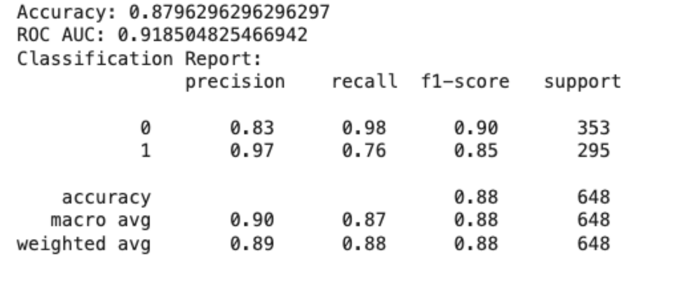
```
GRU with Attention - dataset 11627
              precision    recall  f1-score   support

           0       0.74      0.77      0.75       351
           1       0.75      0.72      0.73       335

    accuracy                           0.74       686
   macro avg       0.74      0.74      0.74       686
weighted avg       0.74      0.74      0.74       686

ROC AUC: 0.82
```



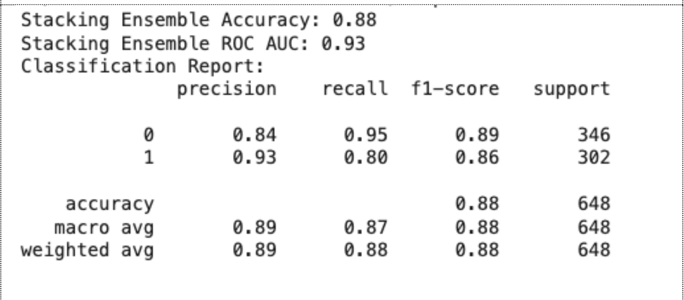
```
CNN with GRU - dataset 11627
              precision    recall  f1-score   support

           0       0.79      0.65      0.71       351
           1       0.69      0.82      0.75       335

    accuracy                           0.73       686
   macro avg       0.74      0.74      0.73       686
weighted avg       0.74      0.73      0.73       686

ROC AUC: 0.84
```



```
Stacking Ensemble of RF + GBM + xGBM - dataset 11627
              precision    recall  f1-score   support

           0       0.85      0.85      0.85       351
           1       0.84      0.84      0.84       335

    accuracy                           0.85       686
   macro avg       0.85      0.85      0.85       686
weighted avg       0.85      0.85      0.85       686

ROC AUC - dataset 11627: 0.93
```

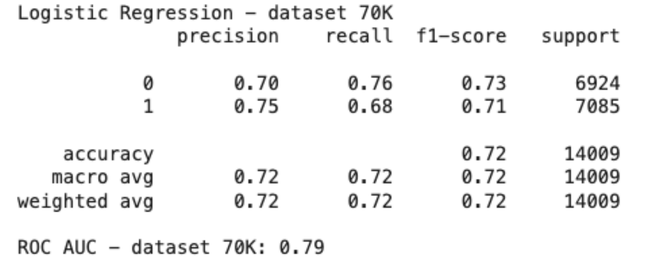


```
Accuracy: 0.8796296296296297
ROC AUC: 0.918504825466942
Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.98      0.90       353
           1       0.97      0.76      0.85       295

    accuracy                           0.88       648
   macro avg       0.90      0.87      0.88       648
weighted avg       0.89      0.88      0.88       648
```

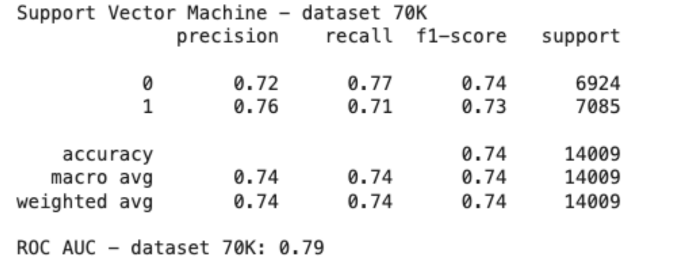


```
Stacking Ensemble Accuracy: 0.88
Stacking Ensemble ROC AUC: 0.93
Classification Report:
              precision    recall  f1-score   support

           0       0.84      0.95      0.89       346
           1       0.93      0.80      0.86       302

    accuracy                           0.88       648
   macro avg       0.89      0.87      0.88       648
weighted avg       0.89      0.88      0.88       648
```

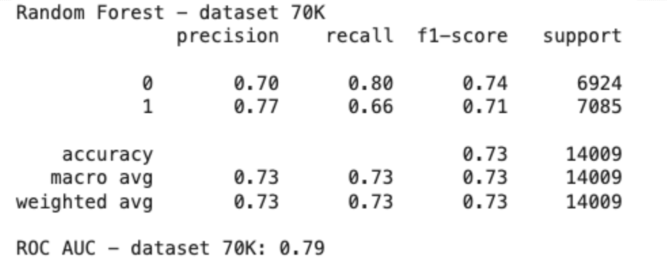
Table 16: Model performances on dataset of 70,000 records



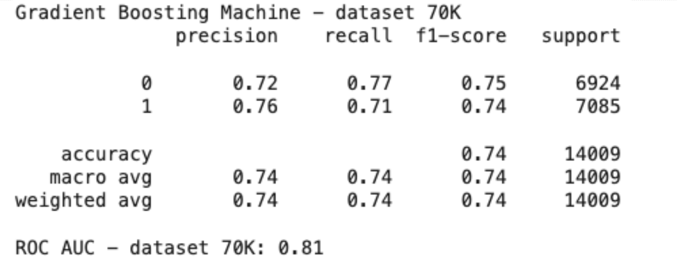
```
Logistic Regression – dataset 70K
              precision    recall  f1-score   support

           0       0.70      0.76      0.73      6924
           1       0.75      0.68      0.71      7085

    accuracy                           0.72     14009
   macro avg       0.72      0.72      0.72     14009
weighted avg       0.72      0.72      0.72     14009

ROC AUC – dataset 70K: 0.79
```



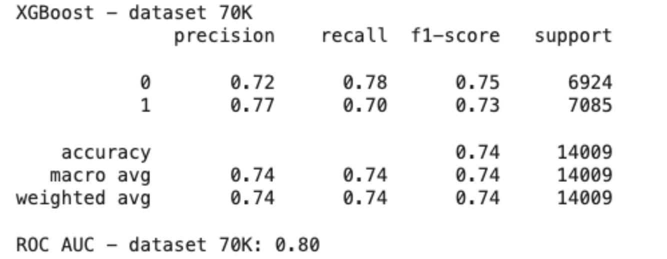
```
Support Vector Machine – dataset 70K
              precision    recall  f1-score   support

           0       0.72      0.77      0.74      6924
           1       0.76      0.71      0.73      7085

    accuracy                           0.74     14009
   macro avg       0.74      0.74      0.74     14009
weighted avg       0.74      0.74      0.74     14009

ROC AUC – dataset 70K: 0.79
```



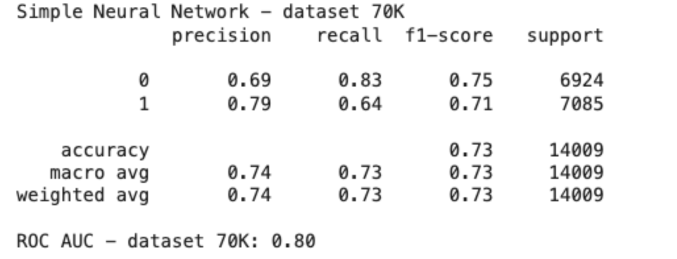
```
Random Forest – dataset 70K
              precision    recall  f1-score   support

           0       0.70      0.80      0.74      6924
           1       0.77      0.66      0.71      7085

    accuracy                           0.73     14009
   macro avg       0.73      0.73      0.73     14009
weighted avg       0.73      0.73      0.73     14009

ROC AUC – dataset 70K: 0.79
```



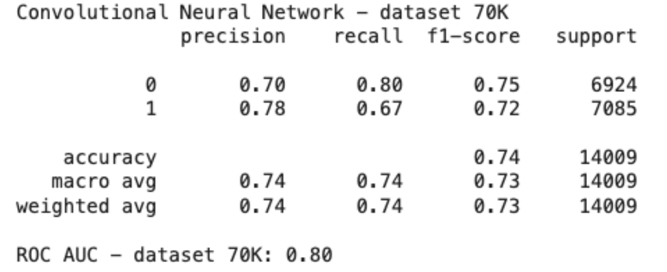
```
Gradient Boosting Machine – dataset 70K
              precision    recall  f1-score   support

           0       0.72      0.77      0.75      6924
           1       0.76      0.71      0.74      7085

    accuracy                           0.74     14009
   macro avg       0.74      0.74      0.74     14009
weighted avg       0.74      0.74      0.74     14009

ROC AUC – dataset 70K: 0.81
```



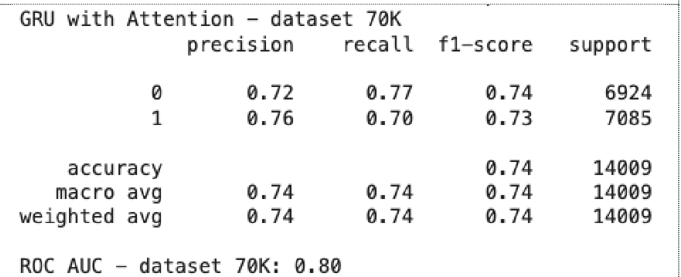
```
XGBoost – dataset 70K
              precision    recall  f1-score   support

           0       0.72      0.78      0.75      6924
           1       0.77      0.70      0.73      7085

    accuracy                           0.74     14009
   macro avg       0.74      0.74      0.74     14009
weighted avg       0.74      0.74      0.74     14009

ROC AUC – dataset 70K: 0.80
```



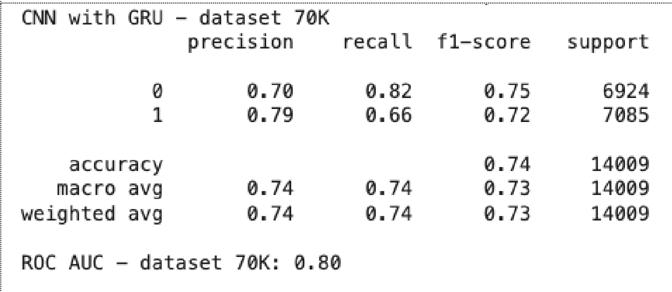
```
Simple Neural Network – dataset 70K
              precision    recall  f1-score   support

           0       0.69      0.83      0.75      6924
           1       0.79      0.64      0.71      7085

    accuracy                           0.73     14009
   macro avg       0.74      0.73      0.73     14009
weighted avg       0.74      0.73      0.73     14009

ROC AUC – dataset 70K: 0.80
```



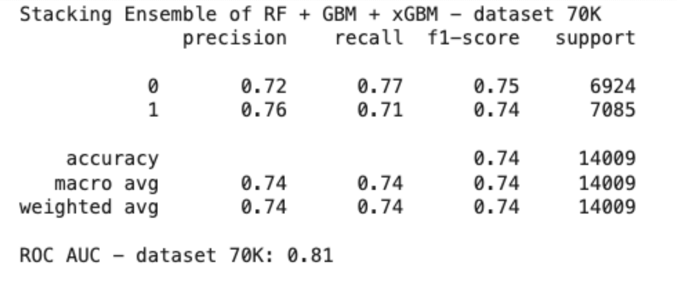
```
Convolutional Neural Network – dataset 70K
              precision    recall  f1-score   support

           0       0.70      0.80      0.75      6924
           1       0.78      0.67      0.72      7085

    accuracy                           0.74     14009
   macro avg       0.74      0.74      0.73     14009
weighted avg       0.74      0.74      0.73     14009

ROC AUC – dataset 70K: 0.80
```



```
GRU with Attention – dataset 70K
              precision    recall  f1-score   support

           0       0.72      0.77      0.74      6924
           1       0.76      0.70      0.73      7085

    accuracy                           0.74     14009
   macro avg       0.74      0.74      0.74     14009
weighted avg       0.74      0.74      0.74     14009

ROC AUC – dataset 70K: 0.80
```

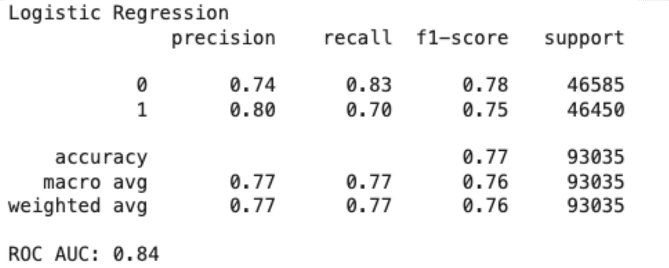


```
CNN with GRU – dataset 70K
              precision    recall  f1-score   support

           0       0.70      0.82      0.75      6924
           1       0.79      0.66      0.72      7085

    accuracy                           0.74     14009
   macro avg       0.74      0.74      0.73     14009
weighted avg       0.74      0.74      0.73     14009

ROC AUC – dataset 70K: 0.80
```



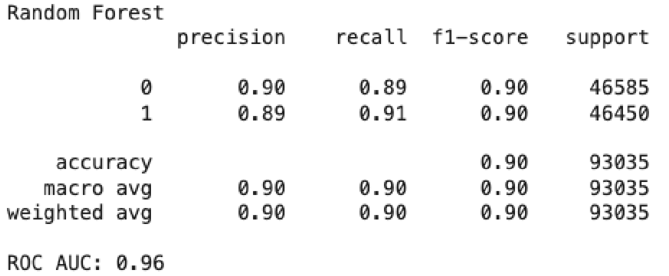
```
Stacking Ensemble of RF + GBM + xGBM – dataset 70K
              precision    recall  f1-score   support

           0       0.72      0.77      0.75      6924
           1       0.76      0.71      0.74      7085

    accuracy                           0.74     14009
   macro avg       0.74      0.74      0.74     14009
weighted avg       0.74      0.74      0.74     14009

ROC AUC – dataset 70K: 0.81
```

Table 17: Model performances on dataset of 400,000 records

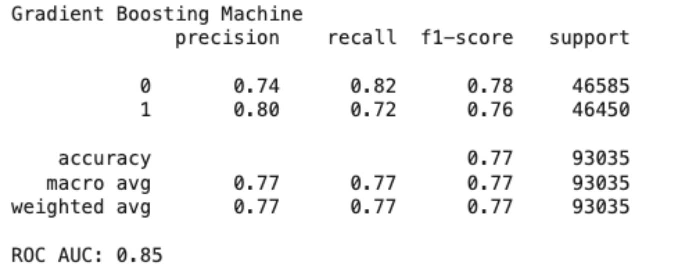


```
Logistic Regression
              precision    recall  f1-score   support

           0       0.74      0.83      0.78     46585
           1       0.80      0.70      0.75     46450

    accuracy                           0.77     93035
   macro avg       0.77      0.77      0.76     93035
weighted avg       0.77      0.77      0.76     93035

ROC AUC: 0.84
```

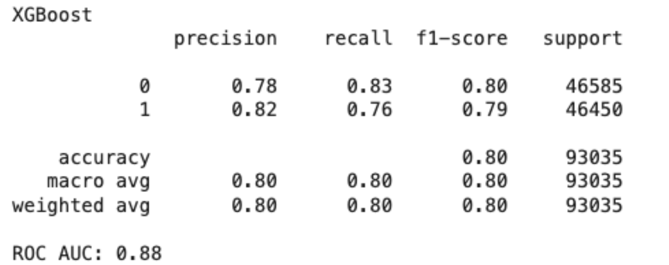
NA



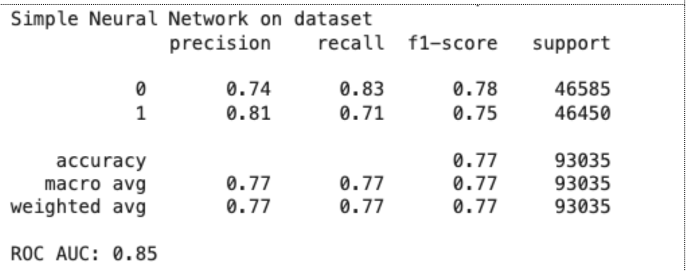
```
Random Forest
              precision    recall  f1-score   support

           0       0.90      0.89      0.90     46585
           1       0.89      0.91      0.90     46450

    accuracy                           0.90     93035
   macro avg       0.90      0.90      0.90     93035
weighted avg       0.90      0.90      0.90     93035

ROC AUC: 0.96
```



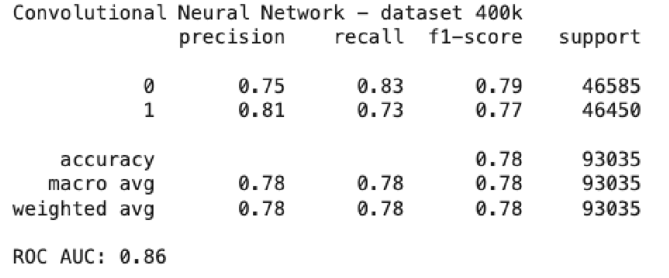
```
Gradient Boosting Machine
              precision    recall  f1-score   support

           0       0.74      0.82      0.78     46585
           1       0.80      0.72      0.76     46450

    accuracy                           0.77     93035
   macro avg       0.77      0.77      0.77     93035
weighted avg       0.77      0.77      0.77     93035

ROC AUC: 0.85
```



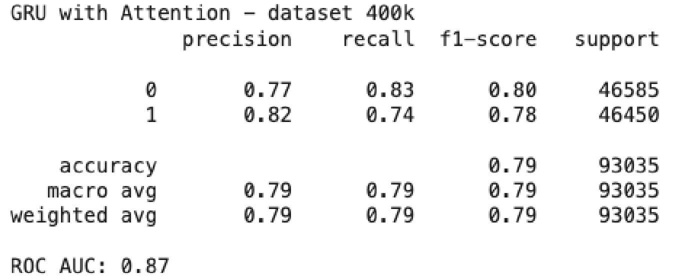
```
XGBoost
              precision    recall  f1-score   support

           0       0.78      0.83      0.80     46585
           1       0.82      0.76      0.79     46450

    accuracy                           0.80     93035
   macro avg       0.80      0.80      0.80     93035
weighted avg       0.80      0.80      0.80     93035

ROC AUC: 0.88
```



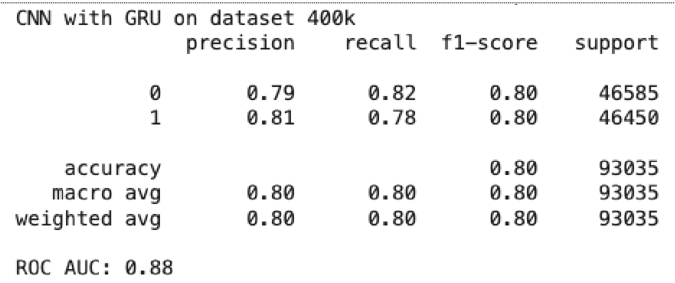
```
Simple Neural Network on dataset
              precision    recall  f1-score   support

           0       0.74      0.83      0.78     46585
           1       0.81      0.71      0.75     46450

    accuracy                           0.77     93035
   macro avg       0.77      0.77      0.77     93035
weighted avg       0.77      0.77      0.77     93035

ROC AUC: 0.85
```



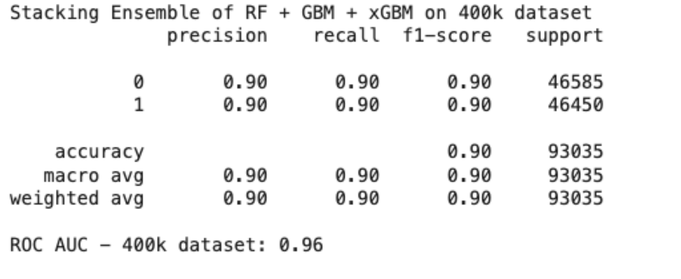
```
Convolutional Neural Network - dataset 400k
              precision    recall  f1-score   support

           0       0.75      0.83      0.79     46585
           1       0.81      0.73      0.77     46450

    accuracy                           0.78     93035
   macro avg       0.78      0.78      0.78     93035
weighted avg       0.78      0.78      0.78     93035

ROC AUC: 0.86
```



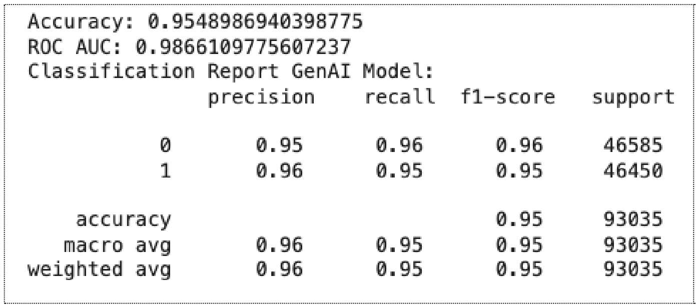
```
GRU with Attention - dataset 400k
              precision    recall  f1-score   support

           0       0.77      0.83      0.80     46585
           1       0.82      0.74      0.78     46450

    accuracy                           0.79     93035
   macro avg       0.79      0.79      0.79     93035
weighted avg       0.79      0.79      0.79     93035

ROC AUC: 0.87
```



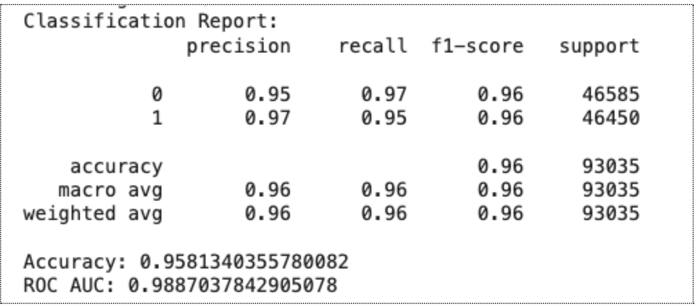
```
CNN with GRU on dataset 400k
              precision    recall  f1-score   support

           0       0.79      0.82      0.80     46585
           1       0.81      0.78      0.80     46450

    accuracy                           0.80     93035
   macro avg       0.80      0.80      0.80     93035
weighted avg       0.80      0.80      0.80     93035

ROC AUC: 0.88
```



```
Stacking Ensemble of RF + GBM + xGBM on 400k dataset
              precision    recall  f1-score   support

           0       0.90      0.90      0.90     46585
           1       0.90      0.90      0.90     46450

    accuracy                           0.90     93035
   macro avg       0.90      0.90      0.90     93035
weighted avg       0.90      0.90      0.90     93035

ROC AUC - 400k dataset: 0.96
```



```
Accuracy: 0.9548986940398775
ROC AUC: 0.9866109775607237
Classification Report GenAI Model:
              precision    recall  f1-score   support

           0       0.95      0.96      0.96     46585
           1       0.96      0.95      0.95     46450

    accuracy                           0.95     93035
   macro avg       0.96      0.95      0.95     93035
weighted avg       0.96      0.95      0.95     93035
```



```
Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.97      0.96     46585
           1       0.97      0.95      0.96     46450

    accuracy                           0.96     93035
   macro avg       0.96      0.96      0.96     93035
weighted avg       0.96      0.96      0.96     93035

Accuracy: 0.9581340355780082
ROC AUC: 0.9887037842905078
```

************ End of Proposal ********** Thank you for reviewing ************