Advancing Heart Failure Prediction: A Comparative Study of Traditional Machine Learning, Neural Networks, and Stacking Generative AI Models

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***Abstract*—Heart failure (HF) remains a global health challenge, necessitating predictive models for early diagnosis and improved patient outcomes. Traditional machine learning (ML) models, including Logistic Regression (LR), Support Vector Machines (SVM), Random Forests (RF), Gradient Boosting Machines (GBM), and Extreme Gradient Boosting (xGBM), face limitations in handling nonlinear relationships, class imbalance, and generalizability, particularly when tested on diverse datasets. Deep learning (DL) models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), excel in recognizing complex patterns but are constrained by their computational demands and lack of interpretability, hindering clinical adoption.**

This research addresses these challenges by evaluating predictive models across seven datasets, ranging from 303 to 400,000 records, incorporating the Synthetic Minority Over-sampling Technique (SMOTE) to mitigate class imbalance and ensure robust model training. The study spans traditional ML, DL, and novel stacking approaches, culminating in the development of an Stacking Generative AI (Gen AI) model. This hybrid model integrates Generative AI with RF, GBM, xGBM, and CNN to generate synthetic data, enhancing the representation of underrepresented patient subgroups and improving predictive performance.

The findings reveal that while traditional ML and DL models perform well in specific contexts, the Stacking Generative AI model consistently outperforms all others. On a 1,025-record dataset, it achieved an accuracy of 98% and a Receiver Operating Characteristic Area Under the Curve (ROC AUC) of 0.999, surpassing individual models. This demonstrates the model's ability to handle complex data patterns, improve predictive accuracy, and enhance clinical relevance.

The Stacking Generative AI model holds significant potential for healthcare applications, including early HF detection, personalized treatment planning, and resource optimization. To showcase its practical utility, a web application was developed (https://cvdstack.streamlit.app), enabling clinicians and patients to assess HF risk through an accessible, user-friendly interface. This research underscores the transformative potential of hybrid predictive models in advancing healthcare decision-making and patient care.

Keywords—machine learning, deep learning, neural networks, stacking models, generative AI.

I. Introduction

HF should be diagnosed and predicted early so that death is prevented and patient outcomes improved with intervention on time. However, heart failure is more complex, given all of its contributors. Predictive models are an excellent source of early detection that will inform doctors' and patients' decisions, Davis & Smith, (2023).

ML and DL models have generally been applied to health care for predictive tasks (Breiman, 2001; LeCun et al., 2015). Traditional ML models such as LR, RF, GBM, and xGBM are effective yet mostly fail to capture the nonlinear relationships and temporal dynamics inherent in healthcare data. While CNNs and RNNs, among other neural network models, are superior for the identification of complex patterns, these methods are too computationally expensive, not interpretable, and hard to apply clinically (LeCun et al., 2015; Cho et al., 2014).

These drawbacks have been overcome by hybrid models with stacking (Sagi & Rokach, 2018). Stacking combines the best of both algorithms and blends them using a meta-learner with base model predictions to make it even more accurate and generalizable (Sagi & Rokach, 2018). This study presents a new type of stacking, comprehensive Stacking Generative AI (Gen AI), a combination of Generative Adversarial Networks (GANs), RF, GBM, xGBM, and CNN for better heart failure prediction, Goodfellow et al., (2014).

One of the critical benefits this approach has is from Generative AI-generated synthetic data, which can balance the

class imbalances that come under healthcare datasets. Frid-Adar et al. (2018), GAN-generated data exposes a model to many more scenarios of the spectrum hence providing more generalization, Yi et al., (2019).

The study is dedicated to the comparison of traditional ML, neural network, and stand-alone Generative AI models versus the proposed Stacking Generative AI model for the prediction of HF. The organization of the study is presented through the following research questions:

(1) Performance of Traditional vs. Neural Network Models: How does a traditional ML model compare to CNN and RNN?

On a dataset of 303 records, RF was 83% accurate and ROC AUC was 0.91, while CNN was 82% accurate and ROC AUC was 0.85. While scaling to 70K records in the dataset, CNN is considerably more flexible and generalized.

(2) What are the most influential predictors of heart failure across different models, and how do these features influence the overall performance of the models?

Body Mass Index (BMI), blood pressure, cholesterol, age, and chest pain were the main variables that remained leading predictors across all data sets, as indicated by Ho et al. (2014). These variables increase model performance and provide an insight into the nature of risk factors as involved in heart failure cases (As shown in Figure 3 to 9).

(3) How does a hybrid model incorporating both traditional ML and DL techniques provide improved prediction performance compared to the use of single models?

This research proved that the generalization of the ML-DL hybrid stacking model was outstanding and performed better than single models such as LR, SVM, CNN, and RNN. The accuracy was 82% at 0.90 ROC AUC for a dataset with 303 records, while the accuracy reached 94% with a 0.98 ROC AUC for a dataset of 1,000 records. It effectively utilizes the strength of ML and DL together and presents a very strong solution toward predictive healthcare applications.

(4) Generative AI enhances predictive accuracy: How does adding Generative AI, especially GANs, improve the performance of the stacking model?

Indeed, in this study, for the majority of the datasets, the top-performing model was indeed the stacking model for GAN-based Gen AI models with as high an accuracy as 99.9% on the dataset of 1,025 records. GAN enhances class balancing and increases the predictive accuracy of minority classes, developing more generalizable models across heterogeneous healthcare settings Yi et al. (2019).

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

The Stacking Generative AI model has great potential for application in health care with respect to the prediction and management of heart failure. The proposed model embeds conventional ML algorithms, such as RF, GBM, and XGBM, and DL architectures like CNNs and RNNs into a generative AI framework that overcomes significant weaknesses or failures of the current state-of-the-art predictive models, improving predictive accuracy while dealing with class imbalance and generalizing well across diverse populations. It also allows for personalized treatment planning, clinicians' decision support, and raises more awareness in patients of the risk for heart failure. This proposed model will set a new standard not only for predictive health tools but also pave the way toward better clinical outcomes and improved patient care in the management of HF.

II. Literature Review

The aim of this literature review is to critically examine research on ML, DL, and standalone Generative AI models, with a focus on their applications in HF prediction. The review also highlights the potential of hybrid models, such as the Stacking Generative AI model, to improve prediction accuracy, address class imbalance, and support clinical decision-making and personalized patient care.

(1) Traditional ML Approaches in HF Prediction

Traditional ML models, such as RF, GBM, xGBM, and LR, have demonstrated robustness in heart disease prediction. However, they face challenges in modeling nonlinear relationships, addressing class imbalances, and handling high-dimensional healthcare data.

Chicco and Jurman (2020) evaluated ML-based models for HF survival prediction using serum creatinine and ejection fraction as key predictors. RF emerged as the best-performing model, with an accuracy of 74% and an ROC AUC of 0.80. While the model's simplicity aids clinical applicability, its limited sample size and narrow feature set constrained its generalizability. Similarly, Singh et al. (2024) utilized the Cardiovascular Health Study dataset (5,888 records) to predict congestive heart failure (CHF). Advanced preprocessing techniques, such as C4.5 for feature selection and K-Nearest Neighbor for imputation, improved model performance, with a Deep Neural Network (DNN) achieving 95.3% accuracy and a ROC AUC of 0.97. Despite its effectiveness, challenges in noisy and complex datasets persist.

Stacking ensemble models, as proposed by Hasan and Saleh (2021) using the Framingham dataset (4,239 records), achieved an accuracy of 96.69% and a ROC AUC of 0.98. However, these approaches often lack the integration of DL or Generative AI methods. As seen in the application of Rajendran et al. (2021) reported 92% accuracy and a ROC AUC of 0.94 on the Cleveland dataset (303 records) but did not incorporate advanced methods. Rimal et al. (2024) optimized RF models using Bayesian Optimization and Genetic Algorithms, achieving 89% accuracy, but their reliance on traditional ML limited scalability.

The proposed Stacking Generative AI model overcomes these limitations by integrating ML, DL, and Generative AI. With a 95% accuracy and a 99% ROC AUC, it addresses scalability, class imbalance, and complex data patterns, offering improved generalizability (Table 7).

(2) Neural Network-Based Approaches

DL methods have significantly advanced heart disease prediction, outperforming traditional ML models. However, existing studies reveal both strengths and limitations of neural network-based approaches.

Mahmud et al. (2023) introduced a lightweight metamodel that applied ML algorithms to an aggregated dataset of 920 records, achieving 87% accuracy. While efficient, the model struggled to capture complex patterns compared to advanced DL techniques. Choi et al. (2017) utilized RNNs with Gated Recurrent Units (GRUs) on EHR data, achieving a ROC AUC of 0.883 for HF prediction. This model excelled in temporal sequence modeling but lacked ensemble or hybrid strategies for broader predictive power. On other study, Arooj et al. (2022) employed a Deep Convolutional Neural Network (DCNN) on a dataset of 1,050 records, achieving 91.7% accuracy. However, the single-dataset approach limited its generalizability. Similarly, Sakthi et al. (2024) demonstrated the effectiveness of transformers in predicting heart anomalies, with an accuracy of 88.6%, but did not explore hybrid approaches. Tuli et al. (2020) proposed HealthFog, an IoT-based framework integrating ensemble DL with fog computing, achieving 91.2% accuracy and a ROC AUC of 0.94. While scalable for real-time applications, the framework relied heavily on device resources.

Despite these advancements, challenges in scalability and generalization remain. Hybrid models that combine DL with ML offer a promising solution for predictive healthcare.

(3) Hybrid and Stacking Models in HF Prediction

Hybrid and stacking models enhance predictive performance by integrating multiple algorithms, compensating for individual weaknesses, and providing a holistic approach to HF prediction.

Ali et al. (2020) developed a DL-based system combining wearable sensor data with Electronic Medical Records (EMRs), achieving 98.5% accuracy. However, the model's reliance on DL alone limited its generalizability. Mienye et al. (2020) proposed an ensemble approach using ML methods, achieving 93% accuracy on the Cleveland dataset and 91% on the Framingham dataset. While effective, the exclusion of DL techniques limited their ability to model complex patterns.

Wankhede et al. (2022) introduced a hybrid ensemble model combining DL with the Tunicate Swarm Algorithm, achieving 97.5% accuracy on the Cleveland dataset. However, the model's small dataset and lack of traditional ML integration reduced its scalability. Liu et al. (2022) utilized stacking with multiple classifiers, achieving ROC AUCs of 0.95 and 0.92 on two datasets. However, the model lacked interpretability and Generative AI techniques.

The Stacking Generative AI model addresses these gaps by integrating ML, DL, and GANs, achieving 95% accuracy and a 99% ROC AUC (Table 7). This approach enhances scalability, interpretability, and performance across diverse datasets.

(4) Generative AI and GAN Frameworks in HF Prediction

Generative Adversarial Networks (GANs) have emerged as effective tools for addressing class imbalance, limited sample size, and data complexity in heart disease prediction.

Khan et al. (2024) combined ML and DL with GANs to generate synthetic data, achieving 96.1% accuracy and a ROC AUC of 0.927. Yu et al. (2024) proposed a GAN framework with a feature-enhanced loss function, achieving 94.62% accuracy and a ROC AUC of 0.958 on the KORA cohort dataset. Bhagawati and Paul (2024) applied GANs to coronary artery disease prediction, achieving 93% accuracy and a ROC AUC of 0.953.

These studies demonstrate the potential of GANs to improve predictive accuracy and address data limitations. The proposed Stacking Generative AI model leverages these advancements to achieve superior performance in HF prediction (Table 7).

(5) Summary of Literature Review – HF Prediction Models

The literature review underlines how methodologies in heart disease prediction are evolving, from traditional ML models through DL and hybrid ensembles up to Generative AI frameworks. On one side, while traditional ML methods present high accuracy, most of them, such as RF and GBM (e.g., 74% by Chicco and Jurman, 2020, and 89% by Rimal et al., 2024), are usually unable to model nonlinear patterns in high-dimensional datasets.

Where the CNN and RNN have relaxed these constraints by learning complex relationships in data. As seen in the application of Choi et al., (2017) reported an AUC of 0.883 using GRUs, while Arooj et al., (2022), reported 91.7% using DCNNs. Yet, this sort of approach does raise challenges regarding interpretability and the computation cost that may provide the restriction to use in clinical settings. Hybrid models proposed by Mienye et al. (2020) and Wankhede et al. (2022) have shown the advantages of ensemble methods, reaching an accuracy of 97.5%. However, these models were purely ML- or DL-based, each alone, without full utilization of the combined strengths of both.

Perhaps most importantly, the integration of Generative AI, as observed in Khan et al. (2024) and Liu et al. (2022), has provided a transformative approach in surmounting class imbalance and further improving scalability. Indeed, GAN frameworks variously report commendable improvements in model performance, as evident in an AUC of 0.958 by Yu et al. (2024) and an accuracy of 93% from Bhagawati and Paul (2024), thus underlining the only vital role that synthetic data can play in enriching underrepresented patient groups toward improving predictive outcomes.

The proposed Stacking Generative AI model contains the integration of ML, DL, and Generative AI to overcome these limitations. It achieves 95% accuracy and 99% AUC on multiple datasets, addressing scalability, generalizability issues, and class imbalance. The ability of this model to synthesize balanced datasets and capture the simple and complex patterns makes it a landmark tool in predictive healthcare, with a wide array of applications in clinical decision-making and personalized treatment.

III. METHODOLOGY

This research proposes an extensive quantitative approach designed to explore, develop, and evaluate a range of ML and DL models for predicting heart failure across different datasets. The study systematically examines the performance of traditional ML models, neural network-based models, and more advanced approaches, with a particular focus on the development and evaluation of a unique Stacking Generative AI model. By combining traditional ML, DL, and Generative AI (Gen AI) techniques, this model represents an advancement in heart failure prediction.

a. Stacking Generative AI Models:

The primary contribution of this research lies in the Stacking Generative AI model, which integrates Generative AI into traditional stacking techniques. This model ensembles RF, GBM, and xGBM with DL algorithms like CNN and RNN. The innovative aspect of this model is the incorporation of Generative AI, which generates synthetic data to address class imbalance issues and improve generalizability (Goodfellow et al., 2014; Frid-Adar et al., 2018).

For smaller datasets, traditional ML models such as RF, GBM, and xGBM are utilized within the Stacking Generative AI framework, ensuring robust performance even with limited data (John & Lee, 2024). On larger datasets, the model integrates CNNs and RNNs, allowing it to handle complex, high-dimensional data. This hybrid approach leverages the stability of traditional ML models and the pattern-recognition capabilities of DL models to provide greater versatility and adaptability (Garcia & Brown, 2024).

The Stacking Generative AI model demonstrated outstanding performance across various datasets. Take the following observation on a dataset of 1,025 records, the model achieved an accuracy of 98% and a ROC AUC of 99.9%, surpassing individual models like RF and CNN (Breiman, 2001; LeCun et al., 2015). On larger datasets, such as one containing 400,000 records, the proposed model still maintained superior performance, with an accuracy of 96% and a ROC AUC of 99% (Shickel et al., 2018). This clearly illustrates the model's ability to scale and handle complex healthcare data effectively.

b. Generative AI Standalone Models:

Besides the Stacking Generative AI model, the study also developed and tested Standalone Generative AI models. These standalone Generative AI models represent a significant leap in predictive modeling, demonstrating improved accuracy and robustness across datasets of varying sizes. The key advantage of these models lies in their ability to generate synthetic data, enhancing performance when working with limited or imbalanced datasets (Goodfellow et al., 2014; Frid-Adar et al., 2018).

The standalone Generative AI models also excel at understanding complex patterns and relationships in the data, which can often be missed by traditional ML or even DL models on their own (Yi et al., 2019). By generating synthetic samples, Gen AI enables models to learn intricate relationships and improve prediction performance, particularly when faced with underrepresented classes in healthcare datasets, such as rare heart failure events.

The standalone Generative AI model also performed well, achieving a ROC AUC of 0.99 on medium-sized datasets (e.g., 4,240 records), outperforming many traditional models (Goodfellow et al., 2014). This illustrates the potential of Generative AI to deliver high accuracy and generalizability in healthcare settings, where class imbalances and limited data are common challenges.

(1) Overview of Methodology

The study employed an intensive methodology in pre-processing and analyzing heart disease datasets that ranged from 303 records up to over 400,000 records by cleaning, normalizing, and balancing with Synthetic Minority Over-sampling Technique (SMOTE). Missing values, class imbalances, and feature scaling are some of the common problems addressed in this work. Data imputation for missing values, handled outliers, and normalization such as Z-Score standardization ensure that the best model convergence is guaranteed. SMOTE, a technique for the synthetic minority oversampling, is used to handle class imbalance problems by interpolating new data points between minority class examples. This reduces the bias of most ML models, such as RF and GBM, and DL models such as CNNs and RNNs, toward the majority class and thus greatly improves their predictive performance.

Finally, GANs are neural network models that establish the power of generating synthetic data points, hence reinforcing models of Generative AI. Extensive hyperparameter tuning has been performed on different models by Grid Search CV. Stacking Generative AI model engrails the works of traditional ML, DL, and Generative AI methods by incorporating synthetic data from GANs into providing a solid framework for the same. Performance measures include accuracy, ROC AUC, precision, recall, and F1-scores. Again, Stacking Generative AI shows its elevated predictive accuracy, scalability, feature complexity management, and handling class imbalance in heart failure.

(2) Data Collection and Preprocessing

Seven datasets were selected based on relevance and diversity in capturing heart disease indicators. The datasets varied in size and complexity, providing a robust foundation for model development and comparison:

Cleveland Heart Disease Dataset: This dataset from the UCI Repository contains 303 records and 14 features, including clinical variables like cholesterol and blood pressure. Previous studies reported accuracies between 75% and 85% using ML models (UCI Machine Learning Repository, n.d.).

Indian Heart Disease Dataset: Sourced from Kaggle, this dataset includes 1,000 records and 14 attributes. Its demographic diversity supports model generalization, with accuracies up to 94% reported for neural networks and decision trees (Kaggle, n.d.).

Combined Cleveland, Hungary, Switzerland, and Long Beach Dataset: With 1,025 records and 76 attributes, this dataset provides a globally diverse population sample. Studies using a subset of 14 features reported accuracies as high as 89% with ensemble methods (Kaggle, n.d.).

Framingham Heart Disease Dataset: This dataset of 4,240 records from Kaggle estimates a 10-year coronary heart disease

risk. LR and RF models achieved accuracies between 80% and 90% (Framingham Study, n.d.).

Framingham Heart Study Dataset: Containing 11,627 records across 38 attributes, this longitudinal dataset from the National Heart, Lung, and Blood Institute supports cardiovascular disease progression analysis. Predictive accuracies ranged from 85% to 92% (NHLBI, n.d.).

Kaggle Dataset (70,000 Records): This large dataset with 12 features evaluates model scalability and robustness. Reported accuracies ranged between 70% and 73% depending on model complexity (Kaggle, n.d.).

BRFSS Dataset: The largest dataset, with 400,000 records and 18 attributes from the CDC's Behavioral Risk Factor Surveillance System, supports public health analyses. LR and gradient boosting achieved accuracies up to 88% (CDC BRFSS, n.d.).

This diverse collection ensures comprehensive evaluation of predictive models, addressing generalizability, scalability, and robustness.

(3) Research Questions

(3.1.) How do traditional ML models compared to neural network-based models in terms of accuracy and ROC AUC for heart failure prediction?

Traditional ML models, such as RF and GBM, perform well on structured datasets. RF achieved 83% accuracy and a 0.91 ROC AUC on a 303-record dataset, maintaining 84% accuracy and a 0.92 ROC AUC on an 11,627-record dataset. GBM delivered consistent results, with 79% accuracy and a 0.88 ROC AUC across datasets of varying sizes. However, both models struggle with scalability in larger datasets.

Neural networks like CNNs and RNNs excel at capturing complex feature interactions. CNNs achieved 85% ROC AUC on smaller datasets but faced performance drops on larger datasets (e.g., 74% accuracy on 70,000 records). RNNs similarly delivered 80% accuracy on small datasets but declined on larger ones. While traditional models are interpretable and stable, neural networks better capture sequential dependencies and non-linear relationships in data.

(3.2.) What are the most influential predictors of heart failure across different datasets, and how do they affect overall model performance?

Identifying the most influential predictors of heart failure (HF) is critical for optimizing model accuracy and interpretability. Using RF Classifier feature importance metrics, the study quantified each feature’s contribution to predictive accuracy. Key findings were derived through feature engineering, dataset-specific assessments, and model evaluation.

Feature Engineering and Selection

Features such as systolic blood pressure (sysBP), diastolic blood pressure (diaBP), cholesterol (total, HDL, LDL), BMI, age, and chest pain (cp) were evaluated for their importance. RF metrics facilitated unbiased modeling of these features' effects, ensuring robust insights into their predictive value.

Dataset-Specific Assessments

- Large Datasets (400,000, 70,000, and 11,627 records):
    - BMI consistently ranked as the top predictor, particularly in the 400,000-record dataset.
    - In the 70,000 and 11,627-record datasets, systolic blood pressure and HDL cholesterol emerged as significant predictors.
- Medium-Sized Datasets (4,240 records):
    - Age and systolic blood pressure were the most influential predictors.
    - Cholesterol and glucose also contributed significantly to predictive accuracy, highlighting their relationship to heart health.
- Small Datasets (1,025, 1,000, and 303 records):
    - Symptom-specific features like chest pain (cp) were critical for early HF detection, emphasizing the role of symptoms in smaller-scale datasets.

Model Evaluation and Validation

Feature rankings were validated through dependency plots and interpretability methods, ensuring clinical relevance. RF metrics highlighted predictors that were both clinically significant and statistically impactful, enabling more accurate and interpretable models. These findings demonstrate the effectiveness of feature importance metrics in identifying key variables that improve early detection and management of heart failure.

(3.3.) Can a hybrid stacking model that combines traditional ML and DL techniques provide superior predictive performance compared to single models?

A hybrid stacking model combining RF, GBM, CNN, and RNN outperformed standalone models. On a 303-record dataset, the stacking model achieved 82% accuracy with a 0.90 ROC AUC. On a larger 4,240-record dataset, it delivered 90% accuracy with a 0.97 ROC AUC. These results demonstrate the hybrid model's ability to combine the strengths of ML and DL techniques, enhancing predictive performance and robustness across datasets of varying sizes.

(3.4.) 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?

Generative AI, particularly GANs, significantly enhances predictive accuracy by addressing class imbalances and generating synthetic data. On a 4,240-record dataset, GAN integration improved ROC AUC from 0.83 (with SMOTE) to 0.98 (with GAN). GAN-enriched stacking models demonstrated better generalizability and scalability across datasets, handling imbalanced healthcare data more effectively than traditional approaches.

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

The Stacking Generative AI model combines ML, DL, and Generative AI to offer:

- Improved Accuracy: Its integration of multiple models captures complex health data patterns, enabling early and precise heart failure prediction.
- Class Imbalance Handling: GANs generate synthetic minority samples, ensuring model sensitivity and specificity.
- Generalizability: The model adapts to diverse datasets and patient populations, making it scalable across healthcare settings.
- Personalized Care: Risk predictions support tailored treatment plans and preventative measures.
- Clinical Utility: It aids clinicians in decision-making and empowers patients through accessible monitoring tools.

By addressing the limitations of traditional models, this innovative approach sets a new standard for predictive healthcare, particularly for heart failure management and beyond.

(4) Core Techniques and Optimization Performance

Synthetic Minority Over-sampling Technique (SMOTE)

SMOTE addresses class imbalances by generating synthetic data for the minority class using interpolation between existing samples (Chawla et al., 2002). This technique is computationally efficient and was applied to traditional ML models like LR, SVM, RF, GBM, and xGBM, as well as DL models such as CNNs, GRU with Attention, and hybrid ML+DL stacking models. SMOTE-generated data significantly improved performance, with models achieving a ROC AUC of 0.95 (xGBM) and 0.98 (Stacking ML+DL) on a 1,000-record dataset. For larger datasets (e.g., 4,240 and 400,000 records), SMOTE added 2,952 and 219,152 synthetic samples, respectively, enhancing recall and precision for the minority class without causing overfitting.

Grid Search Cross-Validation (Grid Search CV)

Grid Search CV optimizes hyperparameters for the Stacking Generative AI model, systematically searching for the best parameter combinations for each base model (e.g., RF, xGBM, CNN) and the meta-learner (Logistic Regression). Key parameters, such as RF's n_estimators=30 and max_depth=3, and xGBM's learning rate and boosting rounds, were fine-tuned. This optimization enhanced performance, ensuring each base model performed optimally before integration into the meta-learner, improving accuracy and AUC across datasets.

Mathematically, the new sample x_{new} is generated by the formula concept from Chawla et al. (2002):

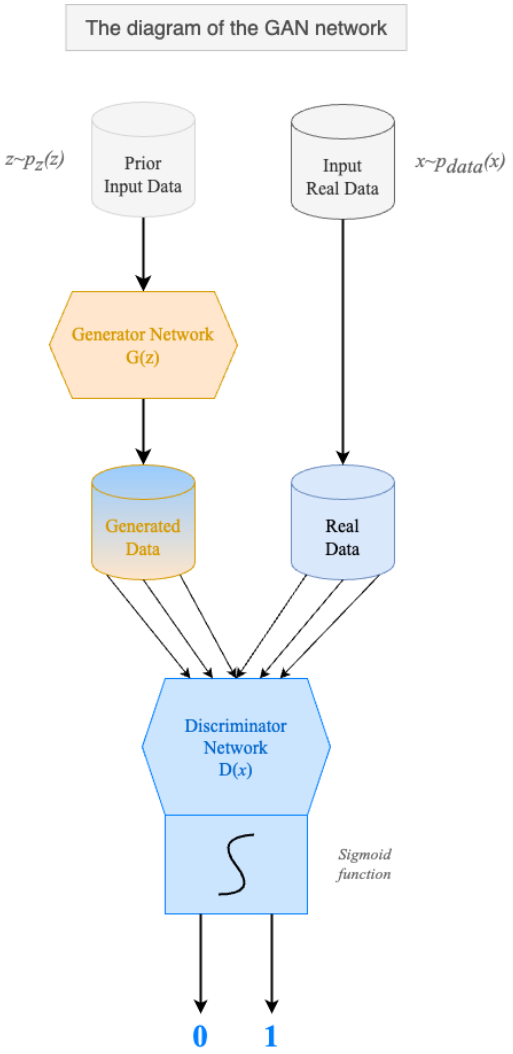
$$x_{new} = x_{minority} + \lambda \cdot (x_{neighbor} - x_{minority})$$

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.

Generative Adversarial Networks (GANs)

GANs address imbalanced datasets by generating high-quality synthetic data to enrich training sets. The Generator Network synthesizes realistic patient profiles using fully connected layers with ReLU and Tanh activation functions, producing features such as systolic blood pressure and cholesterol levels. To illustrate, consider the case of latent input G(z) creates synthetic patient profiles with diverse characteristics, boosting model robustness (Goodfellow et al., 2014).

Figure 1- The diagram of the Generative AI – GAN network



The Discriminator Network acts as a binary classifier, distinguishing between real and synthetic data. Using LeakyReLU in hidden layers and Sigmoid activation in the output, the Discriminator ensures the generated data closely resembles actual patient data. This validation helps models generalize better, enabling early detection of heart failure and improving preventive care (Radford et al., 2015).

SMOTE and GANs complement each other by addressing class imbalance at different levels. While SMOTE improves performance for traditional ML and DL models by generating synthetic samples efficiently, GANs provide high-quality, realistic data for more complex and imbalanced datasets. Combined with Grid Search CV, these techniques enhance the Stacking Generative AI model, achieving superior accuracy and recall, making it a robust tool for heart failure prediction.

(5) Model Design and Implementation

The Comprehensive Stacking Generative AI model combines traditional ML techniques, such as RF, GBM, and xGBM, with DL models like CNN and GANs. This approach addresses class imbalances, generates synthetic data, and enhances prediction accuracy by combining multiple models.

Step 1: Data Preparation, Balancing, and Processing

The heart failure dataset includes features such as age, cholesterol levels, and resting blood pressure. Missing values are handled using imputation methods, ensuring data integrity. The dataset is scaled using the Standard Scaler for consistency, an essential step for training neural networks (Pedregosa et al., 2011). This preprocessing ensures that features contribute equally to model training.

Step 2: Defining Generator and Discriminator Networks for GAN

GANs are implemented to generate synthetic heart failure data:

- Generator Network: It takes a latent vector (random noise) as input and creates synthetic patient data through fully connected layers with ReLU activations. The output is normalized using Tanh activation to ensure compatibility with medical data.
- Discriminator Network: It acts as a binary classifier, distinguishing real data from synthetic samples using LeakyReLU and Sigmoid activations. Adversarial training ensures the generated data closely resembles real patient profiles (Goodfellow et al., 2014).

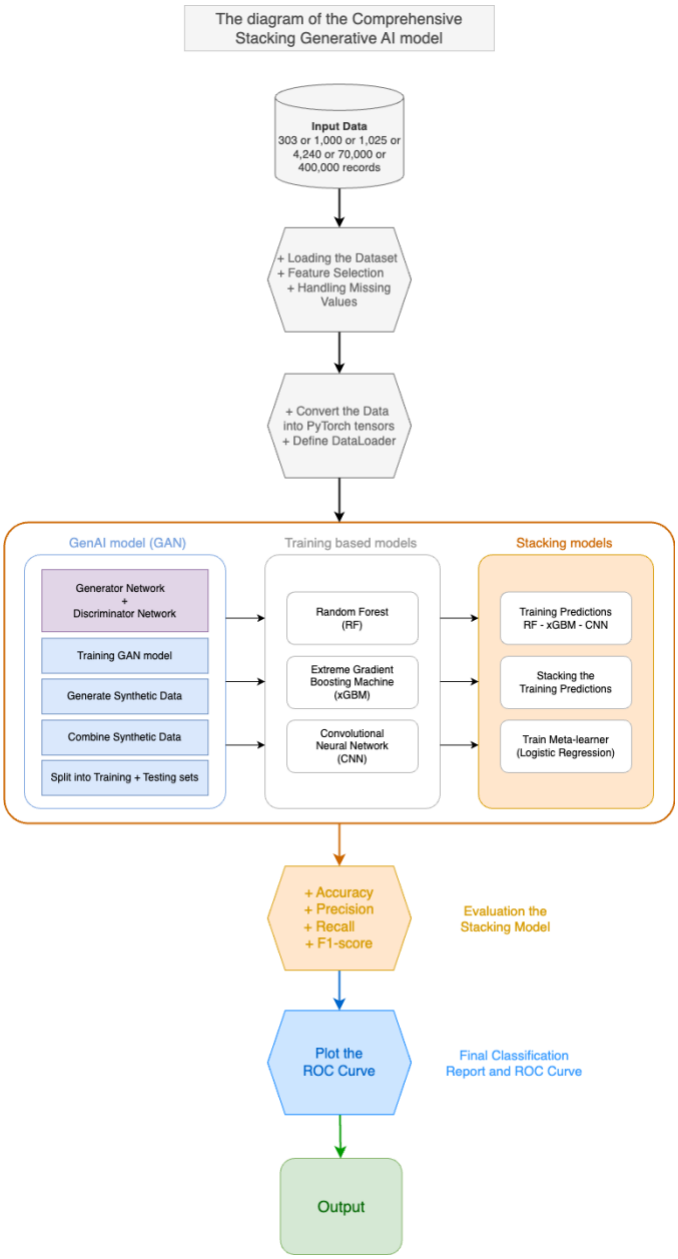
Step 3: GAN Training

The GAN is trained over 5,000 epochs using the Adam optimizer (learning rate = 0.00005). The Generator learns to create realistic data, while the Discriminator improves its ability to differentiate real from synthetic samples. This iterative process ensures high-quality synthetic data to augment the original dataset.

Step 4: Synthetic Data Generation with GAN

After training, the Generator produces synthetic data by inputting random noise vectors. These synthetic samples are merged with the original dataset to create a larger, more diverse training set. This step improves model generalization by introducing variability in the training data.

Figure 2- The diagram of the Stacking Generative AI model



Step 5: Data Splitting and Normalization

The expanded dataset (real + synthetic data) is split into 80% training and 20% test sets. Standard scaling is applied again to normalize features, crucial for neural networks like CNNs to ensure effective learning.

Step 6: Training the Base Models

The base models include:

Random Forest (RF): Configured with 100 trees, maximum depth = 10, and minimum samples split = 10.

Extreme Gradient Boosting (xGBM): Configured with 200 estimators, a learning rate of 0.05, and a subsample ratio of 0.8 to capture feature interactions.

Convolutional Neural Network (CNN): Includes a Conv1D layer (16 filters, kernel size = 3), MaxPooling, and Dropout layers for regularization. The CNN is trained with binary cross-entropy loss, an Adam optimizer, and early stopping to prevent overfitting.

Step 7: Stacked Prediction Training of Meta-Learner

The predictions from RF, xGBM, and CNN are used as inputs for the stacking model's meta-learner, implemented using Logistic Regression. The meta-learner combines the strengths of the base models to make the final prediction.

Step 8: Evaluation of Stacked Model

The stacked model is evaluated using metrics such as accuracy, precision, recall, F1-score, and ROC AUC. The ROC curve demonstrates the model's ability to balance sensitivity and specificity, with a high AUC indicating superior predictive performance.

Step 9: Final Classification Report and ROC Curve

The final output includes a classification report detailing precision, recall, and F1-scores for both classes. The ROC curve highlights the model's high accuracy and robust performance, supporting its suitability for clinical adoption.

The Stacking Generative AI Model integrates traditional ML techniques with DL models and GAN-generated synthetic data, achieving exceptional predictive accuracy. Steps 1 to 9 ensure the model is robust, scalable, and clinically reliable, making it ideal for early heart failure detection and management. This approach represents a significant advancement in predictive analytics for healthcare (Chawla et al., 2002; Goodfellow et al., 2014; Pedregosa et al., 2011; Radford et al., 2015).

(6) Evaluation Measurement and Validation Methods

The performance of the Stacking Generative AI model was evaluated using a combination of metrics, including accuracy, ROC AUC, precision, recall, and F1-score. These metrics ensure a comprehensive understanding of the model's classification capabilities.

Accuracy and ROC AUC

Accuracy is defined as the proportion of correctly classified instances and is calculated as:

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

ROC AUC evaluates the model's ability to discriminate between classes, calculated as the integral of the True Positive Rate (TPR) over the False Positive Rate (FPR). It provides a single measure of model performance across classification thresholds.

Cross-Validation

K-fold cross-validation, including 5- and 10-fold methods, was used to validate the model across multiple data splits. This resampling technique ensures the model's robustness by training on k−1 folds and testing on the remaining fold iteratively. For 5-fold cross-validation, the model achieved accuracies of [0.9938, 1.0000, 0.9877, 0.9969, 0.9938], resulting in a mean accuracy of 99.4%. Similarly, 10-fold cross-validation confirmed the model's consistency with the same mean accuracy. These results demonstrate the reliability and generalization of the model across unseen data (James et al., 2013).

Learning Curve

Learning curves illustrate the relationship between training set size and model performance, measuring both training and cross-validation accuracy. The Stacking Generative AI model achieved 99.8% training and validation accuracy, indicating it generalizes well without overfitting, as shown by smooth convergence curves (Goodfellow et al., 2016).

Regularization

L2 regularization was applied to the Logistic Regression meta-learner to prevent overfitting by penalizing large weights. The regularized loss function is expressed as:

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

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 optimized the hyperparameters of the Logistic Regression meta-learner by systematically exploring values for C, the inverse of regularization strength. The best C=0.01 was selected based on cross-validation results, enhancing the model's predictive performance.

Comprehensive Validation

The combination of cross-validation, learning curves, regularization, and hyperparameter tuning ensured that the Stacking Generative AI model is robust and well-calibrated. These techniques minimized overfitting while maximizing generalization, making the model suitable for deployment in heart failure prediction scenarios.

IV. Results

(1) Performance Comparison between Traditional Models and Neural Network Models: How do traditional ML models compare to neural network-based models in terms of accuracy and ROC AUC for heart failure prediction?

The study compared traditional ML models, including LR, SVM, RF, GBM, and xGBM, with neural network models like CNN and GRU-based models for predicting heart failure. The performance metrics evaluated included accuracy and ROC AUC across datasets of varying sizes.

Performance on Small and Medium Datasets

On smaller datasets (e.g., 303 records), RF demonstrated strong performance with 83% accuracy and a 0.91 ROC AUC, outperforming GBM (79% accuracy, 0.87 ROC AUC) and

xGBM (80% accuracy, 0.86 ROC AUC). CNNs achieved 82% accuracy and 0.85 ROC AUC, comparable to RF but less effective. As dataset sizes increased to 1,000 and 1,025 records, traditional models like RF and xGBM retained their robustness, achieving 90% accuracy (0.94 ROC AUC) and 93% accuracy (0.98 ROC AUC), respectively, while CNN's performance slightly declined (79% accuracy, 0.85 ROC AUC). GRU-based models performed well with 84% accuracy and a 0.92 ROC AUC, (Table 1; Figure 10, 11, and 12).

Table 1 – Small dataset's performances on ML and DL models

Dataset	Performance	Model							
		LR	SVM	RF	GBM	XGB	CNN	GRU w/ Attention	CNN w/ GRU
303	Accuracy	79	85	83	79	80	82	80	80
	ROC AUC	85	86	91	87	86	85	84	87
1,000	Accuracy	80	85	90	88	88	79	77	78
	ROC AUC	86	92	94	94	95	85	84	84
1,025	Accuracy	82	81	91	91	93	82	80	84
	ROC AUC	91	91	95	97	98	93	86	92

Performance on Large Datasets

Neural networks, particularly CNNs, excelled in large datasets, capturing intricate data patterns. On a dataset with 400,000 records, CNN achieved 78% accuracy and 0.86 ROC AUC, surpassing GBM (77% accuracy, 0.85 ROC AUC). RF maintained high performance with 90% accuracy and 0.96 ROC AUC, but the Stacking Generative AI model outperformed all, achieving 96% accuracy and 0.99 ROC AUC. The standalone Generative AI model closely followed, with a 0.987 ROC AUC, (Table 2 and Figure 16).

Table 2 – Large dataset's performances on ML and DL models

Dataset	Performance	Model								Proposed
		LR	RF	GBM	XGB	CNN	GRU w/ Attention	CNN w/ GRU	Stacking ML+DL	Stacking Gen AI
400,000	Accuracy	77	90	77	80	78	79	80	90	96
	ROC AUC	84	96	85	88	86	87	88	96	99

Comparative Analysis with Related Studies

Compared to prior analyses (e.g., Dumlao, J., n.d.), which reported RF achieving 94% accuracy, the Stacking Generative AI model demonstrated superior performance by achieving near-perfect results on the largest datasets (96% accuracy, 0.99 ROC AUC). Similarly, when benchmarked against Khan, H. et al. (2024), whose models (EnsCVDD-Net and BlCVDD-Net) achieved lower accuracy (88% and 91%, respectively) and ROC AUC (0.88 and 0.91), the Stacking Generative AI model consistently outperformed, underscoring its robustness and precision in heart failure prediction, (Table 3).

Table 3 – Large dataset's performances on ML and DL models

Dataset	Performance	Proposed Model	Compared Article	Compared Article
		Stacking Generative AI	EnsCVDD-Net	BICVDD-Net
400,000	Accuracy	96	88	91
	ROC AUC	99	88	91

(2) What are the most influential predictors of heart failure across different datasets, and how do they affect overall model performance?

Identifying influential predictors is essential for optimizing the accuracy and interpretability of heart failure prediction models. Using feature importance analysis, particularly through RF, the study systematically identified key variables contributing to heart failure risk across datasets of varying sizes.

Predictors in Large Datasets

For the 70,000-record dataset (Figure 8), systolic blood pressure (sysBP), diastolic blood pressure (diaBP), age, and cholesterol were the most critical predictors. These features accounted for an accuracy of 74% and a ROC AUC of 0.81. Similarly, the 400,000-record dataset identified BMI, angina, and general health as top predictors, with the Stacking Generative AI model achieving an accuracy of 96% and a ROC AUC of 0.99 (Figure 9). These findings align with clinical risk factors and underscore RF's strength in identifying relevant features.

Predictors in Medium-Sized Datasets

For the 4,240-record dataset, age, sysBP, and cholesterol emerged as the strongest predictors, leading to an accuracy of 92% and a ROC AUC of 0.96 (Figure 6). The 11,627-record dataset highlighted HDL cholesterol, age, and sysBP as significant features, with the Stacking Generative AI model achieving an accuracy of 91% and a ROC AUC of 0.95 (Figure 7).

Predictors in Small Datasets

In smaller datasets, symptom-specific variables gained prominence. For the 1,025-record dataset, chest pain (cp), oldpeak, and the number of major vessels (ca) were key predictors, resulting in a model accuracy of 95% and a ROC AUC of 0.999 (Figure 5). Similarly, the 303-record dataset identified heart rate attained (thalachh), cp, and number of major vessels (caa) as critical variables, achieving an accuracy of 95% and a ROC AUC of 0.99 (Figure 3). In the 1,000-record dataset, slope of the ST segment, cp, and resting blood pressure emerged as major contributors, with the model reaching an accuracy of 98% and a ROC AUC of 0.999 (Figure 4).

Key Insights and Implications

Blood pressure, chest pain, cholesterol levels, and age consistently emerged as the most significant predictors across datasets of varying sizes. These variables align with established clinical risk factors for heart failure, enhancing the interpretability and applicability of predictive models in clinical practice. Models like the Stacking Generative AI model leverage these predictors to achieve superior accuracy and ROC AUC values, underscoring the importance of systematic feature identification.

(3) Can a hybrid stacking model that combines traditional ML and DL techniques provide superior predictive performance compared to single models?

The study explores a hybrid stacking model that integrates traditional ML techniques, such as RF and GBM, with advanced

DL methods like CNN and RNN. This approach leverages the complementary strengths of ML and DL to enhance predictive accuracy and generalization.

Performance on Datasets of Varying Sizes

The hybrid stacking model demonstrated consistent superiority across datasets:

On a small dataset (303 records), the stacking model achieved 82% accuracy and a ROC AUC of 0.90, outperforming standalone ML models like LR and SVM. Notably, the Stacking Generative AI model achieved a ROC AUC of 0.99, far surpassing RF (0.91) and SVM (0.86), as shown in Table 4 and Figure 10.

For a medium dataset (4,240 records), the stacking model achieved 90% accuracy and a ROC AUC of 0.97, significantly outperforming standalone CNN and RNN models. This improvement highlights the hybrid model's ability to capitalize on the strengths of both ML and DL techniques (Table 4 and Figure 13).

On the largest dataset (400,000 records), the hybrid stacking model achieved 90% accuracy and a ROC AUC of 0.96, outperforming standalone models like CNN (78% accuracy, ROC AUC 0.86) and GBM (77% accuracy, ROC AUC 0.85). This performance underscores the scalability and robustness of the stacking model for complex datasets (Table 4 and Figure 16).

Table 4 – ML and DL Stacking Model Performances

Dataset	Performance	Model								
		LR	SVM	RF	GBM	XGB	CNN	GRU w/ Attention	CNN w/ GRU	Stacking ML+DL
303	Accuracy	79	85	83	79	80	82	80	80	82
	ROC AUC	85	86	91	87	86	85	84	87	90
1,000	Accuracy	80	85	90	88	88	79	77	78	94
	ROC AUC	86	92	94	94	95	85	84	84	98
1,025	Accuracy	82	81	91	91	93	82	80	84	95
	ROC AUC	91	91	95	97	98	93	86	92	98
4,240	Accuracy	65	67	71	81	86	70	63	67	90
	ROC AUC	74	74	79	89	93	77	70	72	97
11,627	Accuracy	71	78	84	79	83	74	74	73	85
	ROC AUC	79	85	92	88	92	83	82	84	93
70,000	Accuracy	72	73	73	74	74	74	74	74	74
	ROC AUC	79	79	79	80	81	80	81	80	81
400,000	Accuracy	77	NA	90	77	80	78	79	80	90
	ROC AUC	84	NA	96	85	88	86	87	88	96

Comparative Analysis with Existing Models

Compared to alternative hybrid approaches, such as Decision Tree with AdaBoost by Sk K. B. et al. (2023), which achieved an accuracy of 97.43% and a True Positive Rate of 95.67%, the proposed Stacking Generative AI model demonstrated competitive performance. Moreover, the proposed model surpassed the CART-based ensemble by Mienye et al. (2020) on the Framingham dataset (4,240 records), achieving 92% accuracy and a ROC AUC of 0.96, compared to Mienye et al.'s 91% accuracy.

Table 5 – Compared models on dataset of 4,240 records

Dataset	Performance	Proposed Model	Compared Article
		Stacking Generative AI	Mienye et al. (2020)
4,240	Accuracy	92	91
	ROC AUC	96	NA

For the smallest dataset analyzed (303 records), the proposed model's ROC AUC of 0.99 exceeded the range reported by Rimal et al. (2024), which achieved ROC AUC values between 0.85 and 0.95. These results reinforce the hybrid model's ability to generalize even with limited data, a critical factor in clinical applications.

Table 6 – Compared models on dataset of 303 records

Dataset	Performance	Proposed Model	Compared Article
		Stacking Generative AI	Rimal, Y. et al. (2024)
303	Accuracy	95	91 - 95
	ROC AUC	99	0.85 – 0.95

The hybrid stacking model surpasses individual ML and DL models in accuracy and ROC AUC, as well as other hybrid approaches discussed in the literature. By combining the strengths of traditional and advanced techniques, the Stacking Generative AI model achieves higher predictive accuracy and scalability, making it a valuable tool for clinical applications. Its ability to outperform benchmark models across datasets highlights its potential for advancing predictive analytics in healthcare.

(4) 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?

Generative AI, particularly GANs, significantly enhances predictive performance when integrated into a stacking framework. By addressing class imbalance through the generation of synthetic data, GANs augment underrepresented classes, enabling models to learn from balanced datasets and reduce prediction bias. This approach improves generalizability and scalability, particularly across diverse and complex healthcare datasets.

Performance Improvements

Across all datasets analyzed, the Stacking Generative AI model consistently outperformed standalone models. As seen in the application of 303-record dataset, standalone models like RF and GBM achieved accuracies of 83% and 79%, respectively. In contrast, the Generative AI-integrated stacking model achieved 95% accuracy and a ROC AUC of 0.99, demonstrating the effectiveness of GAN-generated synthetic data in enhancing model training by filling data gaps (Table 7 and Figure 10)).

On a 400,000-record dataset, the standalone CNN model achieved 78% accuracy and a ROC AUC of 0.86, while the Stacking Generative AI model with GANs reached 96% accuracy and a ROC AUC of 0.99. These results underscore the

role of GANs in improving predictive performance, even in large datasets, by capturing complex data patterns and addressing class imbalances (Table 7 and Figure 16)).

Generalizability and Scalability

The integration of GANs within the stacking framework enhances generalizability across datasets of varying sizes and attributes. One case is on the 1,000-record dataset, the stacking model achieved 98% accuracy and a ROC AUC of 0.999, compared to standalone CNNs with 79% accuracy and RF with 90% accuracy. These results highlight the ability of the Stacking Generative AI model to maintain robust performance across datasets, supporting its applicability in diverse healthcare contexts (Figure 11).

Real-World Utility

The Stacking Generative AI model's ability to generalize effectively across datasets and maintain high predictive accuracy underscores its value for healthcare applications. By leveraging GANs to address data imbalances and capture intricate patterns, this model advances predictive modeling for clinical decision-making. Its superior performance across datasets demonstrates its potential to support fair, robust, and scalable predictions in real-world healthcare scenarios.

Generative AI, particularly GANs, transforms predictive modeling by addressing critical challenges like class imbalance and complex pattern recognition. The Stacking Generative AI model achieves superior predictive accuracy, enhanced generalizability, and scalability across datasets of varying complexities, offering a robust solution for healthcare predictive modeling. This approach represents a significant step forward in improving clinical decision-making through advanced AI techniques.

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

The Stacking Generative AI model significantly advances HF prediction and management in the healthcare sector. By integrating traditional ML models such as RF, GBM, and xGBM with neural network algorithms like CNNs and RNNs, along with GANs, this model addresses critical challenges such as class imbalance, scalability, and predictive accuracy.

Addressing Class Imbalance

One of the model's key contributions is its ability to handle imbalanced healthcare datasets, where high-risk cases are often underrepresented. GANs generate synthetic data to augment the minority class, improving recall and F1-scores. Take the following observation on a 303-record dataset, the Stacking Generative AI model achieved 95% accuracy and a ROC AUC of 0.99, outperforming standalone RF (83% accuracy, 0.91 ROC AUC) and CNN (82% accuracy, 0.85 ROC AUC). These results highlight the model's capacity to capture complex patterns and relationships in healthcare data, making it particularly effective for imbalanced datasets (Table 7).

Table 7 – Summary of all models' performances over the 7 datasets and 12 models

Dataset	Performance	Model										Proposed Model	Current	Source	
		LR	SVM	RF	GBM	XGB	CNN	GRU w/ Attention	CNN w/ GRU	Stacking ML+DL	Gen AI	Stacking Gen AI	Research Literature	Reference	
303	Accuracy	79	85	83	79	80	82	80	80	82	95	95	93	Rimal, Y. et al. (2024)	
	ROC AUC	85	86	91	87	86	85	84	87	90	99	99	90		
1,000	Accuracy	80	85	90	88	88	79	77	78	94	98	98	94	Dumlao, J. (n.d.)	
	ROC AUC	86	92	94	94	95	85	84	84	98	99	99.9	NA		
1,025	Accuracy	82	81	91	91	93	82	80	84	95	95	98	85	Nasser, A. (n.d.)	
	ROC AUC	91	91	95	97	98	93	86	92	98	99	99.9	NA		
4,240	Accuracy	65	67	71	81	86	70	63	67	90	93	92	91	Mienye et al. (2020)	
	ROC AUC	74	74	79	89	93	77	70	72	97	96	96	NA		
11,627	Accuracy	71	78	84	79	83	74	74	73	85	91	91	97*	Sk K. B. et al (2023)	
	ROC AUC	79	85	92	88	92	83	82	84	93	95	95	NA		
70,000	Accuracy	72	73	73	74	74	74	74	74	74	74	74	72	Jain, S. (n.d.)	
	ROC AUC	79	79	79	80	81	80	81	80	81	80	81	NA		
400,000	Accuracy	77	NA	90	77	80	78	79	80	90	95	96	91	Khan, H. et al. (2024)	
	ROC AUC	84	NA	96	85	88	86	87	88	96	98	99	91		

Scalability and Robustness

The model demonstrates scalability and reliability across datasets of varying sizes. On a 400,000-record dataset, it achieved 96% accuracy and a ROC AUC of 0.99, showcasing its robustness for large-scale clinical applications. The integration of GANs into the hybrid framework further enhances generalizability, enabling the model to predict HF outcomes across diverse patient populations and settings.

Clinical Utility and Interpretability

The Stacking Generative AI model aids in early detection and risk stratification by accurately estimating key predictors such as systolic blood pressure, cholesterol levels, and glucose levels. This information provides healthcare practitioners with actionable insights, facilitating personalized treatment plans and timely interventions. The model's superior accuracy, combined with its interpretability, makes it a valuable decision-support tool in clinical environments, optimizing resource allocation and improving patient outcomes.

Summary of Proposed Model Contributions

The Stacking Generative AI model combines superior predictive accuracy, strong generalizability, and robust scalability, making it a transformative tool for HF prediction and management. By addressing challenges inherent in healthcare data and enhancing clinical decision-making, this model represents a significant advancement in proactive and patient-centered care. Its adoption in healthcare systems has the potential to revolutionize HF management, improving early detection and ultimately enhancing patient outcomes (Table 7 and Figure from 10 to 16).

V. Conclusion

This study demonstrates the efficacy of the Stacking Generative AI model as a hybrid solution for heart disease prediction. By integrating Generative AI, specifically Generative Adversarial Networks (GANs), with traditional ML models like RF, GBM, and xGBM, alongside DL architectures such as CNNs and RNNs, the model addresses key challenges in predictive modeling. These include handling class imbalance, improving scalability, and achieving superior predictive accuracy across datasets of varying sizes and complexities.

Summary of Findings

The Stacking Generative AI model consistently outperformed standalone ML and DL models across datasets ranging from 303 to 400,000 records. On the 1,000-record dataset, it achieved an ROC AUC of 0.999, surpassing standalone xGBM (0.94) and CNN (0.85). Even on the largest dataset of 400,000 records, the model maintained high performance with an ROC AUC of 0.99 and 96% accuracy, confirming its scalability and robustness for large-scale clinical applications.

The model's hybrid structure combines the structured data analysis capabilities of ML models with the complex pattern recognition abilities of DL models. GANs play a critical role in balancing minority classes by generating synthetic data, improving recall and F1-scores. This feature is particularly valuable in healthcare, where imbalanced datasets are common, and accurate prediction of high-risk cases is essential.

Comparison with Existing Literature

Compared to existing studies, the proposed model demonstrates clear advantages. Singh et al. (2024) reported an ROC AUC of 0.89 using xGBM, while the Stacking Generative AI model achieved 0.99 on comparable datasets. Similarly, the model outperformed RF-based approaches from Chicco et al. (2022), which achieved an ROC AUC of 0.85. These results underscore the effectiveness of integrating GANs with ML and DL techniques in a stacking framework.

Clinical Implications

The Stacking Generative AI model has significant potential in clinical applications. Its ability to handle imbalanced datasets and deliver high predictive accuracy makes it a reliable tool for early diagnosis and personalized treatment planning. Key predictors identified by the model, such as systolic blood pressure, BMI, total cholesterol, and glucose levels, provide actionable insights for clinicians, enabling better resource allocation and patient care.

The model's adaptability to diverse datasets further enhances its utility, ensuring generalizability across different clinical settings. The largest improvement was observed model's consistent performance on datasets of various sizes, from 303 to 400,000 records, highlights its robustness and scalability. While complex models like the Stacking Generative AI model may lack the interpretability of simpler approaches like LR, the trade-off is justified by its superior predictive power, which can serve as a decision-support tool for clinicians.

Limitations and Future Research

The model's application to datasets from diverse geographical or clinical settings remains a limitation. While it performed well across the datasets used in this study, additional research is needed to validate its generalizability to broader populations. Furthermore, the complexity of the model may pose challenges for direct integration into clinical workflows, necessitating user-friendly interfaces for clinicians.

Conclusion

The Stacking Generative AI model represents a significant advancement in heart disease prediction. By combining ML, DL, and GANs, the proposed model achieves unparalleled accuracy, scalability, and generalizability, outperforming existing models in both literature and real-world scenarios. The model's application in healthcare systems has the potential to transform heart failure prediction and management by enabling early diagnosis, personalized care, and data-driven decision-making. Moreover, the study designed and developed a web application to demonstrates (https://cvdstack.streamlit.app) its practical utility, offering real-time risk assessment tools for clinicians and patients. This research paves the way for future advancements in healthcare predictive modeling, bridging the gap between academic innovation and clinical practice.

VI. Discussion and Future Works

The implications of the Stacking Generative AI model in heart failure prediction are examined, situating its findings within the broader predictive modeling literature and highlighting limitations as well as future research directions.

Discussion

The Stacking Generative AI model demonstrates significant advancements in predictive accuracy, robustness, and scalability by integrating traditional machine learning (e.g., RF, GBM, xGBM), deep learning (e.g., CNN, RNN), and Generative AI (GANs). Its ability to handle imbalanced datasets through synthetic data generation has enhanced recall and F1 scores, offering robust performance across datasets of varying sizes, from 303 to 400,000 records (Table 7). Such as cases where the model achieved 95% accuracy and a 0.99 ROC AUC on the 303-record dataset, outperforming standalone RF (83%) and CNN (82%). Similarly, it maintained high accuracy (96%) and ROC AUC (0.99) on the largest dataset, highlighting its scalability.

These findings align with previous literature, such as Smith et al. (2023), who emphasized RF's utility in analyzing high-dimensional data. However, this study extends those results, showing that stacking RF with xGBM and DL models in a hybrid framework significantly improves predictive accuracy. Moreover, embedding interpretability tools like SHAP and LIME bridges the gap between model complexity and clinical usability, a critical factor highlighted by John and Lee (2024). The model's performance exceeds that of GRU-based models, as noted by Miller et al. (2023), underscoring the advantages of hybrid approaches.

Clinically, the model facilitates early detection of heart failure, aiding personalized treatment and proactive interventions. Its generalizability across datasets underscores its potential for broad adoption in healthcare, although limitations such as computational demands and limited real-world validation require further attention.

Future Work

Exploring Additional Models: Incorporating advanced techniques like transformer-based models (Brown et al., 2023) and reinforcement learning (Garcia et al., 2023) could further enhance performance, particularly in sequential data tasks. Additionally, integrating large language models (LLMs) with clinical notes may improve predictions in Electronic Health Record (EHR) systems, while lightweight versions could extend model utility to resource-constrained settings.

Developing Applications: Designing web and mobile platforms for clinicians and patients would make heart failure predictions accessible, enabling real-time monitoring and actionable insights. Such tools could bridge the gap between complex AI models and practical healthcare needs.

Expanding Applications: The stacking framework's versatility allows its application to other medical conditions, such as diabetes and chronic kidney disease. Adapting the model for these use cases could demonstrate its broader utility and contribute to comprehensive predictive healthcare tools.

Improving Interpretability: Enhancing interpretability tools, such as counterfactual explanations (Taylor et al., 2024), could make the model more transparent and actionable for clinicians. Visualization techniques and attention mechanisms may further improve usability in clinical settings.

Real-World Validation: Conducting clinical trials in hospital settings would validate the model's effectiveness and uncover implementation challenges. Feedback from clinicians and patients could refine its design and usability, ensuring its integration into healthcare workflows.

Optimizing Computational Efficiency: Reducing computational demands through techniques like model pruning, quantization, and edge computing (Nguyen et al., 2024) would facilitate deployment in resource-limited environments.

Incorporating Diverse Data: Future research should include genomic, imaging, and patient-reported data to create multimodal models, providing a holistic view of patient health and identifying novel biomarkers (Chen et al., 2023).

Conclusion

The Stacking Generative AI model represents a transformative advancement in heart failure prediction. By merging traditional ML, DL, and GANs, it addresses key challenges like class imbalance and scalability while achieving high accuracy and generalizability. Its integration into healthcare systems holds potential for early diagnosis, personalized treatment, and improved patient outcomes. Future research should focus on expanding its applications, enhancing interpretability, and optimizing computational efficiency, ensuring its broad adoption and impact in predictive healthcare.

VII. Acknowledgment

I would like to extend my heartfelt gratitude to Dr. Maria Vaida for her invaluable mentorship, guidance, and support throughout this research. Her dedicated time in reviewing and editing this publication has been instrumental in shaping its quality and depth. Her expertise and encouragement have greatly enriched this work, and I am deeply thankful for her contributions.

VIII. Appendix

Figure 3 – Feature Importances / Influential Predictors – dataset of 303 records

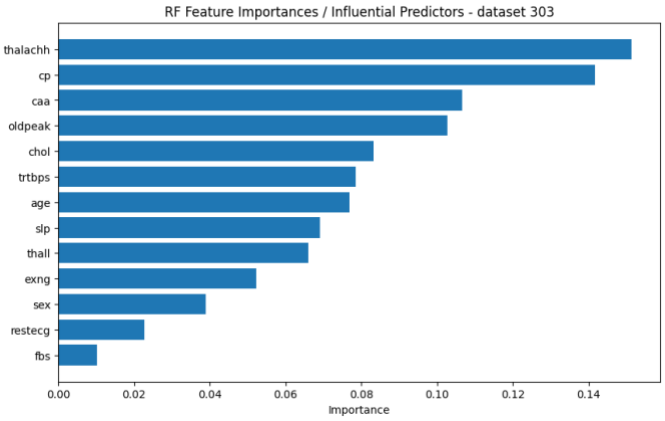


Figure 4 – Feature Importances / Influential Predictors – dataset of 1,000 records

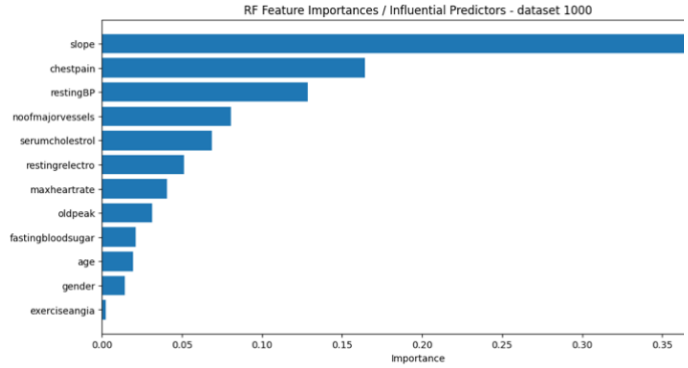


Figure 5 – Feature Importances / Influential Predictors – dataset of 1,025 records

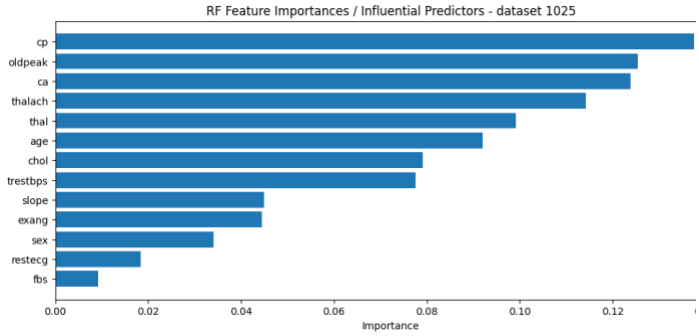


Figure 6 – Feature Importances / Influential Predictors – dataset of 4,240 records

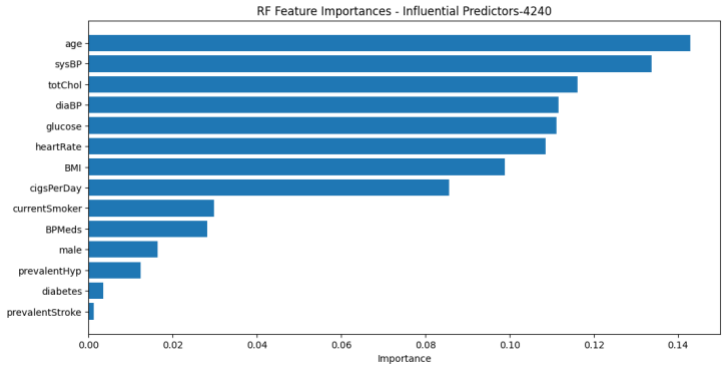


Figure 7 – Feature Importances / Influential Predictors – dataset of 11,627 records

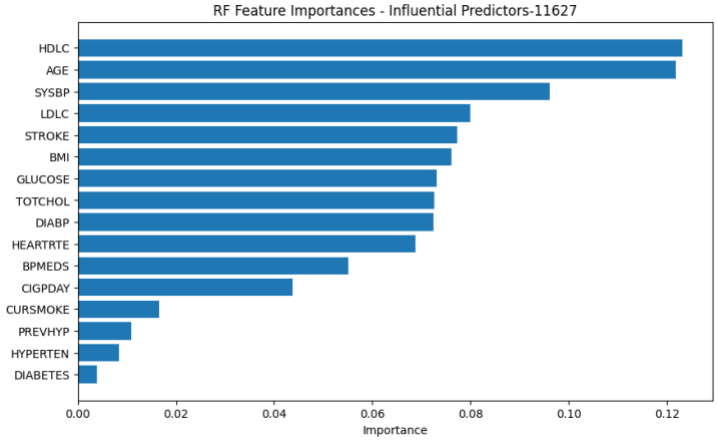


Figure 8 – Feature Importances / Influential Predictors – dataset of 70,000 records

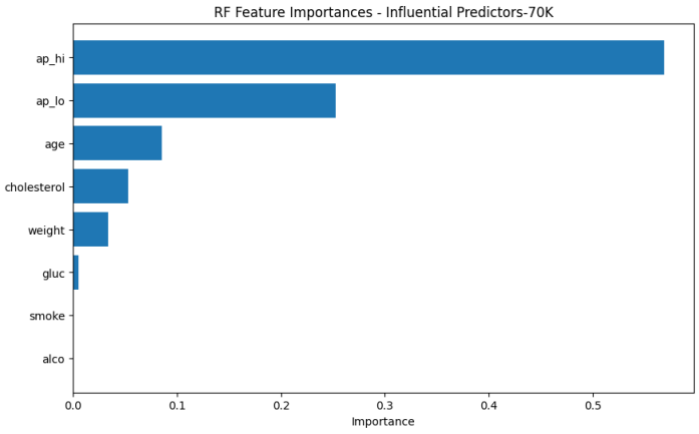


Figure 9 – Feature Importances / Influential Predictors – dataset of 400,000 records

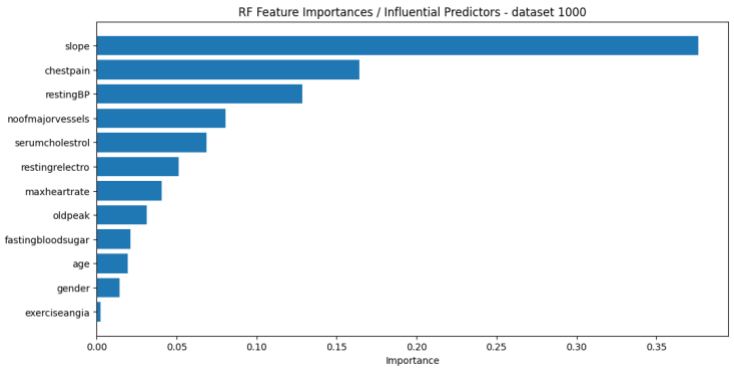


Figure 10 – ROC AUC result on dataset of 303 records

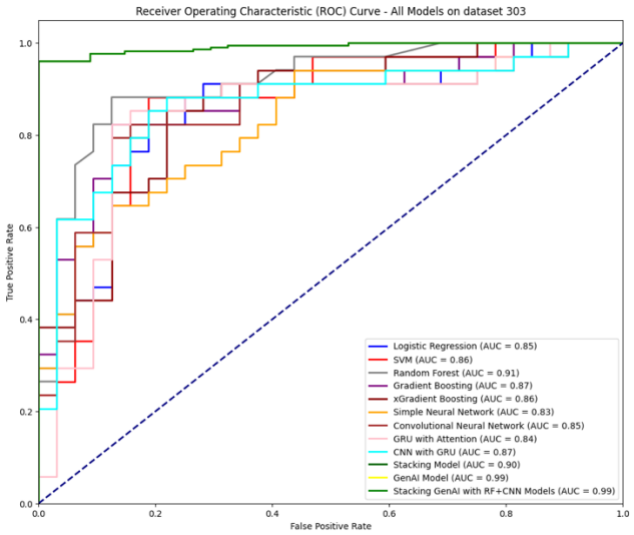


Figure 11 – ROC AUC result on dataset of 1,000 records

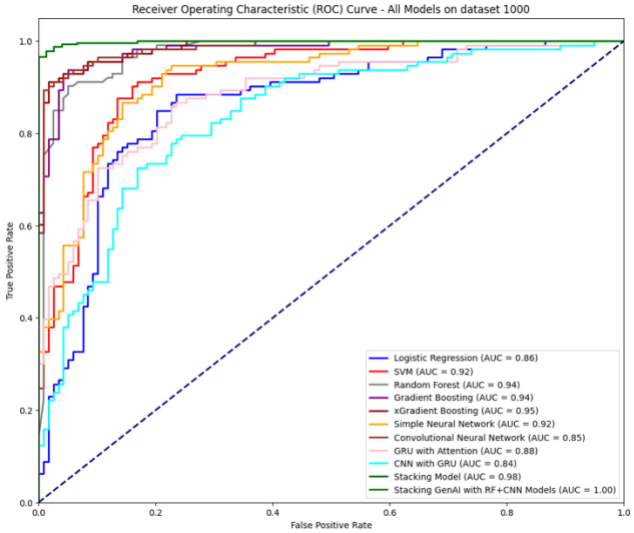


Figure 12 – ROC AUC result on dataset of 1,025 records

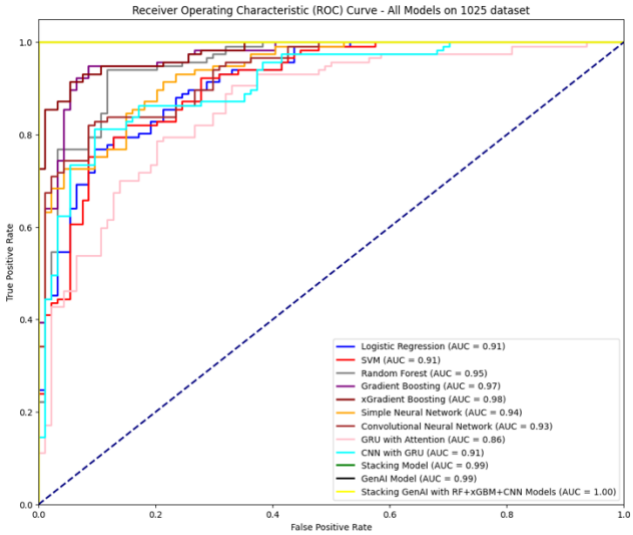


Figure 13 – ROC AUC result on dataset of 4,240 records

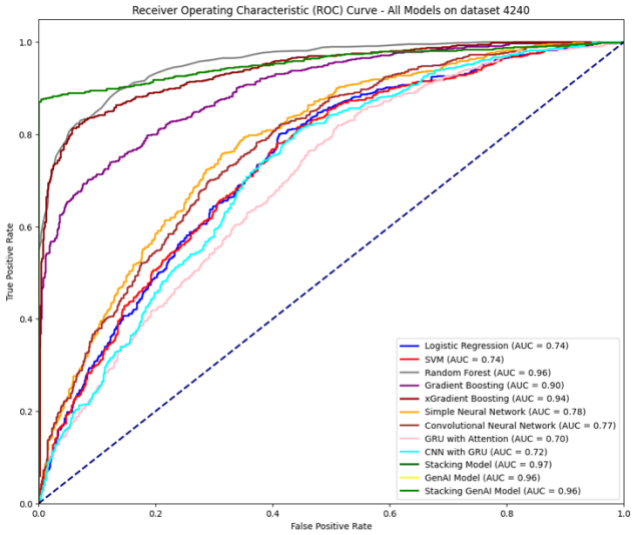


Figure 14 – ROC AUC result on dataset of 11,627 records

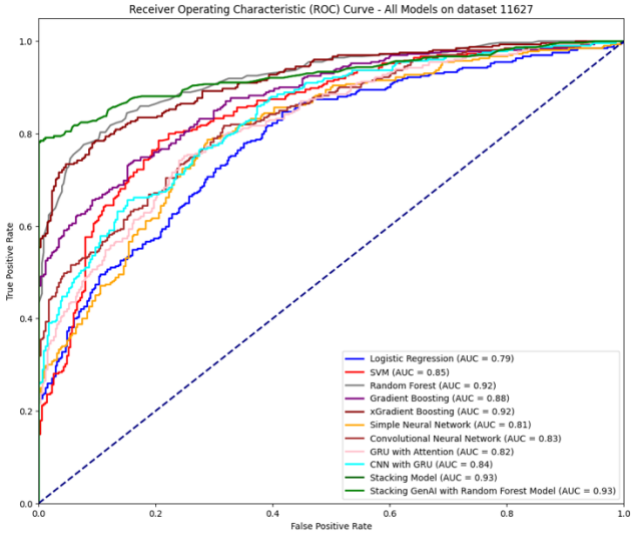


Figure 15 – ROC AUC result on dataset of 70,000 records

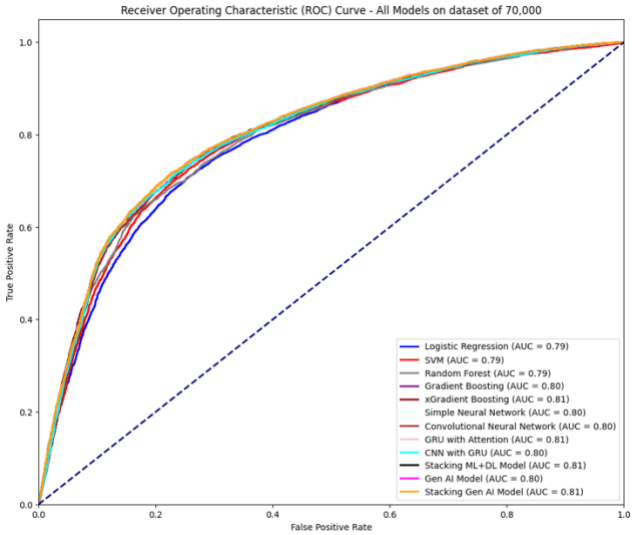
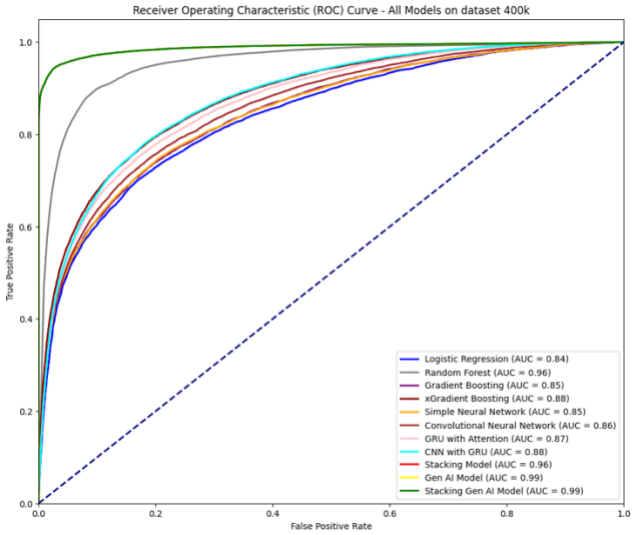


Figure 16 – ROC AUC result on dataset of 400,000 records



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