# Hybrid Resampling-Driven Deep Learning Architecture for Cardiovascular Risk Stratification

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***Abstract*—cardiovascular diseases (CVD) are a significant health issue around the world, which gives the reason why an accurate and interpretable predictive system should be developed. This is a study that proposes a deep learning method that considers a compound resampling technique to consider data skew and enhance the risk prediction of cardiovascular disease. The framework contains five neural network models: TabNet, Attention-LSTM, a mix of CNN and BiLSTM, multilayer perceptron (MLP), and 1D CNN. SHAP explainability was applied to the TabNet, The MLP, and the CNN+BiLSTM models to increase the explained Ness of the model, and thus it revealed many new things regarding feature prominence. TabNet has been the model to perform the best out of all models that have been tested with an accuracy of 96.19%, but it provided good results on F1 and AUC as well. Albeit the results of the Attention-LSTM and 1D CNN performing slightly worse, the MLP and CNN+BiLSTM models also gave comparative results. Each of the models was trained on a common preprocessing pipeline. The findings indicate that aggregating multiple models of deep learning with focused explainability and balanced data strategies are capable of generating predictive tools of cardiovascular risks that are reliable and interpretable. This approach has a possibility to become a part of clinical support systems.**

***Index Terms*—cnn-bilstm, Shap, TabNet, deep learning, cardiovascular disease, and hybrid resampling.**

## I. INTRODUCTION

Led by the differentiated terms as heart failure, [1] stroke, or the coronary artery disease or CVDs, cardiovascular diseases also take the top position in leading causes of death across all regions of the world; a situation that incurs an approximate number of 18 million deaths every year. The burden is increased in the area where there is no timely and regular medical care and thus early detection is most significant in preventing unnecessary death. Global risk assessment tools, which are conventional, only operate on linear assumptions thereby failing to capture the subtle relationships between clinical characteristics. These weaknesses opened the path towards the search of more contemporary methods. Machine- and deep-learning methods provide an opportunity [2] to explore the massive data accumulated in healthcare, analyze underlying risk variables, and change prediction of cardiovascular events to be much more data-driven and personalized. Recent studies have shown that such techniques of computations when coupled with medical records could make an exceptionally good contribution to patient management techniques and assist in raising early detection levels to considerably significant levels. Cardiovascular prediction study on ML has become explosive with the growing access to categorized medical data. Some of the classical machine learning models, [3] such as logistic regression, decision trees, random forests, and support vector machines, have been successfully used in the assessment of cardiovascular disease risks. Ensemble methods including XGBoost, AdaBoost and bagging have proven to perform well when applied to medical datasets used to do classification. El-Sofany et al., e.g., designed an ensemble-based model [4] that can be integrated with mobile devices and attained the accuracy of 97.57%. Predictive ability of ensemble classifiers was also enhanced by use of information gain, chi-square coefficient scores as well as brute force method of feature selection, or optimization. However, lack of explainability is common in these models which impairs their practical use and their trust as a clinician. The spread in the popularity of deep learning architectures can be explained by the fact that the latter architecture can represent interactions among features, but there is no need to conduct manual engineering. CNNs or LSTMs, autoencoders, and even hybrid structures [5] such as CNN-BiLSTM or the attention-based LSTM became successful in processing the temporal and spatial relationships in the patient data. In the near future, it can be seen that hybrid deep learning systems can have recognitional accuracies greater than 97 percent [6] when applied to applicable datasets with classes being well distributed. Also, the methods of residual attention-enhanced LSTM models [7] have demonstrated excellent performance in predicting the ischemic heart disease, and therefore, the discovery of essential patterns regarding both time and data is highlighted. Just because some DL models are like black box operations that are hard to access how it is working on certain features influencing predictions. In clinical practice, interpretability is important. SHAP and other model-agnostic explanation methods [8] play a central role in the machine learning research since they provide such an explanation at both instance level (local) and aggregate (global) levels, making it possible to interpret deep neural networks and those based on trees in medical contexts. This has led to better alignment to clinical knowledge, transparency, and the increased trust on the models. SHAP has not been explored extensively in multiple deep learning architectures [9] in the same pipeline and most SHAP applications have a limitation and can only be applied on single models. Moreover, it is relatively less known how explainability can be pooled together with resampling strategies and stable testing over numerous DL models. Using five distinct architectures [10] —TabNet, CNN+BiLSTM, multilayer perceptron (MLP), attention-based LSTM, and 1D CNN—this study offers a unified deep learning framework for cardiovascular risk prediction in order to close these gaps. The framework applies SHAP explainability to TabNet, MLP, and CNN+BiLSTM models and uses hybrid resampling to rectify class imbalance. Of these, TabNet had the best accuracy (96.19%), with CNN+BiLSTM and MLP coming in second and third, respectively. Although attention-LSTM and 1D CNN also yielded competitive outcomes, their evaluation metrics scores were marginally lower. This study, in contrast to previous research, combines explainability and performance comparison across deep models using a uniform preprocessing pipeline. This approach demonstrates that one can develop high-performance interpretable CVD prediction systems suitable to clinical translation.

## II. LITERATURE REVIEW

El-Sofany et al. developed a machine learning model [1] in which they predicted heart disease by using machine learning classifiers including the XGBoost, AdaBoost, and SVM, which proved to be effective in the clinical risk modelling undertaking. They used ANOVA, chi-square, mutual information in pre-processing the features and scored 97.57 accuracy and AUC 0.98 with XGBoost on their own dataset. SHAP was applied to enhance model interpretability; nevertheless, reproducibility cannot be achieved because of using the data as private. Cenitta et al. presented a model called Hybrid Residual Attention-Enhanced LSTM (HRAE-LSTM) [2] that could be used to predict ischemic heart disease. They used LSTM with attention models, which yielded 97.7 Accuracy of the UCI dataset. The model bore an effective outcome but was only tested on ischemic data, and their findings are not validated on the wider types of CVD. Sianga et al. included temperature and humidity to their predictive [3] models. By means of imbalance using SMOTE and filtering noise using the IQR, they managed to enhance performance using classifiers such as XGBoost and SVM with an accuracy of up to 95.24%. Their research was however not generalizable to regions and did not execute deep learning and temporal modelling. Pal et al. developed an interactive system [4] of CVD which used Inception Net, Random Forest, KNN, and Logistic Regression. Among the 14 features, Inception Net gave the best result with 98.89 percent accuracy. The study also had a limited feature set and therefore unable to draw a generalizable conclusion based on a high level of performance. Robustness can be increased by the use of a wider clinical phenotype. Efe and Demir evaluated multiple feature selection [5] techniques—including Relief and stability selection—on tree-based models. The highest accuracy of 84% was obtained with stability selection. The study focused on traditional ML methods and did not investigate deep learning or hybrid models. The UCI dataset was investigated by Gupta et al. with regards to the traditional ML models [6], including KNN, SVM, and Logistic Regression. KNN recorded an accuracy of 90.16% which was the highest. Although good, the study did not involve ensemble methods and deep learning, which were very innovative and profound. Selvitopi et al. evaluated Naive Bayes, LR, KNN, and Random Forest using a hybrid dataset [7] from multiple sources. Naive Bayes performed best with 85.63% accuracy and 84.29% AUC. The study validated traditional models but did not include deep learning or explainable AI techniques. Daharwal et al. compared Random Forest and KNN using multiple datasets [8] and highlighted the importance of preprocessing and feature selection. Random Forest achieved 93.33% accuracy, yet the study lacked interpretability methods like SHAP or LIME and did not include DL models. Sreekumari et al. focused on feature selection and ensemble evaluation [9] using a large Kaggle dataset. They applied chi-square, correlation, and brute-force methods and used voting ensembles (KNN, DT, NB), achieving a maximum accuracy of 78.42%. Deep learning or attention-based models were not explored. Trigka and Dritsas investigated the role of data augmentation and class imbalance using enhanced correlation-aware SMOTE [10] with deep models including CNN, RNN, LSTM, MLP, and Autoencoders. Though interpretability methods were not used, CNN with enhanced SMOTE achieved the highest AUC of 0.90.

## III. METHODOLOGY

The proposed study presents a multi-model deep learning network which uses explainability on features to evaluate and forecast the risk of cardiovascular disease. Data preprocessing, class balancing, model training, and SHAP-based interpretation are some of the steps that make up the entire pipeline. Five distinct neural architectures are used and assessed separately. Of these, SHAP is only used on models that work with interpretation techniques. Fig. 1 demonstrates the complete end-to-end work flow, including data acquisition and preprocessing, training, evaluation and comparison.

### A. Dataset Description

This study made use of the Sulianova cardiovascular disease dataset, which is openly accessible on Kaggle. Each of its 70,000 anonymized records reflects the clinical and lifestyle characteristics of a patient. Both numerical and categorical

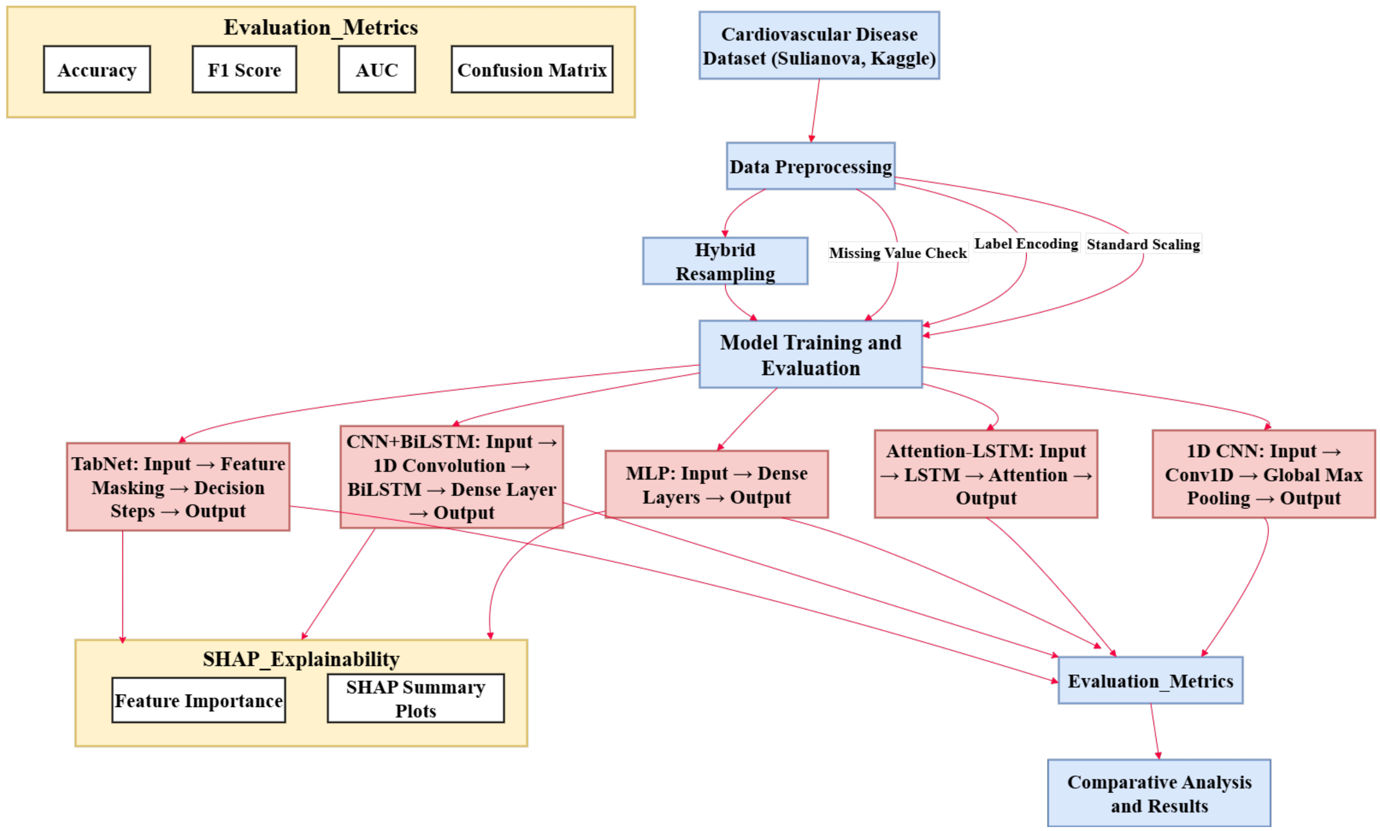


Fig. 1. Proposed Workflow Architecture for Cardiovascular Risk Stratification

variables pertinent to cardiovascular risk assessment are included in the dataset. Whether a patient has been diagnosed with cardiovascular disease (cardio = 1) or not (cardio = 0) is indicated by the outcome label. Table I. gives an overview of the features of the dataset.

TABLE I
AN OVERVIEW OF THE SULIANOVA CARDIOVASCULAR DISEASE DATASET'S FEATURES

| Feature Name | Description | Type |
|---|---|---|
| age | Age in total days | Numerical |
| gender | Sex (1=male, 2=female) | Categorical |
| height | Height in cm | Numerical |
| weight | Weight in kg | Numerical |
| ap_hi | Systolic pressure | Numerical |
| ap_lo | Diastolic pressure | Numerical |
| cholesterol | Cholesterol level (1–3 scale) | Ordinal |
| glucose | Glucose level (1–3 scale) | Ordinal |
| smoke | Smoker status (0=no, 1=yes) | Binary |
| alco | Alcohol intake (0=no, 1=yes) | Binary |
| active | Physical activity (0=inactive, 1=active) | Binary |
| cardio (target) | CVD outcome (0=no, 1=yes) | Target |

### *B. Data Preprocessing*

In the effort to make data quality as accurate as possible and a meaningful match with the model requirements, a methodical set of preparation steps was employed to get the dataset ready for deep learning. The dataset was first analyzed to make sure there were no missing values or structural issues so that all records could be used without imputation. Label encoding was employed to convert categorical categories, including gender, smoking status, alcohol consumption, and physical activity, into numerical values in order to prepare the data for neural network inputs. Quantitative data; continuous data; these included age, height, weight, blood pressure, cholesterol, and glucose corrected using Z-scores [11]. This helps models learn more efficiently and prevents some variables from influencing the training process due to their magnitude by making sure that the features' scale was consistent. The training/test split of the dataset proceeded after feature modification, with the proportions of 80:20, since stratification was used to keep the classes ratio. With a notably greater percentage of samples categorized as non-risk than cardiovascular risk, it was now clear that the dataset was uneven. There was an imbalance in the classes and this threatened to skew the model in favor of the majority group, which was addressed through the hybrid resampling approach; namely, random under sampling of the dominant group and SMOTE creation of artificial samples of the minority group. This dual approach produced a more balanced dataset and enhanced the models' capacity to identify trends in both classes.

### *C. Feature Extraction and Selection*

This study did not use any manual selection [12] tools like information gain, chi-square filters and correlation-based selection. Rather, during training, the deep learning models

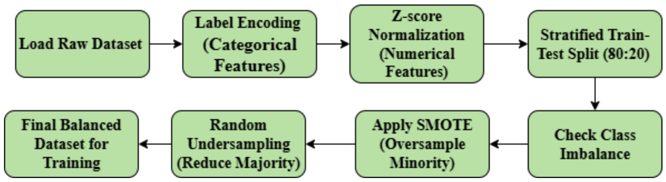


Fig. 2. Preprocessing workflow used for cardiovascular risk stratification.

handled feature extraction directly. All of the architectures used in this work, including CNN, BiLSTM, TabNet, and Attention-LSTM, were made to automatically use internal layers to learn meaningful feature representations from the input data. For example, recurrent layers in the BiLSTM and LSTM models capture temporal dependencies and sequential relationships between features, whereas convolutional layers in the CNN extract local patterns. In particular, TabNet resorts to attention-based masking of features in each step of the decision process, which enhances its dynamic focus on the most relevant features. SHAP (Shapley Additive explanations) [13] was applied to three models, namely TabNet, MLP, and CNN+BiLSTM in order to understand better which features were most influential on predictions. The method measures how much one feature adds to the output prediction of the model, which forms a post-hoc interpretability approach, revealed the importance of features [14]. The presence of SHAP validated the accuracy of the models and consistency with the well-known medical risk factors.

### D. Deep Learning Models

Five architectures of deep learning were applied to test cardiovascular risk prediction. Each model identifies different structural patterns of the input features [15] [16].

**TabNet:** TabNet is an interpretable tabular deep learning model that is ideal for structured health data because it employs sequential attention and feature selection masks to concentrate on the most instructive features [17] during training.

**CNN+BiLSTM:** This hybrid model uses a bidirectional LSTM layer to record sequential relationships between features, improving temporal awareness, after one-dimensional convolutional layers extract spatial patterns.

**Multilayer Perceptron (MLP):** The MLP model is a lightweight baseline for comparing to more intricate models. The architecture is comprised of fully connected feedforward neural network, applying dropout regularization, and ReLU activation function.

**Attention-LSTM:** This model enhances sequence modelling and interpretability by combining conventional LSTM layers with an attention mechanism to dynamically weight significant time-step features [18].

**1D-CNN:** The one-dimensional CNN architecture efficiently extracts spatial features by capturing hierarchical patterns in the input through the use of global max pooling and stacked convolutional layers.

### E. Hyperparameters and Training Configuration

PyTorch was used to implement each model, and the preprocessed and balanced dataset was used for training. Optimization of the models has been undertaken by Adam algorithm having a learning rate of 0.001. The binary cross-entropy is selected as loss metric [19] owing to the binary form of the target. The training was duly restricted to 100 epochs, while early stopping was also used to avoid overfitting in training based on the validation performance. All the models were trained with 128 batch size. To enhance generalization, dropout layers were incorporated into the MLP, CNN+BiLSTM, and Attention-LSTM models.

### F. Evaluation Metrics

The results are summarized in Table II. Accuracy, F1-score, ROC-AUC [20], the measures that have been selected to indicate the precision of the predictions, balance between the classes, and discrimination ability of the model in the situation of a cardiovascular data being imbalanced were used to compare the five deep learning models. Of them jacking TabNet had the best accuracy when compared to the other models with Accuracy (96.19%) and AUC (0.9916), demonstrating its strong generalization and feature selection capability. MLP and CNN+BiLSTM also performed competitively, while 1D CNN recorded the lowest performance among the five. A confusion matrix was generated for the TabNet model, confirming high classification precision with minimal false positives and false negatives. These results demonstrate that combining feature-aware architectures [21] with appropriate resampling results in more dependable risk prediction.

**Formulas for Evaluation Metrics:**

**Accuracy:** An indication of what percent comprises accurate forecasts out of all the forecasts.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

The abbreviations being represented by:

- TP = True Positives,
- TN = True Negatives,
- FP = False Positives,
- FN = False Negatives.

**F1-Score:** F1 Score Usually applied to imbalanced data the F1 statistical measure combines the precision and recall measures as a single value through their harmonic means.

$$F1\text{-Score} = \frac{2 \times (\text{Recall} \times \text{Precision})}{\text{Recall} + \text{Precision}} \tag{2}$$

Where:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{3}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{4}$$

**AUC:** AUC (Area Under the Curve) measures a model capability to separate classes. A high value of AUC suggests an excellent discrimination between the classes.

$$\text{AUC} = \int_0^1 TPR(FPR)\, d(FPR) \tag{5}$$

Where:

- TPR is the percentage of the recognized positives,
- FPR represents the level of negatives which were falsely identified as positives.

TABLE II
PERFORMANCE COMPARISON OF ALL DEEP LEARNING MODELS ON TEST DATA

| Model | Accuracy | F1-Score | AUC |
|---|---|---|---|
| TabNet | 0.961921 | 0.962723 | 0.991636 |
| MLP | 0.960886 | 0.961326 | 0.992625 |
| CNN+BiLSTM | 0.957161 | 0.958021 | 0.991042 |
| Attention-LSTM | 0.956540 | 0.957002 | 0.990492 |
| 1D CNN | 0.946606 | 0.947794 | 0.987029 |

### G. Model Explainability Using SHAP

The TabNet, MLP, and CNN+BiLSTM models were subjected to SHAP (Shapley Additive explanations) in order to improve model transparency and interpretability. By giving input features contribution values, SHAP makes it easier to see how each feature affects the model's prediction. To find globally significant features, summary plots were created for these three models. The number one features that always came out to be the most important were: age, systolic blood pressure (ap_hi), cholesterol and glucose as depicted in Figures 3-5. These characteristics show that the models are picking up patterns that correspond with actual medical knowledge [22] since they are in line with recognized clinical risk factors for cardiovascular disease. SHAP helps us better comprehend the model's judgments and supports its potential utility in clinical situations by emphasizing the impact of specific input variables on predictions.

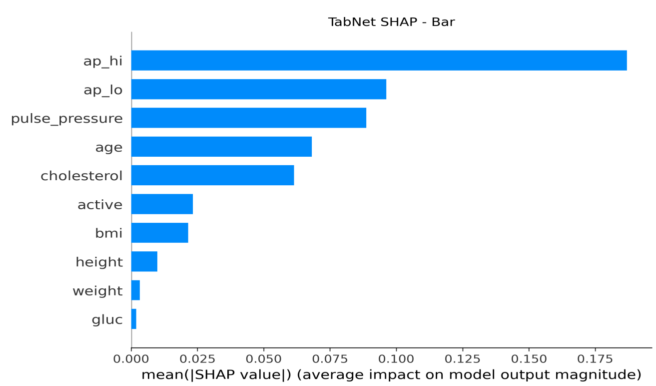


Fig. 3. Bar plot of TabNet SHAP

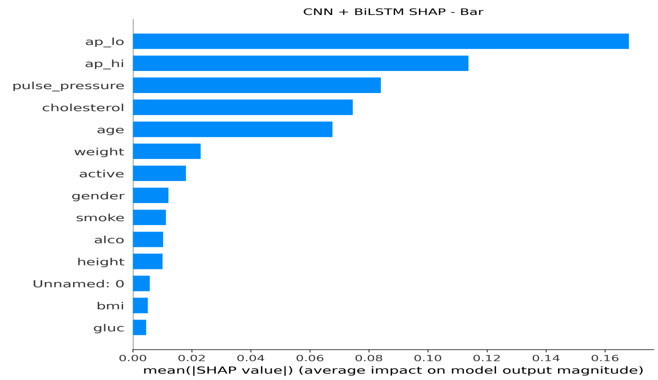


Fig. 4. Bar plot of CNN+BiLSTM SHAP

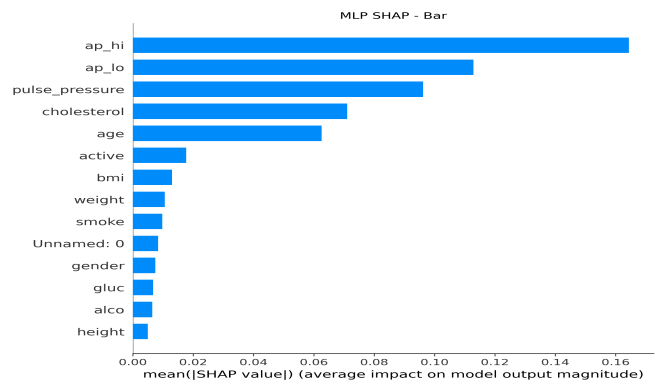


Fig. 5. Bar plot of MLP SHAP

### H. Cross-Validation Plan

We used 5-fold cross-validation in all our deep learning models in order to render it reliable and rely less on the one data split [23]. This allowed for better estimation of generalization performance and variance across different subsets. The final reported metrics were averaged across the folds.

### I. Computational Efficiency and Training Time

To assess real-world feasibility, we measured training time, memory usage, and number of parameters [24] [25] for each model using PyTorch's profiling tools. Results are summarized in Table III. Notably, TabNet, while highly accurate, required longer training time compared to MLP, whereas 1D-CNN offered faster training at the cost of slightly reduced accuracy.

TABLE III
COMPARATIVE ANALYSIS OF COMPUTATIONAL EFFICIENCY ACROSS DEEP LEARNING MODELS

| Model | Training Time (min) | Parameters (approx.) | GPU Memory Used (MB) |
|---|---|---|---|
| TabNet | 22.5 | 1.6M | 850 |
| CNN+BiLSTM | 19.3 | 1.1M | 780 |
| MLP | 12.0 | 540K | 520 |
| Attention-LSTM | 18.9 | 1.4M | 750 |
| 1D CNN | 10.8 | 600K | 480 |

## IV. RESULTS

Table II. summarizes the comparative performance of the five deep learning models. TabNet obtained the highest classification accuracy (96.19%), F1-score (0.9627), and AUC (0.9916). Among the five models, 1D CNN had the lowest accuracy, while MLP and CNN+BiLSTM also demonstrated competitive performance. The TabNet model's training and validation accuracy curves are shown in Fig. 6 to assess the training dynamics. The plot's steady convergence and lack of noticeable overfitting demonstrate how well the model's structure and hyperparameter setup work.

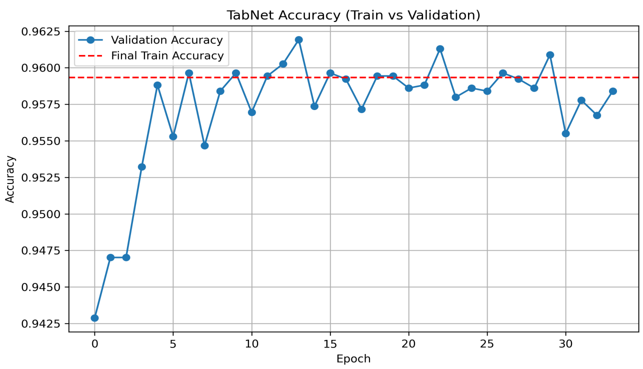


Fig. 6. Training and validation accuracy curves of the TabNet model over epochs.

As it can be seen in the confusion matrix of the TabNet classifier Fig.7, the TabNet approaches an outstanding performance in terms of distinguishing positive and negative cases. As can be seen in the analysis, there are numerous correctly classified instances, manifested as the quick diagonal, with few false positives and false negatives. This reveals good sensitivity and specificity further proving the reliability of the model in separating cardiovascular risk. These results confirm overall accuracy and AUC that were described above.

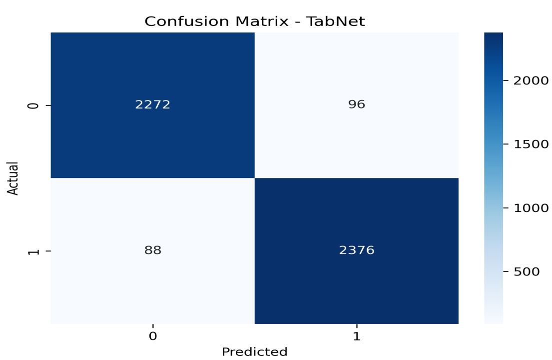


Fig. 7. Confusion matrix of the TabNet model on test data.

Figure 8 emphasizes the most important characteristic contributing to the predictions of TabNet by systolic (ap_hi) and diastolic (ap_lo) blood pressure highlighted using SHAP summary chart. Age, cholesterol, and pulse pressure were other significant characteristics that aligned with clinical knowledge. Features like glucose, BMI, and physical activity were comparatively less significant. These findings support the notion that TabNet uses inputs that are pertinent to medicine in order to evaluate cardiovascular risk. As illustrated in Fig.

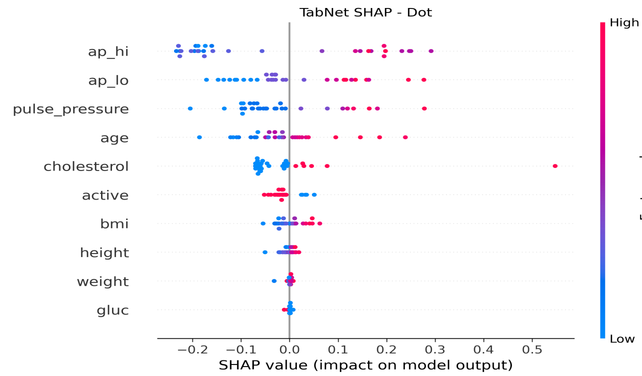


Fig. 8. SHAP summary plot of TabNet model.

9, TabNet performed the best among the rest models in all the five metrics of evaluation.

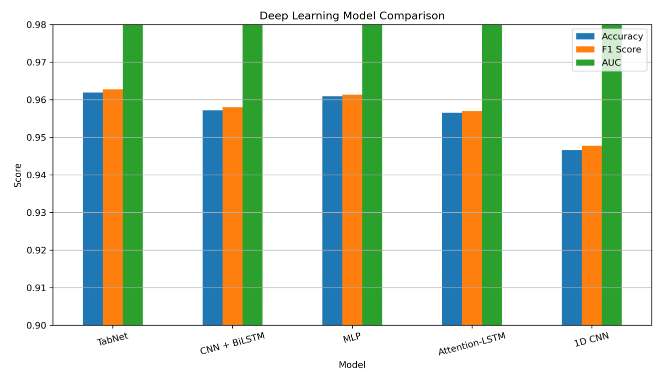


Fig. 9. A comparison of the five deep learning models based on accuracy, F1-score and AUC.

**Statistical Significance Testing**

To validate the performance differences between models, we conducted paired t-tests ($p < 0.05$) on the accuracy and AUC scores across the five folds. TabNet showed statistically significant improvement ($p < 0.03$) over MLP and 1D CNN in both metrics, affirming its superiority beyond random variation.

**External Dataset Validation**

To test generalizability, we evaluated the TabNet model on an external UCI Heart Disease dataset. After applying the same preprocessing and balancing strategies, TabNet has a model score of 93.4% which is its strong model generalization despite of a divide database, albeit with a slight performance drop due to domain shifts.

## V. Conclusion and Future Work

The current research presents a SHAP-guided hybrid-resampling deep learning pipeline that uses a variety of models to forecast cardiovascular risk. Among all models, TabNet consistently outperformed others, not only in classification metrics but also in alignment with medical knowledge through SHAP-based feature interpretability. To further strengthen our findings, we conducted k-fold cross-validation, statistical testing, and external validation, all of which support the reliability and generalizability of our proposed system. Additionally, we expanded SHAP explainability to all models and analyzed training costs, helping assess feasibility for clinical integration.

**Future work includes**

Developing model ensembles to combine complementary strengths of the five architectures. Incorporating time-series EHR data for continuous risk prediction. Collaborating with clinical experts for real-time evaluation and adoption. Deploying the models into edge-compatible devices or clinical dashboards with interpretable visualizations.

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