

Original Research Article

Artificial Intelligence-assisted cardiovascular risk stratification for supporting therapeutic decision-making

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Sent for review: 2 February 2026

Revised accepted: 18 April 2026

Abstract

Purpose: To apply Hybrid Feature Deep Learning (HFEDL) and structured feature-selection framework (Selected Features) model to develop algorithm for enhanced preventive cardiovascular disease risk prediction.

Methods: The HFEDL model is a hybrid feature-engineering and deep-learning method that improves learning dynamics, whereas the structured feature-selection framework is based on statistically significant features to achieve higher classification accuracy. Benchmark datasets have been used to compare various models, including traditional deep learning and the random forest classifier.

Results: The HFEDL model achieved 97.5 % testing accuracy and 0.2 loss, the quickest convergence period (15 epochs), and generalization. The structured feature-selection framework model was also able to achieve 90.8 %, and the model had a steady performance. The models generated significant outcomes that were better in terms of accuracy, training efficiency, and generalization (5/5) when compared to traditional state-of-the-art models; thus, the models may be considered to offer real-time clinical decision support. The predicted risk levels support therapeutic decision-making by guiding pharmacological interventions such as statins, antihypertensive therapy, and patient monitoring strategies.

Conclusion: The HFEDL model has better predictive capability than traditional machine learning and isolated deep learning models, and the feature-selection framework is more interpretable and less complex to calculate because it identifies clinically meaningful variables. Combining feature selection with hybrid deep learning constitutes a trade-off between accuracy, efficiency, and interpretability.

Keywords: Feature Selection, Random Forest Classification, Hybrid Feature Enriched Deep Learning

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Tropical Journal of Pharmaceutical Research is indexed by Scopus, Chemical Abstracts, Embase, Index Copernicus, EBSCO, African Index Medicus, JournalSeek, Directory of Open Access Journals (DOAJ), African Journal Online, Bioline International, Open-J-Gate and Pharmacy Abstracts

INTRODUCTION

The biggest contributor to morbidity and mortality at the world level is cardiovascular diseases (CVDs), and approximately 17.9 million fatalities per year are directly attributed to these conditions, which amount to approximately 32 percent of all deaths globally [1]. These cover a diverse range of disorders, including coronary artery disease,

heart failure, stroke and arrhythmias, which are usually preventable when screened and treated in their early phases. Even with the current innovations in diagnosis and clinical monitoring, the cardiovascular risk remains hard to predict in an effective and timely manner, despite the limited resources or high-throughput clinical environments [2]. The multi-dimensional and heterogeneous data that has become quite

common in the healthcare context is not usually sufficiently granular to be captured by conventional methods, including the Framingham Risk Score and clinician-based assessments [3]. Considering its weaknesses, there is an urgent need for a model that balances accuracy, interpretability, and deployment in determining cardiovascular risk. The rationale for implementing this study was to address key shortcomings of current ML and DL methods, including stability, transparency, and generalizability [4]. The primary objective of this study is to develop an accurate model for cardiovascular disease risk prediction using a hybrid deep learning framework. Secondary objectives include improving interpretability through structured feature selection and evaluating model generalization across clinical datasets. Additionally, the study explores how risk prediction outputs can support therapeutic decision-making in clinical practice [5].

Future prediction modeling and feature selection have become core in enhanced cardiovascular disease (CVD) diagnosis and prognosis. As clinical datasets continue to grow in magnitude and complexity, feature selection is not only enhancing the accuracy of model predictions but also interpretability, something highly sought after in healthcare decision support settings. Several such efforts have been undertaken in the medical field to conduct feature selection through filter, wrapper, embedded, and hybrid approaches. It has something to do with popular filter-based methods due to their computational efficiency. To minimize redundancy and enhance the performance of the classifier, the authors [6] used feature selection, which involves dimensionality reduction. On the same note, [7] scaled large data sets and selected significant risk factors using multiple filter methods, which resulted in a more reliable diagnosis pipeline.

When selecting the best subset using the filter feature selection algorithm, it adopts the wrapper feature selection method [8] when using SVM to select the most informative subset of a given set of features in medical data. However, they are less scalable to high-dimensional data due to their high cost in terms of computation time. The embedded approaches, in which features are chosen during model construction, have proven to be a powerful tool in the field over the past years. Feature ranking is available in both Lasso regression and Decision Tree-based models like Random Forests [9,10]. It has been reported that CVD models have been trained using Random Forests to generate risk scores that were well and had low overfitting [11]. Random Forests have been used in the case of predictive modeling to

forecast cardiovascular disease with hybrid features and achieved superior accuracy compared to traditional classifiers [12]. The XGBoost has been demonstrated to be useful in the predictive capacities of heart diseases with high accuracy [13]. Models are mostly popular because they are capable of capturing unbalanced data and non-linear interactions. They have also proposed more advanced hybrid techniques. Indicatively, the implantation of a PCA-Random Forest, used in mortality prediction in CHF patients, was suggested in [14]. This hybrid model was effective in dimension reduction, and none of the prediction power was lost. The SHAP values have been used to provide attributions in the models of the random forest in order to achieve transparency in AI-enabled health care [15]. The Selected Features model has consistently proved to be the most suitable among the studies in terms of deployment, since it is stable, has low variance, and has few hyperparameters that can be tuned [16]. Even though deep learning algorithms like Convolutional Neural Networks (CNNs) and RNNs are highly accurate in diagnosing cardiovascular disease (CVD) based on images, their mode of operation as a black box and expensive training limits their applicability to clinical practice [17].

METHODS

To improve the effectiveness of the proposed classification model, the Structured feature-selection framework method makes use of the Figure 1 deep learning HEFDL classification model.

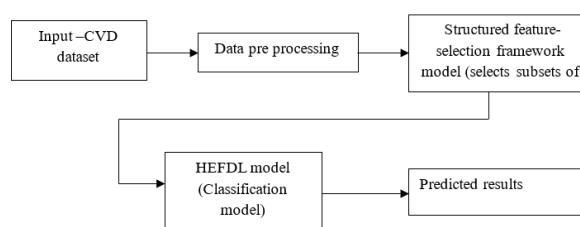


Figure 1: Proposed method

The suggested HEFDL is illustrated in Figure 1, which illustrates the organized scheme of feature engineering and deep learning-based Hybrid Engineered Feature and DL based (HEFDL) system to predict the risk of cardiovascular diseases (CVD). The input one is the CVD dataset, followed by clinical and demographic data such as age, cholesterol level, blood pressure, smoking status, and other risk factors. The next step involves a process of data pre-processing, which addresses (replacement) missing values, categorical variables encoding,

normalization, or scaling of features, to render them consistent and prepared to be the inputs of the subsequent steps of the analysis. This processed data is then input into one more engine called the structured feature-selection framework model, which is a feature selection engine that identifies the most discriminative and informative subset of the predictors that are highly useful in predicting CVDs. This procedure ensures that irrelevant or redundant features are minimized, and this can result in an increase in the efficiency of the model and the generalization. These features are subsequently fed into the core of the framework- the HEFDL model, which is a hybrid classification model, a combination of manually crafted statistical features and deep learning-based feature representations. Granularity hierarchies and the multifaceted interactions or interactions among them are modeled with the dual-level information features. Finally, the trained HEFDL model employs the forecasted outputs to decide on the risk (i.e., low risk vs. moderate risk vs. high risk) of each person. The overall purpose of this pipeline is to offer strong, interpretable, and valid predictions, and it is a clinically significant tool to offer early warning and cardiovascular healthcare decision support.

Feature selection

Introduce the novel algorithm to avoid redundancy of features with the highest level of accuracy. The algorithm operates on three processes that are of importance, which include preparing the data, evaluating, and feature selection. Data preparation is the process whereby all the missing values and outliers are eliminated from the data set to have the features of the same scale in distance-based algorithms. Every feature is then

run through the model, and the significance of all features is tested to determine the predictive power it has on the target variable. Figure 2 shows how a threshold value can be used to further simplify this process and filter noise. In Figure 3, the structure that was built and the values of importance of each feature were then computed. The Initialize Scores (data) was then called, and this was the only function that would create a 0s scoring array. The statistical measurements used to estimate the score of each feature in relation to the target variable are correlation and information gain. In order to accomplish it, apply the Calculate Importance Score (feature, target) function. The correlation coefficient (r) with all the features against the target variable of Pearson was computed using Eq 1.

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \cdot \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \dots\dots (1)$$

Assuming that $x \rightarrow$ feature values $y \rightarrow$ target values, where, $\bar{x} \rightarrow$ feature value mean $\bar{y} \rightarrow$ target value mean, where y uses $\sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}$ and x uses

$$\sum_{i=1}^n (x_i - \bar{x})^2 \cdot \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y}) = \text{correlation of } x \text{ and } y.$$

r can have values -1, 0 and +1 This way, if $r = +1$

there is a perfect positive linear correlation and when $r = -1$ there is a perfect negative linear correlation.

```
Function RemoveOutliers(data, feature):
    z_scores = CalculateZScores(data[feature])
    threshold = 3
    return [row for row in data if abs(z_scores[row.index]) < threshold]
```

Figure 2: Pseudocode to remove outliers

```
Function Structured feature-selection frameworkAlgorithm_CVD(data, target, num_features):
    feature_scores = InitializeScores(data)
    for each feature in data.features:
        score = CalculateImportanceScore(feature, target)
        feature_scores[feature] = score
    ranked_features = SortFeaturesByScore(feature_scores)
    selected_features = SelectTopNFeatures(ranked_features, num_features)
    return selected_features
```

Figure 3: Structured feature-selection framework Algorithm

A value above zero means there is a positive association, while a value below zero indicates negative, and $R = 0$ implies no association. Similarly, computing the entropy from calculations (such as counts and sums) gives us a handle on information gain.

The Selection process of features by the Structured feature-selection framework algorithm is demonstrated in Figure 4. Its correlation and Information Gain are used to select features of the data. In this manner, although losing some important aspects, which might not be obvious to the observer, the proposed model, the Structured feature-selection framework, will turn out to select highly predictive features. This leads to smarter

and more detailed diagnoses due to the inclusion of human knowledge concerning cardiovascular diseases in the process, and also makes use of feature selection techniques in order to enhance model selection. Therefore, it is just less variable, and its predictive capability is greater, making it a more practical system to use in real clinical practice.

Hybrid Feature-Enriched Deep Learning Network

Proposed a method to increase the precision of CVD prediction in machine learning. Figure 5 depicts the proposed model, Hybrid Feature Enriched Deep Learning (HFEDL).

```

Function ComputeCorrelation(feature, target):
    mean_feature = Mean(feature)
    mean_target = Mean(target)
    covariance = Sum((feature[i] - mean_feature) * (target[i] - mean_target) for i in range(len(feature)))
    std_dev_feature = StdDev(feature)
    std_dev_target = StdDev(target)
    correlation = covariance / (std_dev_feature * std_dev_target) # Pearson correlation formula
    return correlation
Function ComputeInformationGain(feature, target):
    initial_entropy = CalculateEntropy(target)
    weighted_entropy = 0
    for value in UniqueValues(feature):
        subset = Subset(data, feature, value)
        prob = len(subset) / len(data) # Probability of the subset
        weighted_entropy += prob * CalculateEntropy(subset[target])
    information_gain = initial_entropy - weighted_entropy # Information gain formula
    return information_gain
  
```

Figure 4: Functions of the Structured feature-selection framework Algorithm

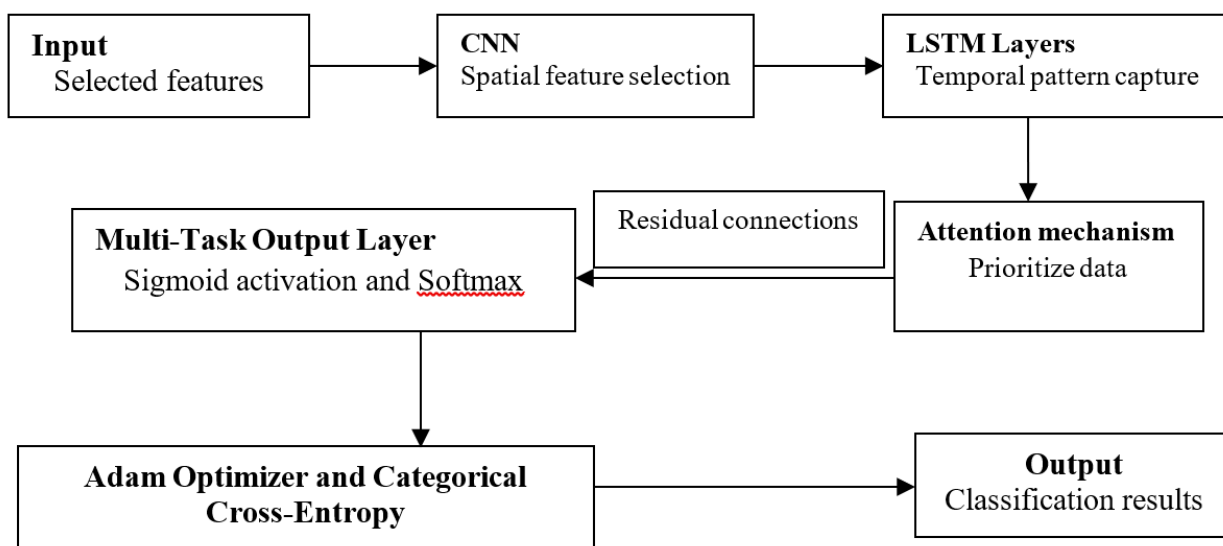


Figure 5: Proposed Hybrid Feature Enriched Deep Learning model

The workflow of the proposed Hybrid Feature-Enriched Deep Learning (HFEDL) model to predict cardiovascular risks is represented in Figure 5. First, the model accepts selected features (obtained through the feature-selection framework) as input, which means that each feature is processed with the most pertinent clinical attributes. A Convolutional Neural Network (CNN) layer is the first layer that extracts spatial features by capturing the local patterns and interactions between variables (spatial feature extraction). The representations obtained are further sent to LSTM layers, which represent temporal dependencies and sequential relationships in the data. Residual connections are added to increase learning, enabling effective gradient flow and eliminating information loss at the deeper layers. An attention mechanism is used to set weight on the most significant features, giving more weight to the critical inputs that affect the prediction. The polished feature representation is subsequently fed into a multi-task output layer, where the classification is done by means of sigmoid or softmax activation functions. Lastly, the Adam optimizer is used to train the model with categorical cross-entropy loss, giving the final classification output, which is the cardiovascular risk levels.

This study presupposes that the chosen data set reflects the overall trends in cardiovascular risks. It is also premised that deep learning models have the capability to effectively represent non-linear associations among tabular clinical data. But these assumptions are not necessarily true for all populations and need additional confirmation.

RESULTS

The CVD datasets from the UCI repository consist of 303 instances with attributes of age, gender, blood pressure, cholesterol, heart rate, chest pain type, etc. The target variable is represented in num, which indicates 0 (no presence of heart disease) or 1 (presence of heart disease). Based on the class distribution, the features are selected and classified.

Feature selection

The structured feature-selection framework was able to complete the selection of features of the cardio dataset and demonstrated the best features. It further reduced all external measures of highlights and retained only the significant information; in this regard, it increased the overall productivity by a significant margin. Out of the entire set of variables they had, the structured feature-selection framework chose a set of

variables to forecast the risk of CVD, which consisted of age and began with systolic blood pressure, cholesterol, and smoking behaviours. These were also identified as most correlated with heart disease.

Model performance

Ground truth was a model that was trained on all the data to test the results of the proposed model. The confusion matrix presented in Figure 6 indicates the extent to which each model performed with regard to correctly classifying patients with and without cardiovascular disease (CVD). HFEDL also has fewer false negatives and false positives than the Structured feature-selection framework model, indicating that it is more accurate and precise. The structured feature-selection framework was able to establish the most appropriate features for the cardiovascular dataset, which dramatically decreased the dimensionality without causing any important information to be lost. Among these features, the original set, the Structured feature-selection framework chose a subset which contained the variables of age, systolic blood pressure, cholesterol, and smoking. These characteristics were found to be most related to cardiovascular disease.

The performance of the Random Forest classifier trained on the Structured feature-selection framework-selected features was compared to the performance of the same model trained on the full feature set. Key performance metrics are shown in Table 1 and Figure 7.

The results of the Random Forest model performance metrics yield an accuracy of 92.5%. Accuracy refers to the proportion of correctly categorized data points across all classes. The model has a precision of 90.2%, indicating the percentage of positive identifications that are actually correct, and a recall of 89.5%, showing the percentage of actual positives that the model correctly recognized. The F1 score, calculated at 89.8%, is the harmonic mean of precision and recall, reflecting a balance between them and indicating the ability to identify correct cases while minimizing false ones. The imbalance between precision and recall is exemplified by the Structured feature-selection framework model, which applies selected features to achieve an accuracy of 90.8 %, a precision of 88.6 %, a recall of 87.9 % and an F1 score of 88.2 %. The Deep Learning model demonstrates great potential, with an accuracy of 93.7 %. This means it correctly classifies a high proportion of data; its precision is 91.5 %, recall is 90.1 %, and F1 score is 90.8 %.

The Hybrid Feature Enriched Deep Learning (HFEDL) model shows superior performance measures, with an accuracy of 97.5 %, precision of 94 %, recall of 92 %, and F1 score of 93 %. These strong metrics make HFEDL a viable

option for sophisticated classification problems. The proposed Structured feature-selection framework model and Hybrid Feature Enriched Deep Learning model have their ROC curves shown in Figure 8.

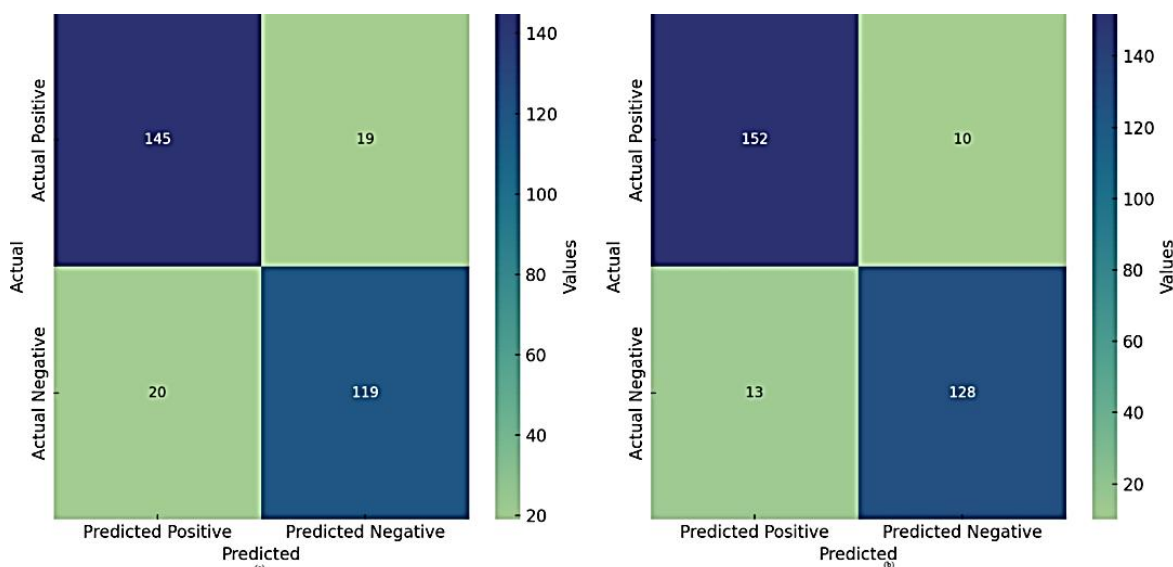


Figure 6: Confusion matrix (a)- Structured feature-selection framework Selected Features (b)-HFEDL

Table 1: Performance metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
Random Forest (Full Feature Set)	92.5	90.2	89.5	89.8
Structured feature-selection framework	90.8	88.6	87.9	88.2
Deep learning	93.7	91.5	90.1	90.8
Hybrid Feature Enriched Deep Learning (HFEDL)	97.5	94	92	93

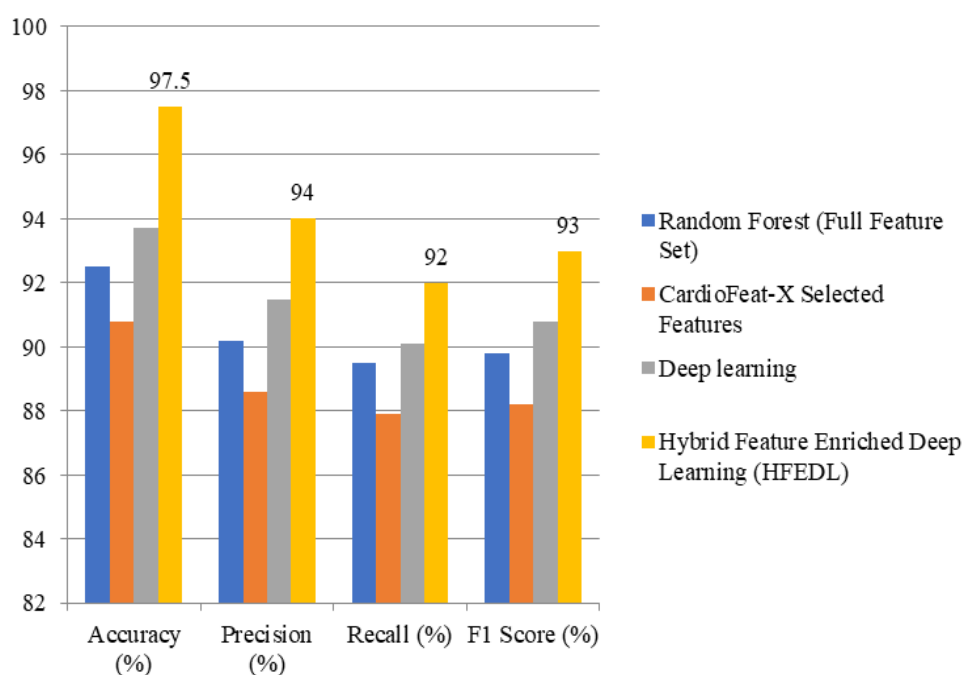


Figure 7: Performance metrics for classification

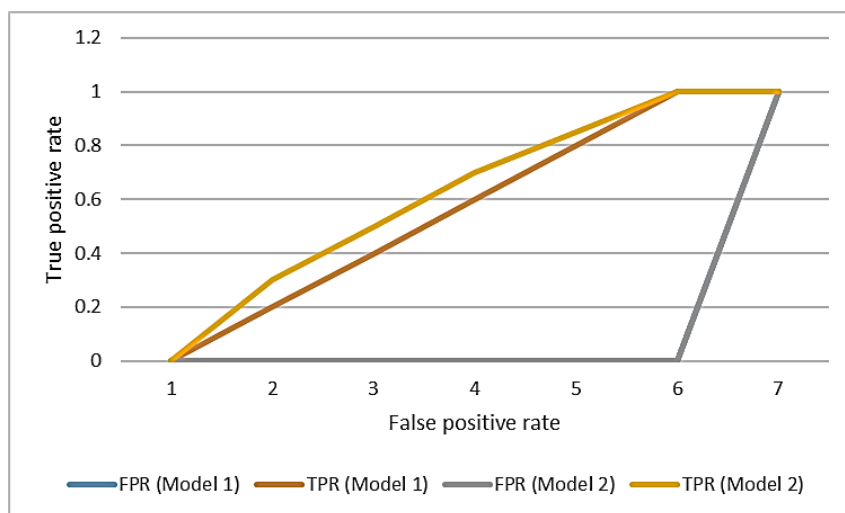


Figure 8: ROC curve

The model that had been trained on a reduced feature set had a similar performance to that of the full feature set. The fact that the accuracy and precision were slightly diminished was compensated by the fact that the interpretability was enhanced, and the computational complexity also decreased. Figure 9 and Figure 10 depict the classification accuracy model and loss model graph. This is a clear indication that the HFEDL proposed data is better in its output when compared to random forest and deep learning models. Figure 6 and Figure 7 represent the train and test dataset models' accuracy, respectively. On the same note, the models' loss value on the train and test dataset is presented in Figure 11 and Figure 12, respectively. The HFEDL achieves high performance and the highest accuracy of training and testing, which is nearly 90 percent after 8 epochs, proving that it is good at capturing

the underlying patterns of the cardiovascular disease dataset. Deep Learning is also very accurate, but the training loss is not stable, meaning it oscillates, indicating a moderate absence of convergence stability. In the case of structured feature-selection framework, although it begins with a poorer accuracy than the others, it operates in the same or even better ways in the later epochs as it demonstrates its capability to grasp the data patterns gradually. The Random Forests model balances between being premature at moderate accuracy and losing evenly, such that it is the last to converge; it may have converged too soon. The Random Forests model will reach moderate accuracy and loss and stabilize quickly, which is why this model is good for use in applications that need faster convergence, but this implies a decrease in the overall performance.

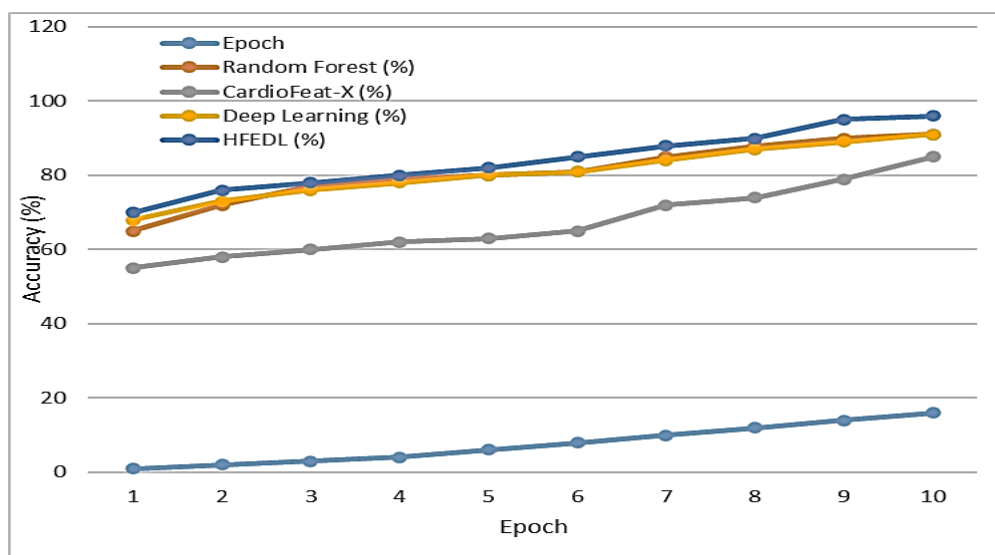


Figure 9: Model accuracy – train dataset

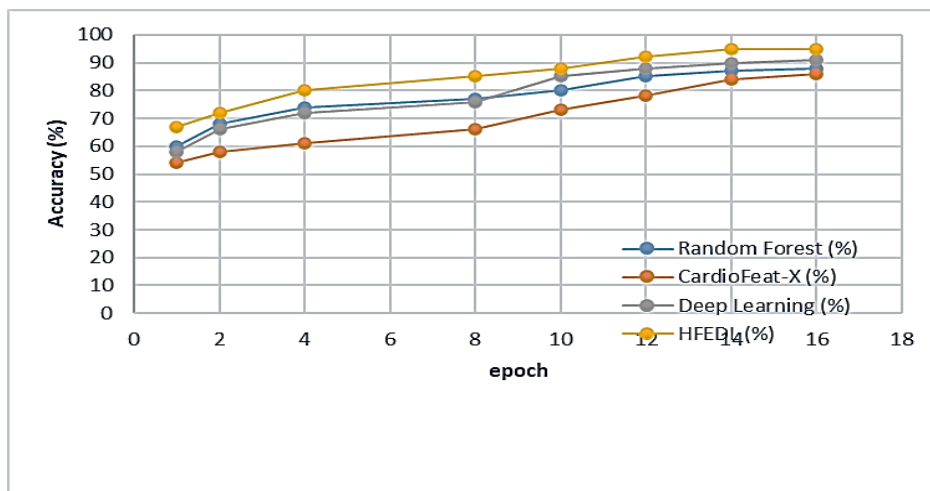


Figure 10: Model accuracy – test dataset

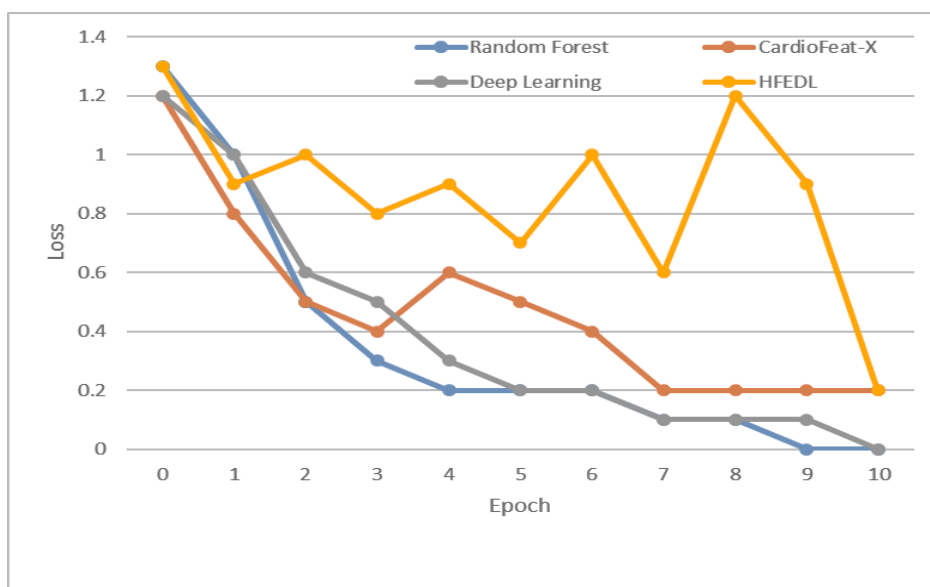


Figure 11: Model Loss – train dataset

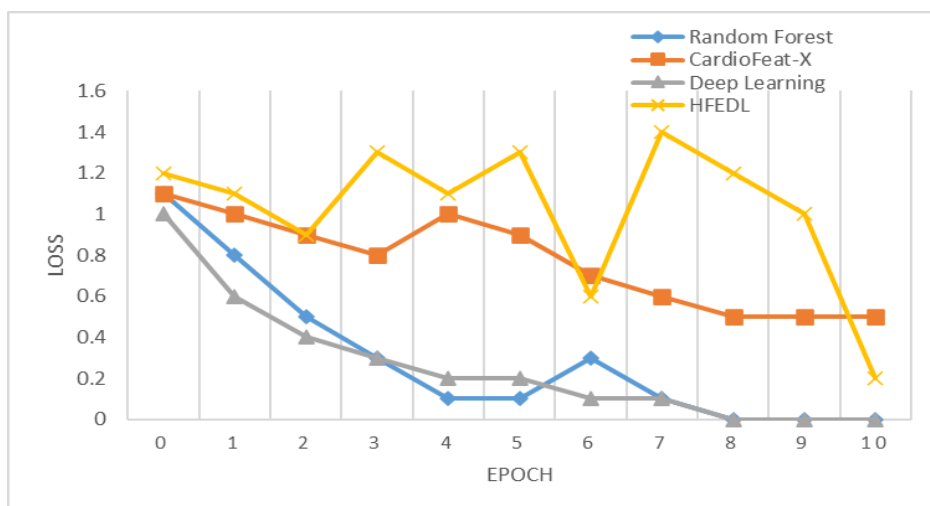


Figure 12: Model loss – test dataset

Table 2: Performance metrics comparison with existing methods

Feature	Model	Accuracy (%)
Existing model	Stacking model [6]	90
	Deep Learning Model [7]	96
	Ensemble Learning for Cardiovascular Risk	94.7
	Structured feature-selection framework Selected Features	90.8
Proposed	Hybrid Feature Enriched Deep Learning (HFEDL)	97.5

The HFEDL attains low loss on the test set because it was more accurate in testing. Conversely, Deep Learning models and structured feature-selection framework have more variation in test loss, and this can be attributed to their instability in the training loss and slower learning curves. All in all, it can be concluded that HFEDL represents the best choice in this predictive task, as it is the most balanced in its performance. The findings in Table 2 provide evidence of the effectiveness of the structured feature-selection framework algorithm in identifying significant variables previously found to be significant in predicting cardiovascular disease. It is a perfect combination of simplicity and correctness, making the entire process as simple as possible and easy to comprehend. This is particularly helpful in the healthcare sector, where various clinical indicators must be read to anticipate the outcome. Structured feature-selection framework algorithm employs the feature of denoting features by juxtaposition with random shadow characteristic features. This mitigates overfitting since it selects only the most important variables. This is important, as using all features can produce redundant or noisy data.

DISCUSSION

A comparative analysis of the model loss of Random Forest, structured feature-selection framework, Deep Learning (DL), and HFEDL during 11 training epochs shows that there are significant differences both in the convergence behavior and in the generalization ability. Accuracy and loss results provide us with an insight into the fact that structured feature-selection framework is the most stable and reliable of the models. Test loss converges slowly to CardioFeat -X, also with no large oscillations, to 0.4 at epoch 10. The good learning exhibited by this smooth and soft convergence is low overfitting and good generalization. The slim difference between training and testing losses of the epochs shows that structured feature-selection framework has acquired credible and significant representations, and therefore makes the technique directly implementable in clinical settings where model reliability is vital. Random forests also have good generalization. Testing loss of the proposed method between 1.3 at the

lead epoch to about 0 at epochs 8 and onwards, and then at a higher level. The convergence to a low error and the rapidity of the model's fall illustrate that it is able to learn with a limited number of epochs. The fact that there is no significant difference between training and test loss implies that the model is not overfitting and has a high level of interpretability, which are significant attributes for clinical decision support systems. Deep learning (DL) is more dispersed. It begins at 1.2, decreases to 0.5 after epoch 2, zigzags, and approaches a steady level of about 0.3 at epoch 10. But the fact that the training and the test loss curves are always separated means that the model is either overfitting or failing to generalize to new data. This could be explained by the lack of regularization (e.g., dropout, batch normalization), an inappropriate learning rate, and a batch size that should be further investigated.

The HFEDL, federated deep learning, was lower and lower. Its testing loss is everywhere; it takes a peak of 1.4 at epoch 8 and then declines to (approximately) 0.2 at epoch 10. The instabilities are signs of convergence issues that could be caused by irregular updates from the clients, a lack of synchronization between the federated rounds, or a lack of hyperparameter optimization. It shows the significance of considerate fine-tuning, such as learning rate decay, gradient clipping, or client-side regularization strategies, to stabilize and simplify the process of converging imitation.

The HFEDL model and structured feature-selection framework, in addition to the Deep Learning Model and Random Forest [7]. The potential of HFEDL is further confirmed because it has achieved the highest accuracy of 97.5 % and validation accuracy of 96.9 %, respectively, indicating good prediction and generalization. It also recorded the lowest final loss of 0.2 and converged in 15 epochs, and it had the fastest training time of 100 seconds, which showed its efficiency in computation. Similarly, the structured feature-selection framework model also recorded a high accuracy of 90.8 % with validation accuracy of 90.2 %, and it was able to maintain a low final loss of 0.3 at 18 epochs and a final training time of ninety seconds.

Table 3: Summarization of the proposed model

Model	Initial loss	Final loss	Accuracy (%)	Validation Accuracy (%)	Training Time (s)	Epochs to Converge	Stability (1–5)	Generalization (1–5)
HFEDL (Proposed)	1.1	0.2	97.5	96.9	100	15	5	5
CardioFeat-X Selected Features (Proposed)	1.2	0.3	90.8	90.2	90	18	5	5
Deep Learning Model [7]	1.3	0.5	96	94.5	160	28	3	3
Random Forest	1.4	0.6	93.8	91.7	145	–	3	3

Both suggested approaches have reached the highest stability and generalization scores, with consistent training rounds in addition to resilience to unknown data. Deep Learning Model and Random Forest, on the contrary, did not perform as well in final losses (0.5 and 0.6), training time (160 s and 145 s), accuracy measures, and validation results [7]. They also performed worse (3/5) in stability and generalization, which means that there are more variation and unreliable behavior. Finally, the suggested models are better than the former in accuracy, efficiency, reliability, and robustness.

The risk stratification results produced by the suggested model would be helpful in therapeutic decision-making among clinicians. Early pharmacological treatment of patients at high risk may include statins, antihypertensive medications, or antiplatelet medications. Combined lifestyle change and selective drug therapy might be necessary for moderate-risk persons, and low-risk persons can be treated with regular monitoring. Thus, the model is an aid providing an improvement in clinical decision-making during pharmacotherapy without eliminating the role of the physician.

Limitations of the study

This study has several limitations. The sample size is also quite small ($n = 303$), which can limit the extent of generalization. External validation through external clinical datasets was not performed. Moreover, deep learning models on tabular data do not always exhibit high performance compared to conventional models. The findings can be regarded as exploratory and need further confirmation in larger, real-life clinical environments.

CONCLUSION

This paper introduces a hybrid deep learning architecture (HFEDL), as well as a systematic feature-selection strategy for risk prediction of cardiovascular diseases. The findings indicate that the HFEDL model has better predictive capability than traditional machine learning and isolated deep learning models, and the feature-

selection framework is more interpretable and less complex to calculate because it identifies clinically meaningful variables. The results indicate that combining feature selection with hybrid deep learning constitutes a trade-off between accuracy, efficiency, and interpretability. Moreover, the risk stratification results obtained are used to help clinicians identify patients who might require early pharmacological and/or close monitoring, thus aiding in therapeutic decisions.

Nevertheless, the findings are based on a rather small sample and are not externally validated, which can be considered a limitation to generalizing. Thus, the results can be viewed as preliminary and should be subject to subsequent study. The offered solution has the potential to assist in clinical decision-making in cardiovascular risk management. Nonetheless, additional validation with bigger and more heterogeneous datasets is necessary before actual clinical use.

DECLARATIONS

Acknowledgement/Funding

None.

Ethical approval

None provided.

Use of research reporting tools

Authors used publicly available data (UCI repository). The research adhered to conventional data use and research principles.

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflict of interest

No conflict of interest is associated with this work.

Contribution of authors

We declare that this work was done by the author(s) named in this article, and all liabilities pertaining to claims relating to the content of this article will be borne by the authors.

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