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A Deep Learning Framework for Multimodal Cardiovascular Disease Prediction Using Structured and Unstructured Data

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KEYWORDS

Multi-modal, CNN, FNN, Issues, Data Preprocessing, Performance, and Hybrid model

ABSTRACT

The death rates of people in the global community are increasing due to deadly diseases, unpredictable type is cardiovascular disease. The datasets come with heterogeneous data like such as structured table format, and unstructured data, meaning image types. Before initiating the pre-processing pipeline, the issues to be solved are noise, class imbalance, and missing values. To overcome these, a hybrid approach such as a combination of CNN and FNN is used. In these, FNN uses embedded imputation, feature normalization, and CNN is applied by using adaptive spatial pooling to address resolution variability in the images. The cross-model attention layer is defined for fusing the features from both modalities. The issues, such as class imbalance, are overcome using synthetic minority oversampling called SMOTE as part of the data preprocessing pipeline, as well as missing data is overcome by using dropout augmented training. This model outperforms specific machine learning models and unimodal deep learning models. This model ensures a scalable, efficient solution for CVD prediction early, in personalized clinical care. The multi-modal fusion support, better interpretability with adjusting attention weights, may highlight key factors, and robustness to missing data with imputation and dropout augmentation.

1. INTRODUCTION

Globally, heart disease is one of the biggest threats that increases mortality, as well as a critical cause of death. Significant challenges would be raised, such as class imbalance, noise, and missing data, due to the heterogeneity of data ranging from tabular-structured records to unstructured imaging data. To overcome these, a hybrid model that uses a combination of a convolutional neural network and a feedforward neural network. The embedded imputation and feature normalization of the Feedforward neural network are used for handling structured data, whereas adaptive spatial pooling of the convolution neural network is used for handling unstructured imaging data. The fusing of features from both modalities requires cross model attention layer. Synthetic minority Oversampling technique (SMOTE) is used to address class imbalance, whereas missing data is addressed using a dropout augmented training approach..

Table 1. Trends showing risk factors and diagnostic issues

Year	Global CVD Deaths (Millions)	Leading Risk Factors	Diagnostic Challenges
2010	18	Cholesterol, smoking habits, and hypertension	Less support of multi-modal data
2015	19	Lifestyle of sedentary, diabetes, and obesity	The datasets with class imbalance exist
2020	20	Pollution in the air, and aging	EHRs possess missing values
2025	21.2	More stress and DNA predisposition	Variability in image resolution

Table 1 demonstrates that when recent year 2025 is reached, technology advancement has occurred in diagnosing the scanned images. The risk factors considered are genetic predisposition and stress as critical, along with earlier factors such as diabetes, obesity, cholesterol, etc.

The machine learning models are refined and used for heart disease detection so that health experts can suggest prescription as well as physical recommendations. In machine learning, training is a significant stage where the system learns from samples, and logic is built, so that any future sample that comes would be predicted the category of the sample. Table 2 demonstrates a comparison among a few methods, in terms of benefits and drawbacks.

Table 2. Methods used in CVD prediction

Method	Data Type to be Handled	Benefits	Drawbacks
Traditional ML (Logistic Regression, SVM)	Structured (Tabular)	Speedy Training and Interpretability	Unstructured data results in poor performance
Unimodal Deep Learning (CNN-only)	Unstructured (Images)	Image classification ensures High accuracy	Tabular clinical data are not supported
Unimodal Deep Learning (FNN-only)	Structured (Tabular)	Feature-based prediction is effective	Image data involves complexity
Proposed Hybrid (CNN + FNN + Attention)	Both (Structured & Unstructured)	Robust to missing data, and supports multimodal fusion	Computational cost is higher

2. 2. LITERATURE SURVEY

Although there were many approaches that were used over cardiovascular disease prediction, and a few have worked significantly on risk assessment, other few worked on just detecting and classification of CVD. Its evolution made steps towards efficient review, and some of the studies' descriptions were reviewed for better proposed system framing. From P. Nandakumar, R. Subhashini (2024)[1], a discussion on reducing death rates of CVD using data preprocessing over unnecessary data, and a bio-inspired approach, Elephant Herding optimization, to address better feature selection. The hybrid model of CNN with Inception-ResNet-V2 works well on UCI repository, and used in the third layer of the architecture, would procedure a promising accuracy of 99%. The future directions given towards this method would be refined to suit other diseases also. From Purnima Pal, Harsh Vikram Singh et al. (2025)[2], a demonstration on CVD prediction using a bunch of ensemble machine learning models in which Random Forest made a competitive prediction approach, whereas a bunch of deep learning models, which Inception Net, would produce better accuracy. Before classification, the dataset is preprocessed using cleaning approaches, which results quality dataset, which ensures the performance of classification.

As per Peng M, Hou F, Cheng Z, Shen T, Liu K, Zhao C, Zheng W. [3], their model XGBH operates by constructing a histogram in a specific software against few other models, and proves accuracy is more by considering few important contributing factors. The results alone with XGBH and then by adding BMI identifier are compared and proved latter pattern achieves more percentage. The inputs are taken from chinese shangui dataset and kaggle set. From the study of Pal M, Parija S, Panda G, Dhama K, Mohapatra RK.[4], the methods such as MLP and KNN are applied over California university dataset, and these approaches in which former method verified with more accuracy than latter method. The efficiency also enhanced by eliminating the outliers and null values. In the view of Yang, L., Wu, H., Jin, X. et al.[5], their model random forest against other models like regression variants were computed, analyzed, and compared. The comparison states that former model achieves more accuracy of AUC than others. The dataset taken is from eastern china. In regard to Farshad Farzadfar [6], it demonstrates the many challenges against the population capacity levels like overestimate and underestimate, and needs to be addressed with categories of population. From Deb S, Dasgupta A (2008)[7], demonstrates various reasons that cause cardiovascular disease such as stress in working hours, lack of physical activity, hypertension, diabetes, lack of proper diet, age, and others. Analysis is done over Kolkata center, and reported increase in cases. The conclusion says above 50% of cases from india when compared against the world cases. In regard to Muhammad, Y.(2020)[8], demonstrates reduce the death rates due to heart attacks when supply of blood stops to other parts of the body. The full feature and optimal feature spaces are taken, four feature selection methods are considered, ET and GB are identified as better among 10 classifications algorithms. The GB (Gradient Boosting) and ET (Extra tree classifier) results improved accuracies. In the view of Kyoung Ae Kong et al (2021)[9], demonstrates analysis on korea people when COVID-19 are there. There are reasons noticed like diabetes, hypertension, and other respiratory symptoms caused many deaths during COVID-19. The severity is increased when multiple risk factors are present. From Rezaianzadeh, A. (2023)[10], demonstrates the make and female deaths of a city in south iran, and used the long rank test, Firth's bias reduction of multiple cox reduction to know the factors that caused the CVD. The reasons were modifiable factors noted such as hypertension, diabetes, and alcoholic.

Given Muthiah Vaduganathan et al (2022)[11], discuss significant risk factors like modifiable and non-modifiable factors that affect heart attacks. Detecting the disease in advance would help to follow effective strategies in order to prevent CVD. There are GBC as well as national efforts would search for effective ways to prevent these diseases. From Blankenberg et a (2023)[12], discusses five modifiable factors that cause cardiovascular diseases globally. One of the methods, such as Cox regression, is applied to predict the risk factors over 10 years in terms of incidence and mortality. From [13], a discussion is made on awareness of risks and getting training on how to control such risks. The risks are traditional risks and risk-enhancing like modifiable and non-modifiable factors. Regarding Mengxiao Peng et al (2023)[14], the risk factors (BP, Cholesterol, and age) using XGBH are found initially normal, but later, by adding the BMI factor in the dataset, results in high accuracy. Later, accuracy is guaranteed more by considering new and main attributes. From N. S. Kurian et al (2022[15]), analyzes various machine learning models for cardiovascular disease prediction, and compares these models for better model recommendation. These models' analysis helps to prevent disease.

In the view of A. Jeba Sheela et al (2024)[16], the usage of inception v3, VGG16, and non-invasive image analysis techniques reduces noise and enhances contrast over the images. This early detection would prevent the risk of getting cardiovascular disease. From Surjeet Dalal et al (2023)[17], demonstrate various machine learning models on Kaggle dataset and ensure high accuracy in the cardiovascular disease prediction. This early detection helps to overcome biases and improve outcomes. From Xavier Rossello et al (2020)[18], demonstrate analysis on various risk prediction tools and sites, where one significant site acts as risk prediction and assessment for all categories of patients suggested by the European association. From Yekai Zhou et al(2024)[19], discuss two models against the proposed model P-CARDIAC, over Chinese people. Many attributes are considered, in which the drug interaction variable is considered a significant factor. This model provides improved individual treatment guidance. In the view of Nadella Mounika et al (2024)[20], demonstrate awareness of cardiovascular disease and its consequences in the northeast India as a case study over tribal people. Models such as logistic regression and other specific prediction equations are discussed. In regard to Juan Wang et al (2017)[21], demonstrates various bio markers that affect heart failure and immediate death. A few significant developments were designed in which microRNA is one significant model to predict the heart status over certain biomarkers. From Sadiya S. Khan et al (2023)[22], demonstrates PREVENT equation model that evaluates the patients of ages 30 to 79, and summarizes the status of patients who possess kidney, CVD, and metabolic issues. Many scenarios and contexts are analyzed using PREVENT model. In regard to Achyut Tiwari et al (2022)[23], discusses datasets of type such as Cleveland, and others, and various machine learning models like extra tree classifier with stacking ensemble method. The accuracy is compared against other methods and ensures good accuracy. From A. Sreeniwas Kumar et al (2020)[24], demonstrates the Indian people life styles and their diseases in which CVD is major disease affecting three states such TN, Kerala, and Punjab. A lot analysis is done over the past years and percentages are computed based on factors such as diabetes, hypertension, and other factors individually. From Zidian Xie et al (2019)[25], describes attributes and their impact of causing Type2 diabetes in which sleeping is one significant factor for duration less than 6 hours and more than 9 hours. Various ML techniques applied and identify Type2 diabetes, which is a typical disease that causes other health issues. From Dhafer G. Honi et al (2024)[26], the focus went on CVD prediction over a train-test model, Cross K validation, CatBoost model using a specialized CNN called a one-dimensional CNN for achieving more accuracy and optimization of network architecture. Based on A. Jaiswal et al (2023)[27], the demonstration went on to analyze various models to predict CVD, in which CNN is proven to have more accuracy than other models. From Dr V. Gokula Krishnan et al(2024)[28], the demonstration focuses on the integration of two approaches lion model and butterfly optimization, for selecting the best features, and classifies patients into healthy or unhealthy based on pre-trained CNN models. From Bhatt, C.M. et al (2023) [29], the focus is on applying models such as XGBoost, Random Forest, Multilayer perceptron, and Decision Trees with and without Cross-validation in predicting CVD. Among these, the Multilayer perceptron proved more accurate than the others. Based on Nissa, N. et al (2024)[30], the focus is on predicting the CVD using various boosting techniques like AdaBoost, Light GBM, Gradient Boosting, Cat Boosting, and etc. Among these, Adaboost has superior performance than other models. From S. H. Raju et al (2023)[31], a demonstration in the brain disease, and detects the uncertainty using CNN. The accuracy, performance are the metrics used for judging the method's effectiveness. From Hrushikesava Raju et al (2022)[32], a discussion was conducted on the estimation of future day food diet events based on the history of previous days. It uses sensors and suggests nutrient food for the present food consumption, by scanning and generating a report to the user.

3. 3.PROPOSED METHODOLOGY

In this, the proposed model accepts input which consists of the images, and table data. Then, data preprocessing is applied over both data and converted into quality data. Then, the hybrid model that consists of FNN-CNN is applied, then fusion the features for better detection. Then, effectiveness of the modal is assessed using measures such as accuracy, and performance. This description is depicted in Fig.1.

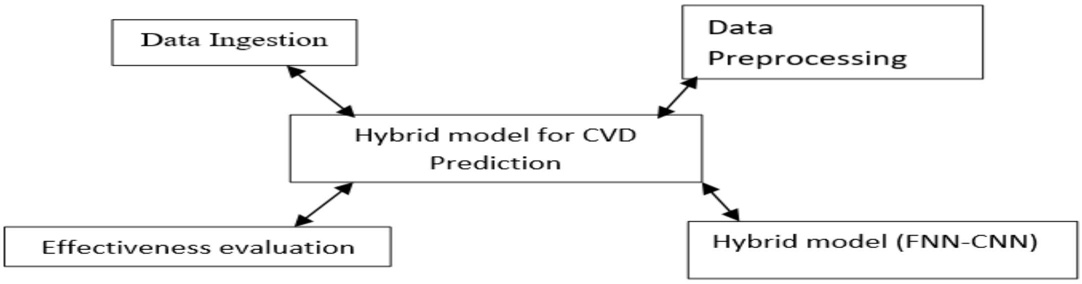

Fig.1. Modules involved in FNN-CNN hybrid model

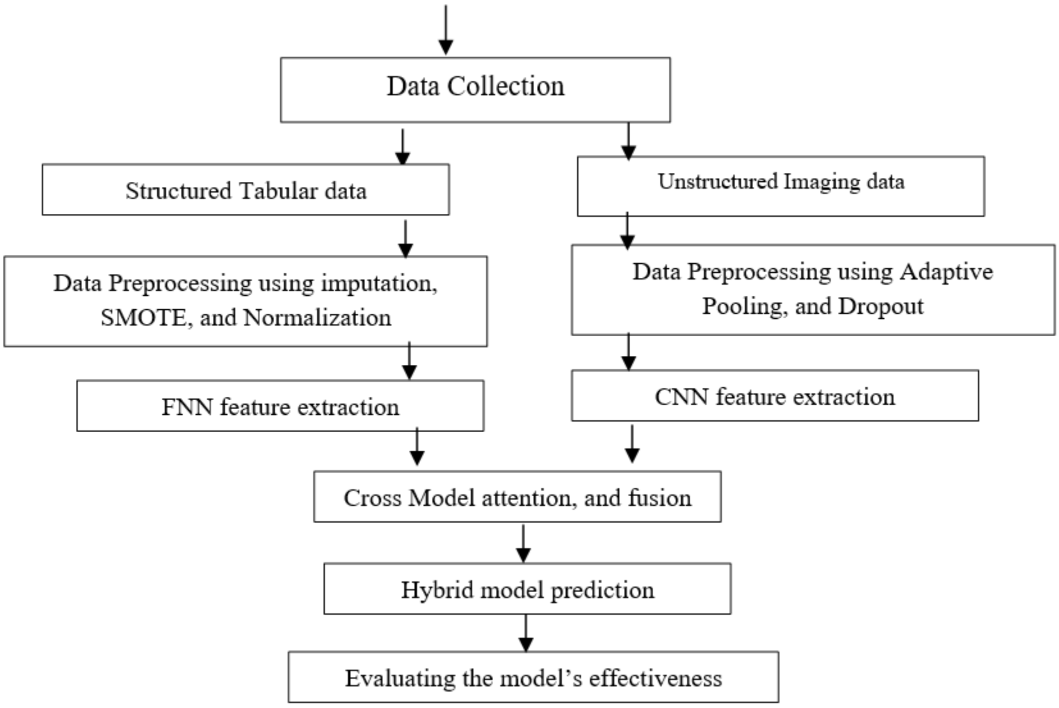

Fig.2. Flow of activities in the FNN-CNN hybrid model

From Fig.2, the data would be given in tabular, and image type which could be preprocessed for quality data by removing the noise, then features are extracted as per their method such as FNN over structured, and CNN over unstructured. Then, the key features are fusion from both FNN and CNN features. The hybrid model FNN-CNN is applied for better CVD detection due to efficient data preprocessing pipeline. Then, comparing our proposed model against specific existing models would assess the effectiveness of the proposed model.

PS1: Pseudo_Procedure Hybrid_FNN_CNN_model (Dataset1[][], Dataset2[][], Accuracy):

Input: Dataset1[][],Dataset2[][] where Dataset1 denote tabular data, and Dataset2 denote images

Output: Accuracy

Step1: Collect the data in terms of loading tabular data, and loading of image data

Step2: Apply Preprocessing pipeline

2.1 For tabular data to handle

2.1.1. Use embedded imputation for missing values data

2.1.2. Normalize features using FNN

2.1.3. Balance classes using SMOTE in which minority class samples are processed with k-nearest neighbor by randomly selecting a neighbor, then creating a synthetic sample using the difference, and multiplying by a random weight. Then, combine majority class, minority class, and synthetic samples are combined, shuffled to avoid bias.

2.2 For images to handle

2.2.1 Use Adaptive spatial Pooling for resolution variability

2.2.2 Use Dropout augmentation to simulate missing data to ensure robustness

Step3: Define Hybrid model FNN-CNN

3.1 Do training on tabular data using FNN

3.1.1 Use embedded imputation for replacing missing values (like empties) with learned representations.

3.1.2 Use feature normalization for scaling numerical features with batch normalization layers.

3.1.3 Apply Feature extraction for transforming input using fully connected layers with ReLU into high level embeddings, and produce feature vector.

3.2 Do training on images data using CNN to extract spatial features

3.2.1 Use Adaptive spatial pooling for handling image resolutions by adjusting pooling kernels. It uses Global Average Pooling for flattening.

3.2.2 Use hierarchical feature learning to detect edges over early layers, capture complex patterns over deeper layers.

3.2.3 Use Dropout augmentations to drop 20% activations randomly to simulate missing image regions.

3.3 Use Cross modal attention in order to fuse the features to improve performance

3.3.1 Setup Query key value in which one modal features as Query via FNN embeddings, and (Key,Value) for other modalities via CNN embeddings.

3.3.2 Calculate attention weights, compute similarity score, weight increases due to one component correlates with other component. In formula, Q,K, and V denote Query, Key, and Value.

$$\text{Attention}(Q,K,V)=\text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

3.3.3 Define fused representation, do the weighted sum of V based on scores, and prepare a unified feature vector.

Step 4: Evaluate accuracy, Precision, and Recall

Accuracy=True Positives + True Negatives / Total Number of Cases Where

Precision=True Positives (TP) / (True Positives (TP)+False Positives (FP))

Recall (Sensitivity)=True Positives (TP) / (True Positives (TP)+False Negatives (FN))

PS1 demonstrates processing the tabular data (Dataset1) and images (Dataset2) to predict CVD. First, it loads tabular inputs, it handles missing values via FNN-based embedded imputations, normalizes the features, and balances classes with the SMOTE approach. In parallel, for images, it applies adaptive spatial pooling to manage resolution variability and dropout augmentation for robustness. The hybrid model then trains an FNN on tabular data (extracting embeddings via ReLU layers) and a CNN on images (using hierarchical feature learning and adaptive pooling). A cross-modal attention layer fuses by computing similarity scores between FNN-derived queries (Q) and CNN-derived keys/values (K, V) based on both FNN and

CNN features, generating a weighted unified representation. The model then evaluates performance using accuracy, precision, and recall measures to assess the effectiveness of the proposed model

4. 4. RESULTS

Based on Fig.1, Fig.2, and PS1, the proposed hybrid model, such as the hybrid FNN-CNN model, is evaluated and compared against existing methods such as Logistic Regression, Support Vector Machines, Decision Trees, Random Forest, Unimodal FNN, Unimodal CNN, and ResNet. The comparison is made and depicted in Table 3. The results are demonstrated in Fig.3, which denotes the effectiveness of the modals used.

Table 3. Specific measures against the approaches for CVD detection

Approach	**Data Type Handled**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**Remarks**
Logistic Regression	Tabular	78	75	76	Nonlinear relationships in heterogeneous data, are not supported.
Support Vector Machine (SVM)	Tabular	82	80	79	Improve performance with Kernel but fail with image data.
Decision Trees	Tabular	83	81	82	Overfitting issue; ignores spatial features in images.
Random Forest	Tabular	85	84	83	Still limited to structured data.
Unimodal Deep Learning (CNN-only)	Images	88	86	87	Misses critical tabular risk factors.
Unimodal Deep Learning (FNN-only)	Tabular	87	86	85	Lacks image feature extraction.
ResNet	Images	89	88	87	Its still unimodal
Proposed Hybrid (CNN + FNN + Attention)	Tabular + Images	99	98	97	Improves fusion, outperforming than unimodal baselines.

From Table 3, the performance measures such as precision and recall are shown against the considered modals, and accuracy is measured against the considered models.

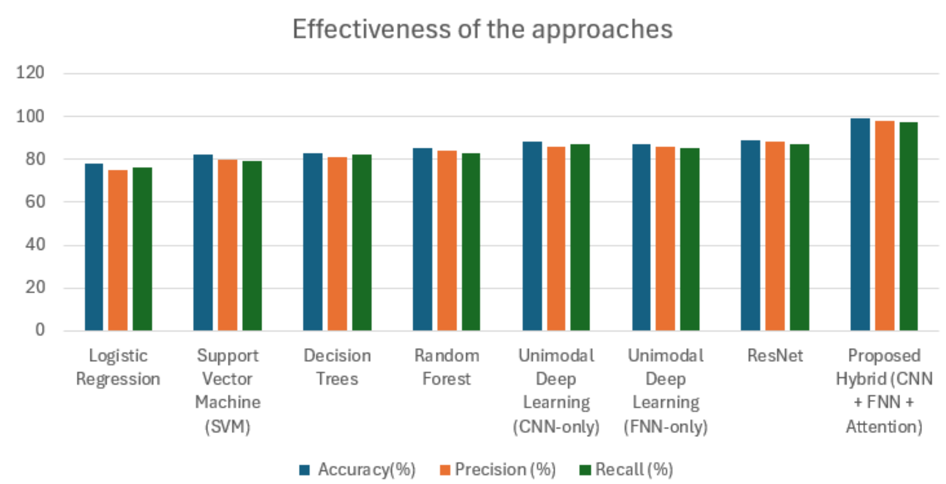

Fig.3. Effectiveness of the models against the proposed model

From Fig.3, the hybrid FNN-CNN modal outperforms than existing models in terms of measures such as accuracy, precision, and recall. Fig.3 proves hybrid FNN-CNN model is better than other models of this study.

Table 4. Interpretability, and Robustness of the approaches

Approach	Interpretability	Robustness	Remarks
Logistic Regression	100	50	Sensitive to outliers and nonlinearity.
Support Vector Machine (SVM)	65	60	Adds complexity with kernel, and moderate robustness to noise.
Decision Trees	98	50	Prone to overfitting.
Random Forest	85	90	Partial interpretability and Ensemble improve robustness.
Unimodal DL (CNN-only)	30	90	Robust to spatial variations, and Black-box for images.
Unimodal DL (FNN-only)	50	70	Limited interpretability, handles tabular noise better.
ResNet	40	99	Computationally opaque, but ensures robustness.
Proposed Hybrid (CNN+FNN+Attention)	**85**	**100**	**Highlight key features for interpretability,** robust to missing data, and multimodal noise.

From Table 4, the hybrid FNN-CNN approach experiences above partial interpretability from a range like above medium to high, then ensures no bias means better robustness due to cross-layer attention fusion, and is robust to the multi-modal data. Compared to other approaches, the balancing approach in understanding and being free from bias is a hybrid FNN-CNN model.

5. 5. CONCLUSION

The hybrid FNN-CNN model integrates tabular clinical data and medical images, and ensures better performance in CVD prediction. Unlike conventional machine learning methods such as Logistic Regression, Support Vector Machines, Decision Trees, Random Forests, Unimodal methods like FNN, CNN, and ResNet, the proposed hybrid model proves better performance and accuracy. The challenges, like missing data, class imbalance, are overcome using embedded imputation and SMOTE, and in parallel, dropout augmentation and adaptive pooling, such as average global pooling, would address the missing data, image resolution variability, and ensure clinically relevant features for effective detection. To assess the models in terms of robustness and interpretability, a hybrid FNN-CNN model would be a better approach for easy decision making. The hybrid model ensures cross-modal attention, effective data preprocessing, and adaptive learning approaches for multi-modal dataset support. The hybrid model provides a real-world solution for early CVD detection in personalized healthcare.

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