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Hybrid Deep Learning Model For Accurate Heart Disease Prediction

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Abstract: Millions of people around the world are suffering from cardio vascular diseases(CVD) and has the highest mortality rate among other diseases. It is essential to develop a system that can accurately predict the chance of getting a CVD. Developments in the fields of AI and Machine Learning are helpful in creating an effective prediction system. Existing systems either use numeric data or ECG(Electro Cardio Gram) graph for predictions.Despite significant progress in these individual domains, there remains a gap in the literature concerning the integration of numerical and image datasets for comprehensive CVD risk assessment. The proposed system aims to bridge this gap by introducing an innovative methodology that seamlessly integrates both numerical and image datasets to enhance CVD risk assessment. By combining numerical datasets extracted from EHRs with image datasets obtained from ECG recordings, the proposed system aims to provide a comprehensive analysis of patient health status, leveraging both clinical measurements and insights from ECG images.

I. INTRODUCTION

Cardiovascular diseases (CVDs) are a significant health concern globally, necessitating the development of advanced methodologies for risk assessment to enable timely interventions and prevention strategies. This study introduces an innovative approach that integrates numerical datasets derived from electronic health records (EHRs) and image datasets obtained from electrocardiogram (ECG) recordings to enhance the accuracy and comprehensiveness of cardiovascular disease risk prediction.

The combination of numerical and image datasets enables a comprehensive analysis of patient health status, utilizing both clinical measurements and detailed insights from ECG images. To preprocess and harmonize the disparate data sources, various techniques are employed tailored to each data type.

For image preprocessing, methods such as image resizing and data augmentation are utilized to improve the quality and diversity of the ECG image dataset. These preprocessing steps are essential for ensuring robust model performance and generalization to unseen data. Subsequently, convolutional neural networks (CNNs) are employed to extract features and patterns from the image data, providing valuable insights into cardiovascular abnormalities.

In parallel, numerical datasets extracted from EHRs undergo preprocessing steps aimed at feature reduction and normalization. Traditional machine learning techniques including logistic regression, naive Bayes, and random forests are employed to process the numerical data, offering additional insights into cardiovascular risk factors.

To combine the processed numerical and image datasets effectively, various techniques such as Label Encoding, standard scaling, and concatenation are employed. These techniques facilitate the seamless integration of heterogeneous data sources, enabling comprehensive analysis and prediction of cardiovascular disease risk.

Furthermore, the model architecture incorporates advanced Neural Networks such as image input layers and structured input layers, allowing for parallel processing of image and numerical data streams. Dense layers, convolutional layers, and max-pooling layers are strategically utilized to extract features and capture complex relationships within the combined dataset, resulting in a powerful predictive model for cardiovascular disease risk assessment.

II. PROBLEM IDENTIFICATION

The critical challenge lies in developing a CVD prediction system that seamlessly integrates numerical and image datasets for a comprehensive risk assessment is different data types. Current methodologies predominantly rely on either numerical or image data, leading to incomplete analyses and sub optimal predictive accuracy. By bridging this gap, an innovative approach can leverage both datasets to provide a more thorough evaluation of patient health status, potentially revolutionizing cardiovascular care by enabling personalized risk assessment and targeted intervention strategies. This necessitates the development of novel methodologies to harness the combined potential of numerical data from electronic health records and insights derived from electrocardiogram images.

III. LITERATURE SURVEY

Cardiovascular diseases (CVDs) represent a significant global health challenge, necessitating innovative methodologies for risk assessment to enable timely interventions and preventive strategies. Previous research has predominantly focused on two primary areas: leveraging numerical data from electronic health records (EHRs) and analyzing image data from electrocardiogram (ECG) recordings. Various machine learning algorithms, including logistic regression, naive Bayes, and random forests, have been applied to process numerical data extracted from EHRs, showcasing promising efficacy in identifying critical risk factors associated with CVD development and progression [1].

Similarly, recent advancements in medical imaging technology have led to the emergence of deep learning models, particularly convolutional neural networks (CNNs), for analyzing ECG images. These CNN-based models have demonstrated considerable potential in detecting abnormalities and aiding clinical diagnosis, thereby enhancing the capabilities of healthcare professionals in cardiovascular care [2].

Despite significant progress in these individual domains, there remains a gap in the literature concerning the integration of numerical and image datasets for comprehensive CVD risk assessment. Few studies have explored the synergistic integration of these diverse data modalities to provide a holistic view of cardiovascular health status and risk prediction [3].

The existing systems have laid a foundation by showcasing the effectiveness of individual approaches—numerical data analysis from EHRs and image data analysis from ECG recordings. However, the proposed system aims to bridge this gap by introducing an innovative methodology that seamlessly integrates both numerical and image datasets to enhance CVD risk assessment. By combining numerical datasets extracted from EHRs with image datasets obtained from ECG recordings, the proposed system aims to provide a comprehensive analysis of patient health status, leveraging both clinical measurements and insights from ECG images.

To prepare the image dataset for analysis, various preprocessing techniques such as image resizing and data augmentation are employed to ensure dataset quality and diversity, critical for optimizing model performance and generalization. Subsequently, CNNs are utilized to process the image data, extracting intricate patterns and features indicative of cardiovascular abnormalities.

In parallel, numerical datasets undergo preprocessing steps aimed at feature reduction, normalization, and advanced imputation techniques to address missing values and reduce dimensionality. Traditional machine learning techniques such as logistic regression, naive Bayes, and random forests are then employed to process the numerical data and identify key risk factors associated with CVD.

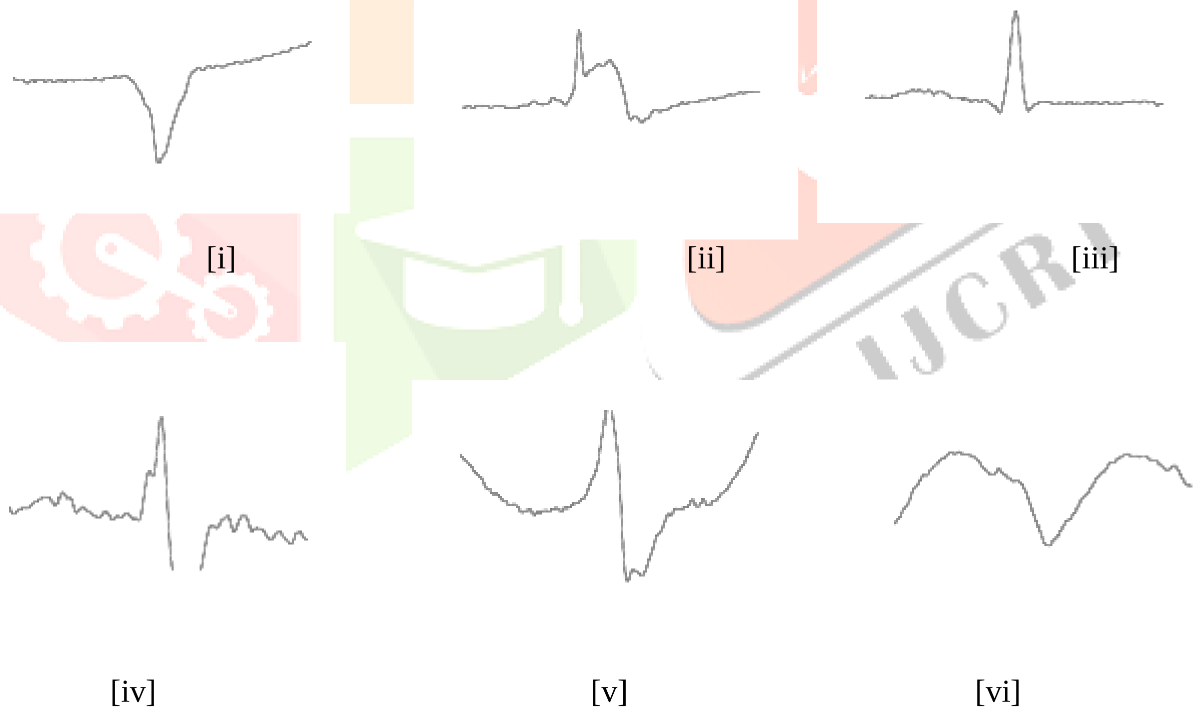
The proposed system's model architecture encompasses both image and numerical data processing streams, leveraging CNN techniques for image processing and tailored layers for numerical data. Through this integrated approach, the system aims to leverage the strengths of both data modalities for enhanced predictive performance and accuracy in CVD risk assessment.

IV. DATASETS

4.1 ECG(Electro Cardio Gram) Image Dataset

This dataset used is derived from kaggle, which composed of two collections of heartbeat signals derived from two famous datasets in heartbeat classification, the MIT-BIH Arrhythmia Dataset and The PTB Diagnostic ECG Database. The number of samples in both collections is large enough for training a deep neural network.[19]

This dataset has been used in exploring heartbeat classification using various deep neural networks, and observing some of the capabilities of transfer learning on it. The signals correspond to electrocardiogram (ECG) shapes of heartbeats for the normal case and the cases affected by different abnormalities such as arrhythmias ,myocardial infarction etc. These signals are preprocessed and segmented into six different categories, with each segment corresponding to a heartbeat.



i - Left Bundle Branch Block
ii - Premature Atrial Contraction
iii - Normal
iv - Right Bundle Branch Block
v - Premature Ventricular Contractions
vi - Ventricular Fibrilation

Figure.1 Different types of ECG peaks

4.2 UCI Heart disease Dataset

The dataset used for this research purpose was the Public Health Dataset and it is dating from 1988 and consists of four databases: Cleveland, Hungary, Switzerland, and Long Beach V. It contains 76 attributes, including the predicted attribute, but all published experiments refer to using a subset of 14 of them. The "target" field refers to the presence of heart disease in the patient. It is integer-valued 0 = no disease and 1 = disease. Now the attributes which are used in this research purpose are described as follows and for what they are used or resemble:

- Age — age of patient in years, sex—(1 = male; 0 = female).
- Cp — chest pain type.
- Trestbps — resting blood pressure (in mm Hg on admission to the hospital). The normal range is 120/80 (if you have a normal blood pressure reading, it is fine, but if it is a little higher than it should be, you should try to lower it. Make healthy changes to your lifestyle).
- Chol — serum cholesterol shows the amount of triglycerides present. Triglycerides are another Lipid that can be measured in the blood. It should be less than 170 mg/dL (may differ in different Labs).
- Fbs — fasting blood sugar larger than 120 mg/dl (1 true). Less than 100 mg/dL (5.6 mmol/L) is normal, and 100 to 125 mg/dL (5.6 to 6.9 mmol/L) is considered prediabetes.
- Restecg — resting electrocardiographic results.
- Thalach — maximum heart rate achieved. The maximum heart rate is 220 minus your age.
- Exang — exercise-induced angina (1 yes). Angina is a type of chest pain caused by reduced blood flow to the heart. Angina is a symptom of coronary artery disease.
- Oldpeak — ST depression induced by exercise relative to rest.
- Slope — the slope of the peak exercise ST segment.
- Ca — number of major vessels (0–3) colored by fluoroscopy.
- Thal — no explanation provided, but probably thalassemia (3 normal; 6 fixed defects; 7 reversible defects).
- Target (T) — no disease = 0 and disease = 1, (angiographic disease status).

Variables Table

Variable Name	Role	Type	Demographic	Description	Units	Missing Values
age	Feature	Integer	Age		years	no
sex	Feature	Categorical	Sex			no
cp	Feature	Categorical				no
trestbps	Feature	Integer		resting blood pressure (on admission to the hospital)	mm Hg	no
chol	Feature	Integer		serum cholestoral	mg/dl	no
fbs	Feature	Categorical		fasting blood sugar > 120 mg/dl		no
restecg	Feature	Categorical				no
thalach	Feature	Integer		maximum heart rate achieved		no
exang	Feature	Categorical		exercise induced angina		no
oldpeak	Feature	Integer		ST depression induced by exercise relative to rest		no
slope	Feature	Categorical				no
ca	Feature	Integer		number of major vessels (0-3) colored by flourosopy		yes
thal	Feature	Categorical				yes
num	Target	Integer		diagnosis of heart disease		no

Figure.2 Numerical dataset description

V.RESEARCH METHODOLOGY

5.1 Data PreProcessing

5.1.1 UCI Dataset PreProcessing

The UCI dataset needs to processed before giving it to the model for training. The dataset does not have any null values. But many outliers needed to be handled , and also the dataset is not properly distributed. Two approaches were used.

- One without outliers and feature selection process and directly applying the data to the machine learning algorithms, and the results which were achieved were not promising.
- But after using the normal distribution of dataset for overcoming the over fitting problem and then applying Isolation Forest for the outlier's detection, the results achieved are quite promising. [5]
- Various plotting techniques were used for checking the skewness of the data, outlier detection, and the distribution of the data. All these pre processing techniques play an important role when passing the data for classification or prediction purposes.
- The distribution of the data play key for predicting or validation of results.
- We see that the target - 1has 54.46% of the time in the dataset, whilst 45.54 accounts for target - 0.

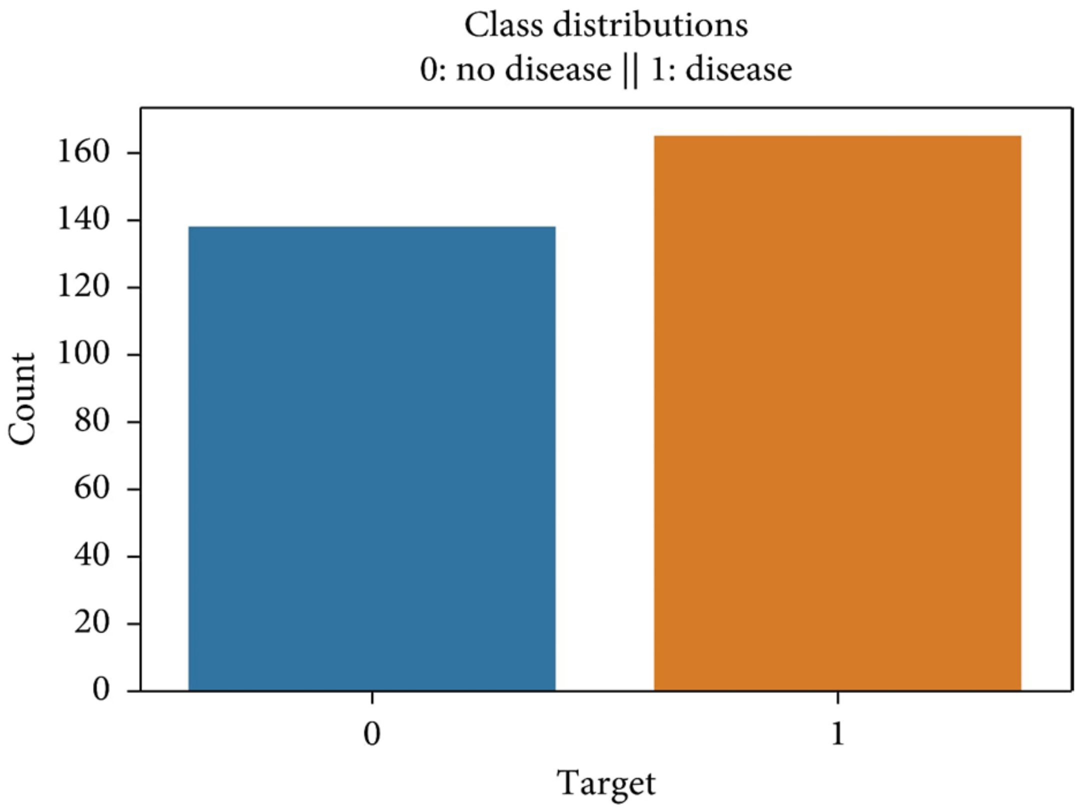


Figure.3 Number of samples with target value equal to '0' and '1'

5.1.2 ECG Dataset Preprocessing

The images are classified into six categories namely Left Bundle Branch Block, Premature Atrial Contraction, Normal,Right Bundle Branch Block, Premature Ventricular Contractions, Ventricular Fibrilation. The images are splitted in 70:15:15 ratio for training, validation and final evaluation purpose. We developed a function for preprocecssing images.

```
def preprocess_images(image, label):
    new_label = tf.where(label == 2, 0, 1)
    new_image = tf.cast(image, tf.float32) / 255.0
    return new_image, new_label
```

The preprocess_images function takes as input an image and its corresponding label, performing a series of preprocessing operations to prepare the data for training or inference within a neural network architecture.

Label Transformation:

- The original label associated with the image is evaluated to identify instances where the label equals 2, indicating a specific class of interest.
- Utilizing TensorFlow's tf.where function, the original label is replaced with binary values, mapping instances of the specified class to 0 and all other classes to 1. This transformation facilitates binary classification, a common requirement in certain image classification scenarios.

Image Normalization:

- The input image undergoes normalization to ensure consistent and standardized data across the dataset.
- Each pixel value in the image is rescaled to the range [0, 1] by dividing by the maximum pixel intensity value (255.0), thereby converting the image into a floating-point representation.
- Normalization is crucial for stabilizing training, accelerating convergence, and improving the model's ability to generalize across different datasets.

Function Output:

- The preprocess_images function returns the preprocessed image (new_image) and its corresponding transformed label (new_label), both of which are ready for consumption by subsequent stages of the machine learning pipeline.

5.2 Classifiers

Three different deep learning neural networks were constructed. The neural networks were designed to be simple in structure and appropriate for their respective input type. The first neural network to be constructed was based off image input (ECG graphs), the second on numerical data presented in a CSV file and the third was a combination of the prior two neural networks taking both a image and numerical values as input. The intention of creating three different deep neural networks was not to test the effectiveness of each input datatype but to determine if the third, hybrid neural network would produce a better result than the individual image based and numerical based neural networks. The classifiers were made using python and mainly the deep learning focused libraries TensorFlow and Keras. They were produced in the python environment jupyter notebook. Other libraries such as pandas and sklearn were used in forming training and validation data in proper deep learning input form.

5.3 Numeric Based Classifier

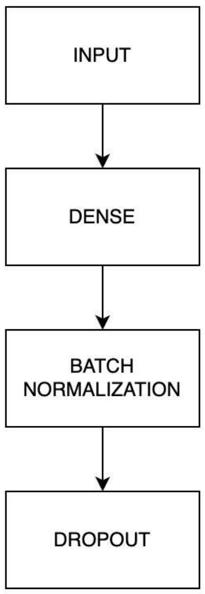


Figure.4 Numeric data classifier branch

- **Input Layer**: The structured input layer accepts structured data with a shape determined by the number of features (num_structured_features) = 13 i.e., number of columns in the numeric dataset.
- **Dense Layer (256 neurons)**: This layer processes the structured data using a dense (fully connected) neural network with 256 neurons and ReLU activation, allowing the model to learn complex patterns from the structured features.
- **Batch Normalization**: Batch normalization normalizes the activations of the previous layer, which helps in stabilizing and accelerating the training process.
- **Dropout (30%)**: Dropout is applied to prevent overfitting by randomly dropping out 30% of the neurons during training, forcing the network to learn more robust features.

5.4 Image Based Classifier

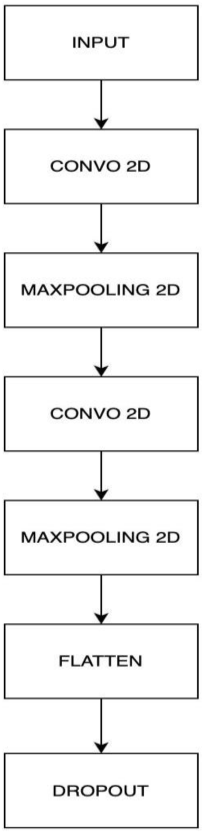


Figure.5 Image data classifier branch

- **Input Layer**: The image input layer accepts images with a size of 64x64 pixels and three channels (RGB).
- **Convolutional Layers**: Two convolutional layers with 128 filters each and a kernel size of 3x3 are applied to extract spatial features from the images. ReLU activation functions introduce non-linearity.
- **Max Pooling Layers**: Max pooling layers with a pool size of 2x2 are used to downsample the feature maps obtained from the convolutional layers, reducing computational complexity and focusing on the most important features.
- **Flatten Layer**: The flatten layer reshapes the output of the convolutional layers into a one-dimensional array to be fed into the subsequent dense layers.
- **Dropout (40%)**: Dropout is applied to the flattened image features to prevent overfitting.

5.5 Hybrid classifier

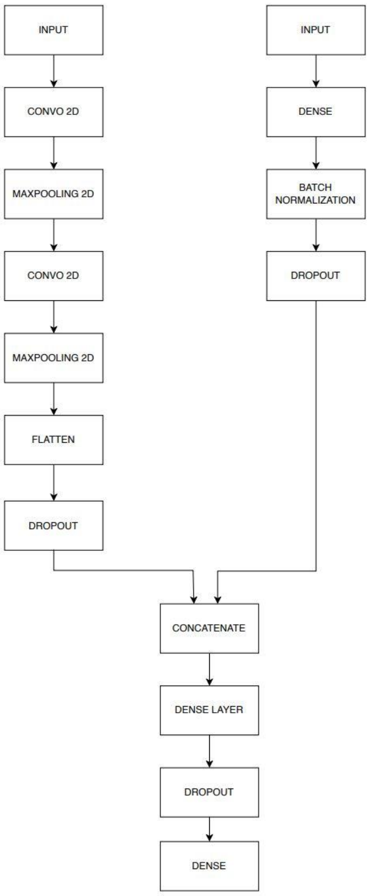


Figure.6 Hybrid Classifier

Combined Layers:

- **Concatenation:** The outputs from the structured input branch and the image input branch are concatenated to combine the learned features from both data types.
- **Dense Layer (256 neurons):** Another dense layer with 256 neurons and ReLU activation further processes the combined features.
- **Dropout (40%)**: Dropout is again applied to the combined features for regularization.

Output Layer:

- **Dense Layer (1 neuron)**: The final dense layer with a single neuron and sigmoid activation outputs the binary classification prediction (0 or 1).

VI.EVALUATION

A. Mathematical Background

a. Confusion Matrix: An in-depth analysis of a machine learning model's performance on a set of test data is provided via a confusion matrix. Based on the model's predictions, it shows the quantity of accurate and inaccurate instances.

- True positives (TP): When a positive data point is correctly predicted by the model, this is known as a true positive.
- True Negatives (TN): When a negative data point is correctly predicted by the model, this is known as a true negative.
- False positives (FP): When a positive data point is incorrectly predicted by the model, this is known as a true positive.
- False negatives (FN): When a negative data point is incorrectly predicted by the model, this is known as a true negative.

b. Accuracy: The percentage of correctly identified cases relative to the total number of examples is known as accuracy. The model performs better the higher its precision.

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

c. Precision: The percentage of correctly identified true positive predictions among all positive predictions made by the classifier is known as precision. A high precision means that while the algorithm can detect most fake job listings, it can miss some genuine ones.

$$\text{Precision} = TP / (TP + FP)$$

d. F1 score: The harmonic mean of recall and precision is the F1 score. It offers a solitary score that harmonizes recall and precision.

$$\text{F1 Score} = 2*(\text{Recall} * \text{Precision}) / (\text{Recall} + \text{Precision})$$

e. ROC-AUC: It measures the area under the Receiver Operating Characteristic (ROC) curve, which plots the true positive rate against the false positive rate at various threshold settings Plotting the true positive rate (TPR) versus the false positive rate (FPR) yields this result. It measures the model's ability to discriminate between the positive and negative classes.

$$\text{True Positive Rate (TPR)} = TP / (TP + FN)$$
$$\text{False Positive rate (FPR)} = FP / (FP + TN)$$

Figure.7 Graphs showing hybrid model's performance during training and Validation.

VII. RESULTS

Inorder to correctly evaluate the performance of the hybrid model, we have developed two other models a basic CNN(Convoltuional Neural Network) and a LSTM model and compared the model's performance based on metrics such as Accuracy, Precision, F-1Score, Recall and ROC_AUC.

	Accuracy (TP+TN)/(TP+TN+FP+FN)	F1-Score (2*precision*recall)/(precision+recall)	Precision TP/(TP+FP)	Recall TP/(TP+FN)	AUC-ROC
Hybrid	88.52	90.66	85.36	0.97	87.03
LSTM	70.81	69.41	87.06	0.57	73.08
CNN	68.8	70.76	76.66	0.65	69.32

Table.1 Evaluating models performance across various evaluation metrics.

VII. CONCLUSION:

The results suggest a significant enhancement in accuracy with the hybrid data input neural network compared to both the LSTM and CNN models. This implies that integrating both structured numerical data and image data into the model architecture can substantially improve its performance in predicting cardiovascular disease (CVD). Although the increase in accuracy is not dramatic, it indicates promising potential for the hybrid model to outperform purely image or numerically based classifiers.

Analyzing the model performances, we observe consistent behavior in the LSTM and CNN models, with both showing expected patterns in their accuracy and loss metrics. However, the hybrid model stands out by combining the strengths of both approaches. It exhibits a rapid increase in accuracy similar to the CNN model in the early epochs, while maintaining stability in loss akin to the LSTM model. As training progresses, the accuracy curve of the hybrid model begins to plateau, reflecting the behavior of the CNN model. This indicates that the hybrid model strikes a balance between learning speed and stability, resulting in improved accuracy compared to the individual models.

Overall, the hybrid model demonstrates promise in enhancing CVD prediction accuracy, achieving an accuracy rate of 88.52%. This outperforms both the LSTM and CNN models, suggesting that the hybrid approach has the potential to significantly improve the performance of cardiovascular disease classifiers.

IX. FUTURE PROSPECTS:

Moving forward, there are several promising avenues for further exploration and enhancement of the hybrid data input neural network in cardiovascular disease (CVD) prediction:

- **Refinement of Model Architecture:** Continual refinement and optimization of the hybrid model architecture could lead to even higher predictive accuracy. This may involve experimenting with different combinations of layers, activation functions, and regularization techniques to further improve model performance.

- **Incorporation of Advanced Techniques:** Integration of advanced techniques such as attention mechanisms, transfer learning, and ensemble methods could enhance the model's ability to extract meaningful features from both structured and image data, thereby improving predictive accuracy.

- **Expansion of Dataset:** Expanding the dataset with a larger and more diverse set of patient data could provide the model with a richer understanding of CVD patterns and risk factors. Additionally, incorporating longitudinal data could enable the model to capture temporal trends and improve long-term prediction accuracy.

- **Clinical Validation and Deployment:** Conducting rigorous clinical validation studies to evaluate the real-world performance of the hybrid model is essential. Collaboration with healthcare institutions and clinicians can facilitate the integration of the model into clinical workflows, enabling early detection and intervention for individuals at risk of cardiovascular disease.

- **Interpretability and Explainability:** Enhancing the interpretability and explainability of the model predictions is crucial for gaining trust and acceptance from healthcare professionals. Developing techniques to provide insights into the model's decision-making process and highlighting the most influential features could improve its usability in clinical settings.

- **Continuous Monitoring and Adaptation:** Implementing mechanisms for continuous monitoring and adaptation of the model to evolving data distributions and clinical guidelines is essential. This ensures that the model remains accurate and reliable over time, even as new data and insights emerge.

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