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DEEP LEARNING-BASED HEART DISEASE PREDICTION USING MULTI-INPUT CNN AND ASSOCIATION RULE ANALYSIS

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Abstract—**One of the most dangerous health problems in the world, heart disease still affects a lot of individuals each year. In order to avoid serious problems and enhance patient outcomes, early prognosis is essential. However, manual analysis is a common component of traditional diagnosis techniques, which can be laborious and may not always identify hidden patterns in medical data.**

This study proposes a deep learning-based heart disease prediction system that integrates association rule analysis with a multi-input Convolutional Neural Network (CNN). The model learns more intricate correlations between inputs by using 13 clinical variables and processing each one separately. Association rule mining is used to find important risk factors and provide a relevant explanation of the prediction results in order to increase interpretability.

Users can submit clinical data and receive real-time predictions and risk explanations thanks to the system's web-based implementation. In addition to achieving good prediction accuracy, the suggested method increases transparency, which makes it more useful for actual healthcare applications.

Index Terms—**Heart Disease Prediction, Deep Learning, Convolutional Neural Network, Association Rule Mining, Explainable AI, Healthcare Analytics**

I. INTRODUCTION

Heart disease continues to be one of the world's top causes of mortality, impacting millions of people annually. Early disease detection can greatly lower risks and enhance treatment results. However, because it depends on a number of clinical criteria, including age, blood pressure, cholesterol, and other medical signs, diagnosing heart disease is not always simple. Conventional diagnostic techniques mostly rely on medical experts' experience. Even though these techniques are dependable, they may occasionally have limitations when handling substantial amounts of patient data or intricate correlations between various variables. Intelligent solutions that can help analyze medical data more effectively are needed in these situations.

Healthcare applications have made extensive use of machine learning and deep learning approaches as artificial intelligence has grown. Large datasets may be processed by these methods, which can also find patterns that manual analysis might miss. Nevertheless, a lot of deep learning models operate as" black boxes," which means they make predictions without providing an explanation. Users may find it challenging to trust the system as a result of this lack of openness, particularly in crucial areas like healthcare.

This study suggests a hybrid strategy that blends association rule mining and deep learning to overcome these issues. The method applies association rules to provide explanations in the form of risk factors and uses a multi-input CNN model to provide precise predictions. A web-based interface is also created to make it simple for users to interact with the system and get results in real time.

This work's primary contribution is the combination of explainability and prediction into a single system, which makes it efficient and easy to apply for real-world applications.

II. RELATED WORK

Numerous studies have been conducted throughout the years to create automated systems for the prediction of heart disease. Traditional machine learning techniques like logistic regression, decision trees, and support vector machines were the mainstay of early methods. Although these models could make predictions with a respectable degree of accuracy, they frequently had trouble capturing intricate correlations between various clinical parameters.

Researchers started investigating deep learning methods for medical prediction jobs as processing power grew. When com- pared to conventional models, neural networks—especially deep feed forward networks—have demonstrated better performance. Convolutional neural networks (CNNs) have been used in the healthcare industry more lately because of their superior pattern recognition capabilities. However, most of these models treat the input features as a single combined vector, which may limit their ability to capture feature-specific behavior.

Interpretability is a crucial component of healthcare systems. Many of the deep learning models that are now in use function as" black boxes" and don't offer concise justifications for their predictions. Users may become less trusting as a result of this lack of transparency, particularly if the technology is utilized to assist with medical decisions.

In parallel, associations between various symptoms and diseases have been found using association rule mining techniques in healthcare analytics. Finding recurring patterns and connections in the dataset is made easier by techniques like the Apriori algorithm. Although these methods are helpful for comprehending data, they are not usually intended for prediction problems.

The suggested system combines both strategies to overcome these drawbacks. While association rule mining is utilized to offer insightful explanations, the multi-input CNN model is intended to capture intricate feature-level patterns. This combination guarantees that, in comparison to current techniques, the system not only performs well in prediction but also provides greater interpretability.

III. PROBLEM STATEMENT

To assess a patient's risk for heart disease, a variety of clinical indicators are analyzed. While a number of deep learning and machine learning models have been created for this goal, many of them ignore interpretability in favor of prediction accuracy.

The majority of conventional systems either need manual analysis or use models that handle all input features collectively, which might not adequately capture the behavior of individual features. Furthermore, a lot of deep learning models make predictions without elucidating the underlying causes, which makes them unreliable in actual healthcare situations.

Therefore, there is a need for a system that can:

- Accurately predict the presence of heart disease using clinical data
- Capture detailed relationships between individual features
- Provide clear explanations for predictions in terms of risk factors
- Offer an interactive and user-friendly interface for real-time usage

In order to ensure accuracy and interpretability, the goal of this work is to create and execute such a system by integrating deep learning with association rule analysis.

IV. OBJECTIVES OF THE PROPOSED WORK

The primary goal of this research is to create an intelligent system that can reliably forecast cardiac illness and offer insightful justifications for its predictions. The following are the proposed work's precise objectives:

- To design a deep learning model using a multi-input CNN architecture for improved prediction performance
- To utilize clinical data consisting of multiple features relevant to heart disease diagnosis
- To apply data preprocessing techniques such as scaling and class balancing for better model training
- To incorporate association rule mining for identifying important risk factors
- To develop a web-based application that enables real-time prediction and visualization
- To store prediction history and generate reports for user reference

These objectives aim to create a system that is not only accurate but also practical and easy to use in real-world scenarios.

V. PROPOSED SYSTEM

The suggested method uses a combination of deep learning and data mining approaches to deliver a precise and comprehensible forecast of cardiac disease. It combines association rule analysis for risk factor identification with a multi-input CNN model for prediction. To make the system accessible and user-friendly, a web-based interface is also created.

User input is the first step in the whole workflow, which is then followed by preprocessing, prediction, risk analysis, and result visualization.

A. System Overview

The system uses a structured pipeline to process and analyze user-provided clinical data step-by-step. The input features are first scaled and confirmed. The CNN model, which forecasts the likelihood of heart disease, receives these processed information. Key contributing factors are identified using association rules based on this prediction. Lastly, risk explanations and the results are presented via a web interface.

B. Dataset Description

Thirteen clinical characteristics that are frequently used to diagnose heart disease make up the dataset used in this study.

Age, sex, kind of chest pain, blood pressure, cholesterol, fasting blood sugar, ECG results, maximal heart rate, exercise- induced angina, ST depression, slope of ST segment, number of major vessels, and thallium test results are some of these characteristics.

Each aspect offers crucial details about the patient's health, and when combined, they aid in determining whether or not cardiac disease is present.

C. Data Preprocessing

Preprocessing data is crucial to enhancing model performance. The StandardScaler method, which converts the data into a normalized range, is used in this system to apply feature scaling. This guarantees consistent training and improves the model's ability to learn.

Additionally, the SMOTE technique is used to address class imbalance in the dataset. In order to prevent the model from becoming biased toward one class during training, this strategy creates synthetic samples for the minority class.

D. Feature Selection

A conditional probability-based method is used for feature selection. Every characteristic is examined to ascertain its impact on the existence of heart disease. Higher influence score features are prioritized, while less pertinent features are eliminated.

This stage enhances the model's overall effectiveness and reduces needless complexity.

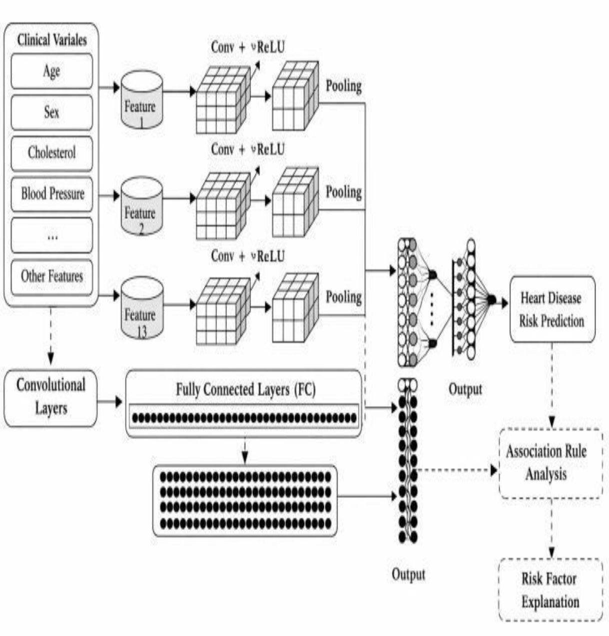

Fig. 1. Multi-Input CNN Architecture for Heart Disease Prediction

E. CNN Model Architecture

The suggested system makes use of a multi-input Convolutional Neural Network (CNN) architecture, in which a specific convolutional route processes each clinical feature separately. The model extracts feature-specific patterns by passing each input feature through a Conv1D layer, max pooling, and flattening processes.

A concatenation layer is then used to merge the outputs of all feature-specific branches, capturing the correlations between various clinical attributes. To avoid overfitting, this composite representation is run through several fully linked (dense) layers with dropout regularization.

Lastly, the output layer predicts the likelihood of heart disease using a sigmoid activation function. Because of its architecture, the model can efficiently learn the contributions of individual features as well as their combined effects, leading to excellent generalization capabilities and high prediction accuracy.

F. Association Rule Analysis

The Apriori technique is used in association rule mining to improve interpretability. First, categorical ranges like low, medium, and high are created using numerical features. This makes it possible for the system to provide useful rules.

Support, confidence, and lift are used to assess each rule. Strong correlations between characteristics and the target variable can be found with the use of these measurements.

When a forecast is made, the algorithm extracts the most pertinent patterns by comparing the patient input with the generated rules. The forecast is explained in detail by presenting these patterns as risk factors.

G. Web-Based Implementation

Flask is used to implement the system as a web application. A user-friendly interface for data entry and result display is provided by the frontend, which is created using HTML, CSS, and JavaScript.

Features like report production, prediction history tracking, and user authentication are all included in the program. In addition to viewing prediction results and entering patient data, users can obtain reports for additional analysis.

The system is useful and simple to use in real-world situations since backend processing and frontend visualization are integrated.

VI. METHODOLOGY

The suggested system uses a structured method to anticipate cardiac illness and provide relevant explanations. The approach is made to handle user input, use the trained model to make predictions, and employ association analysis to generate findings that are easy to understand.

A. Input Collection

The user inputs clinical data via the online interface to start the process. Age, sex, kind of chest pain, blood pressure, cholesterol level, fasting blood sugar, ECG results, maximum heart rate, exercise-induced angina, ST depression, slope, number of vessels, and thallium test scores are among the 13

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input features that the system needs. The system verifies that all data fall within authorized medical ranges before processing. This keeps data consistent and prevents against prediction errors.

B. Data Preprocessing

The input is transformed into a numerical representation appropriate for the model after it has been verified. The StandardScaler method is then used to scale the data. By ensuring that all features are on a similar scale, scaling enhances the CNN model's stability and performance.
The processed data is reshaped into the required format so that it can be passed into the multi-input CNN model.

C. Prediction Using CNN Model

The trained CNN model receives the scaled input data. Convolutional layers process each information separately, enabling the model to identify intricate patterns.
To create a final forecast, the outputs from each feature branch are pooled and run through dense layers. The possibility of heart disease is indicated by the model's probability value, which ranges from 0 to 1.
Based on this probability, the system classifies the result into two categories:

- Presence of heart disease
- Absence of heart disease

In addition, a risk level is assigned (low, moderate, or high) based on the predicted probability.

D. Risk Factor Identification

The method uses association rule analysis to find relevant factors if the forecast suggests the presence of heart disease. The input data is transformed into categorical values that correspond to the format utilized in the creation of the rules. After that, the system contrasts these values with the association rules' antecedents.
Confidence and lift values are used to choose matching rules. Risk factors are extracted using the most pertinent rules and shown to the user in an understandable fashion.

E. Result Generation and Visualization

The dashboard shows the risk level, probability value, predicted outcome, and discovered risk factors. To enhance visualization, a graphical depiction of the probability is also shown.
The technology makes sure that even non-technical users may easily comprehend the output.

F. Data Storage and Report Generation

Along with the input values and outcomes, every forecast is kept in the database. Users are able to monitor their prediction history as a result.
Additionally, the system offers the ability to create a comprehensive report in PDF format. The report is helpful for future reference because it contains prediction findings, likelihood, risk level, and related rules.

G. Overall Workflow

The complete workflow of the system can be summarized as follows:

1. User enters clinical input data
2. Input validation is performed
3. Data is scaled using StandardScaler
4. CNN model predicts disease probability
5. Risk level is determined
6. Association rules identify risk factors
7. Results are displayed on the dashboard
8. Prediction is stored in the database
9. Report is generated if requested

The system is accurate and comprehensible because to this methodical approach, which makes it appropriate for real-world healthcare applications.

VII. MATHEMATICAL MODEL

To forecast cardiac illness and offer comprehensible in-sights, the suggested system integrates deep learning and association rule mining techniques. The many parts of the system are represented mathematically in this section.

A. Feature Scaling

The StandardScaler method is used for feature scaling in order to guarantee that each input feature contributes equally to the model. The result of the transformation is:

$$X_{scaled} = \frac{X - \mu}{\sigma} \quad (1)$$

where μ is the feature mean, σ is the standard deviation, and X is the original feature value. The data is transformed into a standardized format with a zero mean and unit variance.

B. CNN Feature Processing

The multi-input CNN model processes each feature separately. The transformation for a given input feature x_i can be expressed as follows:

$$h_i = \mathrm{ReLU}\,(W_i x_i + b_i) \quad (2)$$

where b_i stands for bias, W_i for weight, and ReLU is the activation function, which is defined as:

$$\mathrm{ReLU}\,(x) = \max(0, x) \quad (3)$$

This process aids in deriving significant patterns from every feature.

C. Feature Combination
A concatenation process is used to combine the results of each distinct feature:

$$H = \bigoplus_{i=1}^{N} h_i \tag{4}$$

This composite image depicts the connections between several aspects.

D. Prediction Function
The final prediction is derived by applying a sigmoid activation function to the combined representation after it has been passed through thick layers:

$$\hat{y} = \frac{1}{1 + e^{-(WH+b)}} \tag{5}$$

where $\hat{y}$ is the anticipated likelihood of heart disease.

E. Loss Function
Binary Cross Entropy loss, which calculates the discrepancy between the actual and predicted values, is used to train the model:

$$L = -[y \log(\hat{y}) + (1 - y) \log(1 - \hat{y})] \tag{6}$$

where y is the actual label and $\hat{y}$ is the predicted probability.

F. Association Rule Metrics
Relationships between characteristics and heart disease are found by association rule mining. A rule is shown as:

$$X \rightarrow Y \tag{7}$$

where X is the set of input conditions and Y is the outcome.
The following metrics are used to gauge how strong rules are:

Support:

$$Support(X) = \frac{Count(X)}{N} \tag{8}$$

Confidence:

$$Confidence(X \rightarrow Y) = \frac{Support(X \cup Y)}{Support(X)} \tag{9}$$

Lift:

$$Lift(X \rightarrow Y) = \frac{Confidence(X \rightarrow Y)}{Support(Y)} \tag{10}$$

Strong and significant correlations between clinical characteristics and the existence of cardiac disease can be found using these measurements.

G. Risk Level Determination
The predicted probability $\hat{y}$ is used to classify the risk level:

$$Risk = \begin{cases} \text{Low,} & \hat{y} < 0.3 \\ \text{Moderate,} & 0.3 \leq \hat{y} < 0.7 \\ \text{High,} & \hat{y} \geq 0.7 \end{cases} \tag{11}$$

Users can easily and clearly comprehend the severity of the problem thanks to this classification.
All things considered, these mathematical formulations guarantee the system's accuracy and interpretability by fusing predictive power with understandable insights.

VIII. ALGORITHM / WORKFLOW
The suggested system processes user input, makes predictions, and produces findings that may be explained using a structured workflow. Below is a step-by-step description of the entire method.

A. Algorithm for Heart Disease Prediction System
Input: 13 features make up the clinical data input.
Output: Probability, risk level, risk variables, and disease prediction.

1. Turn on the system
2. Use the web interface to receive clinical input data from the user
3. Verify that the input values are within approved medical ranges
4. Transform input data into a numerical format that can be processed by models
5. Normalize the input data by applying feature scaling with StandardScaler
6. Reshape the scaled data to fit the CNN model's input format
7. Fill the trained multi-input CNN model with the processed data
8. Determine the expected likelihood of heart disease
9. Categorize the forecast as:
   - The presence of heart disease (if likelihood ≥ 0.5)
   - Absence of Heart Disease (if probability ¡ < 0.5)
10. Calculate the degree of risk using probability:
    1. Minimal Risk
    2. Moderate Danger
    3. Elevated Risk
11. Convert input features into categorical format for association rule matching
12. Examine the processed input against the association rules that have been saved

13. Determine matching rules using lift values and confidence
14. From the matching rules, identify the most pertinent risk variables
15. Show the dashboard's forecast outcome, probability, risk level, and risk variables
16. Save the forecast information in the database for further use
17. Make it possible to create and download a PDF report
18. End the process

B. Workflow Description

When the user inputs clinical information into the system, the workflow starts. To guarantee accuracy, the data is first preprocessed and confirmed. Based on the input features, the CNN model then forecasts the probability of heart disease. Association rule analysis is performed to determine contributing elements if the model predicts a positive case. By presenting these variables to the user as risk indicators, the forecast becomes easier to comprehend. The outcomes are then saved in the database, shown on the dashboard, and can be exported as a report. This procedure guarantees the system's effectiveness and usability.

IX. EXPERIMENTAL SETUP

The environment, instruments, and technologies utilized to create and assess the suggested heart disease prediction system are described in this section. Web technologies, data processing libraries, and deep learning frameworks are all used in the implementation.

A. Software Environment

Python is the main programming language used in the system's development because of its ease of use and robust support for web development and machine learning. The implementation makes use of the following frameworks and libraries:

- **TensorFlow and Keras:** Used for designing and training the CNN model
- **Scikit-learn:** Used for assessment, feature scaling, and data preprocessing
- **Pandas and NumPy:** Used for numerical operations and data processing
- **mlxtend:** This tool is used to implement the association rule mining Apriori algorithm.
- **Flask:** Used to create the web application's backend
- **HTML, CSS, and JavaScript:** Used for building the frontend interface
- **SQLite:** This database is used to store user and prediction data.

B. Model Training Setup

Thirteen features of preprocessed clinical data are used to train the CNN model. To guarantee that every feature is on a comparable scale, the dataset is standardized using Standard-Scaler prior to training. The SMOTE technique, which creates synthetic samples for the minority class, is used to address class imbalance.

The Adam optimizer, which effectively modifies weights during training, is used to train the model. Since the problem is a binary classification task, the loss function is Binary Cross Entropy. Based on feature patterns, the model gains the ability to differentiate between the presence and absence of cardiac disease.

C. Hardware Configuration

Without the need for specialist hardware, the system is created and tested in a typical computing environment. With the following setup, the implementation can operate on a standard desktop or laptop:

- Processor: Intel or equivalent CPU
- RAM: 8 GB or higher
- Storage: Sufficient space for dataset and model files

The model is accessible for widespread use because it is optimized to function effectively even in the absence of GPU support.

D. Web Application Setup

A web application built with Flask incorporates the trained model. The program manages user input, makes predictions, and shows outcomes instantly. Additionally, it controls report production, prediction history, and user authentication. Users can enter clinical data and comprehend the results with ease thanks to the frontend interface's straightforward and user-friendly design. The system runs smoothly thanks to the integration of frontend visualization and backend processing.

E. Evaluation Setup

Standard classification metrics including accuracy, precision, recall, and F1-score are used to assess the model's performance. The number of accurate and inaccurate classifications is determined by analyzing the prediction results using a confusion matrix.

This configuration guarantees that the system is tested in practical settings and yields dependable performance out-comes.

X. RESULTS AND DISCUSSION

The performance of the suggested heart disease prediction system is shown in this part, along with an analysis of its predictability and explainability.

A. Prediction Performance

Using clinical input features, the CNN model is trained to determine if a patient has heart disease. To ascertain if the disease is present or not, the model generates a probability value.

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A confusion matrix, which offers a comprehensive perspective of accurate and inaccurate predictions, is used to assess the model's performance.

TABLE I
CONFUSION MATRIX (CNN TEST SET EVALUATION)

	Predicted No	Predicted Yes
Actual No	162	2
Actual Yes	2	139

B. Confusion Matrix

The test dataset, which comprises 20% of the total records (305 samples), is used to create the confusion matrix. It gives a clear picture of how effectively the model works with unknown data.

The model properly identified 162 cases as negative (true negatives) and 139 cases as positive (true positives), according to the matrix. Only 2 instances were incorrectly classified as false positives and 2 as false negatives.

This suggests that there are far more accurate predictions than incorrect classifications. The model's ability to accurately distinguish between the presence and absence of cardiac disease is demonstrated by the extremely low frequency of false positives and false negatives.

Overall, our findings show that the suggested multi-input CNN model is appropriate for real-world healthcare applications since it makes accurate predictions and generalizes well to new data.

C. Performance Metrics

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (12)$$

$$Precision = \frac{TP}{TP + FP} \quad (13)$$

$$Recall = \frac{TP}{TP + FN} \quad (14)$$

$$F1\text{-}Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (15)$$

The model achieves balanced precision and recall and good accuracy based on the confusion matrix. This suggests that the system does a good job of both identifying affirmative cases and preventing false alarms.

D. Training Performance Analysis

Accuracy and loss curves from several epochs were used to evaluate the training performance of the suggested CNN model. The accuracy graph demonstrates a consistent improvement in both training and validation accuracy, suggesting that the model is successfully learning from the input.

Throughout the training phase, it is evident that the validation accuracy stays quite close to the training accuracy. This implies that the model does not suffer from overfitting and generalizes well to new data.

In a similar vein, the training and validation loss values consistently decline in the loss graph. Stable learning and appropriate model parameter optimization are indicated by the curves' smooth convergence.

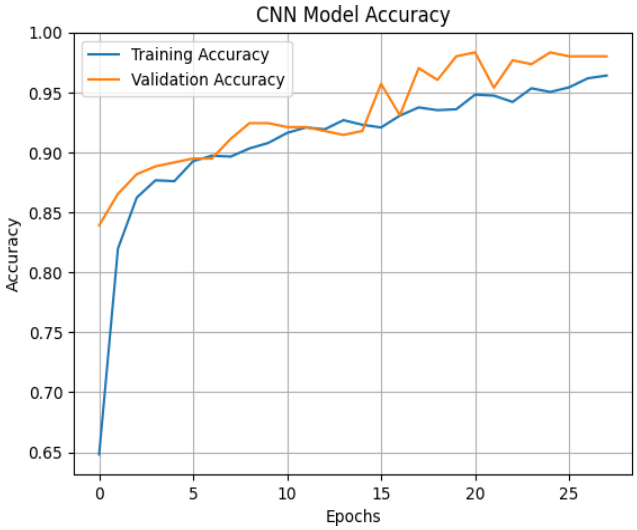

Fig. 2. Training and Validation Accuracy of CNN Model

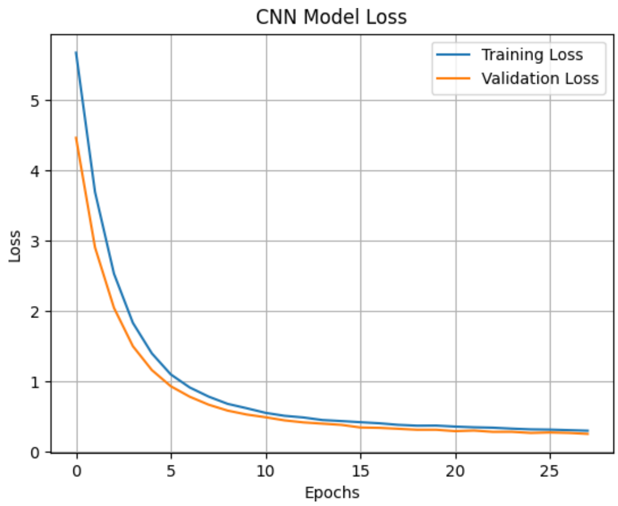

Fig. 3. Training and Validation Loss of CNN Model

Overall, the accuracy and loss curves show that the CNN model is stable, well-trained, and able to provide accurate predictions for the classification of heart disease.

E. Interpretability Through Association Rules

The capacity of the suggested method to explain predictions is one of its main advantages. Association rule analysis is performed to find contributing factors when the model predicts the existence of heart disease.

For instance, excessive cholesterol, angina brought on by exercise, and irregular ECG readings are frequently linked to increased risk. The user is shown these relationships in an easy-to-understand style after they have been retrieved using association rules.

By bridging the gap between explanation and prediction, this method improves the system's dependability and usability.

F. System Behavior and Usability

Users can interact with the system with ease when the model is integrated into a web-based application. Users can view prediction results, input clinical data, and comprehend risk variables.

In addition, the technology lets users record and examine previous forecasts and offers a visual depiction of prediction likelihood. Usability is further improved by the ability to create a report.

G. Discussion

The findings show that association rule analysis and a multi-input CNN model work well together to forecast heart disease. While association rules offer insightful explanations, the CNN model guarantees excellent prediction performance. The suggested system provides a better balance between interpretability and accuracy than conventional models. Because of this, it is more suited for practical healthcare applications where transparency and performance are crucial. All things considered, the technology offers a workable way to support medical decision-making and enhance early cardiac disease identification..

XI. ADVANTAGES OF THE PROPOSED SYSTEM

The suggested heart disease prediction system has a number of benefits that make it useful and efficient for practical uses.

- **High Prediction Accuracy:** The system can identify intricate patterns in clinical data by using a multi-input CNN model, which produces accurate predictions.
- **Explainable Results:** In contrast to conventional deep learning models, the system uses association rule analysis to give consumers concise explanations that help them comprehend the logic behind predictions.
- **Feature-Level Learning:** Because each clinical feature is evaluated separately, the model is better able to identify particular patterns and associations.
- **Real-Time Prediction:** Users can submit clinical data into the web-based implementation to get immediate results.
- **User-Friendly Interface:** Even non-technical individuals can utilize the system because of its straightforward and engaging interface.
- **Prediction History Tracking:**The technology allows users to examine and evaluate earlier outcomes by storing historical forecasts.
- **Report Generation:** Comprehensive reports that can be used for documentation and additional analysis can be created and downloaded by users.

XII. LIMITATIONS

The suggested system has several drawbacks that should be taken into account despite its benefits.

- **Limited Dataset:** The dataset used to train the model might not accurately reflect all potential medical problems or variances.
- **Dependency on Input Quality:** The correctness of the user-provided input data determines how accurate the forecast is.
- **Lack of Real-Time Medical Integration:**Real-time monitoring equipment and hospital databases are not directly connected to the system.
- **Model Complexity:** Implementation complexity may rise due to the multi-input CNN architecture's need for meticulous design and tuning.
- **Generalization Challenges:** Applying the model to various datasets or populations may necessitate retraining or fine-tuning.

XIII. FUTURE SCOPE

There are numerous ways to expand and enhance the suggested system.

- **Integration with Healthcare Systems:** Real-time data analysis can be made possible by connecting the system to hospital databases.
- **Use of Larger Datasets:** The model's capacity for generalization can be enhanced by training it on bigger and more varied datasets.
- **Mobile Application Development:** For more accessibility, the system might be expanded into a mobile application.
- **Incorporation of IoT Devices:** Continuous data input can be provided by integrating real-time health monitoring equipment.
- **Advanced Explainable AI Techniques:** Deeper insights into model predictions can be obtained by incorporating more sophisticated explainability techniques.
- **Improved Model Architectures:** For improved performance, future research can investigate sophisticated deep learning models like transformers.

XIV. CONCLUSION

This study introduced a deep learning-based heart disease prediction system that integrates association rule analysis with a multi-input CNN model. Through the identification of risk factors, the system is intended to deliver precise forecasts together with lucid explanations.

Prediction performance is enhanced by the model's ability to efficiently learn feature-specific patterns thanks to the multi-input CNN design. Additionally, by emphasizing significant connections between clinical characteristics and the existence of cardiac disease, association rule mining improves interpretability.

The system is useful and simple to use because the model is integrated into a web-based application. Clinical data entry, forecasts, risk factor comprehension, and real-time report generation are all possible for users.

All things considered, the suggested system offers a well-rounded strategy that blends precision, interpretability, and usability. Because of this, it is a viable way to improve decision-making and aid in early identification in healthcare applications.

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