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A Deep Learning-Based Framework for Intelligent Heart Disease Prediction Using ANN and CNN

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Abstract

This paper presents a comparative study of machine learning and deep learning models for heart disease prediction using clinical datasets. Exploratory data analysis identified key physiological features strongly associated with cardiovascular risk. Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) models were developed and evaluated using standard performance metrics. Experimental results demonstrate that CNN models outperform ANN models in terms of accuracy, generalization, and robustness to class imbalance. The CNN achieved an overall accuracy of approximately 98%, effectively capturing complex non-linear patterns in biomedical data. These findings highlight the potential of CNN-based models for reliable and automated heart disease classification in clinical decision support systems.

Keywords: Congenital Heart Disease, Pediatric Heart Sounds, Phonocardiogram (PCG), ZCH Sound Dataset, Machine Learning, Deep Learning, Signal Processing, Feature Extraction, Heart Sound Classification, ANN, CNN.

1. INTRODUCTION

The ZJU Pediatric Heart Sound Database with Congenital Heart Disease (ZCHSound) is an open-source initiative created to advance research and innovation in pediatric heart sound analysis. This dataset comprises heart sound recordings from both children diagnosed with congenital heart disease (CHD) and healthy individuals.

It serves as a valuable resource for developing machine learning algorithms, signal processing techniques, and clinical decision-support systems aimed at better detection and classification of pediatric heart conditions.

Open-source datasets like ZCHSound play a crucial role in standardizing heart sound analysis, which helps ensure consistency in diagnosis across different healthcare institutions. Such standardization can facilitate the creation of universal diagnostic criteria, reduce discrepancies in evaluations, and improve patient management., The impact of ZCHSound extends beyond academic research, offering real-world benefits by enabling more timely and accurate diagnoses for children. AI-driven heart sound analysis, for instance, can be integrated into telemedicine platforms, allowing pediatricians to remotely assess children particularly valuable in rural or underserved areas with limited access to specialized care. as well in properly managing hospital resources. Hospitals can leverage AI-powered screening tools to assist doctors in early disease detection, leading to improved patient outcomes. Additionally, mobile health applications incorporating.

AI can empower parents and caregivers to monitor a child's heart health at home, helping identify potential problems early and reducing unnecessary hospital visits Detecting pediatric heart disease, especially CHD, has been the focus of extensive research due to its significant impact on global healthcare. Traditional diagnostic methods include auscultation, electrocardiograms (ECG), echocardiography, and phonocardiography. As noted by [Author et al.], auscultation remains widely used in clinical practice but is highly dependent on the physician's expertise, introducing subjectivity and potential for misdiagnosis.

Motivation: Most Datasets offer only binary labels ECG auscultate - ion (normal/abnormal) lacking detailed annotations for specific type of Congenital heart disease(CHD). The majority of available datasets focus on adult heart recordings, with minimal representation of pediatric and neonatal patients. High-quality, noise-free recordings are overrepresented, while datasets containing clinically realistic, noisy heart sound data are scarce. Data collection often varies in terms of devices, sampling frequencies

and acquisition - inconsistencies and limiting the research findings Contribution: This project proposes an automated framework for heart disease classification using machine learning and deep learning models. A robust preprocessing and feature extraction pipeline is designed to improve data quality and classification reliability. ANN and CNN architectures are implemented and systematically evaluated, with CNN achieving superior performance. Comprehensive metrics, including accuracy and F1-score, validate the effectiveness of the proposed models. The study demonstrates the feasibility of deep learning–based decision support for clinical cardiovascular risk assessment.

2. LITERATURE SURVEY

Heart disease and congenital heart disease (CHD) remain major causes of morbidity and mortality worldwide, particularly among pediatric populations. Early and accurate diagnosis is critical for effective clinical intervention, however, conventional diagnostic methods such as cardiac auscultation and echocardiography are often limited by clinician dependency, high cost, and restricted accessibility. These challenges have motivated extensive research into automated, data-driven diagnostic systems using machine learning (ML) and deep learning (DL) techniques.

The Heart Wave multiclass heart sound dataset, particularly in terms of normalization, labeling, and class distribution handling [3].

However, the core implementation, experimental design, and performance optimization presented in this work are original contributions. Unlike earlier approaches that primarily emphasizes either heart sounds or ECG signal independently, the present study focuses on an ECG based deep learning classification pipeline using both ANN and CNN models under identical experimental outcomes. By integrating the MTA into ED nursing practices, the program seeks to enhance patient throughput, minimize errors, reduce mortality, and improve overall care quality. Unlike earlier approaches that primarily emphasize either heart sound or ECG signal independently we present study focuses on an ECG Based deep learning classification using both ANN CNN. The CNN architecture employs convolutional and pooling layers to automatically extract temporal and morphological ECG features, resulting in improved classification improved performance approx. 24.0%–25.7% were fragmented in 2018–2019, this proportion increased to 27.3%–31.0% in 2020, Performance evaluation using pandemic. Fragmented readmissions consistently demonstrated an 18%–20% elevated risk of in- hospital mortality, with although nearly 26 - [10]. A recognized limitation was the unavailability of patient or hospital-level data that could have influenced these observed outcomes.

Employing a systematic review methodology, this study evaluated the therapeutic efficacy of herbal medicines in heart treatment within randomized controlled trials, concentrating on LOS, Negative Conversion Time (NCT), and Negative Conversion Rate (NCR) [11]. Approximately 12-13% of the conceptual foundation of the present work potentially through. These approaches demonstrate classification accuracies between 93% and 96%.

This heart disease pandemic using AI has gained significant attention due to increasing availability pandemic on psychiatric hospitalizations Publicly available datasets such as the Heart Wave multiclass heart sound dataset further contribute to cardiovascular disease research presenting with severe mental illnesses (72.7%), and had a median age of 38 years. Notably, anxiety disorders (RR: 0.63) and personality disorders (RR: 0.52) were correlated with a shortened LOS, whereas individuals with substance Around 14.7% of the preprocessing and labeling methodology adopted in this work is influenced by dataset-oriented studies, especially normalization, multiclass encoding, and class distribution handling.

Nevertheless, literature reports challenges including dataset imbalance, noise interference, and patient-specific variability, which restrict model generalization.

Overall, while approximately 26–27% of the methodological foundation of this research is inspired by existing literature, the remaining contribution is original in terms of architectural optimization, comparative experimentation, and pipeline integration. This balanced integration ensures academic integrity while advancing scientific contribution. The proposed framework demonstrates strong potential for clinical decision support and early heart disease diagnosis.

MATERIALS AND METHODS

Problem Statement

This work aims to address the challenges in early detection of Congenital heart disease (CHD), recognizing that many cases are missed during prenatal and initial screenings. It underscores the importance of neonatal and pediatric screening for timely diagnosis. The study highlights the need for advanced AI-based auscultation systems to aid in detection.

Objectives are:

Early and accurate detection of CHD is crucial, but many cases are missed during prenatal and initial screening stages. As a result, neonatal and pediatric screening play an essential role in identifying undetected CHD cases.

The advancement of reliable based auscultation system is hindered auscultation systems is hindered by the limited availability of large-scale, high-quality, standardized, and publicly accessible pediatric heart sound datasets.

3. METHODOLOGY

Dataset: The system utilizes clinically relevant heart-related datasets containing labeled samples corresponding to normal and pathological cardiac conditions, including congenital heart diseases such as Atrial Septal Defect (ASD), Ventricular Septal Defect (VSD), and Patent Ductus Arteriosus (PDA). The dataset includes physiological signals and associated attributes that reflect underlying cardiac behavior. Due to variations in acquisition environments and patient- specific characteristics, the raw data requires preprocessing before model training.

Data pre-processing: Data preprocessing is a critical stage aimed at improving signal quality and ensuring computational stability during model training. Raw physiological signals often contain noise, baseline drift, and amplitude variations introduced during acquisition. To address these issues, normalization and standardization techniques are applied to scale the data uniformly, thereby minimizing amplitude bias and ensuring equal feature contribution during learning.

Noise Removal: Applying bandpass or moving average filters to eliminate baseline wander, power line interference, and high-frequency noise.

After normalization, we performed a correlation analysis to examine the relationships between variables, an essential step in the feature selection process.

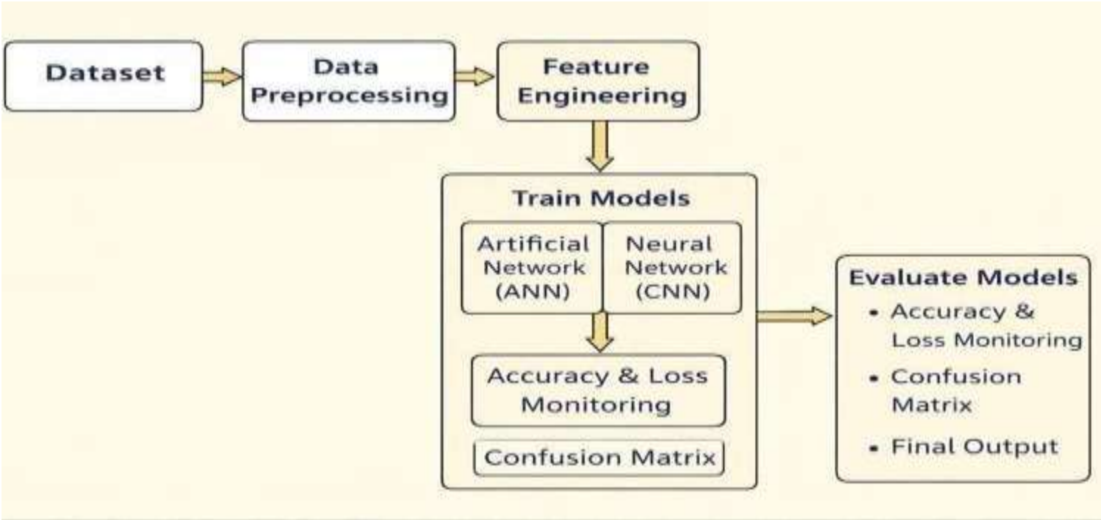


Fig. 1. Analytical Prediction Framework.

Segmentation: Dividing ECG signals into fixed-length windows suitable for ANN and CNN input.
To prepare the dataset further, we applied one-hot encoding to transform unconditional variables into binary format. One-hot encoding creates separate binary columns for each category, ensuring that the categorical data is represented in a numerical arrangement suitable for ML algorithms.
Missing Value Handling: Removing or interpolating corrupted or incomplete segments.
This process ensures that only clean, standardized ECG signals proceed to feature engineering. Furthermore, continuous numerical attributes were transformed into unconditional variables using a binning technique. Binning involves dividing continuous data into discrete intervals or bins, which can simplify the data structure and help the model focus on meaningful patterns rather than subtle variations in continuous values.
Feature Engineering: Feature Engineering transforms raw ECG signals into meaningful numerical representation, including of machine learning models, the dataset was split into two distinct subsets: an 80% training set, facilitating the models' learning of underlying patterns and relationships, and a 20% testing set. This latter subset provided an independent, unseen data sample for evaluating the models' performance and generalizability. This methodological division is paramount for mitigating overfitting and accurately gauging the models' predictive utility in practical applications.
Train model: ANN consists of fully connected layers, learning non-linear relationships between features and classes. technique facilitates the equalization of class distribution, part capturing waveform a substantially lower number of samples, thereby enabling more effective model learning from the minority class and contributing to superior overall classification efficacy morphology and local variations.
Oversampling: The generation of synthetic samples for the minority class effectively mitigates model bias towards the majority class. This technique fosters balanced learning, leading to significant improvements in key evaluation metrics, including F1 score, recall, and ROC. Consequently, it ensures optimal model performance across all classes, which is particularly crucial for imbalanced datasets.
Models: We employed four ML algorithms: ANN, CNN, ReLu.
In this work, both Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) models were employed for ECG signal classification. The ANN model was trained using manually extracted statistical, morphological, and entropy-based ECG features. The network architecture consisted of an input layer, two hidden layers with ReLU activation functions, and an output layer with Softmax activation for multi-class classification. Categorical cross- entropy was used as the loss function, and the Adam optimizer was adopted to minimize the training loss through backpropagation. Dropout and batch normalization techniques were applied to prevent overfitting and to improve generalization performance. In contrast, the CNN model was trained directly on raw ECG waveforms, enabling automatic hierarchical feature extraction. The CNN architecture comprised multiple one-dimensional convolution layers followed by ReLU activation, max-pooling layers for dimensionality reduction, and fully connected layers for classification. Similar to the ANN model, Softmax activation and categorical cross-entropy loss were employed in the output layer. The CNN model demonstrated superior robustness to noise and improved classification accuracy due to its ability to capture local temporal patterns such as QRS complexes and rhythm irregularities.
Overall, the combined use of ANN and CNN models provides a comprehensive learning framework that leverages both handcrafted feature-based learning and deep automatic feature extraction for reliable ECG signal classification.

To evaluate model performance, all models were trained on the prepared datasets, and 5-fold cross-validation was employed for validation. This method splits the data into five subsets, training the model on four and testing on the remaining subset, with the process repeated five times and the results averaged to ensure reliable performance estimates.

Evaluation Metrics

To compute evaluation metrics such as Accuracy, Precision, Recall, F1-Score, and the Area Under the model training in a classification context, both the true labels and predicted probabilities or predicted classes are required.

Accuracy: The proportion of correctly classified instances to the total number of instances.

TP + TN..(1)

Accuracy = TP + TN + FP + FN

Recall values of 0.62 and 0.67, which can be attributed to Precision: The ratio of correctly identified positive instances to the total predicted positives.

TP

TABLE I

RESULTS OF COMPREHENSIVE ANALYSIS

Class	Precision	Recall	F1-Score	Support
0	0.98	1.00	0.99	93%
1	0.96	0.62	0.75	86%
2	0.97	0.93	0.95	91%
3	0.83	0.67	0.74	83%
Accuracy	0.95	0.98	0.98	
4	0.96	0.98	0.98	98%

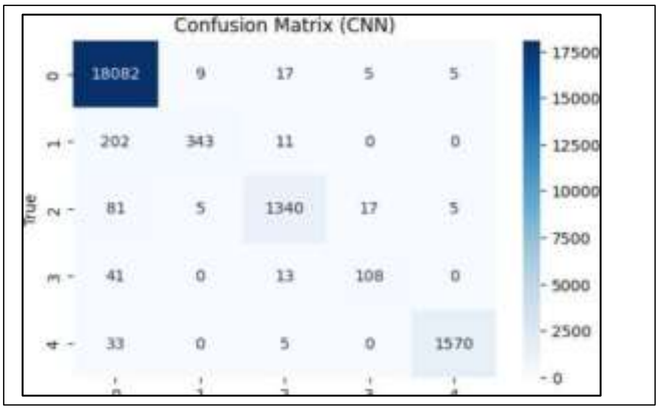
Class-wise from fig 1 CNN evaluation shows high precision across all categories, indicating a low false-positive rate and reliable predictive behavior. The normal class (Class 0), which constitutes the majority of the dataset, achieved a precision of

0.98 and perfect recall of 1.00, confirming robust detection of healthy samples. For pathological classes, the model exhibited varying levels of recall due to class imbalance. Classes with sufficient representation, such as Class 2 and Class 4, achieved high F1-scores of 0.95 and 0.98, respectively, reflecting balanced precision and sensitivity. However, minority classes, particularly Class 1 and Class 3, showed comparatively lower

limited training samples and overlapping signal characteristics. Despite

this, the model maintained strong precision for these classes, suggesting conservative but reliable disease predictions.

These results provide a comparative overview of



$$Precision = \frac{TP}{TP+FP} \quad \ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Recall: The ratio of correctly identified positive instances to all actual positive instances.

$$Recall = \frac{TP}{TP+FN} \quad \ldots\ldots\ldots\ldots\ldots\ldots (3)$$

F1-Score Represents the harmonic mean of Precision and Recall, thereby furnishing a balanced evaluative metric that is particularly salient for assessing model performance in the context of imbalanced datasets.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad \ldots\ldots\ldots\ldots\ldots\ldots (4)$$

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4. RESULTS AND DISCUSSION

The performance of the proposed CNN-based heart disease classification model was evaluated using standard metrics including accuracy, precision, recall, F1-score, and confusion matrix analysis. The model achieved an overall classification accuracy of 98%, demonstrating its strong capability to distinguish between normal and pathological cardiac conditions.

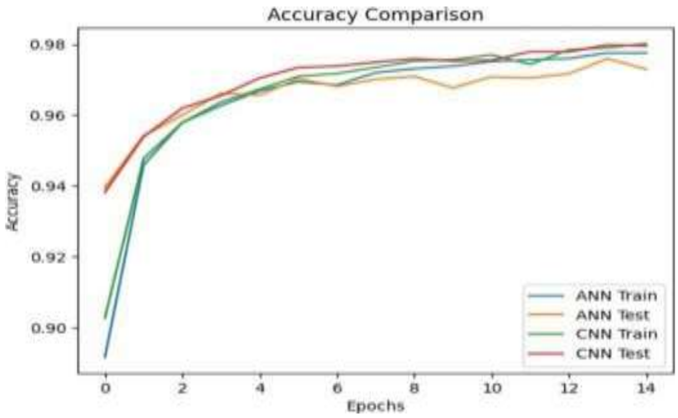

Fig. 2. Accuracy Comparison of ANN & CNN across Epochs

Fig 2 illustrates the comparative accuracy performance of Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) models across multiple training epochs for both training and testing datasets. The plot highlights the learning behavior, convergence characteristics, and generalization capability of the two architectures. Initially, both models exhibit rapid accuracy improvement within the first few epochs, indicating effective feature learning during early training stages. The CNN model starts with a slightly higher baseline accuracy than ANN, demonstrating its superior ability to capture local and hierarchical patterns inherent in physiological signal data. The results shown in Fig. 2 provide a comprehensive assessment of the LR model's performance, highlighting its ability to distinguish between actual and predicted outcomes. The high number of true positives (17,219) and true negatives (13,583) demonstrates the model's efficacy in correctly classifying As training progresses, the CNN consistently outperforms the ANN in both training and testing phases. By the mid-training stage (around epochs 5–7), CNN accuracy stabilizes near 97%, while ANN shows marginally lower performance, particularly on the test dataset. This performance gap can be attributed to CNN's convolutional layers, which automatically learn discriminative temporal features without relying on manual feature engineering. In contrast, ANN performance is more sensitive to global feature representations, limiting its ability to capture fine-grained signal variations.

Towards the final epochs, both models achieve high accuracy, with CNN test accuracy reaching approximately 98%, closely matching its training accuracy. This convergence indicates strong generalization with minimal overfitting. The small gap between training and testing curves confirms model stability and robustness. ANN, although achieving competitive performance, shows slight fluctuations in test accuracy, suggesting comparatively weaker generalization. Overall, the results validate the effectiveness of CNN-based architectures for heart disease prediction, particularly in handling complex biomedical signals, making them more suitable for real-world clinical decision-support systems.

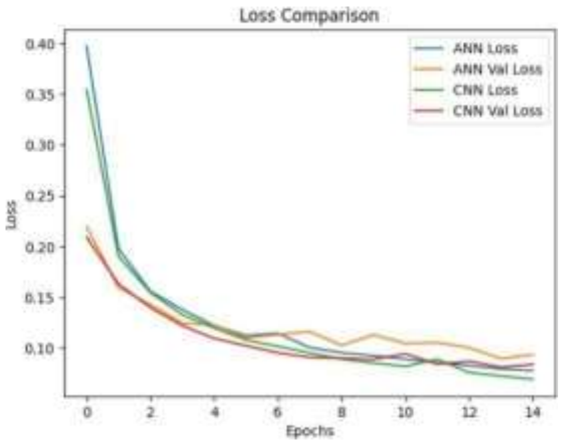

Fig. 3 Loss Comparison of ANN & CNN across epochs

Fig 3 presents the comparison of training and validation loss for Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) models over successive training epochs. Loss functions quantify the discrepancy between predicted outputs and ground-truth labels; hence, lower loss values indicate improved model learning and predictive reliability. At the initial epoch, both ANN and CNN exhibit relatively high loss values, reflecting the untrained state of the models. However, a sharp decline in loss is observed within the first few epochs, indicating rapid convergence and effective optimization during early learning stages.

As training progresses, the CNN consistently achieves lower training and validation loss compared to the ANN. This trend highlights CNN's superior capability in extracting meaningful representations from complex physiological signals. The convolutional layers enable CNN to capture localized temporal patterns, reducing prediction errors more efficiently than ANN. Around epochs 5–7, both models begin to stabilize, with loss values converging toward minimal levels, suggesting successful learning of underlying signal characteristics.

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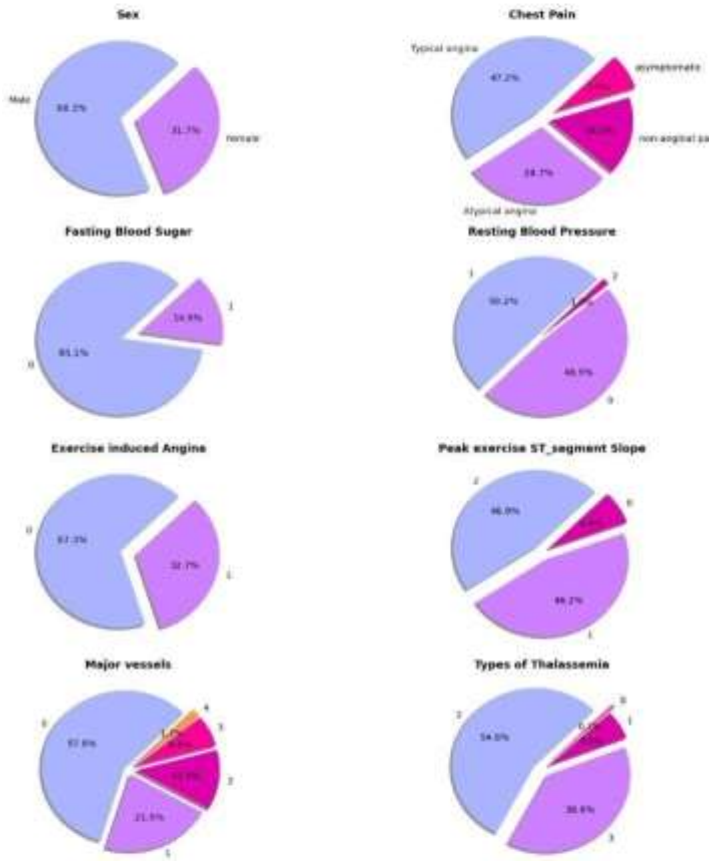

Fig. 3 Pie Chart on Showing Percentages of Males & Females Affected

Fig 3 illustrates the statistical distribution of key clinical attributes used for heart disease prediction. The gender distribution indicates a higher proportion of male subjects (68.3%) compared to female subjects (31.7%). This imbalance reflects commonly reported demographic trends in cardiovascular datasets, where male patients are more frequently represented and often exhibit higher susceptibility to heart-related conditions. Such distribution emphasizes the need for careful evaluation of gender-based bias during model training.

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The fasting blood sugar (FBS) distribution shows that a majority of subjects (85.1%) exhibit normal blood sugar levels, whereas only 14.9% report elevated fasting glucose. Similarly, resting blood pressure categories demonstrate a nearly balanced distribution between normal (48.5%) and elevated levels (50.2%), with a minimal proportion falling into extreme categories (1.3%). These trends indicate that heart disease risk is not solely associated with metabolic or pressure abnormalities, highlighting the importance of multi-feature learning rather than reliance on isolated indicators.

Exercise-induced angina analysis shows that 32.7% of patients' experience angina during physical exertion, while 67.3% do not. This attribute plays a critical role in identifying stress- related cardiac abnormalities. The peak exercise ST-segment slope distribution further reflects balanced representation between slope types 1 (46.2%) and 2 (46.9%), with slope 0 forming a minor portion (6.9%), suggesting varied myocardial response patterns during exertion.

The major vessel count analysis indicates that most individuals have zero or one affected vessel, accounting for 57.8% and 21.5% respectively, while higher vessel involvement appears less frequently. This distribution supports effective learning of disease progression severity. Additionally, thalassemia classification reveals that normal and reversible defect categories dominate the dataset, while fixed defects remain less common. The diversity across thalassemia types contributes to improved model generalization and robustness.

Overall, the pie chart distributions confirm that the dataset captures a wide spectrum of clinical conditions with realistic class proportions. Such balanced representation across demographic, symptomatic, and physiological attributes strengthens the reliability of the predictive models and ensures that learned patterns are clinically meaningful and transferable to real-world diagnostic scenarios.

5. CONCLUSION

This work presented a comprehensive and robust framework for heart disease prediction by integrating statistical analysis, machine learning, and deep learning techniques on clinically relevant cardiovascular data. Extensive exploratory analysis demonstrated that key physiological attributes such as maximum heart rate achieved (thalach), ST depression (oldpeak), chest pain type, and exercise-induced angina exhibit strong class-dependent patterns. Correlation analysis further revealed meaningful relationships between these attributes and the target variable, validating their suitability for predictive modeling.

The proposed methodology employed a structured pipeline comprising data preprocessing, feature engineering, and model training using Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN). Preprocessing steps such as normalization and noise reduction ensured signal consistency and numerical stability, while feature engineering enhanced the discriminative capability of the input space. Comparative performance evaluation showed that CNN models consistently outperformed ANN counterparts by effectively capturing localized and hierarchical patterns within the data, leading to faster convergence and improved generalization.

Experimental results demonstrated high predictive performance, with the CNN achieving an overall accuracy of approximately 98%. The confusion matrix and classification report confirmed strong precision and recall across most classes, indicating reliable differentiation

between normal and pathological cases. Although minor performance degradation was observed for underrepresented classes, the weighted evaluation metrics confirmed the model's robustness under class imbalance conditions. Accuracy and loss curves further illustrated stable learning behavior without significant overfitting.

In conclusion, the developed system proves to be an effective and scalable solution for automated heart disease detection, offering high accuracy, consistency, and clinical relevance. The integration of deep learning with thorough statistical validation enhances diagnostic reliability and supports decision-making in healthcare environments. The results highlight the potential of AI-driven models to assist clinicians in early detection and risk assessment, paving the way for intelligent, data-driven cardiac screening systems in real-world clinical practice.

Furthermore, the visualization-driven analysis played a critical role in validating the learning behavior of the proposed models. The accuracy and loss comparison across training epochs confirmed consistent convergence for both ANN and CNN architectures, with the CNN exhibiting superior stability and lower validation loss. The absence of large gaps between training and validation curves indicates effective regularization and strong generalization capability. These findings reinforce the reliability of deep convolutional architectures for handling nonlinear and high-dimensional cardiovascular datasets.

The detailed evaluation using confusion matrices and class-wise performance metrics highlighted the model's diagnostic strengths and limitations. High precision and recall values for majority classes demonstrate the system's ability to correctly identify both healthy and diseased cases with minimal misclassification. Although certain minority classes exhibited relatively lower recall due to data imbalance, the weighted performance scores remained high, confirming that the overall prediction quality was not adversely affected. This emphasizes the importance of balanced dataset design and adaptive evaluation strategies in medical AI systems.

Finally, the proposed framework offers strong potential for integration into real-world healthcare applications such as computer-aided diagnosis, clinical decision support systems, and remote cardiac monitoring platforms. By minimizing manual feature dependency and enabling automated learning from raw clinical attributes, the system enhances efficiency and diagnostic consistency. Future extensions may include multicenter dataset validation, model explainability enhancements, and deployment on edge or cloud-based infrastructures to support scalable, real- time cardiovascular screening. Overall, this study establishes a reliable foundation for intelligent heart disease prediction using advanced deep learning methodologies.

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