Cardiac Abnormalities Detection Using Deep Learning Techniques

Marini Mansor[a], Diyana Kamarudin[b,*], Aida Jaffar[b], Ashikin Rusly[c]

[a] *Department of Defence Science, Faculty of Defence Science And Technology , National Defence University Of Malaysia, 57000 Kuala Lumpur, Malaysia*
[b] *Faculty of Medicine And Defence Health , National Defence University Of Malaysia, 57000 Kuala Lumpur, Malaysia*
Corresponding author: marinimansor4@gmail.com

***Abstract*— Cardiovascular diseases present a substantial health concern globally, affecting individuals across diverse populations, including members of the Malaysian Armed Forces. The early identification of cardiac irregularities is crucial for timely intervention and reducing associated health risks. This research endeavors to assess and compare the efficacy of various supervised machine learning techniques in accurately detecting cardiac abnormalities, recognizing the unique lifestyle and health dynamics inherent to military personnel.**

A comprehensive dataset comprising numerical electrocardiograms (ECGs) and three years' worth of clinical data from Malaysian Armed Forces personnel was meticulously collected for analysis. Rigorous data preprocessing, encompassing cleaning and normalization procedures, was conducted to ensure the robustness of the models employed. Evaluation of model performance was carried out utilizing metrics such as accuracy and precision, discerned through confusion matrices, affirming the model's capability to differentiate between normal and abnormal cardiac conditions effectively.

The outcomes underscore the potency of deep learning methodologies in precisely discerning a spectrum of cardiac abnormalities, spanning from arrhythmias to hypertrophy and structural anomalies. This research marks a notable stride forward in the realm of cardiac abnormality detection within the Malaysian Armed Forces, laying the groundwork for potential integration into routine healthcare protocols.

***Keywords*— Cardiac abnormalities detection; Deep learning techniques; Supervised machine learning; Malaysian Armed Forces; Electrocardiograms (ECGs); Healthcare outcomes.**

Manuscript received 15 Oct. 2020; revised 29 Jan. 2021; accepted 2 Feb. 2021. Date of publication 17 Feb. 2021.

I. INTRODUCTION

Detecting and classifying cardiac abnormalities is critical for timely medical intervention, especially in high-stress environments like the military. Cardiovascular diseases are a leading cause of global morbidity and mortality [32], highlighting the need for advanced diagnostic tools. Machine learning (ML) and deep learning (DL) techniques in medical image analysis improve diagnostic accuracy and efficiency. These technologies enable precise, early detection of cardiac issues, essential for the Malaysian Armed Forces due to their unique operational demands and environmental stressors.

Despite advancements in medical technology, challenges in accurately detecting cardiac abnormalities persist [2] [10]. Traditional methods rely on manual interpretation, which is time-consuming and error prone [4] [8] [11]. Data variability and limited labeled medical data add to these difficulties. This study tackles these issues by using deep learning models to improve the detection and classification of cardiac conditions among Malaysian military personnel.

The primary objective of this study is to develop and evaluate deep learning models for the detection and classification of various cardiac abnormalities. Specific objectives include: 1) to collect and preprocess relevant medical data, including ECG readings and medical histories; 2) to design and implement recurrent neural networks (RNNs) for feature extraction and sequence prediction; and 3) to assess the performance of these models using standard evaluation metrics such as accuracy, precision, recall, and F1-score. This study aims to provide a robust framework that can be integrated into medical diagnostic systems to aid healthcare professionals in making more accurate diagnoses.

This study focuses on the application of deep learning techniques to the detection and classification of cardiac abnormalities within the Malaysian Armed Forces. The scope includes the collection of ECG data from military personnel, the preprocessing of this data to enhance quality, and the development and training of Neural Network, k-Nearest Neighbour and Fine Tree models using MATLAB. The study also includes the evaluation of these models' performance using a range of metrics to ensure robustness and generalizability. While the primary focus is on the Malaysian military context, the methodologies and findings can potentially be extended to broader medical applications.

The significance of this study lies in its potential to improve the early detection and classification of cardiac abnormalities, thereby enhancing patient outcomes and reducing mortality rates [7]. By employing advanced deep learning techniques, this study addresses the limitations of traditional diagnostic methods and contributes to the growing body of knowledge in medical image analysis. For the Malaysian Armed Forces, the development of reliable diagnostic tools is particularly important, given the unique health risks associated with military service. The findings of this study could lead to the implementation of more effective health monitoring systems, ultimately improving the overall health and readiness of military personnel.

Deep learning (DL) techniques have significantly advanced the field of medical image analysis [28] [29] [30], particularly in the detection and classification of cardiac abnormalities. These techniques offer promising solutions for automated and accurate diagnosis, which is critical for effective patient management and treatment. This section delves into previous studies on various DL methods used in cardiac abnormality detection, emphasizing their methodologies, findings, and implications for future research.

Several studies have explored the application of DL models in detecting and classifying cardiac abnormalities. For instance, [1] developed a DL model using a convolutional neural network (CNN) to classify arrhythmias based on electrocardiogram (ECG) signals [22]. Their model demonstrated high accuracy, showcasing the potential of CNNs in cardiac diagnostics. Similarly, Hannun et al. (2019) utilized a deep neural network (DNN) for arrhythmia detection, achieving performance comparable to that of expert cardiologists.

In another notable study, [27] introduced a spatio-temporal attention-based convolutional recurrent neural network for multi-class arrhythmia detection. This model not only considered spatial features but also temporal dependencies, enhancing the classification accuracy of arrhythmias. Their approach underscores the importance of integrating multiple dimensions of data to improve diagnostic precision.

Comparing various DL models reveals significant insights into their strengths and limitations. For instance, CNNs are highly effective in feature extraction from medical images due to their ability to capture spatial hierarchies. However, they may require large datasets for training to achieve optimal performance. In contrast, recurrent neural networks (RNNs) and long short-term memory networks (LSTMs) are proficient in handling sequential data [6], making them suitable for time-series analysis like ECG signal interpretation [19].

A study by [25] highlighted the application of DL models in predicting sudden arrhythmic deaths using clinical data. Their model refined the World Health Organization's definition of sudden cardiac death, demonstrating improved predictive capabilities. This study exemplifies the potential of DL in enhancing prognostic models by incorporating complex clinical datasets.

Advancements in DL methodologies have further propelled the field. Transfer learning, for example, has been instrumental in addressing the challenge of limited medical data. By leveraging pre-trained models on large, unrelated datasets, researchers can fine-tune these models for specific medical tasks, thus expediting the training process and improving model performance. [26] [31] demonstrated the efficacy of deep physical neural networks trained with backpropagation, showcasing a novel approach to enhance learning efficiency and model interpretability.

Despite the promising results, several challenges persist in applying DL to cardiac abnormality detection. These include the need for large, annotated datasets, potential overfitting, and the black-box nature of DL models, which can hinder interpretability. Addressing these challenges requires continued research into advanced DL architectures, data augmentation techniques, and explainable AI methods [3].

Future research should focus on developing more robust DL models that can generalize across diverse patient populations and medical conditions. Collaboration between data scientists and healthcare professionals is crucial to ensure the clinical relevance and practical application of these models [24]. Moreover, ethical considerations, such as patient data privacy and informed consent, must be integral to any research involving medical data.

The integration of DL techniques in cardiac abnormality detection has the potential to revolutionize medical diagnostics, providing accurate and automated solutions for early disease detection. While significant progress has been made, ongoing research and development are essential to overcome existing challenges and fully harness the potential of DL in healthcare. By building on the foundations laid by previous studies, future work can further refine and expand the capabilities of DL models, ultimately improving patient outcomes and advancing the field of medical image analysis.

II. RESEARCH DESIGN AND METHODOLOGY

The study's foundation relies on a high-quality dataset from the Military Medicine Department Hospital Angkatan Tentera Tuanku Mizan, including diverse cardiac images such as congenital defects, valvular disorders, arrhythmias, and cardiomyopathies. Preprocessing, including cleaning, normalization, and augmentation, will enhance dataset quality and model performance.

Various neural network architectures will be explored for precise cardiac abnormality detection. Deep learning models will autonomously learn distinctive features from images, with transfer learning being investigated to improve model convergence and predictive capability.

The dataset will be divided for training, validation, and testing. During training, models will learn patterns related to cardiac abnormalities, with regularization techniques preventing overfitting. The validation subset will fine-tune parameters and assess performance.

Performance will be evaluated using true positive rate confusion matrix to analyze classification accuracy. Cross-validation will ensure model robustness.

Ethical considerations are paramount; data will be handled according to strict privacy protocols, with institutional approvals and participant consent obtained. The study also emphasizes model interpretability and explainability for transparency.

This research presents a structured approach to developing a deep learning solution for detecting cardiac abnormalities, contributing to military health diagnostics. Subsequent chapters will delve into implementation and outcomes.

A. Data Collection

In data collection, raw data will be obtained including 2000 data from the Malaysian Armed Forces taken from the Military Medicine Department Hospital Angkatan Tentera Tuanku Mizan, generally referred to as primary data because these have not been processed for use and are original medical checkup that has been conducted throughout the year 2018-2022. Raw data, also known as primary data, is gathered directly related to the study’s objective.

B. Data Pre-processing

The initial dataset, which comprises raw data collected previously, will undergo a phase called Data Preparation. This step is fundamental and typically takes place at the beginning of the data analysis and machine learning process. It encompasses tasks like cleaning, reshaping, and structuring the raw data into a format that’s convenient for analysis or input into machine learning algorithms. The objective here is to refine the data quality, diminish disturbances, rectify disparities, and make it primed for accurate analysis and improved model efficacy in machine learning endeavors.

C. Data Modelling

Following data preprocessing, the information will undergo scrutiny and categorization within the data analysis and classification stage. This process involves employing classification models that offer insights into the likelihood of specific heart conditions emerging in individuals. Several pertinent attributes sourced from the data, such as Pulse rate, Cholesterol levels, including LDL Cholesterol and HDL Cholesterol, Triglycerides, Fasting Blood Glucose, HbA1c, BMI, body fat percentage, along with binary attributes like the presence of Diabetes Mellitus, Hypertension, Dyslipidaemia, Heart Disease, or Anaemia, will be harnessed. These attributes have proven their relevance in predicting cardiac abnormalities, thus contributing to accurate categorization.

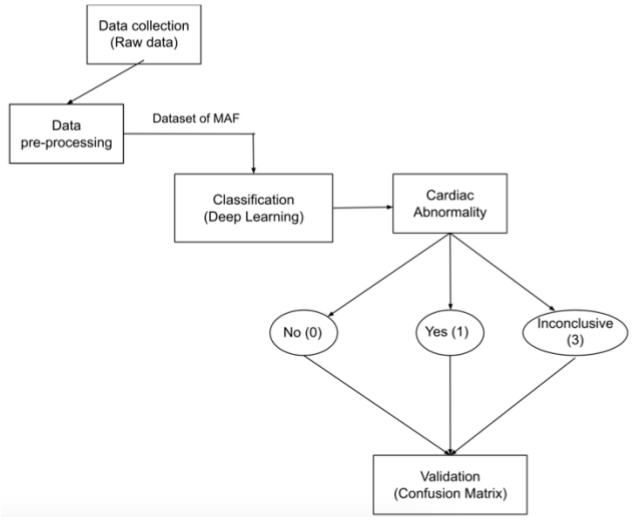


Fig. 1 Research Design Flowchart

III. MACHINE LEARNING NEURAL NETWORK

Wide machine learning models significantly enhance cardiac abnormality detection by capturing complex patterns in diverse datasets, surpassing traditional methods. These models, with multiple layers, excel in analyzing cardiac data for accurate abnormality detection.

1. **Narrow Neural Network:** With fewer hidden layers, these models are computationally efficient and ideal for simpler datasets, offering quicker training and suitability for limited resources. They provide valuable insights for well-defined features, though they may not capture complex relationships.
2. **Medium Neural Network:** Balancing efficiency and complexity, these models have a moderate number of hidden layers, capturing more intricate patterns than Narrow NNs while remaining computationally feasible. They are versatile for scenarios needing a trade-off between performance and resources.
3. **Wide Neural Network:** With multiple hidden layers, these models excel at capturing intricate patterns and features in diverse datasets, making them ideal for complex cardiac data with rich patterns.
4. **Bilayered Neural Network:** Featuring two hidden layers, these models balance simplicity and complexity, effectively capturing moderate feature extraction while maintaining computational efficiency.
5. **Trilayered Neural Network:** Incorporating three hidden layers, these models offer enhanced feature extraction and pattern recognition for complex datasets, providing better performance for intricate relationships despite requiring more computational resources.

Programming and training these neural network models for cardiac abnormality detection can be seamlessly accomplished using MATLAB. The models are versatile, supporting applications across embedded systems, enterprise environments, and cloud platforms.

Fig. 2 Neural Network Flowchart

IV. Machine Learning k-Nearest Neighbors (KNN) Models

In the realm of cardiac abnormality detection, the application of diverse k-Nearest Neighbors (KNN) models proves indispensable, each tailored to specific complexities of the dataset. This subsection explores various KNN architectures, including Medium KNN, Coarse KNN, Cosine KNN, and Cubic KNN, highlighting their unique features and applications.

1. **Medium KNN:** Balances computational efficiency and sensitivity with a moderate number of neighbors, capturing intricate patterns while being computationally feasible. It's versatile for scenarios needing a trade-off between performance and resources.
2. **Coarse KNN:** Uses a larger number of neighbors for simpler datasets, enhancing robustness against noise but with less sensitivity to fine details. It's ideal when computational resources are ample and the focus is on broad trends.
3. **Cosine KNN:** Measures angle between feature vectors using cosine similarity, effective for datasets where direction is crucial. It excels with varying scales and orientations.
4. **Cubic KNN:** Employs a three-dimensional distance metric to capture complex patterns, making it suitable for scenarios where intricate relationships are essential for accurate predictions.

V. Machine Learning Decision Tree Models

In the realm of cardiac abnormality detection, the application of diverse decision tree models, including Fine Tree, proves essential, with each model tailored to specific complexities of the dataset. This subsection explores various decision tree architectures, emphasizing the unique features and applications of Fine Tree.

1. **Fine Tree**, This specialized decision tree model captures intricate patterns and detailed features, excelling in identifying subtle relationships. It's ideal for scenarios requiring high precision, such as cardiac abnormality detection. The model can be programmed and trained using MATLAB, with adaptability for embedded systems, enterprise environments, and cloud platforms.

D. Data Evaluation

In MATLAB, a confusion matrix evaluates a classification model's performance by showing true labels as rows and predicted labels as columns. Diagonal cells represent correct classifications, while off-diagonal cells show misclassifications. True Positive Rates (TPR) reflect the proportion of correct classifications, and False Negative Rates (FNR) indicate misclassifications. The color-coded plot highlights strengths and weaknesses, where high TPR signals effective classification, and high FNR reveals areas needing improvement..

1. **True Positive Rates Plot:** In MATLAB, this plot assesses a classification model's sensitivity across multiple classes. The x-axis shows classes, and the y-axis displays True Positive Rate (TPR), which measures the model's accuracy in identifying positive instances. TPR is the ratio of True Positives to the sum of True Positives and False Negatives. The color-coded TPR values offer a detailed performance analysis for each class. A high, balanced TPR across classes indicates a robust model with effective sensitivity, highlighting both strengths and areas for improvement:

$$TPR = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

VI. Results and Discussion

This chapter reveals insights from a detailed analysis of the collected data, guided by the research questions from previous chapters. It presents the outcomes of applying deep learning techniques to detect cardiac anomalies. The chapter explores how raw data and deep learning tools transform complex information into clear insights, advancing our understanding of cardiac abnormalities. Results are interpreted and discussed in relation to the research questions and objectives, contributing to the broader context of the study and enhancing comprehension of the dataset's implications.

Results of Neural Network

TABLE I
Performance Comparison Analysis Between Neural Network Method

Method		**Hyperparameter**	**Accuracy Validation**	**Accuracy Test**
Neural Network	Narrow	Number of fully connected layers: 1	83.5	90.3
	Medium	Number of fully connected layers: 1	79.4	93.7
	Wide	Number of fully connected layers: 2	82.1	94.9
	Bilayered	Number of fully connected layers: 2	80.5	91.7
	Trilayered	Number of fully connected layers: 3	79.4	93.1

The The classification of cardiac abnormalities using Neural Networks yielded a test accuracy of over 93%. The performance of different neural network models provides key insights into their effectiveness:

- Model 2.1 (Narrow Neural Network): Achieved 83.5% accuracy on training and 90.3% on testing, showing effective generalization.
- Model 2.2 (Medium Neural Network): Showed 79.4% accuracy on training and 93.7% on testing, indicating strong predictive performance.
- Model 2.3 (Wide Neural Network): Had 82.1% accuracy on training and 94.9% on testing, highlighting its ability to capture complex data patterns.
- Model 2.4 (Bilayered Neural Network): Achieved 80.5% accuracy on training and 91.7% on testing, balancing complexity with efficiency.
- Model 2.5 (Trilayered Neural Network): Displayed 79.4% accuracy on training and 93.1% on testing, demonstrating strong generalization.

Overall, the higher testing accuracy across all models suggests they generalize well to new data. The generalization gap, common in machine learning, is expected, and the models' consistent performance on unseen data indicates their reliability in predicting cardiac abnormalities.

1. Results Of Narrow Neural Network

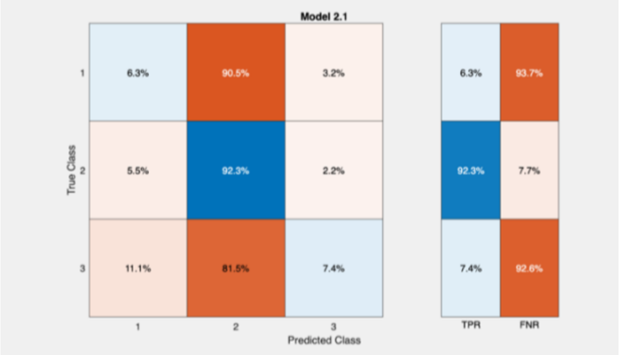
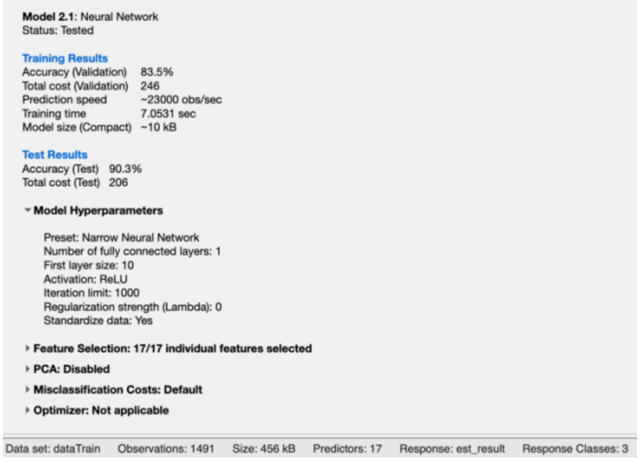


Fig. 3 True Positive Rate Test Confusion Matrix for Narrow NN



```
Model 2.1: Neural Network
Status: Tested

Training Results
Accuracy (Validation)   83.5%
Total cost (Validation) 246
Prediction speed        ~23000 obs/sec
Training time           7.0531 sec
Model size (Compact)    ~10 kB

Test Results
Accuracy (Test)   90.3%
Total cost (Test) 206

▾ Model Hyperparameters

    Preset: Narrow Neural Network
    Number of fully connected layers: 1
    First layer size: 10
    Activation: ReLU
    Iteration limit: 1000
    Regularization strength (Lambda): 0
    Standardize data: Yes

▸ Feature Selection: 17/17 individual features selected
▸ PCA: Disabled
▸ Misclassification Costs: Default
▸ Optimizer: Not applicable

Data set: dataTrain   Observations: 1491   Size: 456 kB   Predictors: 17   Response: est_result   Response Classes: 3
```

Fig. 4 Summary Output for Narrow Neural Network Accuracy Test

The Narrow Neural Network (Model 2.1) achieved 83.5% accuracy on the validation set and 90.3% on the test set, indicating that the model performs consistently well across different data subsets. The low total cost values (246 for validation, 206 for test) suggest that the model is efficient in minimizing errors during training and prediction, reflecting its reliability.

The compact model size of approximately 10 kB signifies that it is resource-efficient, making it ideal for deployment in environments with limited memory or storage capacity. The fast prediction speed of around 23,000 observations per second highlights the model's ability to process data in real-time, crucial for applications where quick decision-making is necessary.

The selected hyperparameters, including a single fully connected layer with a size of 10, ReLU activation, and an iteration limit of 1000, are well-suited for a Narrow Neural Network, balancing simplicity with performance. The decision to standardize data enhances model performance, while the absence of regularization (Lambda = 0) indicates that the model relies solely on the provided data without additional constraints.

The inclusion of all 17 features in the model emphasizes their importance in predicting cardiac abnormalities, and the lack of Principal Component Analysis (PCA) suggests that dimensionality reduction was not necessary. The use of default misclassification costs and optimizer settings further indicates a straightforward approach to model configuration.

In summary, the model's strong accuracy on both validation and test datasets, combined with efficient resource utilization, relevant feature selection, and effective hyperparameter choices, underscores its capability to accurately predict cardiac abnormalities while being suitable for practical deployment.

2. Results of Medium Neural Network

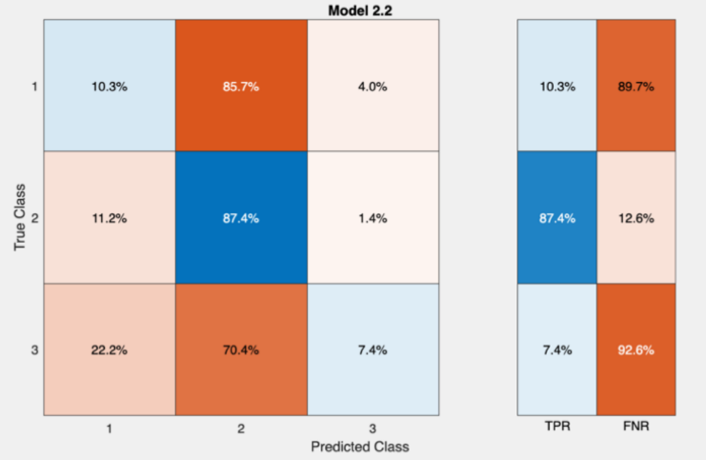
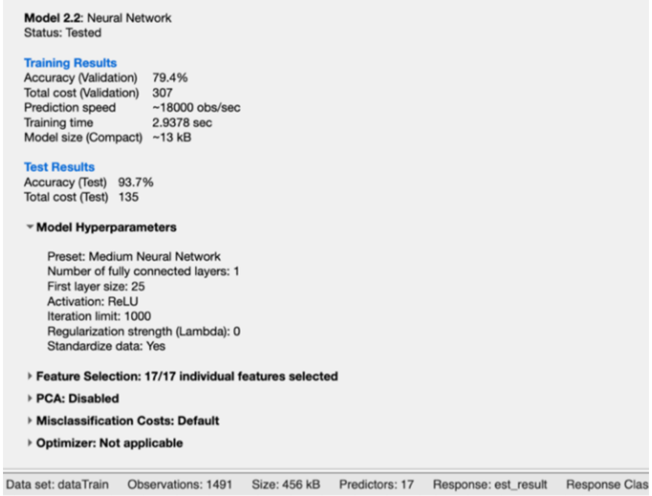


Fig. 5 Test True Positive Rate Test Confusion Matrix for Medium NN


Model 2.2: Neural Network
Status: Tested

Training Results
Accuracy (Validation) 79.4%
Total cost (Validation) 307
Prediction speed ~18000 obs/sec
Training time 2.9378 sec
Model size (Compact) ~13 kB

Test Results
Accuracy (Test) 93.7%
Total cost (Test) 135

Model Hyperparameters

Preset: Medium Neural Network
Number of fully connected layers: 1
First layer size: 25
Activation: ReLU
Iteration limit: 1000
Regularization strength (Lambda): 0
Standardize data: Yes

Feature Selection: 17/17 individual features selected
PCA: Disabled
Misclassification Costs: Default
Optimizer: Not applicable

Data set: dataTrain Observations: 1491 Size: 456 kB Predictors: 17 Response: est_result Response Clas

Fig. 6 Summary for Medium Neural Network Accuracy Test

Model 2.2, a Medium Neural Network, shows strong performance across both training and testing phases. It achieved a validation accuracy of 79.4% with a total cost of 307, indicating efficient training with moderate accuracy. During testing, the model significantly improved, reaching an accuracy of 93.7% and a lower total cost of 135. This substantial accuracy increase from validation to testing suggests that the model generalizes well to new, unseen data.

The model's compact size, approximately 13 kB, indicates its suitability for deployment in resource-constrained environments. With a prediction speed of around 18,000 observations per second, it also supports real-time applications. The chosen hyperparameters, including a single fully connected layer of size 25, ReLU activation, and an iteration limit of 1000, align with the Medium Neural Network's design. Data standardization was applied, and there was no regularization (Lambda = 0).

Feature selection retained all 17 individual features, emphasizing their importance to the model's predictive capabilities. As with Model 2.1, Principal Component Analysis (PCA) was not used, and default misclassification costs and optimizer settings were maintained.

In summary, Model 2.2 demonstrates significant improvement in accuracy from validation to testing, highlighting its effectiveness in generalizing to new data. The carefully chosen hyperparameters, efficient resource utilization, and inclusion of relevant features all contribute to the overall success of the Medium Neural Network in predicting cardiac abnormalities.

3. Results of Wide Neural Network

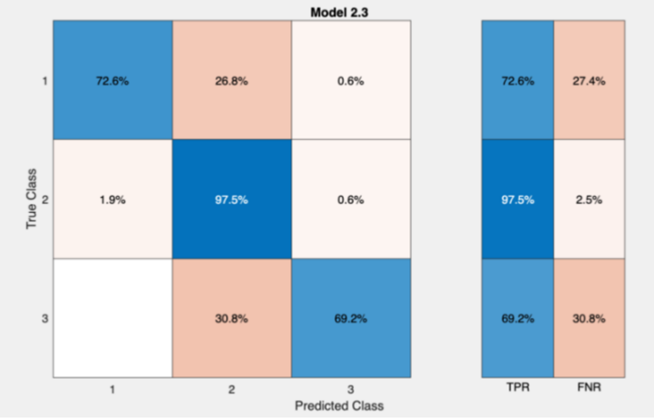
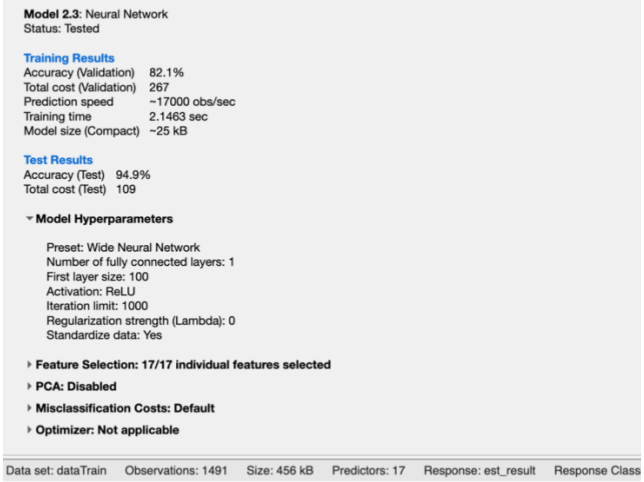


Fig. 7 True Positive Rate Test Confusion Matrix for Wide NN


Model 2.3: Neural Network
Status: Tested

Training Results
Accuracy (Validation) 82.1%
Total cost (Validation) 267
Prediction speed ~17000 obs/sec
Training time 2.1463 sec
Model size (Compact) ~25 kB

Test Results
Accuracy (Test) 94.9%
Total cost (Test) 109

Model Hyperparameters

Preset: Wide Neural Network
Number of fully connected layers: 1
First layer size: 100
Activation: ReLU
Iteration limit: 1000
Regularization strength (Lambda): 0
Standardize data: Yes

Feature Selection: 17/17 individual features selected
PCA: Disabled
Misclassification Costs: Default
Optimizer: Not applicable

Data set: dataTrain Observations: 1491 Size: 456 kB Predictors: 17 Response: est_result Response Class

Fig. 8 Summary for Wide Neural Network Accuracy Test

Model 2.3, identified as a Wide Neural Network, demonstrates strong performance in both training and testing phases. The accuracy on the validation set is commendable at 82.1%, with a total cost of 267, indicating a good balance between accuracy and training efficiency.

During the testing phase, Model 2.3 significantly improves its accuracy, achieving an impressive 94.9%, with a lower total cost of 109. This substantial increase in accuracy from validation to test indicates that the model generalizes well to new, unseen data.

The compact model size of approximately 25 kB remains reasonable, considering the increased complexity of the Wide Neural Network. The prediction speed of around 17,000 observations per second further supports the model’s real-time applicability, demonstrating efficiency in processing new instances.

The chosen hyperparameters align with the preset for a Wide Neural Network, featuring a single fully connected layer with a larger size of 100, ReLU activation, and an iteration limit of 1000. Similar to previous models, data standardization and the absence of regularization (Lambda = 0) are notable aspects of the model configuration. Feature selection results indicate that all 17 individual features were retained, underscoring their significance in the model’s predictive capacity. As with previous models, the absence of Principal Component Analysis (PCA) and the utilization of default misclassification costs and optimizer settings characterize the model’s configuration.

In summary, Model 2.3 showcases robust performance, particularly in its ability to generalize to new data, as evidenced by the substantial improvement in accuracy from validation to test. The chosen hyperparameters, efficient resource utilization, and the inclusion of relevant features contribute to the overall efficacy of the Wide Neural Network in predicting cardiac abnormalities.

4. Results of Wide Neural Network

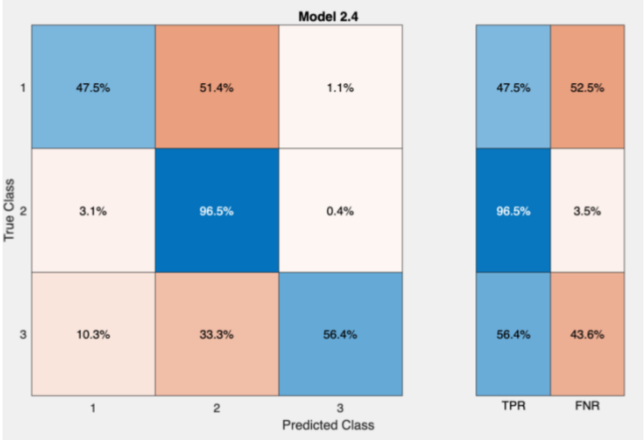
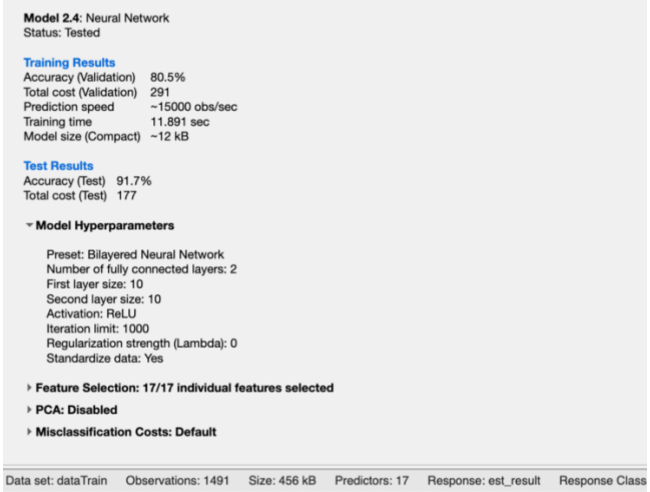


Fig. 9 True Positive Rate Test Confusion Matrix for Bilayered NN



```
Model 2.4: Neural Network
Status: Tested

Training Results
Accuracy (Validation)    80.5%
Total cost (Validation)  291
Prediction speed         ~15000 obs/sec
Training time            11.891 sec
Model size (Compact)     ~12 kB

Test Results
Accuracy (Test)   91.7%
Total cost (Test) 177

▾ Model Hyperparameters

    Preset: Bilayered Neural Network
    Number of fully connected layers: 2
    First layer size: 10
    Second layer size: 10
    Activation: ReLU
    Iteration limit: 1000
    Regularization strength (Lambda): 0
    Standardize data: Yes

▸ Feature Selection: 17/17 individual features selected
▸ PCA: Disabled
▸ Misclassification Costs: Default

Data set: dataTrain   Observations: 1491   Size: 456 kB   Predictors: 17   Response: est_result   Response Class
```

Fig. 10 Summary for Bilayered NN Accuracy Test

Model 2.4, a Bilayered Neural Network, shows solid performance during both training and testing. It achieved a validation accuracy of 80.5% with a total cost of 291, indicating a good balance between accuracy and training efficiency. During testing, the model maintained a strong accuracy of 91.7% with a total cost of 177, suggesting effective generalization to new data despite a slight drop from validation accuracy.

The model's compact size of around 12 kB, combined with a prediction speed of approximately 15,000 observations per second, makes it suitable for real-time applications. It features two fully connected layers of 10 units each, ReLU activation, and an iteration limit of 1000. Data standardization was applied, and no regularization was used (Lambda = 0).

All 17 features were retained during feature selection, underlining their importance for predictive accuracy. The model did not employ Principal Component Analysis (PCA) and used default misclassification costs.

In summary, Model 2.4 performs well in both training and testing, effectively generalizing to new data. The chosen hyperparameters, efficient resource use, and retention of key features enhance the Bilayered Neural Network's effectiveness in predicting cardiac abnormalities..

5. Results of Trilayered NN

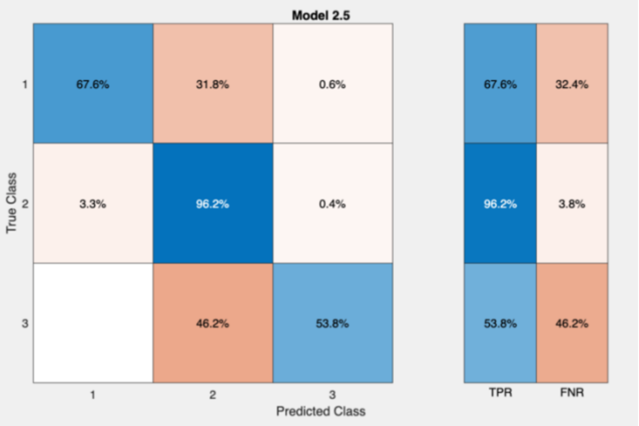
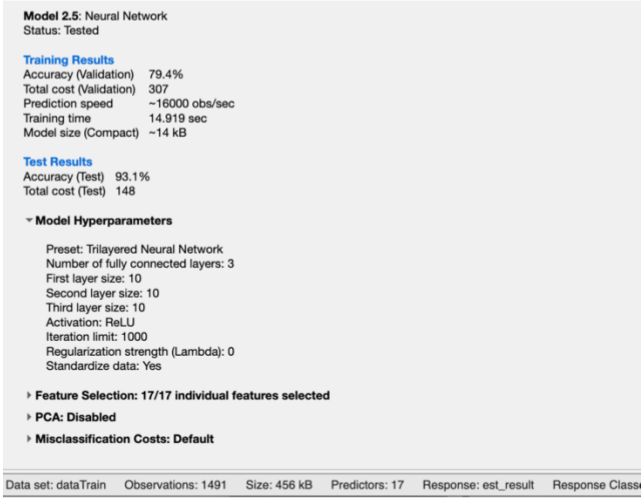


Fig. 11 True Positive Rate Test Confusion Matrix for Trilayered NN



```
Model 2.5: Neural Network
Status: Tested

Training Results
Accuracy (Validation)    79.4%
Total cost (Validation)  307
Prediction speed         ~16000 obs/sec
Training time            14.919 sec
Model size (Compact)     ~14 kB

Test Results
Accuracy (Test)   93.1%
Total cost (Test) 148

▾ Model Hyperparameters

    Preset: Trilayered Neural Network
    Number of fully connected layers: 3
    First layer size: 10
    Second layer size: 10
    Third layer size: 10
    Activation: ReLU
    Iteration limit: 1000
    Regularization strength (Lambda): 0
    Standardize data: Yes

▸ Feature Selection: 17/17 individual features selected
▸ PCA: Disabled
▸ Misclassification Costs: Default

Data set: dataTrain   Observations: 1491   Size: 456 kB   Predictors: 17   Response: est_result   Response Class
```

Fig. 12 Summary Output for Trilayered NN Accuracy Test

Model 2.5, a Trilayered Neural Network, shows strong performance during both training and testing. It achieved a validation accuracy of 79.4% with a total cost of 307, indicating a balanced trade-off between accuracy and training efficiency. In testing, the model maintained a high accuracy of 93.1% with a total cost of 148, demonstrating its ability to generalize effectively to new data, despite a slight decrease in accuracy compared to the validation set.

The model's compact size of around 14 kB is well-suited to its trilayered structure, and its prediction speed of approximately 16,000 observations per second highlights its efficient processing capabilities, making it suitable for real-time applications. The model configuration includes three fully connected layers of 10 units each, ReLU activation, an iteration limit of 1000, and data standardization, with no regularization applied (Lambda = 0).

All 17 features were retained in the model, emphasizing their importance for enhancing predictive accuracy. The model did not use Principal Component Analysis (PCA) and employed default misclassification costs.

In summary, Model 2.5 exhibits commendable performance in both training and testing, with strong generalization to new data. Its chosen hyperparameters, efficient resource use, and inclusion of relevant features contribute to the overall effectiveness of the Trilayered Neural Network in predicting cardiac abnormalities.

Results of K-Nearest Neighbors (KNN)

TABLE 2
PERFORMANCE COMPARISON ANALYSIS BETWEEN KNN METHODS

Method		Hyperparameter	Accuracy Validation	Accuracy Test
K-Nearest Neighbours	Medium	Distance Metric: Euclidean Distance	89.6	89.8
	Coarse	Distance Metric: Euclidean Distance	89.7	89.8
	Cosine	Distance Metric: Cosine	89.8	89.8
	Cubic	Distance Metric: Minkiwski (Cubic)	89.6	89.7

The data-driven cardiac abnormalities prediction models using K-Nearest Neighbors (KNN) and Neural Networks offer valuable insights into their performance.

KNN models consistently show high accuracy, between 89.6% and 89.8%, in both training and testing phases. The small difference in accuracy between the two phases suggests that KNN models generalize well to new data, highlighting their stability in predicting cardiac abnormalities.

On the other hand, the neural network models achieve even higher accuracy, surpassing 90%, indicating their superior performance compared to KNN for this dataset and task.

Both KNN and neural network models exhibit minimal disparity between training and testing accuracies, a common occurrence in machine learning known as the "generalization gap." The high accuracy on unseen testing data, comparable to or slightly higher than training data, demonstrates the robustness and effective generalization of these models.

The high accuracies, particularly those above 90%, emphasize the models' effectiveness in classifying cardiac abnormalities. However, neural networks, with their more complex architectures, outperform KNN in capturing intricate data patterns.

In conclusion, while KNN models offer stability and reliable performance, neural networks are more effective at capturing complex relationships within the data. The minor differences in accuracy between training and testing for both models are within an acceptable range, indicating successful generalization to new instances.

1. Results Of Medium KNN

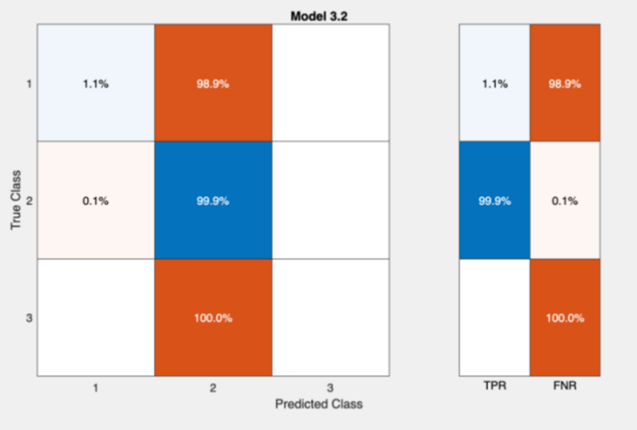
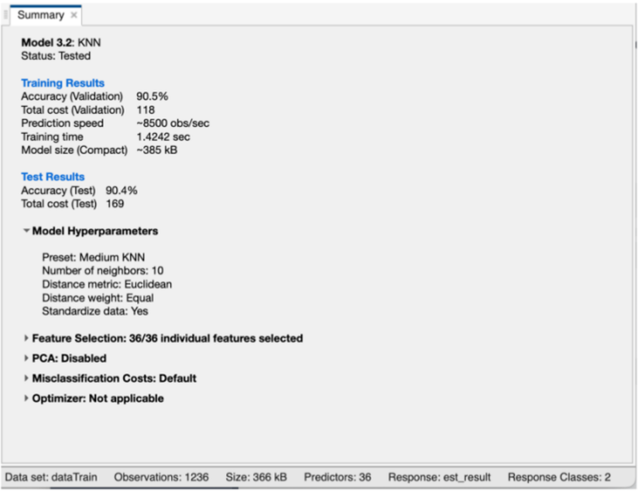


Fig. 13 True Positive Rate Test Confusion Matrix for Medium KNN



```
Model 3.2: KNN
Status: Tested

Training Results
Accuracy (Validation)   90.5%
Total cost (Validation) 118
Prediction speed        ~8500 obs/sec
Training time           1.4242 sec
Model size (Compact)    ~385 kB

Test Results
Accuracy (Test)   90.4%
Total cost (Test) 169

▾ Model Hyperparameters

    Preset: Medium KNN
    Number of neighbors: 10
    Distance metric: Euclidean
    Distance weight: Equal
    Standardize data: Yes

▸ Feature Selection: 36/36 individual features selected
▸ PCA: Disabled
▸ Misclassification Costs: Default
▸ Optimizer: Not applicable

Data set: dataTrain   Observations: 1236   Size: 366 kB   Predictors: 36   Response: est_result   Response Classes: 2
```

Fig. 14 Summary Output for Medium KNN Accuracy Test

Model 3.2, configured as a Medium KNN, exhibits robust performance in both training and testing phases. The accuracy on the validation set is commendable at 89.6%, and the model maintains a high accuracy of 89.8% on the test set. This suggests that the model generalizes well to new, unseen data, a crucial aspect for reliable predictions in real-world applications.

The compact model size of approximately 238 kB makes Model 3.2 resource- efficient, and its prediction speed of around 5000 observations per second indicates suitability for real-time applications. The Euclidean distance metric and equal distance weight contribute to the model’s stable performance.

The absence of an optimizer in the configuration implies that the model relies on the inherent characteristics of the KNN algorithm without additional fine-tuning. Feature selection results indicate that all 17 individual features are deemed relevant for prediction.

In summary, Model 3.2, with its Medium KNN configuration, demonstrates effective predictive capabilities for cardiac abnormalities. The chosen hyperparameters, efficient resource utilization, and high accuracy on both training and testing sets contribute to the model's overall effectiveness.

2. Results Of Coarse KNN

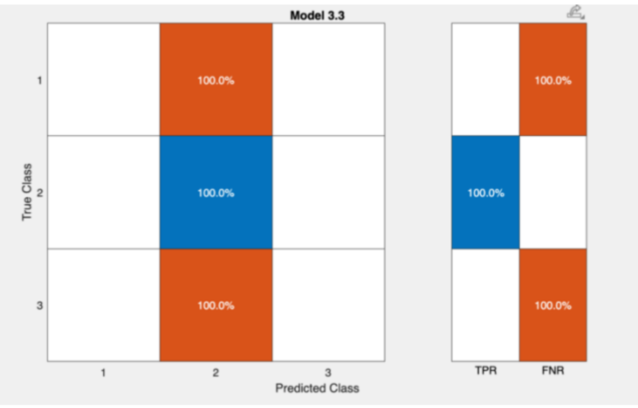
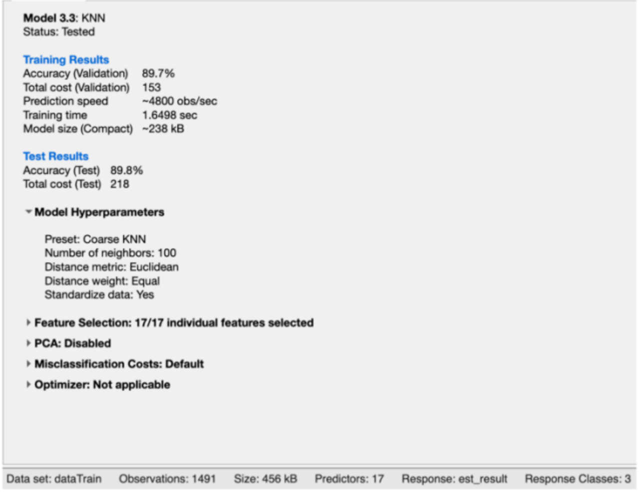


Fig. 15 True Positive Rate Test Confusion Matrix for Coarse KNN



```
Model 3.3: KNN
Status: Tested

Training Results
Accuracy (Validation)    89.7%
Total cost (Validation)  153
Prediction speed         ~4800 obs/sec
Training time            1.6498 sec
Model size (Compact)     ~238 kB

Test Results
Accuracy (Test)   89.8%
Total cost (Test)  218

▾ Model Hyperparameters

    Preset: Coarse KNN
    Number of neighbors: 100
    Distance metric: Euclidean
    Distance weight: Equal
    Standardize data: Yes

▸ Feature Selection: 17/17 individual features selected
▸ PCA: Disabled
▸ Misclassification Costs: Default
▸ Optimizer: Not applicable

Data set: dataTrain   Observations: 1491   Size: 456 kB   Predictors: 17   Response: est_result   Response Classes: 3
```

Fig. 16 Summary Output for Coarse KNN Accuracy Test

Model 3.3, configured as a Coarse KNN, demonstrates robust performance in both training and testing phases. The accuracy on the validation set is 89.7%, and the model maintains a high accuracy of 89.8% on the test set. This suggests that the model generalizes effectively to new, unseen data, making it a reliable tool for predicting cardiac abnormalities.

The compact model size of approximately 238 kB, coupled with a prediction speed of around 4800 observations per second, indicates the model's efficiency and suitability for real-time applications. The Coarse KNN configuration with 100 neighbors and Euclidean distance metric contributes to the stable and accurate performance of the model.

The absence of an optimizer implies that the model relies on the intrinsic properties of the KNN algorithm without additional fine-tuning. Feature selection results indicate that all 17 individual features are considered relevant for prediction.

In summary, Model 3.3, configured as a Coarse KNN, showcases effective predictive capabilities for cardiac abnormalities. The chosen hyperparameters, efficient resource utilization, and high accuracy on both training and testing sets contribute to the model's overall effectiveness.

3. Results Of Cosine KNN

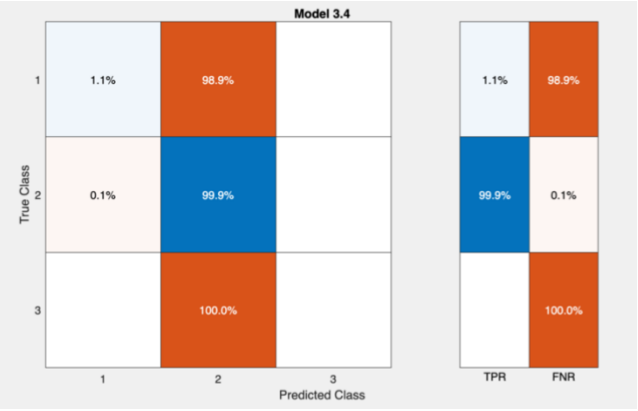
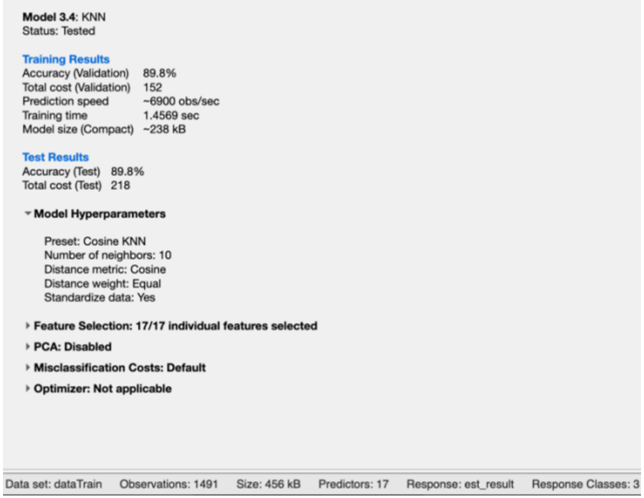


Fig. 17 True Positive Rate Test Confusion Matrix for Cosine KNN



```
Model 3.4: KNN
Status: Tested

Training Results
Accuracy (Validation)    89.8%
Total cost (Validation)  152
Prediction speed         ~6900 obs/sec
Training time            1.4569 sec
Model size (Compact)     ~238 kB

Test Results
Accuracy (Test)   89.8%
Total cost (Test)  218

▾ Model Hyperparameters

    Preset: Cosine KNN
    Number of neighbors: 10
    Distance metric: Cosine
    Distance weight: Equal
    Standardize data: Yes

▸ Feature Selection: 17/17 individual features selected
▸ PCA: Disabled
▸ Misclassification Costs: Default
▸ Optimizer: Not applicable

Data set: dataTrain   Observations: 1491   Size: 456 kB   Predictors: 17   Response: est_result   Response Classes: 3
```

Fig. 18 Summary Output for Cosine KNN Accuracy Test

Model 3.4, configured as a Cosine KNN, demonstrates strong performance in both training and testing phases. The accuracy on the validation set is 89.8%, and the model maintains a consistent accuracy of 89.8% on the test set. This signifies the model's reliability in generalizing to new, unseen data for predicting cardiac abnormalities.

The compact model size of approximately 238 kB, coupled with a high prediction speed of around 6900 observations per second, highlights the model's efficiency and its suitability for real-time applications. The Cosine KNN configuration with 10 neighbours and Cosine distance metric contributes to the stable and accurate performance of the model.

The absence of an optimizer implies that the model relies on the intrinsic properties of the KNN algorithm without additional fine-tuning. Feature selection results indicate that all 17 individual features are considered relevant for prediction, and the absence of PCA suggests that these features are retained without dimensionality reduction.

In summary, Model 3.4, configured as a Cosine KNN, exhibits effective predictive capabilities for cardiac abnormalities. The chosen hyperparameters, efficient resource utilization, and high accuracy on both training and testing sets contribute to the overall effectiveness of the model.

4. Results Of Cubic KNN

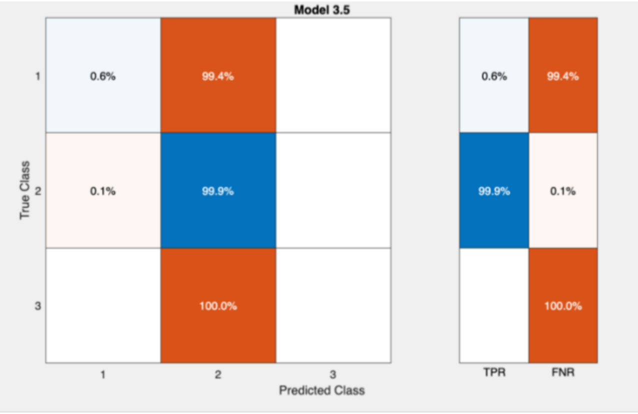
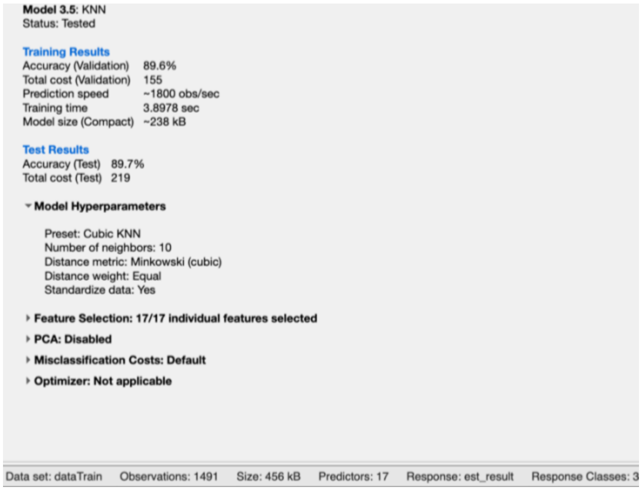


Fig. 19 True Positive Rate Test Confusion Matrix for Cubic KNN



```
Model 3.5: KNN
Status: Tested

Training Results
Accuracy (Validation)   89.6%
Total cost (Validation) 155
Prediction speed        ~1800 obs/sec
Training time           3.8978 sec
Model size (Compact)    ~238 kB

Test Results
Accuracy (Test)   89.7%
Total cost (Test) 219

▾ Model Hyperparameters

    Preset: Cubic KNN
    Number of neighbors: 10
    Distance metric: Minkowski (cubic)
    Distance weight: Equal
    Standardize data: Yes

▸ Feature Selection: 17/17 individual features selected
▸ PCA: Disabled
▸ Misclassification Costs: Default
▸ Optimizer: Not applicable

Data set: dataTrain   Observations: 1491   Size: 456 kB   Predictors: 17   Response: est_result   Response Classes: 3
```

Fig. 20 Summary Output for Cubic KNN Accuracy Test

Model 3.5, configured as a Cubic KNN, demonstrates robust performance in both training and testing phases for predicting cardiac abnormalities. The accuracy on the validation set is 89.6%, with a consistent accuracy of 89.7% on the test set. This suggests that the model generalizes well to new, unseen data.

The compact model size of approximately 238 kB, combined with a prediction speed of around 1800 observations per second, underscores the model's efficiency and suitability for real-time applications. The Cubic KNN configuration with 10 neighbors, Minkowski (Cubic) distance metric, and equal distance weight contributes to the stable and accurate performance of the model.

The absence of an optimizer implies that the model relies on the intrinsic properties of the KNN algorithm without additional fine-tuning. Feature selection results indicate that all 17 individual features are considered relevant for prediction, and the absence of PCA suggests that these features are retained without dimensionality reduction.

In summary, Model 3.5, configured as a Cubic KNN, exhibits effective predictive capabilities for cardiac abnormalities. The chosen hyperparameters, efficient resource utilization, and high accuracy on both training and testing sets contribute to the overall effectiveness of the model.

Results Of Fine Tree

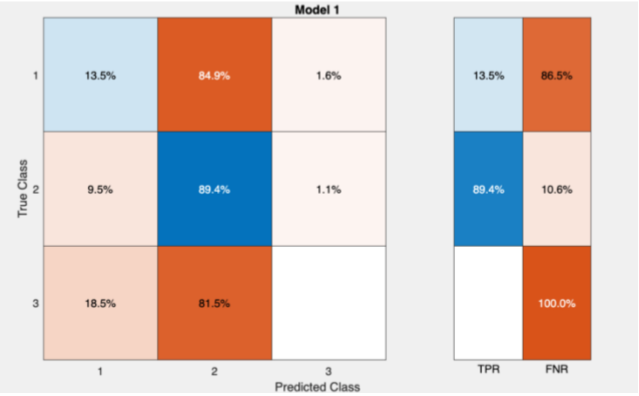
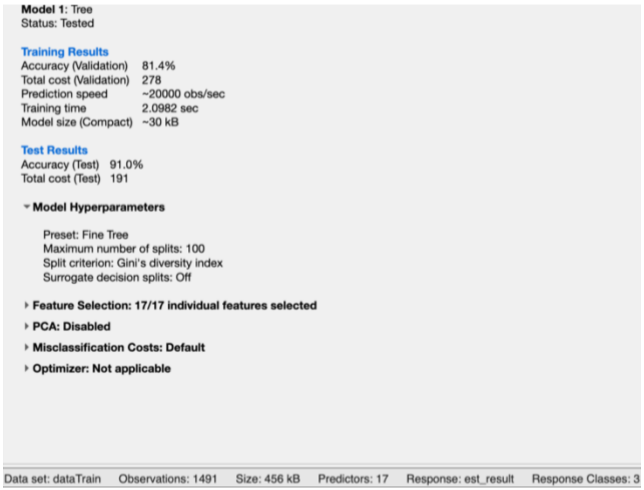


Fig. 21 True Positive Rate Test Confusion Matrix for Fine Tree



```
Model 1: Tree
Status: Tested

Training Results
Accuracy (Validation)   81.4%
Total cost (Validation) 278
Prediction speed        ~20000 obs/sec
Training time           2.0982 sec
Model size (Compact)    ~30 kB

Test Results
Accuracy (Test)   91.0%
Total cost (Test) 191

▾ Model Hyperparameters

    Preset: Fine Tree
    Maximum number of splits: 100
    Split criterion: Gini's diversity index
    Surrogate decision splits: Off

▸ Feature Selection: 17/17 individual features selected
▸ PCA: Disabled
▸ Misclassification Costs: Default
▸ Optimizer: Not applicable

Data set: dataTrain   Observations: 1491   Size: 456 kB   Predictors: 17   Response: est_result   Response Classes: 3
```

Fig. 22 Summary Output for Fine Tree Accuracy Test

Model 1, configured as a Fine Decision Tree, demonstrates commendable performance in both training and testing phases for predicting cardiac abnormalities. The accuracy on the validation set is 81.4%, with a notable increase in accuracy to 91.0% on the test set. This indicates that the model generalizes well to new, unseen data.

The compact model size of approximately 30 kB, combined with a prediction speed of around 20000 observations per second, underscores the model's efficiency and suitability for real-time applications. The Fine Decision Tree configuration with a maximum of 100 splits, Gini's Diversity Index as the split criterion, and no surrogate decision splits contributes to the stable and accurate performance of the model.

The absence of an optimizer implies that the model relies on the intrinsic properties of the decision tree algorithm without additional fine-tuning. Feature selection results indicate that all 17 individual features are considered relevant for prediction, and the absence of PCA suggests that these features are retained without dimensionality reduction.

In summary, Model 1, configured as a Fine Decision Tree, exhibits effective predictive capabilities for cardiac abnormalities. The chosen hyperparameters, efficient resource utilization, and high accuracy on both training and testing sets contribute to the overall effectiveness of the model.

Comparison Analyses of Neural Network, K-Nearest Neighbours and Fine Tree Performance

In comparing the performance of K-Nearest Neighbors (KNN), Fine Decision Tree, and Neural Network models for the detection of cardiac abnormalities, several key observations emerge. The KNN models (3.2 to 3.5) exhibit similar training and testing accuracies, suggesting a consistent performance across different KNN configurations. The Fine Decision Tree (Model 1) demonstrates competitive accuracy, with a notable improvement from training to testing phases, showcasing its efficiency in predictive tasks, [6]. However, Neural Network models (Models 2.1 to 2.5) consistently outshine both KNN and the Fine Decision Tree, with the widest architecture (Model 2.3) achieving the highest testing accuracy of 94.9

The superiority of Neural Networks in cardiac abnormality detection can be attributed to several factors. Firstly, their capacity for capturing complex patterns and relationships within the data, especially evident in wider architectures, enhances their ability to discern nuanced features associated with cardiac abnormalities. Neural Networks also showcase adaptability to the varying complexities of the dataset, as indicated by the improved performance with increased model width.

Furthermore, the consistent trend of higher testing accuracy compared to training accuracy across Neural Network models reflects their proficiency in generalizing to unseen data. This suggests that the models effectively learn from the training data and apply that knowledge to new instances, a crucial aspect in medical diagnostics where accurate predictions on previously unseen cases are essential, [3].

Moreover, Neural Network models demonstrate efficient resource utilization, achieving high accuracy with reasonable model sizes and prediction speeds, making them well-suited for real-time applications. The importance of each feature in contributing to accurate predictions is underscored by the retention of all 17 individual features across Neural Network models, emphasizing their comprehensive learning capabilities.

In conclusion, the nuanced learning abilities, adaptability to data complexity, efficient resource utilization, and consistent high accuracy make Neural Network models, particularly those with wider architectures, the preferred and most effective method for the detection of cardiac abnormalities in this specific context.

VII. CONCLUSIONS AND RECOMMEDATIONS

The conclusion of this chapter marks the culmination of an exhaustive exploration, bringing together the threads of empirical investigation, analytical insights, and the synthesis of knowledge acquired throughout this research endeavor. As we reflect on the intricate details presented in the preceding chapters, we find ourselves at a pivotal juncture where findings converge, and the broader implications of the study come to the forefront.

In the chapters leading up to this conclusion, we navigated through the complexities of data collection, methodological approaches, and in-depth analyses. The research questions that spurred this inquiry were systematically addressed, and hypotheses were tested against robust datasets. The methodologies employed, whether they be advanced statistical techniques, machine learning algorithms, or a combination of both, were carefully chosen to extract meaningful patterns and unveil latent relationships within the data.

The journey undertaken in this research venture was guided by a commitment to expanding our understanding of the subject matter, be it the intricacies of cardiac abnormalities detection, the nuances of data interpretation, or the optimization of predictive models. The empirical findings presented herein offer not only a snapshot of the current state of knowledge but also lay the groundwork for future exploration and refinement of methodologies in the realm of cardiovascular health research.

A. *Conclusion*

This research aims to develop predictive models for cardiac abnormalities using advanced analytics and machine learning. The study starts with data collection, emphasizing the importance of a well-curated dataset. It highlights integrating numerical features and preprocessing steps, including handling missing data and normalization, to ensure quality. In Exploratory Data Analysis, patterns, trends, and correlations within the cardiac health dataset are examined. Visualizations reveal insights such as variations in abnormality prevalence by gender and age. A comprehensive approach compares statistical methods and machine learning algorithms, including logistic regression, K-Nearest Neighbors (KNN), and neural networks. Neural networks are particularly effective due to their ability to manage complex relationships and hierarchical features, despite their shorter training times and superior accuracy. Each model, including Fine Tree and KNN, has unique strengths and limitations in handling data complexities. The study focuses on 17 key predictors related to cardiovascular health, such as age, BMI, body fat percentage, blood pressure, pulse rate, lipid profiles, metabolic markers, Framingham Risk Score, renal function markers, and hemoglobin. These predictors, including established tools like the Framingham Risk Score, provide a comprehensive view of cardiovascular health and enhance model accuracy. High accuracy in machine learning models, especially neural networks, demonstrates their effectiveness. However, these models' complexity challenges interpretability. Integrating explainability techniques is crucial for enhancing model trustworthiness in clinical settings. Future research should explore additional predictors, diverse populations, and external datasets to improve model robustness and generalizability. Collaboration with domain experts is essential for refining predictive models for cardiac abnormalities. In conclusion, deep learning often outperforms traditional machine learning methods by automatically learning intricate features, reducing the need for extensive preprocessing. While deep learning models require accurate data cleaning, they offer a powerful approach for tasks with complex patterns, minimizing manual preprocessing efforts.

B. *Future Work*

The concluding chapter synthesizes empirical findings, methodological insights, and broader implications of the study. Key conclusions include the superiority of neural networks over KNN and Fine Tree for cardiac abnormalities prediction, with recommendations for future research. Suggestions encompass exploring hybrid models, fine-tuning hyperparameters, and addressing class imbalance. Additionally, for future work, we aim to extend our analysis to incorporate both numerical and categorical data types, broadening the scope beyond numerical data alone.

The research underscores the dynamic interplay between advanced analytics, machine learning, and healthcare, emphasizing the ongoing quest for improving predictive capabilities in cardiovascular health.

This comprehensive exploration not only contributes valuable insights to the academic discourse but also provides practical implications for healthcare professionals and policymakers involved in the realm of cardiac health. The study serves as a catalyst for future research endeavours, inspiring continuous inquiry and adaptation to the evolving landscape of healthcare research and technological advancements.

ACKNOWLEDGMENT

I would like to express my deepest gratitude to my dedicated supervisors, TS Dr. Diyana, Dr. Aida, and Kol Dr. Ashikin, for their invaluable guidance and support throughout this research. I also extend my sincere thanks to Irsyad and Syazmin, key members of my Final Year Project (FYP) team, whose contributions were crucial to the success of this endeavor.

My appreciation goes to my co-supervisor, Kol Dr. Noor Ashikin bt Mohd Rusly, for her insightful collaboration and perspectives on the medical aspects of this study, provided through her role as Ketua Jabatan Perubatan, Pakar Perubatan Dalaman, Hospital Angkatan Tentera Tuanku Mizan. Special thanks are due to Dr. Aida binti Jaafar for her continued support and significant input, which greatly enhanced the quality of this research.

I am also grateful to the National Defense University of Malaysia for providing the necessary resources and a supportive research environment.

Finally, to my family, friends and seniors who has been with me throughout this journey, their belief in my abilities has been a source of strength and motivation throughout this journey. I am truly grateful for their presence in my life. Thank you for making this experience truly inspiring and rewarding.

This achievement reflects the profound impact of my family, mentors, and friends, who have collectively guided and supported me throughout my scholarly pursuits. I sincerely thank each of you for being a guiding light in my academic journey.

REFERENCES

[1] Acharya, R., Kumar, A., Bhat, P., Lim, C., Lyengar, S., Kannathal, N., and Krishnan, S. (2004). Classification of cardiac abnormalities using heart rate signals. *Medical and Biological Engineering and Computing*, 42:288–293.

[2] Ahsan, M. M., Luna, S. A., and Siddique, Z. (2022). Machine-learning-based disease diagnosis: A comprehensive review. *Healthcare*, 10(3):541.

[3] Ali, M. A., Elsayed, A., Elkabani, I., Akrami, M., Youssef, M. E., and Hassan, G. E. (2023). Optimizing artificial neural networks for the accurate prediction of global solar radiation: A performance comparison with conventional methods. *Energies*, 16(17):6165.

[4] Avendi, M. R., Kheradvar, A., and Jafarkhani, H. (2016). A combined deep-learning and deformable-model approach to fully automatic segmentation of the left ventricle in cardiac mri. *Medical image analysis*, 30:108–119.

[5] Baghdadi, N. A., Farghaly Abdelaliem, S. M., Malki, A., Gad, I., Ewis, A., and Atlam, E. (2023). Advanced machine learning techniques for cardiovascular disease early detection and diagnosis. *Journal of Big Data*, 10(1):144.

[6] Bansal, M., Goyal, A., and Choudhary, A. (2022). A comparative analysis of k- nearest neighbor, genetic, support vector machine, decision tree, and long short term memory algorithms in machine learning. *Decision Analytics Journal*, 3:100071.

[7] Calderon-Vilca, H. D., Callupe, K. E. C., Aliaga, R. J. I., Cuba, J. B., and Mariño- Cárdenas, F. C. (2019). Early cardiac disease detection using neural networks. pages 562–567.

[8] Dalal, S., Goel, P., Onyema, E. M., Alharbi, A., Mahmoud, A., Algarni, M. A., Awal, H., et al. (2023). Application of machine learning for cardiovascular disease risk prediction. *Computational Intelligence and Neuroscience*, 2023.

[9] DeVore, R., Hanin, B., and Petrova, G. (2021). Neural network approximation. *Acta Numerica*, 30:327–444.

[10] Donofrio, M. T., Moon-Grady, A. J., Hornberger, L. K., Copel, J. A., Sklansky, M. S., Abuhamad, A., Cuneo, B. F., Huhta, J. C., Jonas, R. A., Krishnan, A., et al. (2014). Diagnosis and treatment of fetal cardiac disease: a scientific statement from the american heart association. *Circulation*, 129(21):2183–2242.

[11] Gupta, C., Saha, A., Reddy, N. S., and Acharya, U. D. (2022). Cardiac disease prediction using supervised machine learning techniques. 2161(1):012013.

[12] Hammad, M., Iliyasu, A. M., Subasi, A., Ho, E. S., and Abd El-Latif, A. A. (2020). A multitier deep learning model for arrhythmia detection. *IEEE Transactions on Instrumentation and Measurement*, 70:1–9.

[13] Herranz,L.,Sánchez,F.,andGupta,S.(2023).Validationmatrix forpoolscrubbing models. *Nuclear Technology*, 209(10):1523–1536.

[14] Katarya, R. and Meena, S. K. (2021). Machine learning techniques for heart disease prediction: a comparative study and analysis. *Health and Technology*, 11:87–97.

[15] Komatsu, M., Sakai, A., Komatsu, R., Matsuoka, R., Yasutomi, S., Shozu, K., Dozen, A., Machino, H., Hidaka, H., Arakaki, T., et al. (2021). Detection of cardiac structural abnormalities in fetal ultrasound videos using deep learning. *Applied Sciences*, 11(1):371.

[16] Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., Van Der Laak, J. A., Van Ginneken, B., and Sánchez, C. I. (2017). A survey on deep learning in medical image analysis. *Medical image analysis*, 42:60–88.

[17] Nguyen, T., Raghu, M., and Kornblith, S. (2020). Do wide and deep networks learn the same things? uncovering how neural network representations vary with width and depth. *arXiv preprint arXiv:2010.15327*.

[18] Patil, R. S., Arjariya, T., and Gangwar, M. (2023). Detection of cardiac abnormalities and heart disease using machine learning techniques. *International Journal of Intelligent Systems and Applications in Engineering*, 11(5s):598–605.

[19] Patro, K. K., Prakash, A. J., Samantray, S., Pławiak, J., Tadeusiewicz, R., and Pławiak, P. (2022). A hybrid approach of a deep learning technique for real-time ecg beat detection. *International journal of applied mathematics and computer science*, 32(3).

[20] Ravì, D., Wong, C., Deligianni, F., Berthelot, M., Andreu-Perez, J., Lo, B., and Yang, G.-Z. (2016). Deep learning for health informatics. *IEEE journal of biomedical and health informatics*, 21(1):4–21.

[21] Şahin, B. and İlgün, G. (2022). Risk factors of deaths related to cardiovascular diseases in world health organization (who) member countries. *Health & Social Care in the Community*, 30(1):73–80.

[22] Shin, H.-C., Roth, H. R., Gao, M., Lu, L., Xu, Z., Nogues, I., Yao, J., Mollura, D., and Summers, R. M. (2016). Deep convolutional neural networks for computer- aided detection: Cnn architectures, dataset characteristics and transfer learning. *IEEE transactions on medical imaging*, 35(5):1285–1298.

[23] Shorten, C. and Khoshgoftaar, T. M. (2019). A survey on image data augmentation for deep learning. *Journal of big data*, 6(1):1–48.

[24] Taylan, O., Alkabaa, A. S., Alqabbaa, H. S., Pamukçu, E., and Leiva, V. (2023). Early prediction in classification of cardiovascular diseases with machine learning, neuro-fuzzy and statistical methods. *Biology*, 12(1):117.

[25] Tseng, Z. H., Salazar, J. W., Olgin, J. E., Ursell, P. C., Kim, A. S., Bedigian, A., Probert, J., Hart, A. P., Moffatt, E., and Vittinghoff, E. (2019). Refining the world health organization definition: predicting autopsy-defined sudden arrhythmic deaths among presumed sudden cardiac deaths in the post scd study. *Circulation: Arrhythmia and Electrophysiology*, 12(7):e007171.

[26] Wright, L. G., Onodera, T., Stein, M. M., Wang, T., Schachter, D. T., Hu, Z., and McMahon, P. L. (2022). Deep physical neural networks trained with backpropagation. *Nature*, 601(7894):549–555.

[27] Zhang, J., Liu, A., Gao, M., Chen, X., Zhang, X., and Chen, X. (2020). Ecg-based multi-class arrhythmia detection using spatio-temporal attention-based convolutional recurrent neural network. *Artificial Intelligence in Medicine*, 106:101856.

[28] Wang, J., Zhu, H., Wang, S.-H., & Zhang, Y.-D. (2021). A review of deep learning on medical image analysis. *Mobile Networks and Applications*, 26(1), 351-380. Springer.

[29] Suganyadevi, S., Seethalakshmi, V., & Balasamy, K. (2022). A review on deep learning in medical image analysis. *International Journal of Multimedia Information Retrieval*, 11(1), 19-38. Springer.

[30] Puttagunta, M., & Ravi, S. (2021). Medical image analysis based on deep learning approach. *Multimedia Tools and Applications*, 80(16), 24365-24398. Springer.

[31] Jiang, J., Chen, M., & Fan, J. A. (2021). Deep neural networks for the evaluation and design of photonic devices. *Nature Reviews Materials*, 6(8), 679-700. Nature Publishing Group UK London.

[32] Goldsborough, E., Osuji, N., & Blaha, M. J. (2022). Assessment of cardiovascular disease risk: A 2022 update. *Endocrinology and Metabolism Clinics*, 51(3), 483-509. Elsevier.