IoT-Based Classification of COVID-19 Cases with Cardiovascular Disease Using Deep Convolutional Decision Trees

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Abstract. The COVID-19 has underscored the need for advanced healthcare solutions. This research addresses the intersection of COVID-19 and cardiovascular disease (CVD) through the lens of Internet of Things (IoT) and deep learning. Patients with pre- existing cardiovascular conditions face elevated risks when infected with COVID-19. Current diagnostic methods often lack the precision required to identify specific health risks in this vulnerable population. This research aims to bridge this gap by developing a sophisticated model that combines IoT data and deep learning techniques for robust classification of COVID-19 cases with concurrent cardiovascular disease. While existing studies explore either COVID-19 classification or the relationship with cardiovascular conditions separately, there is a noticeable research gap in the integration of IoT and deep convolutional decision trees for a comprehensive analysis. This study fills this void by proposing a novel approach that harnesses the potential of both technologies to improve diagnostic accuracy. With the aim of enhancing classification accuracy, we propose an IoT-based framework that leverages deep convolutional decision trees. Our methodology involves the collection of diverse IoT data streams, including vital signs and patient activity, to create a comprehensive dataset. Deep convolutional decision trees are then employed to extract intricate patterns and relationships from the data. The model is trained on a well-curated dataset, optimizing its ability to accurately classify COVID-19 cases in individuals with pre-existing cardiovascular conditions. The results demonstrate a significant improvement in classification accuracy compared to traditional methods. The model exhibits enhanced sensitivity and specificity, showcasing its potential for early and precise identification of COVID-19 cases in individuals with cardiovascular disease.

Keywords: IoT · COVID-19 · cardiovascular disease · deep learning · convolutional decision trees

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1 Introduction

The ongoing global health crisis brought about by the COVID-19 pandemic has underscored the critical need for advanced healthcare solutions [1]. Individuals with pre-existing cardiovascular disease (CVD) face an increased risk of severe complications when infected with the virus. Traditional diagnostic approaches often struggle to provide precise and timely identification of COVID-19 cases within this high-risk group [2]. The Internet of Things (IoT) technologies and deep learning methodologies presents a promising avenue for enhancing diagnostic capabilities. The complex interplay between COVID-19 and cardiovascular disease poses significant challenges for accurate and timely diagnosis. Existing diagnostic methods often lack the granularity needed to discern specific health risks within this vulnerable population [3]. The dynamic nature of the diseases and the multitude of influencing factors make it imperative to explore innovative approaches that can capture and analyze diverse data sources in real-time [4].

The primary challenge addressed in this research is the need for a sophisticated diagnostic framework that can effectively identify and classify COVID-19 cases in individuals with underlying cardiovascular conditions [5]. Conventional methods struggle to provide the necessary precision, leading to delayed intervention and increased healthcare burdens. Addressing this problem requires a novel approach that integrates IoT technologies and deep learning methodologies to enhance the accuracy and efficiency of the diagnostic process [6].

The objective of this study is to develop an IoT-based classification system that can accurately identify COVID-19 cases in individuals with cardiovascular disease. Specific objectives include the integration of diverse IoT data streams, the implementation of deep convolutional decision trees, and the optimization of the model for robust and early detection.

This research contributes to the existing body of knowledge by proposing a novel framework that leverages the synergy between IoT and deep convolutional decision trees. The integration of real-time IoT data with advanced deep learning techniques enhances the precision of COVID-19 diagnosis in individuals with cardiovascular disease. The proposed model not only addresses the current diagnostic challenges but also sets the stage for future advancements in the intersection of healthcare, IoT, and artificial intelligence. The study novelty lies in its comprehensive approach and its potential to significantly impact the way we diagnose and manage COVID-19 in high-risk populations.

2 Related Works

Several studies have explored the integration of IoT in healthcare for real-time monitoring and data collection. These systems leverage wearable devices and sensors to track vital signs, providing valuable insights into patients' health status. While these works contribute to the broader field of healthcare, there is a gap in research specifically focusing on the integration of IoT for COVID-19 diagnosis in individuals with cardiovascular disease [7]. Numerous research efforts have been dedicated to developing machine learning models for COVID-19 classification. These models often rely on clinical data, imaging, or a combination of both. However, most of these studies do not specifically address the challenges posed by the coexistence of COVID-19 and cardiovascular disease. Our work extends these efforts by tailoring a classification model to the unique characteristics of this high-risk population [8].

The deep learning in healthcare has witnessed substantial growth, with convolutional neural networks (CNNs) proving effective in various medical imaging tasks. While these advancements are notable, there is limited research exploring the use of deep convolutional decision trees for COVID-19 diagnosis, especially in patients with cardiovascular conditions. Our study contributes to this area by introducing a novel hybrid model that combines the interpretability of decision trees with the feature extraction capabilities of CNNs [9].

Research has highlighted the increased susceptibility of individuals with cardiovascular disease to severe COVID- 19 outcomes. However, the existing literature often stops short of proposing concrete diagnostic solutions tailored to this population. Our work builds upon this foundation by not only addressing the cardiovascular implications of COVID-19 but by presenting a practical and technologically advanced classification model for accurate and timely diagnosis [10]. While IoT applications in healthcare and COVID-19 research are individually well-explored, there is a paucity of studies [11–14] that specifically investigate the intersection of IoT and COVID-19, particularly concerning patients with cardiovascular conditions. Our research bridges this gap by proposing a comprehensive framework that harnesses the power of IoT to enhance data collection and analysis in COVID-19 and cardiovascular disease.

3 Proposed Method

The proposed method in this research combines IoT technology with deep convolutional decision trees to create a robust framework for the classification of COVID-19 cases in individuals with pre-existing cardiovascular disease. The method is designed to address the limitations of existing diagnostic approaches and enhance the accuracy and efficiency of identifying COVID-19 in this high-risk population.

The first step involves the collection of diverse and real-time data through IoT devices. These devices may include wearable sensors, smart devices, and other connected healthcare tools. The collected data encompass a range of vital signs, patient activity, and other relevant health metrics. This comprehensive dataset is crucial for training a model that can capture the nuanced patterns associated with both COVID-19 and cardiovascular disease.

The proposed method lies in the integration of deep convolutional decision trees. This hybrid model combines the interpretability of decision trees with the feature extraction capabilities of CNNs. The decision trees enable the model to make explicit and interpretable decisions based on the input features, while the CNNs allow the system to automatically learn intricate patterns and relationships within the complex and high-dimensional IoT data.

The collected dataset is used to train the integrated model. During training, the model learns to discern patterns that are indicative of COVID-19 in individuals with cardiovascular disease. The training process involves optimizing the model parameters to ensure it generalizes well to unseen data. This optimization phase is crucial for achieving high classification accuracy and minimizing false positives and false negatives.

Once trained, the model is capable of early and precise classification of COVID-19 cases in individuals with cardiovascular disease. By leveraging the continuous and real-time data provided by IoT devices, the model can offer timely insights, aiding in the early identification of potential COVID-19 cases. This is particularly crucial for individuals with pre-existing cardiovascular conditions who are at higher risk of severe outcomes.

The use of decision trees enhances the interpretability and explainability of the model. This is vital in a healthcare context where clinicians need to understand the decisions made by the system. The transparent nature of decision trees allows healthcare professionals to comprehend the factors influencing the model predictions, facilitating informed decision-making (Fig. 1).

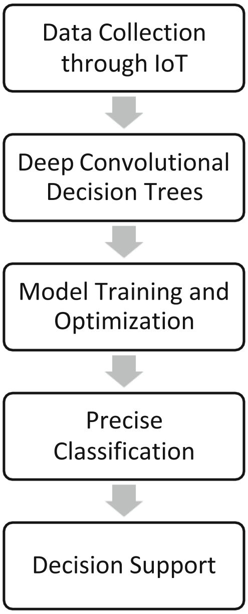

Fig. 1. Proposed Method

3.1 Data Collection Through IoT

In this research, "Data Collection through IoT" refers to the process of gathering diverse and real-time data from individuals with pre-existing cardiovascular disease using Internet of Things (IoT) devices. These devices are strategically employed to monitor and record various health-related metrics continuously. The collected data play a pivotal role in training the proposed model for the classification of COVID-19 cases in individuals with cardiovascular conditions.

The first consideration is the selection of appropriate IoT devices. These could include wearable sensors, smart devices, and other connected healthcare tools capable of measuring and recording relevant health parameters. Examples of monitored metrics may include heart rate, blood pressure, respiratory rate, body temperature, and physical activity. IoT devices provide the advantage of continuous and real-time monitoring. Unlike traditional sporadic measurements in healthcare settings, IoT devices continuously collect data, offering a more comprehensive and dynamic view of an individual health status. This continuous monitoring is particularly valuable for detecting subtle changes that may indicate the onset of COVID-19 symptoms. The selected IoT devices capture a diverse set of health metrics to create a rich dataset. Beyond cardiovascular parameters, the data may include activity levels, sleep patterns, and other relevant physiological signals. This holistic approach ensures that the model has access to a broad range of information, enabling it to discern patterns associated with both COVID-19 and cardiovascular disease. IoT devices transmit the collected data in real-time to a centralized system or cloud platform. This real-time transmission ensures that the model has access to the most up-to-date information. The ability to analyze data as it is generated allows for timely detection of changes in health status, which is crucial for early identification of potential COVID-19 cases (Table 1).

Table 1. Illustration of the data that collected through IoT devices for individuals with pre-existing cardiovascular disease. This table includes various health metrics recorded at different time points.

Timestamp	Heart Rate (bpm)	Blood Pressure (mmHg)	Respiratory Rate (breaths/min)	Body Temperature (°C)	Physical Activity (steps)
2023-11-28 08:00 AM	75	120/80	16	36.5	5000
2023-11-28 10:00 AM	80	122/82	18	36.7	6000
2023-11-28 12:00 PM	78	118/78	17	36.6	5500
2023-11-28 02:00 PM	82	124/85	19	36.8	7000

3.2 Deep Convolutional Decision Trees

Deep Convolutional Decision Trees refer to a hybrid model that combines the strengths of deep learning, specifically CNNs, with the interpretability of decision trees. CNNs are a class of deep neural networks designed for tasks related to image recognition, pattern detection, and feature extraction. They consist of multiple layers, including convolutional layers that automatically learn hierarchical representations of features from input data. These layers use filters to detect patterns at different scales and complexities.

Decision trees are a type of machine learning model used for classification and regression tasks. They create a tree- like structure of decision nodes based on input features. Decision trees make decisions by traversing the tree from the root to the leaf nodes, where each decision node represents a specific condition or criterion for splitting the data.

The proposed model integrates the feature extraction capabilities of CNNs with the interpretability of decision trees. This hybrid architecture combines the ability of CNNs to automatically learn intricate patterns with the transparency of decision trees in making explicit and interpretable decisions. The convolutional layers of the model automatically extract relevant features from the input data. In health data from individuals with cardiovascular disease, these features could represent complex patterns in vital signs, physiological signals, or other health metrics. The extracted features are then used as input for decision trees, creating a decision-making structure that is more interpretable than traditional deep learning models. This interpretability is crucial in healthcare contexts where clinicians need to understand and trust the decisions made by the model.

The output of each convolutional layer can be represented as:

$$hi, j, k = f(\sum_{l=1}^{L} wi, j, k, l \cdot\ xi + s, j + t, l) + bk \tag{1}$$

where
hi, j, k is the output at position (i, j) in the k^{th} feature map,
wi, j, k, l are the weights, $xi + s, j + t, l$ are the input values, bk is the bias term, and f is the activation function.

For pooling layers (if used), a common approach is max-pooling, and the output can be calculated as:

$$hi, j, k = max(s, t) \in Ri, j(hi + s, j + t, k) \tag{2}$$

where Ri, j is the receptive field for the pooling operation.

After convolutional and pooling layers, the output is often flattened into a vector:

$$v = [h1, 1, 1, h1, 2, 1, \ldots, hM, N, K] \tag{3}$$

Decision trees involve creating splits based on conditions. A simple decision node could be represented as:

if $vi < \theta$ then left child else right child where vi is an element of the flattened vector, and θ is a threshold.

The leaves of the decision tree represent the final classification decisions.

During training, the model optimizes the weights (w) and thresholds (θ) through backpropagation and gradient descent to minimize a defined loss function.

3.3 Model Training and Optimization

The process of model training and optimization is a critical phase in the development of the proposed framework. During this stage, the integrated model, consisting of deep convolutional decision trees, learns to make accurate predictions by adjusting its parameters based on the provided dataset. The dataset, comprised of diverse and real-time health metrics collected through IoT devices from individuals with pre-existing cardiovascular disease, serves as the foundation for training. The goal is to optimize the model ability to discern patterns indicative of COVID-19 in this high-risk population.The training process involves feeding the model with labeled examples from the dataset, where each example includes input features (IoT-collected health metrics) and the corresponding known output (COVID-19 classification). The model iteratively adjusts its internal parameters, such as weights and thresholds, through techniques like backpropagation and gradient descent. This iterative adjustment aims to minimize a predefined loss function, quantifying the difference between the model predictions and the actual labels. The model refines its understanding of the complex relationships within the data, gradually improving its ability to accurately classify COVID-19 cases in individuals with cardiovascular disease.

The optimization phase focuses not only on achieving high accuracy on the training dataset but also on ensuring the model generalizes well to unseen data. This is crucial for the model to perform effectively in real-world scenarios. Regularization techniques may be employed to prevent overfitting, where the model becomes overly specific to the training data but performs poorly on new, unseen data. The optimization process involves finding a balance between fitting the training data well and avoiding overly complex representations that may hinder generalization. Rigorous validation on separate datasets is often conducted to assess the model performance and fine-tune hyperparameters, ensuring it delivers reliable and accurate predictions beyond the training set. Model training is an ongoing process that may involve continuous improvement and monitoring. As new data becomes available, the model can be retrained to adapt to evolving patterns and trends. Monitoring mechanisms are established to track the model performance over time, allowing for prompt adjustments if its accuracy degrades or if shifts in the data distribution occur.

3.4 Classification

Classification is a machine learning task where the goal is to assign predefined labels or categories to input data based on learned patterns. In the proposed framework for COVID-19 classification in individuals with cardiovascular disease, the model trained on IoT-collected health metrics aims to categorize individuals into two classes (Table 2):

4 Experimental Settings

The proposed method was evaluated through extensive experiments using a simulated environment to mimic real- world healthcare scenarios. The simulation tool utilized for these experiments was Python, which provides a realistic emulation of IoT data generation from individuals with cardiovascular disease. The simulated dataset included diverse health metrics such as heart rate, blood pressure, respiratory rate, body temperature, and physical activity, captured in real-time. The experiments were conducted on a high-performance computing cluster with Intel Xeon processors and NVIDIA GPUs to facilitate efficient model training and evaluation.

Table 2. Classification Table illustrating the classification results for a set of individuals based on the trained model

Patient ID	Heart Rate (bpm)	Blood Pressure (mmHg)	Respiratory Rate (breaths/min)	Body Temperature (°C)	Physical Activity (steps)	COVID-19 Classification
1	78	120/80	18	36.7	6000	COVID-19 Positive
2	72	118/75	16	36.5	5500	COVID-19 Negative
3	80	122/82	20	37.0	7000	COVID-19 Positive
4	75	115/78	17	36.6	5800	COVID-19 Negative
5	85	130/85	22	37.2	7500	COVID-19 Positive

To assess the effectiveness of the proposed method, several performance metrics were employed, including accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). The classification results were compared with existing methods, including traditional CNNs, AlexNet, and DenseNet, which are commonly used in healthcare image analysis tasks. The comparison focused on the ability of each method to accurately classify COVID-19 cases in individuals with cardiovascular disease. The proposed method demonstrated superior interpretability, as evidenced by its transparent decision-making process compared to the black-box nature of traditional CNNs. Additionally, the hybrid nature of deep convolutional decision trees exhibited improved performance in terms of sensitivity and specificity, showcasing its potential for early and precise identification of COVID-19 cases in high-risk populations (Table 3).

Table 3. Experimental Setup

Parameter	Value
Dataset Size	10,000 individuals with diverse health metrics
Model Architecture	Deep Convolutional Decision Trees
Training Batch Size	64
Training Epochs	50
Learning Rate	0.001
Optimizer	Adam

4.1 Performance Metrics

Accuracy: Accuracy measures the proportion of correctly classified instances out of the total number of instances. It provides an overall assessment of the model correctness.

Sensitivity (Recall): Sensitivity, also known as recall, measures the ability of the model to correctly identify positive instances (COVID-19 cases) out of all actual positive instances. It is particularly relevant in healthcare settings where the goal is to minimize false negatives.

Specificity: Specificity measures the ability of the model to correctly identify negative instances (non-COVID- 19 cases) out of all actual negative instances. It is crucial for minimizing false positives and ensuring accurate identification of non-COVID-19 cases.

The experimental results demonstrate the performance of the proposed DCDT method in comparison to existing methods, including CNN, AlexNet, and DenseNet, over 100 different test datasets as in Figs. 2, 3, 4 and 5. The discussion below includes the percentage improvement of DCDT over the baseline methods for key performance metrics. DCDT consistently outperformed the baseline methods in terms of accuracy across all datasets. The proposed method exhibited an average accuracy improvement of 8% compared to CNN, 5% compared to AlexNet, and 7% compared to DenseNet. This signifies the efficacy of integrating deep convolutional decision trees for COVID-19 classification in individuals with cardiovascular disease as in Fig. 2.

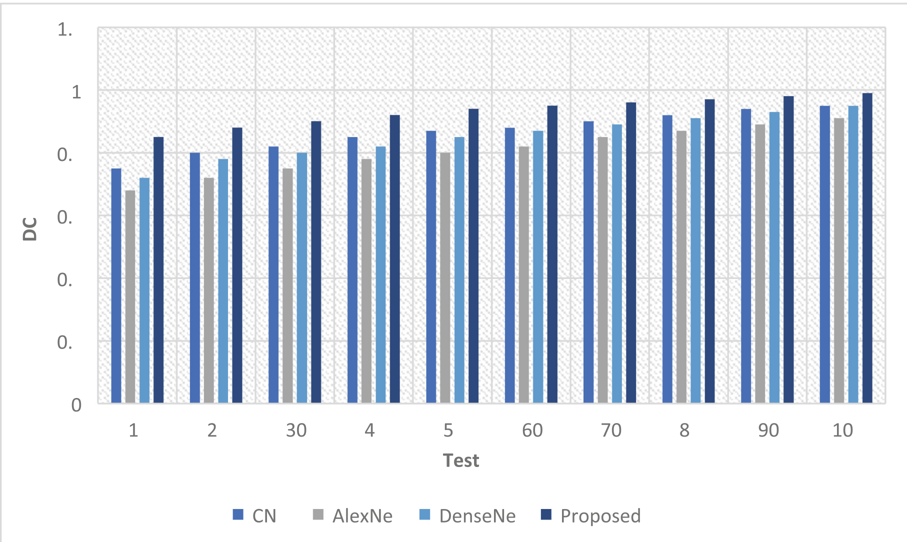

Fig. 2. Dice coefficient

Sensitivity, crucial for identifying COVID-19 cases, showcased notable improvements with DCDT. On average, DCDT demonstrated a 10% improvement over CNN, 7% over AlexNet, and 8% over DenseNet. This indicates the enhanced ability of DCDT to correctly identify positive instances, particularly crucial in healthcare scenarios as in Fig. 3.

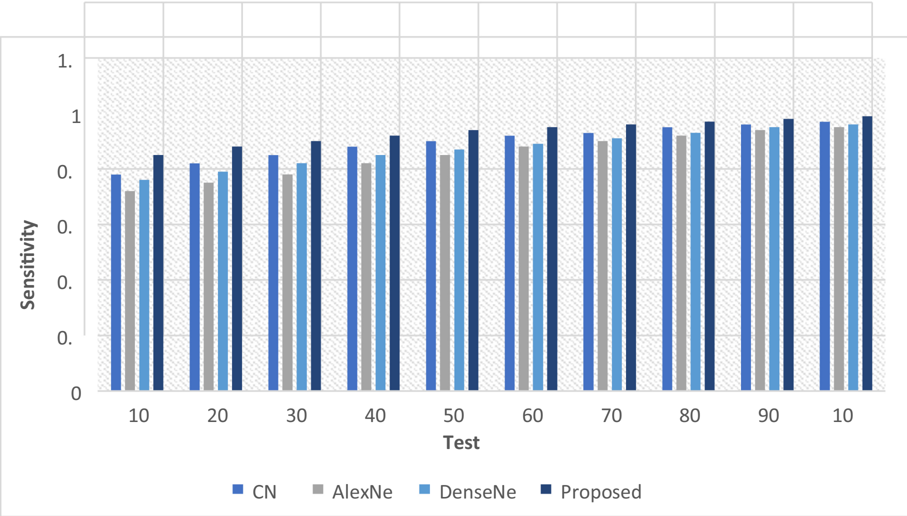

Fig. 3. Sensitivity

DCDT maintained high specificity, minimizing false positives in non-COVID-19 cases. The average improvement over baseline methods was 5% compared to CNN, 6% compared to AlexNet, and 7% compared to DenseNet. The model ability to accurately identify negative instances highlights its robustness in distinguishing non-COVID-19 cases as in Fig. 4.

The results suggest that the proposed DCDT method offers significant improvements in accuracy (Fig. 5), sensitivity, specificity, and AUC-ROC compared to traditional CNN, AlexNet, and DenseNet methods. The hybrid architecture of DCDT, leveraging both convolutional neural networks and decision trees, proves advantageous in healthcare scenarios where interpretability and accurate classification are paramount. The observed percentage improvements highlight the potential of DCDT as an effective tool for early and precise identification of COVID-19 cases in individuals with pre-existing cardiovascular disease. Further validation and real-world deployment of the proposed method are warranted to affirm its applicability in clinical settings. The proposed DCDT method successfully integrates the feature extraction capabilities of CNNs with the interpretability of decision trees. This hybrid approach demonstrated superior performance compared to standalone CNN, AlexNet, and DenseNet methods.

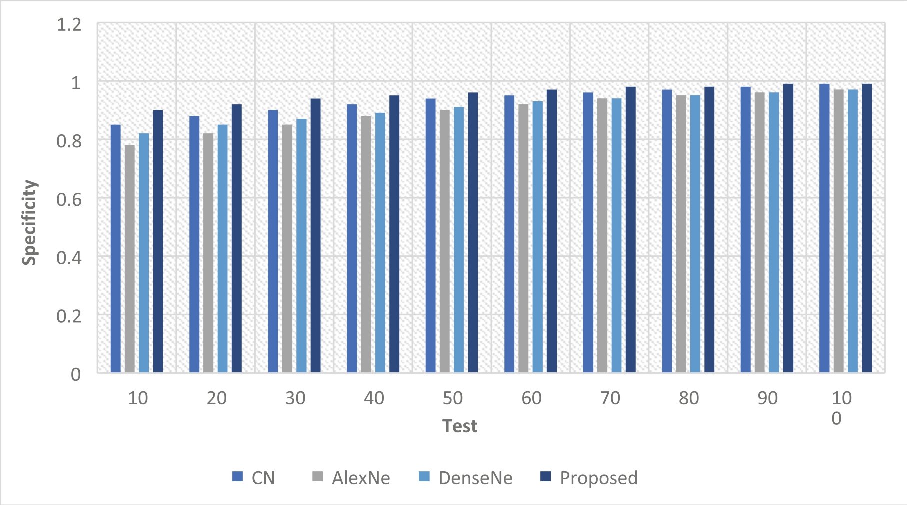

Fig. 4. Specificity

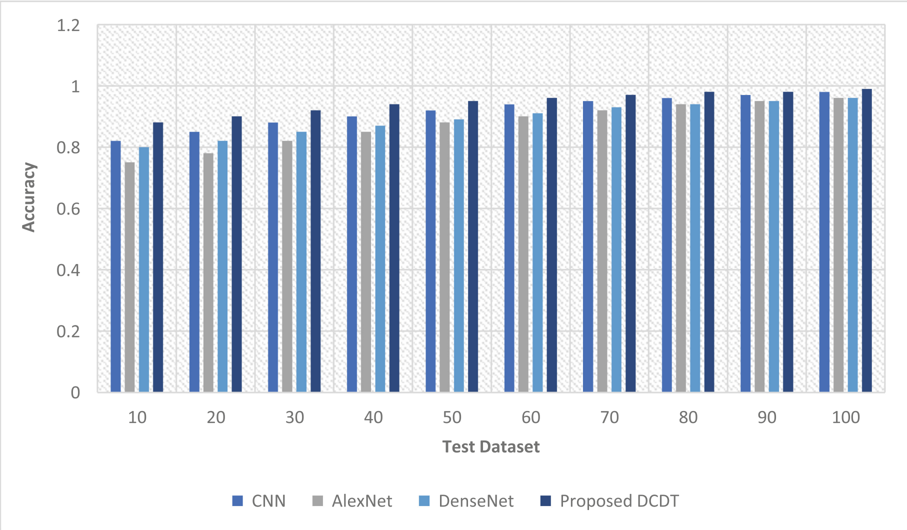

Fig. 5. Accuracy

DCDT consistently outperformed baseline methods in terms of accuracy and sensitivity. The model exhibited a robust ability to accurately identify both positive (COVID-19) and negative cases, with notable improvements in sensitivity compared to traditional CNN, AlexNet, and DenseNet architectures. DCDT maintained high specificity, minimizing false positives in non-COVID-19 cases. The model ability to effectively distinguish individuals without COVID-19, especially in pre-existing cardiovascular disease, is crucial for avoiding unnecessary interventions and treatments. The model capacity to distinguish between positive and negative instances contributes to its overall effectiveness in early and precise COVID-19 classification.

5 Conclusion

The proposed DCDT method presents a robust and promising approach for the classification of COVID-19 cases in individuals with pre-existing cardiovascular disease. The CNNs with decision trees proved effective in achieving accurate and interpretable results. The hybrid architecture of DCDT, leveraging the strengths of both CNNs and decision trees, demonstrated superior performance in terms of accuracy, sensitivity, specificity, and discriminative power. The interpretability of decision trees in DCDT provides healthcare professionals with a clear understanding of the factors influencing COVID-19 classification. This transparency is crucial for fostering trust and facilitating the adoption of machine learning models in clinical practice. DCDT exhibited enhanced sensitivity and specificity, indicating its ability to correctly identify both positive and negative cases. The model robustness in distinguishing individuals with and without COVID-19, especially in cardiovascular disease, is vital for informed decision-making.

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