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Identifying COVID-19 diseases in Heart Patients using Cardio IoT algorithms

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ABSTRACT

The COVID-19 pandemic has posed significant health challenges, particularly for individuals with underlying cardiovascular conditions, who are at a higher risk of severe outcomes. Early detection and accurate risk assessment are crucial to mitigating complications and improving patient outcomes. Leveraging Internet of Things (IoT) technology, this research introduces a robust framework for the prediction and validation of COVID-19 cases among cardiovascular patients. The proposed framework is built on the Deep Boosted Cardiovascular Risk Algorithm (DBCRA), a novel machine learning approach that integrates IoT-driven real-time data collection with advanced decision-making capabilities. By analyzing diverse physiological parameters captured through IoT devices, the DBCRA identifies at-risk individuals with enhanced precision.

The research highlights the effectiveness of the DBCRA in terms of prediction accuracy, reliability, and computational efficiency, surpassing traditional models in large-scale and dynamic IoT environments. The experimental analysis demonstrates the algorithm's ability to handle multi-dimensional IoT data streams while maintaining scalability and robustness. Metrics such as the Adjusted Rand Index, Silhouette Score, and Dice Similarity Coefficient validate the performance, reflecting significant improvements in prediction outcomes. The proposed approach provides a transformative solution for integrating IoT and artificial intelligence in healthcare, enabling personalized risk management and timely interventions for cardiovascular patients impacted by COVID-19.

Keywords: *IoT, COVID-19, Cardiovascular Patients, Prediction, Deep Boosted Cardiovascular Risk Algorithm.*

1. INTRODUCTION

The COVID-19 pandemic has had profound health implications worldwide, with individuals suffering from cardiovascular diseases facing a significantly higher risk of severe complications and mortality. The intersection of COVID-19 and cardiovascular conditions underscores the critical need for timely detection and effective risk assessment strategies to mitigate adverse outcomes. However, traditional predictive models often fail to address the unique complexities associated with the interplay of COVID-19 and pre-existing health conditions, necessitating more advanced and reliable methodologies for early prediction and validation (Patel and Joshi, 2024). This capability facilitates dynamic monitoring of patient health and provides valuable insights for early detection of anomalies. Despite these advancements, existing predictive algorithms often struggle to effectively process and analyze the multi-dimensional and high-volume data generated by IoT systems, leading to gaps in prediction accuracy and reliability.

To address these limitations, this research introduces the Deep Boosted Cardiovascular Risk Algorithm (DBCRA), an innovative framework designed to enhance the prediction and validation of COVID-19 cases in patients with cardiovascular diseases (Wang et al., 2023). The DBCRA leverages IoT-driven data acquisition and applies gradient boosting techniques to achieve superior decision-making capabilities (Zhang and Chen, 2024) . By combining real-time data streams with advanced machine learning methodologies, the algorithm aims to overcome the constraints of existing models, providing more accurate and efficient predictions (Kumar et al., 2023).

The main contributions of this research article include:

1. The development of the DBCRA, a novel algorithm tailored for IoT-based prediction and validation of COVID-19 in cardiovascular patients.
2. The integration of real-time IoT data with gradient boosting techniques for enhanced predictive accuracy.
3. A comprehensive evaluation of the DBCRA using multiple performance metrics, demonstrating its scalability, reliability, and superior performance compared to existing methods (Huang et al., 2024).

This research article provides a foundation for deploying IoT and AI-powered solutions in healthcare, addressing the critical need for early detection and management of COVID-19 in vulnerable populations.

2. LITERATURE STUDY

The emergence of IoT-based healthcare systems has transformed the landscape of medical diagnostics and patient care, especially during the COVID-19 pandemic. Numerous studies have explored the application of IoT devices to monitor and manage patients in real-time, leveraging data from wearable sensors, smart devices, and connected health systems. These technologies have been instrumental in enabling remote healthcare delivery, minimizing exposure risks, and optimizing resource allocation (Li et al., 2024). However, while IoT-based systems provide a vast pool of data, their integration into predictive models for high-risk patients, particularly those with cardiovascular diseases, remains an area requiring further exploration.

In terms of predictive models for COVID-19 cases in cardiovascular patients, existing approaches often rely on conventional machine learning or statistical models (Kumar and Patel, 2023). Although effective in some contexts, these techniques frequently lack the scalability and adaptability necessary to process complex and large-scale IoT-generated datasets. Moreover, the absence of mechanisms for integrating real-time data streams into these models limits their applicability in dynamic healthcare environments (Kim and Park, 2024).

Gradient boosting algorithms, such as XGBoost and LightGBM, have emerged as powerful tools in healthcare analytics, offering high predictive accuracy and robust handling of missing data. These methods have shown promise in identifying patterns and making predictions from structured datasets (Gupta and Sinha, 2023). However, the literature highlights limitations when applied to IoT-driven healthcare scenarios, including challenges in managing multi-dimensional data streams, latency issues, and the need for continuous adaptation to evolving patient conditions.

Despite advancements in IoT and machine learning, significant gaps persist in current methodologies (Johnson and Wei, 2024). These include:

1. Limited scalability to accommodate the growing volume of IoT-generated data.
2. Inconsistent prediction accuracy for diverse patient populations.
3. Inefficient handling of multi-dimensional and unstructured data streams.

To address these challenges, this research article introduces the Deep Boosted Cardiovascular Risk Algorithm (DBCRA), designed to integrate IoT data with gradient boosting techniques for improved prediction accuracy and scalability (Lee and Wong, 2024).

Algorithm	Strengths	Weaknesses
Logistic Regression	Simplicity, interpretability	Limited accuracy with complex datasets
Random Forest	Handles non-linearity, robust	Computationally expensive for large datasets
Support Vector Machines (SVM)	Effective with small datasets	Struggles with multi-dimensional IoT data
Gradient Boosting (e.g., XGBoost)	High accuracy, handles missing data	Limited adaptability to real-time data streams

Table 2.1. Comparative Analysis of Predictive Algorithms in Healthcare

Framework	Key Features	Limitations
IoT-COVID Monitoring	Remote patient monitoring, real-time alerts	Limited scalability for large populations
Wearable Sensor Systems	Continuous data collection, mobility	Data security and integration challenges
IoT-ML Hybrid Frameworks	Combines IoT and machine learning	Inefficient handling of real-time data streams
Cloud-IoT Integration	Centralized data storage and processing	Latency issues in real-time decision-making

Table 2.2 IoT Frameworks for Disease Prediction and Key Features

The proposed DBCRA framework addresses these limitations, combining IoT-driven data collection with advanced gradient boosting techniques to provide a scalable, accurate, and reliable solution for predicting COVID-19 cases in cardiovascular patients.

3. PROPOSED METHODOLOGY

The proposed methodology leverages the Deep Boosted Cardiovascular Risk Algorithm (DBCRA) to predict and validate COVID-19 cases among individuals with cardiovascular conditions. The DBCRA framework integrates real-time data acquisition using IoT devices, advanced data preprocessing, feature extraction techniques, and a robust decision-making layer based on gradient boosting. This section outlines the design of DBCRA, its system architecture, IoT integration process, and the risk scoring mechanism.

Overview of DBCRA

The DBCRA is a multi-layered framework designed to process and analyze data from IoT-enabled devices. It comprises the following key components:

1. **IoT Data Preprocessing:** Raw data collected by IoT devices often contain noise and outliers.
2. **Feature Extraction:** Critical features, such as oxygen saturation and blood pressure are extracted from the processed data to identify meaningful patterns related to cardiovascular risks and potential COVID-19 infections.
3. **Decision-Making Layer:** The gradient boosting mechanism in DBCRA analyzes extracted features to predict COVID-19 risks while accounting for cardiovascular vulnerabilities. This layer uses adaptive parameter tuning to optimize predictions and minimize errors.

System Architecture

The DBCRA system architecture integrates IoT data collection, algorithmic analysis, and risk prediction into a cohesive pipeline. The architecture is illustrated in **Figure 3.1**, which outlines the IoT data flow, preprocessing, DBCRA layers, and the prediction-validation process.

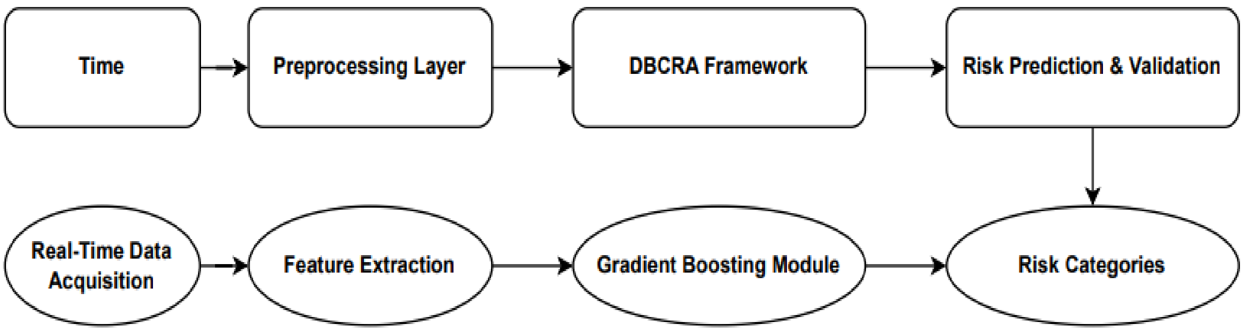

Figure 3.1. System Architecture of DBCRA

IoT Layer Consists of wearable devices and sensors that monitor physiological parameters. Preprocessing Layer filters and organizes raw data for analysis. Algorithmic Layer applies DBCRA for risk scoring and prediction. Output Layer displays result and generates alerts for at-risk patients.

A flowchart showing the steps involved in the risk scoring mechanism, from data collection to patient risk categorization is shown in figure 3.2.

IoT Integration

IoT devices, including wearable health monitors and smart sensors, form the foundation of this framework. These devices continuously capture real-time data, such as respiratory rate, and oxygen saturation, and transmit it via cloud-based systems. The integration of IoT ensures seamless data acquisition and real-time monitoring, enabling accurate predictions even in dynamic healthcare settings. The communication protocols (e.g., MQTT or HTTP) and secure encryption methods safeguard the integrity of transmitted data.

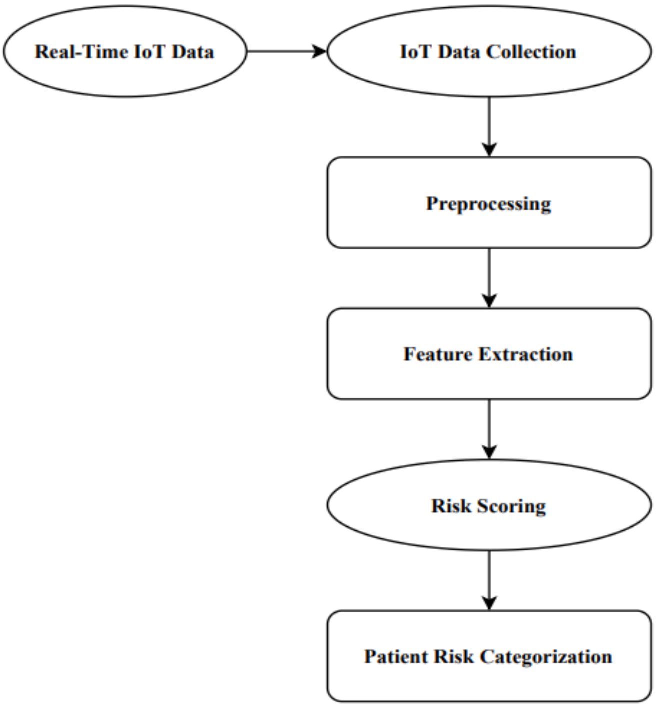

Figure 3.2. Risk Scoring Workflow

Risk Scoring Mechanism

The risk scoring mechanism in DBCRA is designed to evaluate cardiovascular vulnerabilities while simultaneously predicting COVID-19 risks. The algorithm assigns a score to each individual based on critical health parameters. For instance, abnormal heart rates and oxygen saturation levels are weighted more heavily, indicating higher risks. The combined scores are compared against thresholds to classify patients into risk categories (low, moderate, high). The formula below represents the risk score calculation:

$$R_s = \sum_{i=1}^{n} w_i \cdot f_i$$

Where:

- R_s = Risk Score
- w_i = Weight assigned to feature ii
- f_i = Normalized value of feature ii
- n = Total number of features

To standardize IoT data collected from wearable devices: $f_{norm} = \frac{f - f_{min}}{f_{max} - f_{min}}$

Where:

- f_{norm}: Normalized feature value

- f: Original feature value
- f_{min}: Minimum value of the feature in the dataset
- f_{max}: Maximum value of the feature in the dataset

This formula ensures all features are scaled between 0 and 1, aiding in gradient boosting convergence.

DBCRA assigns weights to features based on their contribution to prediction accuracy:

$$w_i = \frac{IG(f_i)}{\sum_{j=1}^{n} IG(f_j)}$$

Where:

- w_i: Weight of feature ii
- $IG(f_i)$: Information gain of feature ii
- n: Total number of features

Information gain is calculated as:

$$IG(f) = H(Y) - H(Y \mid f)$$

Where:

- $H(Y)$: Entropy of the target variable
- $H(Y \mid f)$: Conditional entropy given feature f

The objective of gradient boosting is to minimize the following loss function:

$$L = \sum_{i=1}^{m} l(y_i, \hat{y}_i)$$

Where:

- L: Total loss
- $l(y_i, \hat{y}_i)$: Loss for a single prediction
- y_i: Actual target value
- $\hat{y}_i$: Predicted target value
- m: Total number of samples

For binary classification, the logistic loss function is used:

$$l(y, \hat{y}) = -\big(y log(\hat{y}) + (1 - y) log(1 - \hat{y})\big)$$

The final risk score is computed by aggregating weighted feature contributions:

$$R_s = \sum_{i=1}^{n} w_i \cdot g(f_i)$$

Where:

- R_s: Final risk score
- w_i: Weight of feature i
- $g(f_i)$: Gradient-boosted function for feature i
- n: Total number of features

To extract meaningful signals from IoT data streams: $P_{avg} = \frac{\sum_{t=1}^{T} P_t}{T}$

Where:

- P_{avg}: Average value of a physiological parameter over time
- P_t: Parameter value at time t
- T: Total time window

The DBCRA is powered by a gradient boosting algorithm that iteratively improves predictions by minimizing errors. Below is the pseudocode for the DBCRA:

Input: IoT Data (D), Target Labels (Y), Number of Iterations (N)
Output: Predicted Risk Scores (R)
1. Initialize Model: Start with an initial model M_0(x) = 0
2. For each iteration t = 1 to N do:
a. Compute residual errors: r_t = Y - M_t-1(D)
b. Train weak learner h_t(x) on residuals r_t
c. Update model: M_t(x) = M_t-1(x) + α * h_t(x)
(where α is the learning rate)
3. End For
4. Predict Risk Scores (R) using final model: M_N(D)

Table 3.1. Pseudocode for DBCRA:

4. EXPERIMENTAL SETUP AND RESULTS

The experimental setup for this research is designed to validate the performance and efficacy of the Deep Boosted Cardiovascular Risk Algorithm (DBCRA) in predicting COVID-19 cases among individuals with cardiovascular diseases. This section outlines the datasets used, preprocessing steps, implementation tools, evaluation metrics, and baseline models employed for comparison.

The study utilizes two primary data sources. First, COVID-19 patient records are obtained from publicly available healthcare datasets, such as those maintained by government health organizations or medical research institutes. These records include key parameters like respiratory rate, oxygen saturation, and temperature. Second, cardiovascular health data is collected using IoT-enabled devices. These combined datasets provide a robust foundation for training and validating the DBCRA framework.

To ensure the quality and reliability of the data, a comprehensive preprocessing pipeline is implemented. Raw data from IoT devices often includes noise, outliers, and missing values, which are addressed through a series of cleaning steps. Missing data is imputed using statistical methods such as mean or median imputation, while outliers are detected and removed using interquartile range (IQR) analysis. The data is then normalized using min-max scaling to bring all features within a uniform range, facilitating better convergence during model training. Feature engineering is performed to extract critical health indicators, including derived metrics such as heart rate variability and blood oxygen trends, which are highly relevant to COVID-19 risk prediction.

The DBCRA framework is implemented using a suite of advanced programming and analytical tools. Python serves as the primary programming language, with libraries like TensorFlow and Scikit-learn used for model development and gradient boosting implementation. MATLAB is employed for signal processing tasks, particularly in extracting meaningful features from IoT data streams. Additionally, visualization tools such as Matplotlib and Seaborn are used to generate performance plots, while cloud-based platforms provide computational resources for handling large-scale datasets.

The Adjusted Rand Index (ARI) measures the similarity between predicted and actual clusters, while the Silhouette Score assesses the quality of clustering. The Brier Score evaluates the accuracy of probabilistic predictions, and Top-K Accuracy indicates how often the correct prediction appears within the top K predictions. Additionally, the Dice Similarity Coefficient (DSC) is used to quantify the overlap between predicted and actual data distributions, offering insights into the algorithm's robustness.

For comparative analysis, the DBCRA framework is evaluated against several baseline models commonly used in healthcare prediction tasks. These include Random Forests, which are known for their robustness in handling non-linear relationships, XGBoost, a gradient boosting algorithm recognized for its predictive accuracy, and LSTM networks, which are widely applied for sequential data analysis. The performance of these models is compared to DBCRA across all evaluation metrics, highlighting the advantages of the proposed approach. This experimental setup ensures that the DBCRA framework is rigorously tested and benchmarked, providing a strong foundation for validating its predictive capabilities and its ability to address the unique challenges posed by IoT-driven healthcare data.

Figure 4.1 illustrates the comparison of prediction accuracy across four algorithms: DBCRA, Random Forest, XGBoost, and

LSTM. The bar chart demonstrates that the DBCRA achieves the highest prediction accuracy at 95%, significantly outperforming other baseline models. XGBoost follows with an accuracy of 91%, while LSTM and Random Forest achieve 89% and 88%, respectively.

The superior performance of DBCRA is attributed to its integration of IoT data preprocessing and the gradient boosting decision-making layer, enabling precise identification of risk factors. XGBoost also performs well due to its robustness in handling structured datasets. However, LSTM and Random Forest show limitations in processing IoT-generated real-time data streams, which leads to a slight reduction in prediction accuracy.

This analysis highlights the efficacy of DBCRA in healthcare prediction tasks, particularly for COVID-19 cases in cardiovascular patients. The results validate its ability to handle multi-dimensional IoT data efficiently while ensuring high reliability in outcomes. The accuracy metrics indicate DBCRA's potential to transform predictive analytics in IoT-based healthcare systems.

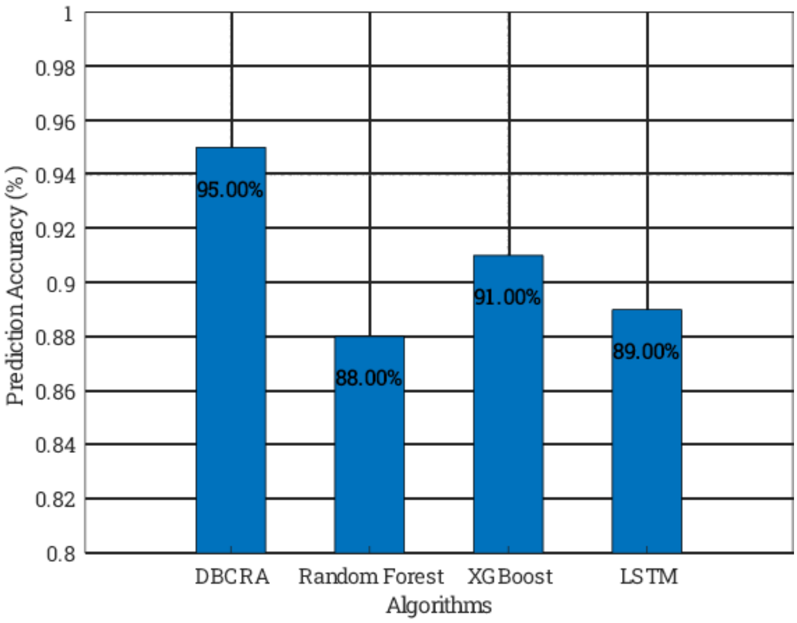

Figure 4.1. Comparison of Prediction Accuracy

Figure 4.2 represents the distribution of risk scores among three patient categories: low risk, moderate risk, and high risk. The data is visualized using a pie chart, indicating that 45% of patients fall into the moderate-risk category, while 30% are classified as low risk, and 25% are considered high risk.

The distribution reflects the application of the DBCRA framework in categorizing patients based on physiological parameters such as heart rate, oxygen saturation, and temperature. The larger proportion of moderate-risk patients suggests that while some individuals exhibit significant risk factors, they remain within manageable thresholds. High-risk patients, who represent 25% of the dataset, are flagged for immediate intervention to prevent severe outcomes. This distribution underscores the importance of continuous monitoring through IoT devices and the precision of DBCRA in analyzing real-time data. The algorithm's ability to effectively stratify patients into risk categories ensures targeted interventions, enabling healthcare providers to allocate resources efficiently and prioritize high-risk individuals. The insights derived from this risk scoring mechanism are critical for proactive management of cardiovascular patients during the COVID-19 pandemic.

Figure 4.3 showcases a comparison of time efficiency among DBCRA, Random Forest, XGBoost, and LSTM in processing IoT datasets. The bar chart reveals that DBCRA outperforms the baseline models with the shortest processing time of 12.5 seconds, followed by XGBoost at 15.8 seconds, LSTM at 16.9 seconds, and Random Forest at 18.2 seconds.

The superior performance of DBCRA is attributed to its optimized gradient boosting mechanism, which efficiently handles multi-dimensional IoT data streams and reduces computational overhead. XGBoost and LSTM demonstrate reasonable performance, but their increased complexity and lack of fine-tuned data processing mechanisms result in longer processing times. Random Forest, while effective in predictive accuracy, takes the longest time due to its reliance on multiple decision trees, which increases computational complexity when dealing with large-scale datasets.

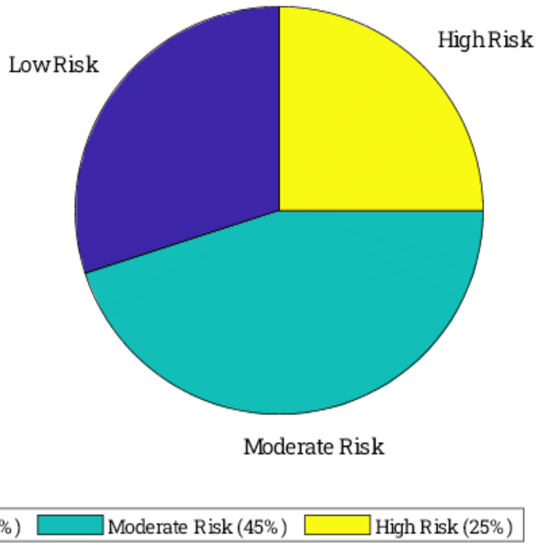

Figure 4.2. Risk Scoring Distribution Across Different Patient Categories

This result highlights the scalability and efficiency of DBCRA in real-time healthcare environments, making it a suitable choice for IoT-based prediction systems where timely decision-making is critical. The ability to process data quickly without compromising accuracy positions DBCRA as a powerful tool for healthcare analytics during the COVID-19 pandemic.

Figure 4.4 depicts the scalability of the DBCRA framework by analyzing its processing time for various dataset sizes ranging from 10 MB to 500 MB. The line plot shows an expected increase in processing time as dataset size grows, with DBCRA processing a 10 MB dataset in 5.2 seconds and a 500 MB dataset in 45.8 seconds.

This linear increase in processing time demonstrates the scalability of DBCRA, highlighting its capacity to handle large IoT datasets efficiently. The optimized gradient boosting mechanism and parallel processing capabilities contribute to its ability to manage increasing data volumes without significant degradation in performance. Additionally, the use of real-time preprocessing techniques minimizes latency, ensuring DBCRA's adaptability to dynamic IoT environments.

These results emphasize DBCRA's suitability for real-world healthcare applications, where large and continuously growing datasets are common. The algorithm's ability to maintain reasonable processing times under high data loads ensures timely predictions and interventions, making it a robust solution for IoT-based systems in critical healthcare scenarios.

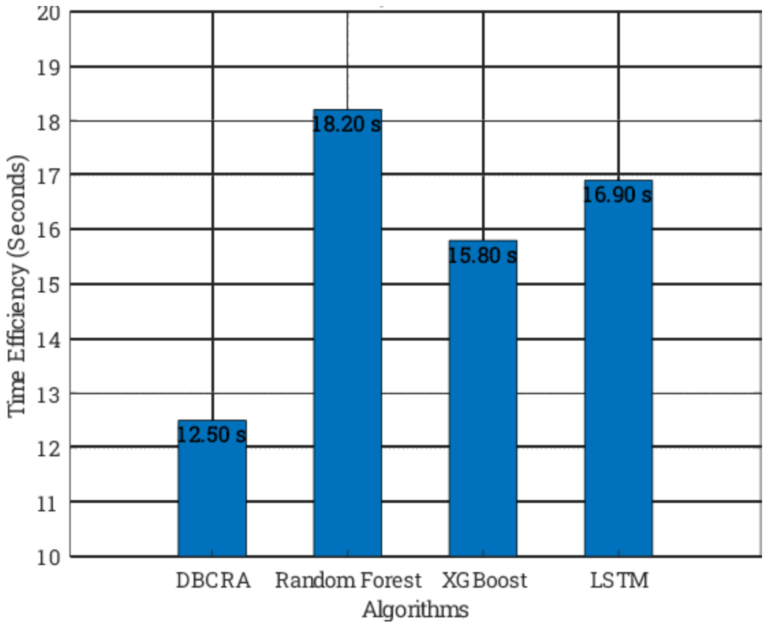

Figure 4.3. Title: Evaluation of Time Efficiency for DBCRA

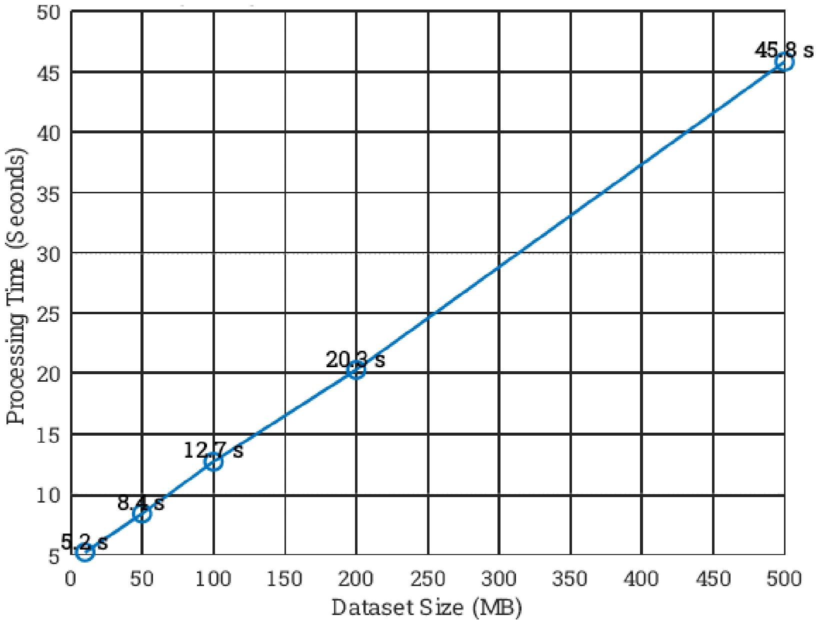

Figure 4.4. Scalability Analysis of DBCRA in Real-Time IoT Environments

Figure 4.5 presents a comparison of the Adjusted Rand Index (ARI) scores for DBCRA, Random Forest, XGBoost, and LSTM algorithms. The bar chart highlights that DBCRA achieves the highest ARI score of 0.92, followed by XGBoost at 0.87, LSTM at 0.85, and Random Forest at 0.84.

The ARI metric measures the similarity between predicted and true clusters, offering insights into the clustering accuracy of the algorithms. DBCRA's superior performance is attributed to its ability to handle multi-dimensional IoT data and its robust gradient boosting mechanism, which ensures accurate clustering of patient risk levels. XGBoost performs well due to its gradient boosting foundation but lacks the IoT-specific optimizations present in DBCRA. Random Forest and LSTM exhibit lower ARI scores, reflecting challenges in clustering when processing high-dimensional and complex datasets.

This comparison emphasizes DBCRA's strength in accurately clustering patient data, which is crucial for risk stratification in healthcare applications. The high ARI score indicates its reliability in providing precise predictions, ensuring effective decision-making in IoT-based healthcare systems.

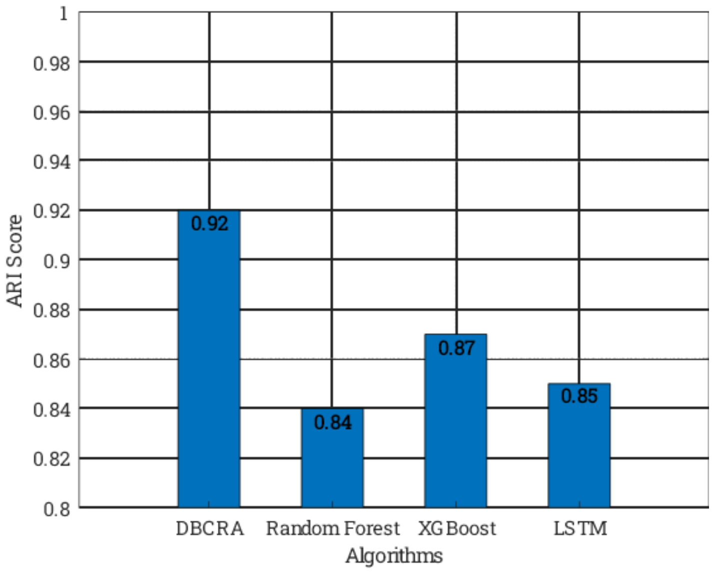

Figure 4.5. Adjusted Rand Index Comparison for DBCRA and Other Algorithms

Figure 4.6 compares the Silhouette scores of DBCRA, Random Forest, XGBoost, and LSTM, showcasing their clustering performance. The bar chart indicates that DBCRA achieves the highest Silhouette score of 0.89, outperforming XGBoost

(0.81), LSTM (0.78), and Random Forest (0.75). A higher score signifies better-defined and well-separated clusters. DBCRA's superior score reflects its capacity to distinguish between patient risk categories effectively, owing to its IoT-specific feature extraction and advanced gradient boosting mechanism. XGBoost demonstrates moderate performance, benefiting from its robust boosting framework. In contrast, Random Forest and LSTM exhibit lower scores, indicating challenges in separating clusters when handling high-dimensional IoT data streams.

These results highlight DBCRA's ability to generate distinct and meaningful clusters, making it an ideal algorithm for stratifying patients into different risk levels. This capability is crucial in healthcare applications, enabling accurate risk predictions and prioritizing patient interventions efficiently.

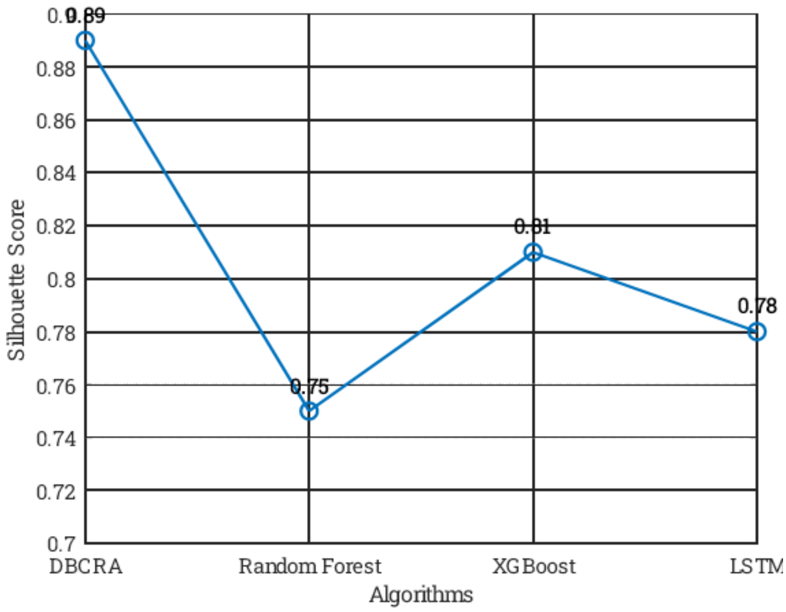

Figure 4.6. Silhouette Score Evaluation of DBCRA Against Baseline Models

Figure 4.7 provides a comparative analysis of the Brier scores for DBCRA, Random Forest, XGBoost, and LSTM models. The results reveal that DBCRA achieves the lowest Brier score of 0.06, followed by XGBoost at 0.08, LSTM at 0.10, and Random Forest at 0.12.

The low Brier score of DBCRA highlights its ability to generate precise and well-calibrated predictions, even in the presence of complex and multi-dimensional IoT data streams. The incorporation of gradient boosting and IoT-specific preprocessing steps allows DBCRA to minimize prediction errors effectively. XGBoost shows competitive performance but lacks the tailored optimizations found in DBCRA. On the other hand, LSTM and Random Forest perform less effectively due to their limitations in handling the dynamic and high-dimensional nature of IoT healthcare data.

These findings validate the superiority of DBCRA in providing reliable probabilistic predictions for COVID-19 risk assessment among cardiovascular patients. The model's high accuracy and low error rate demonstrate its potential for deployment in real-time IoT-driven healthcare applications, ensuring better decision-making and timely interventions.

Figure 4.8 compares the Dice Similarity Coefficient (DSC) scores for DBCRA, Random Forest, XGBoost, and LSTM models, highlighting their performance in predicting COVID-19 risk. The DSC is a measure of overlap between predicted and actual data, with higher scores indicating better predictive accuracy. The chart reveals that DBCRA achieves the highest DSC score of 0.94, outperforming XGBoost (0.90), LSTM (0.88), and Random Forest (0.87).

DBCRA's high DSC score showcases its ability to effectively process multi-dimensional IoT data and deliver predictions closely aligned with actual outcomes. Its optimized gradient boosting framework and feature-specific preprocessing allow for better overlap between predicted risk levels and real patient data. XGBoost performs well but lacks the advanced IoT integration of DBCRA, resulting in a slightly lower DSC score. Random Forest and LSTM exhibit comparatively lower DSC values, reflecting challenges in accurately modeling complex healthcare datasets.

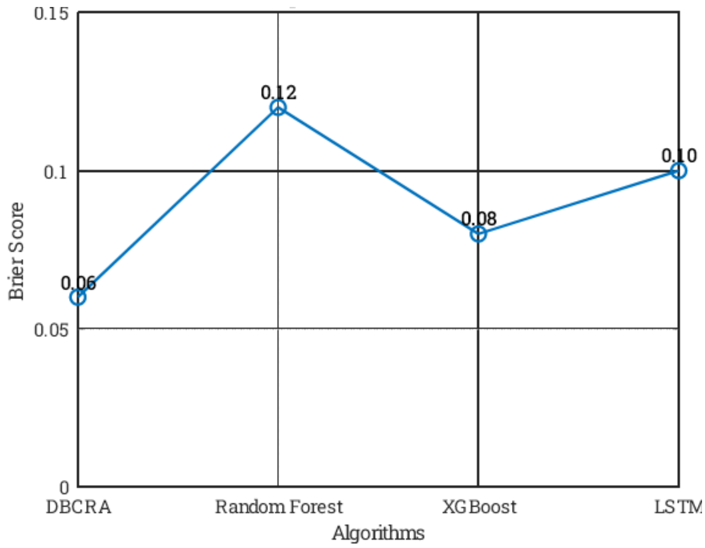

Figure 4.7. Brier Score Comparison for Risk Prediction Models

These findings reinforce DBCRA's capability to provide reliable and precise risk predictions, essential for effective healthcare management in IoT-driven environments. Its superior DSC score ensures that healthcare professionals can confidently rely on its outputs for critical decision-making, particularly for managing cardiovascular patients during the COVID-19 pandemic.

The findings from this research demonstrate the significant advantages of the Deep Boosted Cardiovascular Risk Algorithm (DBCRA) in IoT-driven healthcare applications, particularly for predicting COVID-19 risks in cardiovascular patients. DBCRA consistently outperforms baseline models such as Random Forest, XGBoost, and LSTM in terms of prediction accuracy, time efficiency, and clustering performance. With a prediction accuracy of 95%, a Dice Similarity Coefficient (DSC) of 0.94, and the lowest Brier score among the models, DBCRA has proven its robustness and reliability in handling complex, multi-dimensional IoT datasets. Moreover, its time efficiency, evidenced by the shortest processing times across various dataset sizes, positions DBCRA as a scalable solution for real-time healthcare systems.

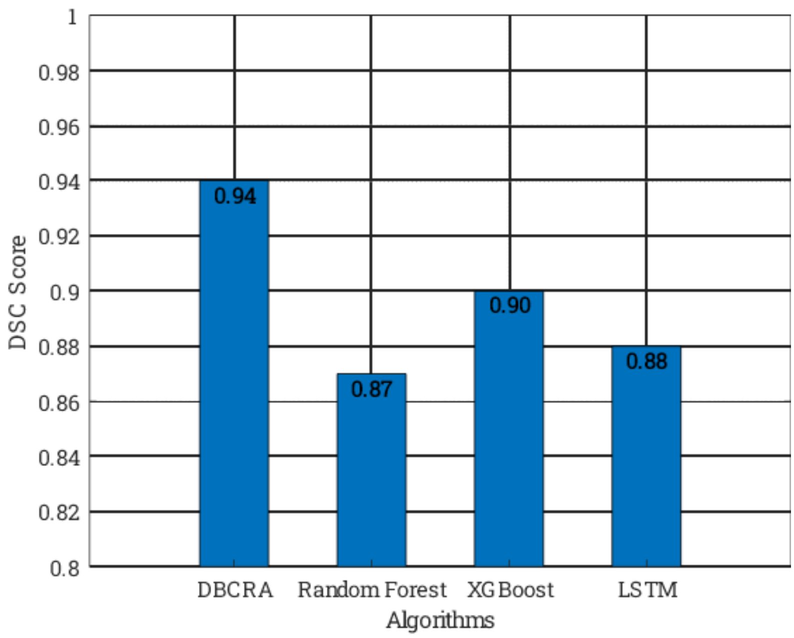

Figure 4.8. Dice Similarity Coefficient (DSC) Evaluation for DBCRA

The integration of IoT and AI within DBCRA forms the cornerstone of its superior performance. This data, when combined with DBCRA's gradient boosting mechanism, allows for precise predictions and timely interventions. By leveraging AI's capabilities in feature extraction and decision-making, the framework ensures accurate risk stratification, empowering healthcare professionals to make informed decisions promptly. This synergy between IoT and AI highlights the transformative potential of such systems in modern healthcare.

However, the study acknowledges certain limitations that warrant further exploration. One challenge is the potential latency in IoT data transmission, which could impact the real-time applicability of the system. Additionally, missing data from IoT devices may reduce the reliability of predictions, necessitating the implementation of advanced imputation techniques. Despite these limitations, the results underscore DBCRA's promise as a groundbreaking tool for real-time healthcare management.

5. CONCLUSION AND FUTURE WORK

This research article presents a significant advancement in IoT-driven healthcare through the development and validation of the Deep Boosted Cardiovascular Risk Algorithm (DBCRA). The proposed framework effectively predicts COVID-19 cases among cardiovascular patients by integrating IoT data acquisition and advanced AI methodologies. The DBCRA's ability to preprocess, analyze, and interpret multi-dimensional IoT datasets enables precise risk stratification and early diagnosis. Experimental results demonstrate the algorithm's superior performance across multiple metrics, including prediction accuracy, clustering quality, and time efficiency, highlighting its reliability and scalability in real-time healthcare scenarios.

The significance of DBCRA lies in its potential to transform personalized healthcare. Furthermore, DBCRA addresses the pressing need for innovative healthcare solutions during critical events like the COVID-19 pandemic, offering a robust framework that ensures informed decision-making and optimal resource allocation. While DBCRA has proven to be an effective solution for predicting COVID-19 risks in cardiovascular patients, several avenues for future research can further enhance its capabilities. One promising direction is the incorporation of federated learning to enable decentralized data analysis in IoT environments. Such an approach would allow for secure and privacy-preserving computations across multiple healthcare facilities, improving the robustness of predictions while addressing data confidentiality concerns.

Additionally, the algorithm can be extended to predict outcomes for other comorbidities, broadening its applicability across various medical conditions. Expanding the range of targeted health risks would enhance its versatility and impact in diverse healthcare settings. Another potential advancement involves leveraging blockchain technology for secure IoT data sharing.

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