Predicting of Heart Disease Using a Hybrid Model in an Internet of Things Environment

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Abstract - The advent of the Internet of Things (IoT) has revolutionized the healthcare landscape by facilitating the comprehensive gathering of patient data. Our research endeavors to anticipate instances of heart disease within an IoT framework, employing a sophisticated hybrid model. In our investigation, we meticulously contrasted this hybrid model with standalone algorithms such as K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), and Logistic Regression. The outcomes of our study unveiled the remarkable synergy embedded within the hybrid model, showcasing its immense potential as evidenced by an outstanding accuracy rate of 94.8%. Particularly noteworthy was the exceptional performance demonstrated by the Artificial Neural Networks (ANN), underscoring the efficacy of deep learning methodologies in discerning intricate patterns within health data generated by IoT devices. Furthermore, our findings shed light on the inherent limitations associated with singular algorithms, emphasizing the paramount importance of embracing interdisciplinary approaches in the realm of healthcare analytics. This research highlights the transformative impact of IoT technology and underscores the necessity of collaborative efforts to optimize healthcare outcomes in an increasingly data-driven era.

Keywords - ANN, heart disease, hybrid model, Internet of Things, KNN, Logistic Regression, prediction.

I. INTRODUCTION

The advent of the Internet of Things (IoT) heralds a transformative era wherein objects are interconnected to the internet through sensors, microcontrollers, and transceivers, facilitating seamless communication among them and with users. This integration has permeated various aspects of modern life, engendering a plethora of IoT applications wherein virtually any physical object can be endowed with internet connectivity via sensor technology. Within the healthcare domain, IoT assumes an increasingly pivotal role in revolutionizing patient care, bolstering accessibility, refining service quality, and curtailing expenditures.

In healthcare, the IoT ecosystem assumes a pivotal role in tailoring medical services through the establishment of digital patient profiles. Conventional healthcare infrastructures often grapple with the challenge of discerning health anomalies owing to restricted access to pertinent medical data. Conversely, IoT-driven systems offer a dynamic solution by perpetually monitoring and scrutinizing patient metrics, enabling real-time data transmission to cloud-based servers. This seamless data flow streamlines the processes of data collection, storage, and analysis, engendering contextually-aware notifications and facilitating ubiquitous access to medical device data via the internet [1].

The early detection and diagnosis of heart disease stand as pivotal imperatives in healthcare. Timely identification affords opportunities for intervention, stymying the progression of the ailment and mitigating associated complications, such as heart failure. Furthermore, early diagnosis facilitates the adoption of personalized treatment modalities, thereby cost-effectively augmenting patient outcomes. Additionally, such diagnostic prowess furnishes invaluable insights for ongoing cardiovascular research, enriching our understanding of disease etiology and catalyzing the development of more efficacious therapeutic interventions. These endeavors collectively redound to the benefit of public health by identifying susceptible individuals, thereby alleviating the societal burden imposed by heart disease.

The motivation for employing hybrid machine learning algorithms in the context of heart disease diagnosis emanates from their capacity to amalgamate disparate data streams and diverse machine learning methodologies, thereby augmenting diagnostic precision and risk prognostication, and ultimately refining patient outcomes and clinical decision-making processes. These hybrid models harness a myriad of data sources including clinical records, medical imaging, genetic profiles, and other pertinent metrics to furnish a more holistic evaluation of cardiovascular health [2].

This article endeavors to explore the overarching research question: "How can hybrid machine learning algorithms, specifically K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), and Logistic Regression, be harnessed for heart disease classification within an IoT milieu, and what level of diagnostic accuracy can be attained vis-à-vis conventional methodologies?" This inquiry underscores the study's objective of scrutinizing the viability and efficacy of employing a hybrid approach leveraging KNN, ANN, and Logistic Regression for heart disease classification in an IoT context, while juxtaposing the outcomes against established benchmarks. By doing so, this research aims to furnish insights that stand to enrich the diagnostic landscape of heart disease within IoT applications, thus contributing to the advancement of healthcare practices in this burgeoning domain.

II. RELATED WORK

Hybrid algorithms play an indispensable role in the prediction of heart diseases owing to their adeptness in harnessing the collective strengths of diverse algorithms while mitigating their individual limitations. By amalgamating disparate techniques, hybrid algorithms serve to bolster the accuracy, resilience, and generalization capabilities of predictive models in the realm of heart disease diagnosis and prognosis. The pivotal significance of hybrid algorithms in the domain of heart disease prediction resides in their innate ability to amalgamate a plethora of data sources and attributes, encompassing medical imaging, patient demographics, genetic profiles, and clinical history. Through this integrative approach, they adeptly discern intricate relationships and patterns within these multifaceted datasets, thereby facilitating more precise risk assessments and early identification of heart-related conditions.

Moreover, hybrid algorithms make significant strides in curbing false positives and false negatives, pivotal considerations in clinical environments where precise diagnosis and timely intervention are paramount. By amalgamating the robust facets of distinct algorithms, they furnish healthcare practitioners with more dependable and interpretable predictive models, ultimately enhancing patient care and outcomes.

In this context, we elucidate a summary of notable research endeavors that have leveraged hybrid algorithms:

Desai et al. (2022) conducted a study focusing on cardiovascular disease prediction, wherein they employed an array of machine learning techniques. The investigation scrutinized traditional algorithms alongside a hybrid model, culminating in a commendable accuracy rate of 93.4%. This scholarly endeavor significantly contributes to the advancement of accurate heart disease diagnosis [3].

Altae et al. (2023) embarked on a study probing multiple classifiers for early heart disease diagnosis, yielding noteworthy accuracies: 93% (PSO-ELM), 96% (PSO_EFLN), 91% (PSO-SVM), and 93% (PSO-DT). The research also introduced a novel Hybrid Model, augmenting diagnostic accuracy and fostering improved early heart disease diagnostics [4].

Sudha, V. K. (2023) presented innovative research featuring a hybrid CNN-LSTM approach tailored for classifying heart diseases, achieving an accuracy of 89%. The methodology underwent validation via k-fold cross-validation technique and surpassed traditional machine learning algorithms like SVM, Naïve Bayes, and Decision Tree, thereby contributing to advancements in heart disease diagnosis [5].

The study by Shrivastava, P.K., et al. (2023) showcased a remarkable achievement with a

96.66% accuracy rate in the hybrid CNN-BiLSTM model. This exceptional performance underscores the promising potential of deep learning techniques in revolutionizing the early diagnosis of heart disease. These results underscore significant progress facilitated through the utilization of advanced data processing methods and feature selection, thereby showcasing the model's efficacy in addressing issues related to missing data and data imbalance. Consequently, this paves the way for the development of more accurate and reliable methods for predicting heart disease [6].

This table highlights the different studies, methods employed, achieved accuracy levels, and specific contributions of each study toward advancing heart disease diagnosis.

TABLE 1. COMPARATIVE ANALYSIS OF HEART DISEASE PREDICTION STUDIES USING HYBRID ALGORITHMS

Study	***Method***	***Accuracy***	***Contribution***
Desai et al. (2022)	*Hybrid*	*93.4%*	*Significantly advances precise heart disease diagnosis.*
Altae et al. (2023)	*Hybrid PSO-ELM, PSO_EFLN, PSO-SVM, PSO-DT*	*93% - 96%*	*Introduces a hybrid model enhancing early heart disease diagnosis precision.*
Sudha, V. K. (2023)	*Hybrid CNN-LSTM*	*89%*	*Improves heart disease diagnosis, surpassing traditional algorithms like SVM, Naïve Bayes, and Decision Tree.*
Shrivastava, P.K., et al. (2023)	*Hybrid CNN-BiLSTM*	*96.66%*	*Revolutionizes early heart disease diagnosis through deep learning techniques. Significantly progresses data processing and feature selection methods.*

III. VISION OF THE APPROACHES USED IN HYBRIDIZATION

K-Nearest Neighbors (KNN) is a pivotal machine learning algorithm that predicts outcomes by analyzing the majority class of its k-nearest neighbors within a dataset [7]. In simpler terms, it assigns an unknown data point to a category based on the classes of its closest neighbors from the known data points. KNN is valued for its simplicity and ease of implementation, functioning as an instance-based learning method that doesn't require a separate training phase. It also performs well in multi-class classification tasks and is non-parametric, making it adaptable to various data distributions. However, KNN faces challenges with large datasets, as computing distances for each prediction becomes computationally demanding. Additionally, the choice of the number of neighbors (K) significantly affects its performance, reducing its effectiveness.

Artificial Neural Networks (ANNs) emulate biological nervous systems, like the brain, and possess a unique structure that enables them to extract meaning from complex or imprecise data, discern patterns, and identify intricate trends [8]. Unlike KNN, ANNs have a wide range of strengths and weaknesses. It can capture complex relationships and learn from extensive datasets, proving versatile in domains like image and text analysis. ANNs automatically extract relevant features from raw data and handle noisy or missing data effectively. However, ANNs require significant amounts of training data to avoid overfitting, leading to challenges in certain contexts. They are computationally intensive and may require lengthy training periods, especially for deep networks. Additionally, tuning hyperparameters such as layer numbers and neuron counts can be complex. Furthermore, ANNs may lack interpretability, making it difficult to understand their decision-making processes.

In contrast to KNN and ANNs, Logistic Regression is a simpler and more interpretable algorithm that offers efficiency and simplicity [9]. It quickly computes probabilities, aiding in prediction ranking. Moreover, Logistic Regression is less prone to overfitting compared to more complex models, enhancing its robustness across various scenarios. However, Logistic Regression assumes a linear relationship between features and the log-odds of the target variable, which may not always hold true. Consequently, it may struggle to capture complex patterns and interactions within the data, limiting its utility in certain contexts, especially those with high-dimensional feature spaces, unless accompanied by careful feature engineering.

IV. INTERNET OF MEDICAL THINGS

The Internet of Medical Things (IoMT) is a combination of applications and medical devices that are intended to use networking technologies to communicate with healthcare IT systems. By creating safe connections between patients and healthcare professionals and enabling the smooth transfer of medical data, its primary goal is to lessen the burden on healthcare systems and cut down on needless hospital stays. Interestingly, a Frost & Sullivan report shows that the global IoMT market grew at an impressive compound annual growth rate of 26.2% in 2016, reaching a significant worth of $22.5 billion [10]. One of the main segments of the IoMT market consists of smart devices specifically designed for the healthcare industry, such as wearables and medical/vital monitors “Fig. 1”.

These devices are useful in a variety of healthcare environments, including individual use at home and community, clinic, and hospital settings. Moreover, telemedicine and real-time location tracking are examples of complimentary services that are included in the IoMT ecosystem [11].

The term "Internet of Medical Things," or "IoMT," refers to the use of internet-connected medical equipment to collect health-related data and offer insightful information on people's health conditions [13].

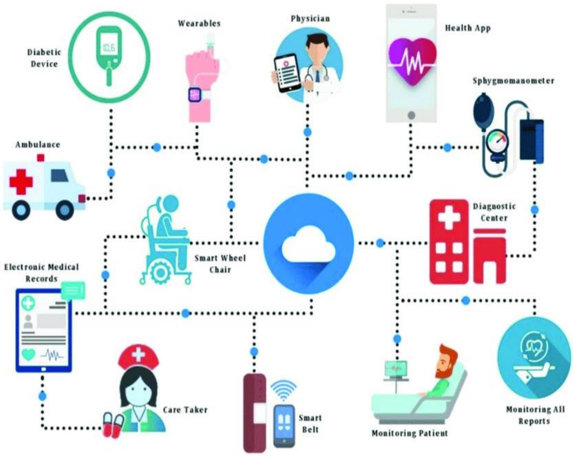

Fig. 1. Examples of IoMT devices and applications [12].

In the context of monitoring heart disease, several illustrative examples of commonly employed connected devices within the IoMT domain include:

A) *Heart Rate Monitors*

These wearable contrivances, typified by smartwatches or wristbands, perpetually gauge an individual's heart rate. Their utility extends to the identification of irregular heart rhythms, surveillance of physical exertion, and tracking overall heart rate trends.

Fig. 2. Example of heart rate monitors [10].

B) *Electrocardiographes (ECG)*

These instruments capture the electrical behavior of the heart. They possess the capability to identify irregular heart rhythms, evaluate cardiac well-being, and track indications of cardiac issues [10].

Fig. 3. Electrocardiogram.

C) *Wearable Health Monitors*

Smart wearable medical monitoring devices, capable of tracking vital signs, medication adherence, and post-surgical patient follow-ups, are now widely prevalent. These devices, available in various forms like rings, watches, glasses, and sensor-embedded clothing, have introduced innovative approaches to the management of conditions such as diabetes, hypertension, heart disease, and more [14].

In the field of IoMT (Internet of Medical Things), a wide variety of connected devices are employed to enhance healthcare delivery and patient outcomes. These devices, ranging from wearable sensors to medical imaging equipment, facilitate data collection, real-time monitoring, and secure communication within healthcare ecosystems. The utilization of such connected devices signifies a promising paradigm shift in healthcare, fostering improved patient care, more efficient diagnostics, and proactive health management.

Fig. 4. Example of wearable medical monitoring devices [14].

V. OMT ARCHITECTURE

In order to monitor heart disease patients remotely and in real-time, it is necessary to use a system which is based on the IOMT architecture, it is necessary to associate each patient with connected intelligent devices that measure data about their health, then send this data via the internet network in secure lines to servers (cloud computing). In the case where the medical service wants to monitor this data momentarily (the case of heart disease data), this data must be saved in servers (edge computing) to ensure the speed of retrieving this data. the two major problems that may exist in this proposal: the first problem is to ensure data security in the network and the other is to ensure connectivity at all times.

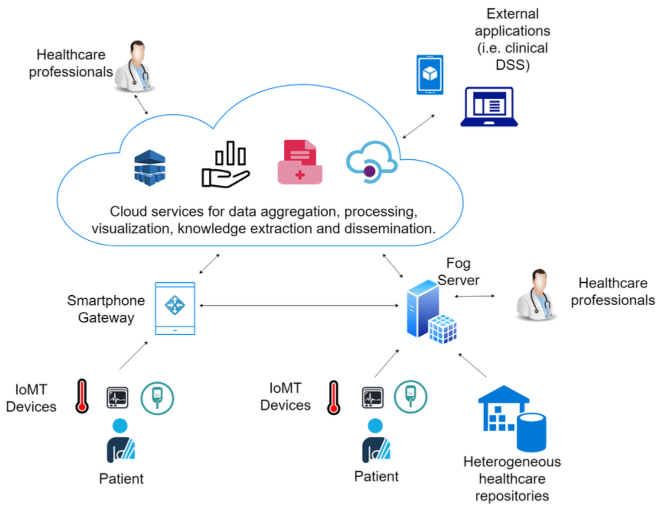

Fig. 5. IOMT Healthcare system architecture [15].

VI. EXPERIENCE AND IMPLEMENTATION

A) *Data Collection*

In order to conduct our experiment, we selected the heart illness dataset from Kaggle, which was collected in 1988. This dataset consists of four separate databases: Cleveland, Hungary, Switzerland, and Long Beach V. There are a total of 76 qualities, one of which is the anticipated attribute. Nevertheless, all recorded tests just employ a limited selection of 14 qualities as indicated in Table 2. The term "target" refers to the binary classification of heart disease in a patient. A value of 0 indicates the absence of disease, while a value of 1 shows the existence of disease.

The limited accessibility of modern medical gadgets and sensors capable of reliably monitoring patients' physiological data poses a substantial obstacle in conducting IOMT (Internet of Medical Things) investigations. These gadgets are essential for acquiring up-to-the-minute and thorough data for in-depth examination of the correlation between heart health and numerous influential elements. Due of the nascent state of medical IoT technologies and their restricted availability to researchers, conducting studies based on IOMT can be arduous. In order to overcome these challenges, we have decided to employ a reputable reference database, such as the UCI Machine Learning directory, which has been subjected to rigorous expert validation to guarantee the dependability and excellence of the data utilised in our research. This technique aids in surmounting the constraints imposed by the scarcity of sophisticated medical Internet of Things (IoT) devices.

TABLE 2. DETAILS OF FEATURES IN DATASET

No	Features	Description	Scale
1	Age	Age in years	29 - 77
2	GD	Gender	Female (0), Male (1)
3	CP	Chest pain type	Typical angina (1), Atypical angina (2), Non-angina pain (3), Asymptomatic (4)
4	trestbps	Resting blood pressure on admission to the hospital (mm/Hg)	94 - 200
5	chol	Serum cholesterol (mg/dl)	126 - 564
6	Fbs	Fasting blood sugar is greater than 120 mg/dl	No (0), Yes (1)
7	Restecg	Resting electrocardiographic results	Normal (0), Having ST-T wave abnormality (1), Showing probable or definite left ventricular hypertrophy by Estes' criteria (2)
8	Thalach	Maximum heart rate achieved (ppm)	71 - 202
9	Exang	Exercise induced angina	No (0), Yes (1)
10	Oldpeak	ST depression induced by exercise relative to rest	0 - 6,2
11	slope	The slope of the peak exercise ST segment	Up sloping (0), Flat (1), Down sloping (2)
12	ca	Number of major vessels colored by fluoroscopy	0-3
13	Thal	The heart status	Normal (3), Fixed defect (6), Reversible defect (7)
14	num	Diagnosis of heart disease	Healthy (0), Patient has heart disease (1)

B) Data cleaning and feature selection

The dataset utilised in this experience, named "heart_disease.csv," is an extensive compilation of medical information containing a diverse range of characteristics. The dataset contains essential data such as patients' age, gender, cholesterol levels, resting heart rate, and other significant characteristics.

The target attribute indicates whether or not the patient has heart disease. Various preprocessing techniques were utilised to prepare the dataset for classification tasks. Initially, any absent values within the dataset were resolved using suitable methods, guaranteeing that the dataset was comprehensive and prepared for analysis. Additionally, feature scaling and normalisation were implemented to standardise the attribute values. This is a widely used technique in machine learning to bring features to a uniform scale, hence avoiding any particular characteristic from overpowering the model. Finally, the dataset was partitioned into separate training and testing sets to simplify the evaluation and validation of the model. During the training phase, 80% of the data is used, whereas during the testing phase, 20% of the data is used. This is seen in “Fig. 6”.

Choosing the optimal attributes for categorising patients with heart disease using hybrid algorithms such as K-Nearest Neighbours (KNN), Artificial Neural Networks (ANN), and Logistic Regression is a crucial process for enhancing the model's effectiveness. Feature selection aids in lowering the number of dimensions, improve the interpretability of the model, and potentially improving the accuracy of the model.

That's which we chose some columns from datasets related to heart diseases that can be considered as candidates for feature selection:

- Age: Age is a major risk factor for heart diseases.
- Sex: Gender can also play a significant role in the prevalence of heart diseases.
- Chest Pain Type: The nature of chest pain can provide crucial information about the type of heart disease.
- Resting Blood Pressure: Is an important indicator of heart health.

- Serum Cholesterol: Elevated blood cholesterol levels are a widely recognised risk factor for cardiovascular illnesses.
- Max Heart Rate: The maximum heart rate achieved during exercise is an indicator of cardiovascular fitness.
- Number of Major Vessels: The number of major blood vessels colored by fluoroscopy can be a critical indicator of the severity of heart diseases.
- Exercise-Induced Angina: The presence of exercise-induced angina can be a significant sign of heart disease.

C) Data Preprocessing

Data preparation plays a vital role in achieving accurate predictions for cardiac disorders, especially when employing a hybrid model that combines KNN, ANN, and Logistic Regression.

Following the process of data cleaning and feature selection, it became imperative to encode categorical variables and normalise the data in order to generate the final dataset.

- Encoding Categorical Variables, such as 'chest pain type', must be transformed into numerical representations to ensure consistency with the model. Methods like one-hot encoding or label encoding facilitate the incorporation of categorical data into the hybrid model.
- Normalisation: Often accomplished using Z-score normalisation, standardises the dataset to conform to a Gaussian distribution. The performance of the hybrid model, especially for KNN, is improved by achieving a uniform data distribution, as shown in “Fig. 6”.

Efficient data preprocessing is a crucial initial stage in utilising a hybrid model consisting of KNN, ANN, and Logistic Regression for the purpose of predicting heart disease. The preprocessing procedures enhance the quality and alignment of the dataset with the hybrid model. The outcome is enhanced prediction precision and dependability, granting doctors and researchers with practical discernments into cardiac well-being.

```
# Diviser les données en ensembles d'entraînement et de test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando

# Normaliser les données
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

Fig. 6. Division and normalisation of data by scikit-learn in python.

D) Experimental Result Analysis

Our study in the field of experimental result analysis relies on heart illness datasets obtained from the prestigious UCI Machine Learning Repository. These datasets contain a vast amount of information about different attributes linked to heart health. To evaluate the prediction capability and effectiveness of our hybrid method, which combines the K-Nearest Neighbours (KNN), Artificial Neural Networks (ANN), and Logistic Regression algorithms: The dataset was partitioned into two separate subsets: a training set comprising 80% of the data and a testing set consisting of the remaining 20%.

This partition enables us to train our model using a significant chunk of the data, while also keeping a separate set for assessment and validation purposes.

D.1. Confusion Matrix

The Confusion Matrix is a vital tool used to assess the effectiveness of our categorization strategy. This matrix offers a thorough analysis of the predictions made by our model. By conducting this thorough evaluation procedure, we enhance our comprehension of the efficiency with which our hybrid algorithm differentiates between cases of heart disease presence and absence. This allows us to derive significant insights on its practical applicability and performance.

The Confusion Matrix, a pivotal instrument in the assessment of categorization, comprises four fundamental elements: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). TP denotes instances where the model accurately forecasts the positive category, whereas TN indicates accurate forecasts of the negative category. FP refers to cases where the model makes wrong predictions of the positive class, while FN refers to faulty predictions of the negative class. The Confusion Matrix is a crucial tool used to assess the effectiveness of our classification model. This matrix offers a thorough analysis of the predictions made by our model. By conducting this thorough evaluation process, we enhance our comprehension of the efficacy of our hybrid algorithm in accurately differentiating between cases of heart disease presence and absence. This enables us to derive significant insights on its practical applicability and performance.

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TABLE 3. CONFUSION MATRIX OF THE HYBRID MODEL.

		Class predicted by the model	
		Class 0	*Class1*
Real class	*Class 0*	*464*	*28*
	Class 1	*25*	*508*

D.2. Performance Assessment Metrics

To evaluate the effectiveness of our hybrid model with the classic models, we employ a range of performance assessment metrics. These metrics encompass accuracy, precision, recall, F1-score, and overall accuracy. Additionally, a confusion matrix is generated to dissect true positive, true negative, false positive, and false negative predictions for each algorithm, providing a comprehensive insight into their predictive capabilities.

Accuracy = (TP + TN) / (TP + TN + FP + FN) = 972 / 1025 = 0,948

Precision = TP / (TP + FP)= 508 / 536 = 0,948

Recall = TP / (TP + FN) = 508 / 533 = 0,953
= 508 / 533 = 0,953

F1 Score = 2 * (Precision * Recall) / (Precision + Recall)= 2*(0,948 *0,953) / (0,948+,953) = 0,95

D.3. Discussion and Analysis of Results

Our work focused on predicting heart disease in an Internet of Things (IoT) setting. By utilizing a hybrid model that combines the advantages of numerous techniques, our research achieved an impressive accuracy rate of 94.8%. This significant outcome represents a significant progress in the domain of healthcare analytics and highlights the potential of predictive models driven by the Internet of Things (IoT).

An essential aspect of our inquiry involved doing a comparison analysis of our hybrid model about the individual algorithms: K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), and Logistic Regression. These algorithms, known for their effectiveness in classification tasks, achieved accuracy rates of 92.5%, 94.02%, and 84.51%, respectively, see “Fig. 7”. The disparity in performance between existing algorithms and our hybrid model warrants thorough examination. The strong performance of our hybrid model, which exceeds that of the solo methods, highlights the synergistic effects achieved by the combination of multiple machine learning approaches. The model's accuracy rate of 94.8% indicates its enhanced ability to accurately categorize occurrences, resulting in a decrease in both false positives and false negatives.

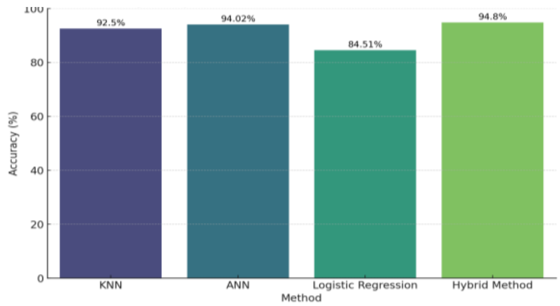

Fig. 7. Accuracy Comparison of prediction methods with Seaborn.

Moreover, the remarkable performance of the artificial neural network (ANN) component in our hybrid model demonstrates the effectiveness of neural networks in extracting complex patterns and representations from health data supplied by the Internet of Things (IoT). This emphasizes the significance of utilizing sophisticated deep learning methods in healthcare applications driven by the Internet of Things (IoT).Although KNN showed decent accuracy, it is not as effective as our hybrid model, indicating that combining different algorithms improves the model's predictive ability. Furthermore, Logistic Regression, renowned for its straightforwardness, demonstrated reduced accuracy, highlighting the constraints of linear models in comprehending the intricacies involved in the prediction of heart disease.

VII. CONCLUSION

This study aimed to predict cardiac disease using the Internet of Medical Things (IoMT) and combining cloud and edge computing approaches. The culmination of our study has yielded noteworthy discoveries that emphasize the importance of hybrid models, which encompass a multifaceted approach that surpasses the performance of individual algorithms.

The main accomplishment of our work is the creation of a hybrid model that effectively combines K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), and Logistic Regression. The combination of various machine learning approaches has resulted in an impressive accuracy rate of 94.8%. The achieved accuracy of this result exceeds that of individual algorithms, demonstrating the inherent effectiveness of merging many models to improve predictive skills.

Moreover, the exceptional performance of Artificial Neural Network (ANN) in our hybrid model highlights the efficacy of deep learning methods in extracting intricate patterns from intricate health data streams. This statement confirms the crucial importance of advanced neural networks in healthcare applications, specifically in the context of the Internet of Medical Things (IoMT).

Our work highlights the constraints of individual algorithms, such as Logistic Regression, in effectively dealing with the complexities of predicting cardiac disease. The differences in accuracy between existing algorithms and our hybrid model emphasize the effectiveness of collaborative and interdisciplinary approaches in healthcare analytics.

VIII. REFERENCES

[1] R.K. Kodali, G. Swamy, B. Lakshmi, "An implementation of IoT for healthcare," *IEEE Recent Advances in Intelligent Computational Systems (RAICS)*, Trivandrum, 2015.

[2] P. Ramesh, G. Manisha, G. Anupama, "Heart disease prediction through the application of hybrid machine learning methods," *Journal of Algebraic Statistics*, 13(2), 3669-3679, 2022.

[3] P.K. Shrivastava, "HCBiLSTM: A hybrid model for predicting heart disease using CNN and BiLSTM algorithms," *Measurement: Sensors*, 25, 100657. Elsevier, 2023.

[4] U. Desai, "Hybrid model of machine learning algorithms for prediction of cardiovascular disease," *Journal of Positive School Psychology*, 6(6), 10551-10560, 2022.

[5] V.K. Sudha, "Hybrid CNN and LSTM network for heart disease prediction," *SN Computer Science*, 4(2), DOI: 10.1007/s42979-022-01598-9, 2023.

[6] A. Altae, "Diagnosing heart disease by a novel hybrid method: Effective learning approach," *Informatics in Medicine Unlocked*, 40, 101275, 2023.

[7] M.J. Islam, "Investigating the Performance of Naive-Bayes Classifiers and K-Nearest Neighbor Classifiers," *In 2007 International Conference on Convergence Information Technology*, pp. 954-961, 2007. IEEE. DOI: 10.1109/ICCIT.2007.148.

[8] M. Al-Shebany, "Artificial Neural Network: A Brief Overview. *International Journal of Engineering Research and Applications*, 4(2), 07-12, 2014.

[9] C.J. Paciorek, "Computational techniques for spatial logistic regression with large data sets," *Computational Statistics & Data Analysis*, 51, 3631–3653, 2007.

[10] O. Larbi, A. Bassou, "Classification of heart disease using fuzzy c-means algorithm (FCM) in an internet of things environment," *International Journal of Applied Engineering and Technology*, 5(3), 69-76. ISSN: 2633-4828, 2023.

[11] AABME, "Internet of medical things revolutionizing healthcare," *AABME ASME*, 2017. https://aabme.asme.org/posts/internet-of-medical-things-revolutionizing-healthcare

[12] A.A. Toor, "Mining Massive E-Health Data Streams for IoMT Enabled Healthcare Systems," *Healthcare*, 8(2), 109, 2020. https://doi.org/10.3390/healthcare8020109

[13] F. Kamalov, "Internet of medical things privacy and security: challenges, solutions, and future trends from a new perspective," *Sustainability*, 15(4), 3317, 2023.

[14] J. Schieszer, "Wearable Medical Monitoring Devices: The Innovation Continues," *Renal & Urology News*, 2022. https://www.renalandurologynews.com/

[15] J.N.S. Rubí, P.R.L. Gondim, "IoMT Platform for Pervasive Healthcare Data Aggregation, Processing, and Sharing Based on OneM2M and OpenEHR," *Sensors*, 19(19), 4283, 2019. https://doi.org/10.3390/s19194283.