

Framework for Cloud-Centric Internet of Medical Things for Real-time Disease Diagnosis

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ABSTRACT: The rapid development in the Internet of Medical Things (IoMT) offers new opportunities for real-time health monitoring; however, several key challenges related to IoMT, such as concept drift, latency, and data privacy issues, hinder their optimal effectiveness. Thus, this paper proposed a cloud-centric IoMT framework, incorporating wearable devices, edge computing, and scalable cloud infrastructure for efficient real-time health monitoring and predictive analytics. The framework employed dynamic data streaming, together with incremental machine learning models such as Modified Gaussian Naive Bayes (MGNB) that are capable of adjusting to evolving data distributions and delivers reliable predictions. GNB showed an accuracy of 100% in a static dataset environment, while the MGNB achieved 90.3% accuracy in dynamic environments, with an area under curve of 0.83. These findings demonstrated the potential of the framework to improve patient-centric healthcare through adaptive, scalable, and low-latency systems by addressing critical limitations in existing IoMT solutions. These findings, also underscored the framework's potential to support adaptive, scalable, and low-latency healthcare systems, thereby advancing patient-centric care.

KEYWORDS: Automated Medicine, Cloud computing, Dynamic data streaming, Incremental machine learning, Internet of medical things, Patient-centric healthcare, Real – time data analytics.

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I. INTRODUCTION

The general well-being of persons depends on how well they understand their health status. The traditional method of studying human health status is to undergo a clinical examination, which requires a person to report physically to the clinic or hospital (Pawar et al., 2024). The process may take useful time, enough to save a life for a condition that may be time critical. One of the solutions towards improving well-being of humans as have been suggested in literature is to monitor the individual using wearable electronic devices, resulting in a new paradigm known as automated medicine (Obasi et al., 2020).

The evolution of automated medicine led to an era of Healthcare 4.0 terms from the Internet of Medical Things (IoMT), which is built on the Internet of Things (IoT) (Sree et al., 2025). The quest to develop this technology has occupied researchers in the last decade. IoMT is a direct product of the fusion of internet services, mobile technologies (including wearable devices) for both remote and local surveillance of the progression of users' health status, with the promise of improved patients' outcome (Kumar & Sobin, 2025). The application of IoMT has found usefulness in filling the gap of shortage of qualified medical personnel in underserved locations, and providing continuous and updated reports of patients, lowers cost of medical services, plus providing early warning notifications to personalised doctors and caregivers (Wal et al., 2022).

The operation of IoMT is heavily data depended for which at its core, wearable and mobile devices are key sources,

generating large volume of unstructured data at an alarming rate (Big Data) (Obasi et al., 2020). The management of such volume of data requires a framework to provide guidelines for dealing with intricate issues and provide intelligence that facilitates the delivery of ambient, patient-centric, predictive, preventive, personalized, and precise healthcare services (Prem et al., 2024; Sambare et al., 2024).

Framework provides a structured blueprint or operational design for an IoMT system. It specifies the integration of IoT devices, fog/edge interface, cloud and data analytics components of the system (Holambe et al., 2024), most of which are constrained embedded devices (Thoma & Steindl, 2023). It should provide clear details on the modalities for data transmission (Holambe et al., 2024) and handling critical steps such as noise reduction (Obasi et al., 2020) and low latency. Cloud-Centric Framework is a framework that is cloud computing enabled, providing additional functionality in a remote application of IoMT, including scalability and computational power. Most cloud services also enable functions such as data sharing, and other business logic to enhance patients-doctor engagement (Michelson et al., 2022). The cloud is an excellent platform for dealing with IoMT big data using Artificial intelligent models and algorithms (Machine Learning, Neural Networks and Deep Learning) to perform analytics (Mehta et al., 2023).

The growth of IoMT has evolved from simple non-cloud-based to complex cloud-based architectures. However, these efforts have not sufficiently developed a framework that holistically integrate components that uses nontraditional data

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analytics concept (Sudha & Viveka, 2022). Traditional batch processing is unable to adaptively manage issues with dynamic data stream from source IoT devices. To fully leverage the potential of IoMT in continuous health monitoring in real-time, it is important to develop an all-inclusive framework that ensures real-time data streaming in an adaptive environment, dealing with the issues of concept drift (Maheshwari et al., 2023).

This present research proposes a comprehensive cloud-centric framework that leverages on the cloud scalability for storage, computational analytics, and real-time handling of dynamic data streaming using an incremental machine learning approach. The framework offers an adaptive solution to concept drift, effectively addressing the limitations of batch processing in real-time scenarios. As a result, it enhances remote health monitoring, particularly in time-critical situations.

The rest of this paper is structured into a section for the review of related works, which highlight works that have been done in related topics. The next section is the material and methods section where the materials and methods used to achieve the proposed framework is presented. Next is the results and discussion section, which present the result of the findings plus the discussion of their implications. Lastly is the conclusion and recommendation sections followed.

II. REVIEW OF RELATED WORKS

The Internet of Medical Things (IoMT) presents a paradigm in healthcare wherein smart devices, sensors, and communication technologies combine to offer better service delivery to patients (Kumar & Sobin, 2025). Remote monitoring of patients' health, real-time diagnosis, and the optimisation of hospital workflow are unlocked in IoMT. This section is presented in two major sub-groups, consisting of cloud-based and non-cloud-based IoMT.

A. Cloud-Based IoMT

While recognising that cloud computing technology forms the backbone of IoMT, this technology has the potentials to scale data storage and providing required computational power for analysing and processing medical data (Huang et al., 2023). Agreeing with this position, the work of Dwivedi et al., (2022), affirms that cloud provide application services that favours real-time disease diagnosis, leading to timely interventions to improve patients' outcomes.

Scalable cloud solutions were found in the works of Cao et al. (2024), and Dankan et al. (2024), who used AWS and Microsoft Azure to scale up healthcare solutions with minimal latency. While these works successfully achieved real-time continuous monitoring with feedback functionalities and storage scalability, they however did not address the method used for managing streamed data on the cloud.

In addressing latency issues in real-time health parameter tracking, Alasmay (2024) presented a framework that was targeted at monitoring mobility-challenged individuals among the aged group. The work was hinged on scalable IoT-based architecture with latency-aware auto-scaling, which helped to adjust resources based on demand on the cloud. This framework however failed to discuss the inclusion of

healthcare data analytics and therefore lacks the ability to deliver useful feedback and predictive health information. This gap was seen to be addressed in the work of Venkateswarulu et al. (2023), who successfully integrated a layer for predictive analytics and early warning was presented. The study proposed a three-tier architecture with tier three being the cloud layer. The cloud layer was achieved using GoogleFit, where machine learning algorithm was used for the data analysis. The study however, used static data and was unable to discuss dynamic data streaming, hence limiting its functionalities with live IoT data.

Another instance addressing predictive analytics on health data was found in the work of Patel & Kumar Pal (2024). The study demonstrated the integration of IoT and cloud services in healthcare for the enhancement of disease prediction and diagnosis. The framework favoured IoT data collection for continuous monitoring of body parameter, while storing data on the cloud for the purpose of scalability and complex computation of the logic of the Long Short-Term Memory (LSTM). However, the absence of edge/fog layer in the framework would impede the performance of the system due to latency in data delivery, coupled with the constraints imposed by the classifier in time-critical application.

In using edge computing layer to reduce latency, Sharma et al. (2021) proposed a smart ontology-based IoT framework that aimed to solve interoperability and data management challenges in remote patient monitoring. By employing ontological models, this framework improved data consistency and facilitated seamless communication among stakeholders. This will also allow the IoT with edge computing to perform real-time monitoring of vital parameters such as ECG and body temperature for low-latency responsiveness. The same framework in resource-constrained settings reduces patients' waiting time and aids healthcare decisions. However, dynamic data streaming management was not discussed in the study.

In like manner, the work according to Ko Ko et al. (2023), a framework for detection of non-communicable lifestyle diseases that integrated IoT devices, wireless sensors, and cloud computing for real-time health monitoring was proposed. This was however limited in functionality due to manual data entry, which is prone to human errors, and static datasets that also limited its real-time validation and performances. This underscore the need for a more automated architecture that is devoid of human interferences, and dynamic data integration features.

Furthermore, Alsadoon et al. (2024) introduced a framework that combined vision sensors and accelerometers to enhance fall detection and vital sign monitoring, such as heart rate (hr) and oxygen saturation. This system allowed health metrics recorded by the Internet of Things interface to be sent in real-time to the cloud. Predictive analysis and scalable data storage were achieved by the study. Despite the use of real-time data transfer, the study did not provide techniques for handling dynamic data, hence there is need to improve the framework by describing the data stream.

B. Non-Cloud-Based IoMT

Few of the literature reviewed used IoT in their real-time health parameter monitoring frameworks but failed to include the cloud components. While their contributions were valid, they are mostly not scalable thus limiting their functionalities. In this category, features of most IoMT technologies are wearable and implantable medical chips, often deployed for the purpose of continuous monitoring (CM) of physiological data, of which blood glucose (bg), blood pressure (bp), heart rate, etc. are among the common

ones. The work of Park et al. (2024) as an example, where deep learning was used to detect arrhythmias using parameters from remote wearable ECG sensors. In like vain, the work of Nagesh et al. (2023) explained how smart glucometer was integrated with mobile application for managing diabetes. In both studies however, it was found out that their proposed frameworks were not cloud-based, which leaves a gap in the study. The inclusion of cloud component in this framework will attempt in achieving the views of Huang and Dwivedi et al.

Table 1: Comparison of the reviews

Article	Architecture	Accuracy	Dynamic Data Streaming	Scalability	Latency	Early Warning	Limitations
Park et al. (2024)	Non-Cloud Based	High	No	Limited	Low	No	No cloud integration for scalability.
Nagesh et al. (2023)	Non-Cloud Based	Moderate	No	Limited	Low	No	No real-time processing; lacks cloud-based scalability
Cao et al. (2024)	Cloud-Based	High	Yes	High	Low	No	Did not address methods for managing streamed data.
Venkateswarulu et al. (2023)	Cloud-Based	High	No	High	Moderate	Yes	Relied on static datasets; lacked dynamic data streaming
Ko et al. (2023)	Cloud-Based	High	No	Moderate	Moderate	No	Manual data entry; static datasets limited validation
Alsadoon et al. (2024)	Cloud-Based	High	Yes	High	Low	Yes	Did not describe techniques for handling dynamic data.
Rafly et al. (2024)	Cloud-Based	High	Yes	High	Moderate	Yes	Lacked edge/fog layer, leading to latency issues.
Sharma et al. (2021)	Edge-Based	High	Yes	High	Low	Yes	Did not address dynamic data streaming management.

The reviews highlighted that while cloud-based IoMT frameworks showed strength in terms of scalability real-time data processing, early warning detection in disease diagnosis, non-cloud-based IoMT frameworks on the other hand also performed well in providing monitoring and alerting services in general IoMT functionalities. However, in all, some important gaps identified in IoMT framework development, which underscore the need for improvement is that no particular framework has been able to sufficiently address the successful integration of fog/edge layer to overcome latency problems, dynamic data streaming approach that ensure that machine learning models deployed on the cloud are adaptive and suppresses concept drift. Moreover, extended interest could be given to security and data privacy by leveraging blockchain technology as empahsised in (Ikharo et al., 2021).

III. MATERIALS AND METHODS

The approach is in two major stages, including:

- 1) Framework development, and
- 2) Experimental implementation of the proposed framework.

A. Framework Development

The framework is a conceptual architecture that is based on 4-layers (see Figure 1), providing a development guideline for the implementation stage.

Stage I: During this stage, different studies were conducted identify the component of the first layer, to include all mobile and wearable devices such as off-the

shelve products and custom-made products, consisting of the physical layer.

Stage II: This stage saw the development of the network layer, which involved a study of the various data compression strategies and communication protocols for IoMT applications with the various potentials. The network layer provided the flexibility and the scheme for seamless data transmission, by specifying the communication protocol. Data stream is the core objective of proposed framework (see Figure 1). Only the communication component of this layer was presented. The outcome reveals that Message Queue Telemetry Transport (MQTT) Protocol, was the most suitable for this application due to its lightweight nature.

Stage III: This stage lead through the development of the data analytic layer (cloud layer). Basically, this stage was developed by conducting an approach for data streaming, cleaning and selecting an algorithm for the online incremental analytics.

Stage IV: This stage saw the deployment of a cloud service for the purpose of data sharing among the various stakeholders. It is the application interface that provides the feedback and stakeholders management.

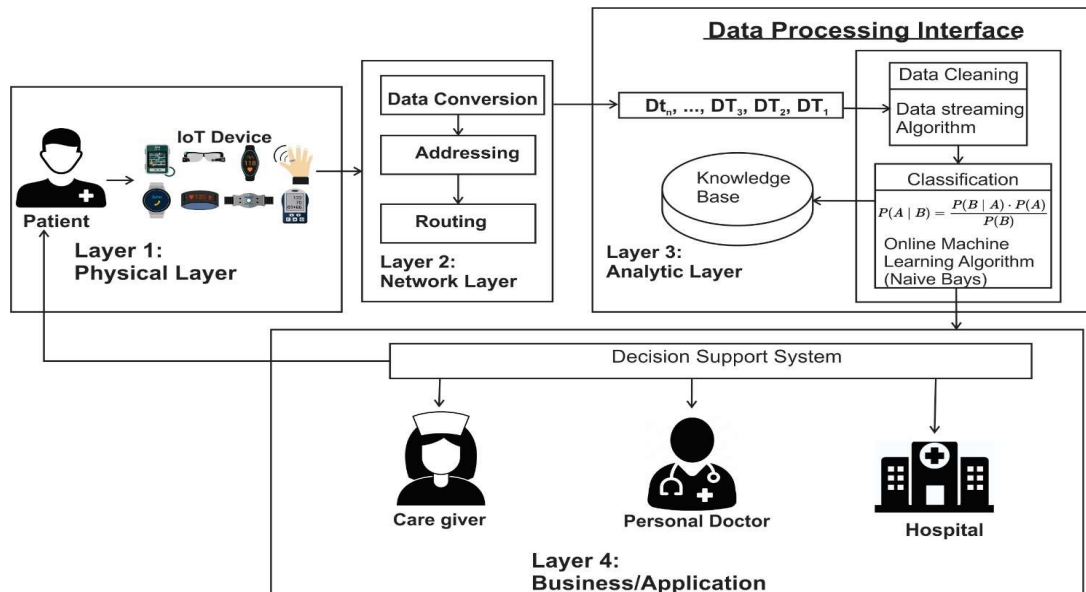


Figure 1 Developed Framework Cloud-Centric Internet of Medical Things for Real-time Disease Diagnosis

B. Experimental Setup

a. Layer 1: Physical Layer

This layer was achieved using simulation in Proteus 8. The compressed circuit in Figure 2 was developed and simulated to generate Body Temperature (BT), Heart Rate (HR), Systolic Blood Pressure (SBP), Diastolic Blood Pressure (DBP), and Blood Glucose (BG) and Body Mass Index (BMI). The materials used to accomplish this are briefly described in Table 2.

Table 2: Materials used for circuit development

SN	Parameters	Device	Features
1	Edge Device	Node MCU (ESP8266)	32 bits RISK CPU, operating at 80 MHz clock speed. Flash memory = 4MB, SRAM = 64KB, Wi-Fi enabled
2	PPG	Custom circuit	Estimates SBP, HR, and DBP
3	Body Temperature	Contactless Infrared Sensor (MLX90615)	Operating range = -20 to 115°, accuracy = 0.2°
4	Body Height	Ultrasonic Sensor (HC-SR04)	Operating range of 0.2m to 4m, at a measuring angle of 15°
5	Body Weight	Load Cell (Custom circuit)	4 single cells x 50kg = total load bearing of 200kg

Figure 2 feature a circuit with four distinct stages, where stage I depicts the perception interface that detects body signals and passes it the next stage using an operational amplifier. In stage II, the signals were digitised using analog-to-digital converter. Stage III represents the Edge component of the physical layer. It is responsible for the pre-processing of the refined signals, including noise reduction,

data compression, re-grouping and encoding. After the encoding, the information was ready for transmission to the next layer.

b. Layer 2: Network Layer

The implementation of the MQTT protocol was achieved using the steps described in figure 3. Arduino JavaScript Object Notation (ArduinoJson) was used for organizing and serializing the data. In this experiment, mosquito broker in Thing Speak was used at <http://mqtt.thingspeak.com>. Five essential steps involved are:

1. The five estimated parameters were converted to json objects and serialised,
2. The wifi network was established,
3. Communication with the broker was established,
4. The instance of the MQTT client was created,
5. Data was published to the health parameter topic on the broker.

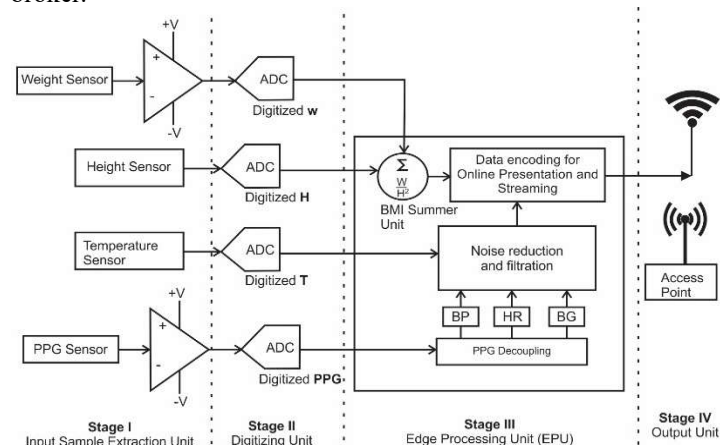


Figure 2 Circuit of the physical layer

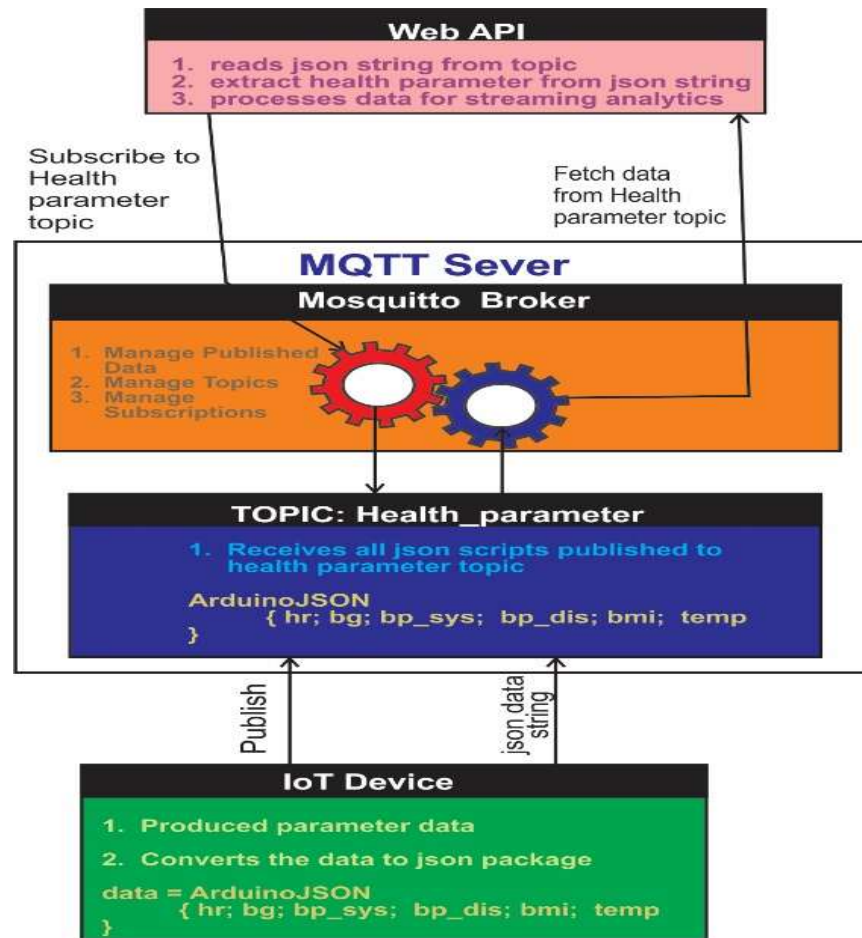


Figure 3 Implementation of the MQTT Protocol

C.

Layer 3: Analytics Layer

Activities in this layer happens on the cloud because of processing power and storage scalability. Figure 4 depicts the transactions of the cloud interface.

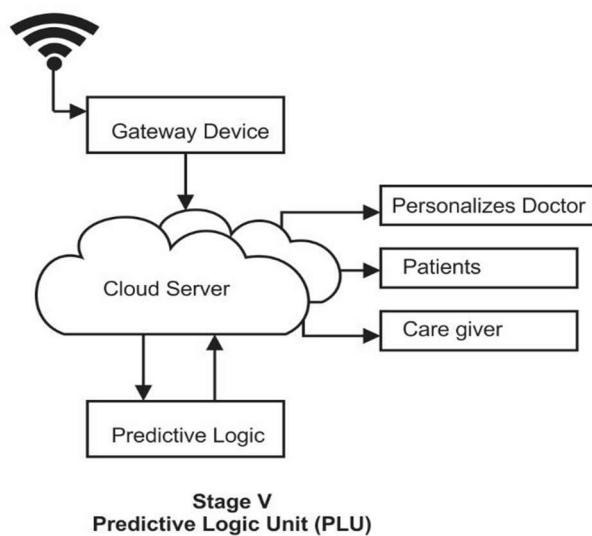


Figure 4 Cloud Layer Interface

The analytics layer is used to analyse the data received from the MQTT topics. An adaptive approach known as Incremental Machine Learning (IML) described in figure 6 was used to implement this layer. The steps involved at this layer is described using Figure 5, which presents five distinct steps.

In step 1, a static model was developed using the traditional Gaussian Naïve Bayes (GNB) given in equation 1.

$$P(B \vee A) = \frac{P(A \vee B) * P(B)}{P(A)} \quad (1)$$

where

$P(A \vee B)$ = Posterior probability (That is the probability of A given the value of B)

$P(B \vee A)$ = Likelihood probability (That is the probability of B given the value of A)

$P(A)$ = Prior probability

$P(B)$ = marginal probability

Let the A = vector of the input features

B = vector of the class label corresponding to each point of the input

The first phase of the data used for the training of the model was obtained from 20 volunteers, who participated in this study under informed consent while ensuring ethical guidelines for data collection protocols, which include:

1. Ethical clearance was obtained from Edo State University Uzairue
2. The consent of all volunteers was sought following the recommendations of the Ethical clearance
3. All personal information were not included in the informed consents obtained

4. Data were collected under strict supervision of health professional

The dataset which is presented in Table 3 was standardised using equation 2 to avoid biases, ensuring that each feature contributed equally to the GNB model.

$$x' = \frac{x_i - \mu}{\delta} \quad (2)$$

Where x' is the scaled sample, x_i is the sample data feature, and δ is the standard deviation.

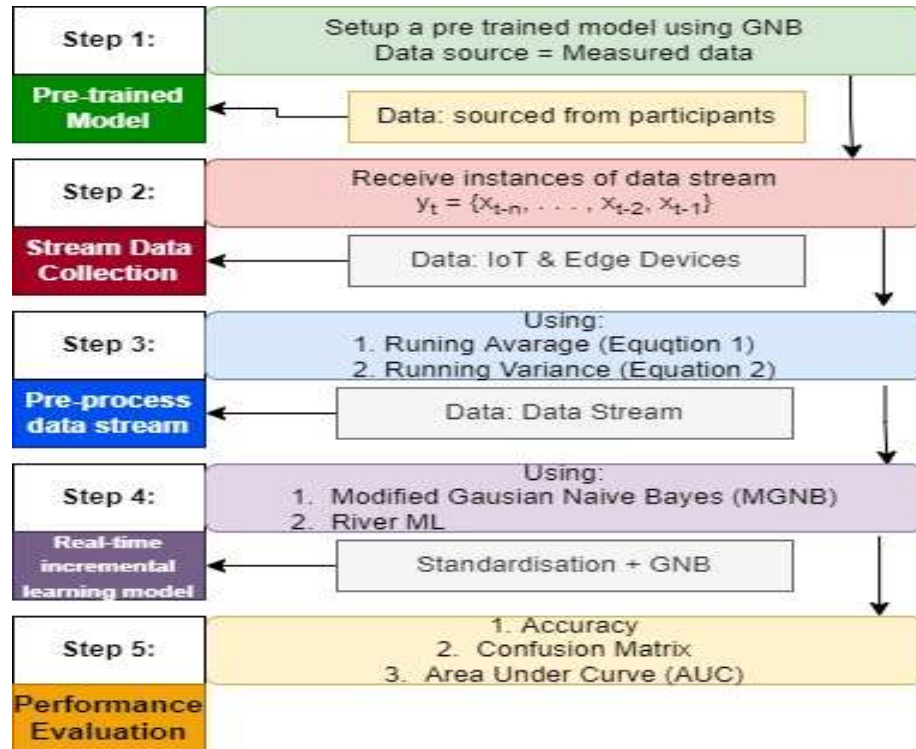


Figure 5. Steps for the implementation of the layer three

Step 2 showed how the data stream was collected in series, where data. In step 3, the data stream was pre-processed using standardization approach. The standardization techniques used were two, involving running average and running variance in Equations 3 and 4, respectively as follows:

$$\mu_{t+1} = \mu_t + \frac{x_t - \mu_t}{n_{t+1}} \quad (3)$$

Where n_{t+1} is the time count of each data sequence, μ_{t+1} is the online average of each data sequence, μ_t is the average at time, t , x_t is the data sample at time, t .

$$\delta^2 = \frac{1}{n_t - 1} \left(\sum_{t=1}^n x_t^2 - \mu_t^2 \right) \quad (4)$$

Where δ^2 is the running variance of data samples, and μ_t is the running average at time, t .

The output of step 4 was used to modify the GNB model by characterising Equation 1 through the infusion of

Equations 2, 3, and 4 into Equation 1, to yield MGNB in Equation 5, which is a maximum likelihood of the expected outcome given the normalized input stream of IoT data given as x in the equation. Simulated data from the circuit in figure 2 were fed into the MGNB and new performance metrics were obtained.

The last step (5) was the evaluation of the overall system performance, which produce the accuracy, confusion matrix, and the AUC of the MGNB.

As demonstrated in Figure 6, an instance of the expected prediction is represented as y_t , IoT data stream enters as a dynamic new data point $\{x_{t-n}, \dots, x_{t-2}, x_{t-1}\}$. Each data point is fed into a model already trained with static data. The system makes a prediction y_t , the cost of the prediction is determined and used to improve the learning parameter, h_t . The model is then re-trained, and a new, y_{t+1} , prediction is made using the next data point in motion. A new cost is determined for re-training the model with a new learning

parameter, h_{t+1} . The process continues for all cases of the data point x_{t-1} to x_{t-n} (as long as the data remain in motion).

$$y = \argMax_y P(y) \prod_{i=1}^6 \left[\frac{1}{\sqrt{2\pi\delta_i^2}} e^{-\frac{(x_i - \mu_i)^2}{2\delta_i^2}} \right] \quad (5)$$

Where $f(x)$ is the distribution function, x is the feature sample, μ is the running mean of each x feature at time t , δ

is the running variance of each x feature, $\argMax_y P(y)$ is the maximum probability of y given x feature.

Layer 4: Business Layer

This layer was achieved by developing a web interface that fetches the outcome of the layer three. Its main responsibility was to direct personalized message of stakeholders concerning the user's health status. The layer consists of the front end developed with the CSS, HTML, and MySQL for the database.

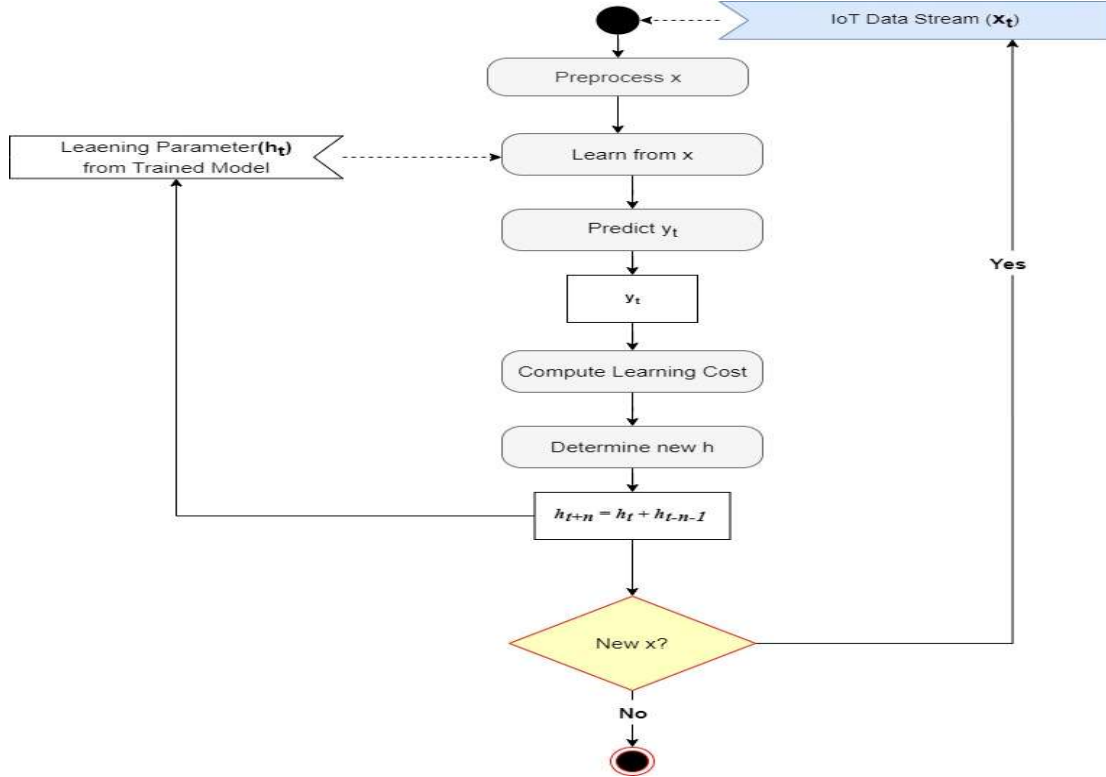


Figure 6 Activity flow for Real-time Analytics in Online Learning

IV. RESULTS AND DISCUSSION

A total of 20 observations were recorded in the dataset. It consists of 6 input feature variables, namely Body Temperature (BT), Heart Rate (HR), Systolic Blood Pressure (SBP), Diastolic Blood Pressure (DBP), and Blood Glucose (BG) and Body Mass Index (BMI), and one target variable, named “heart disease”. The target variable has 2 classes (True and False). It was determined by accessing the volunteers’ health records. The dataset is said to be balanced since it contains equal number of the two classes each. Figure 7 showed the correlation heatmap of the dataset. It showed that last row/column depicts the correlation between each feature and the target variable y . These values range from -1 to +1 and are color-coded according to the colour bar (red = strong positive, blue = strong negative, white = none). The correlation heat map according to Table 4 reveals that input features such as HR, BG, SBP, and DBP have strong positive correlation with the target variable (y), making them good predictors. On the other hand, BMI and BT showed strong negative correlation with y .

Table 3: Training Dataset

BG (mg/dl)	HR (bpm)	BP (mm/Hg)		BMI	BT	y
		SBP	DBP			
72	71	120	80	21.31	35.6	True
76	69	125	80	24.01	35.8	False
73	64	120	80	25.80	36	True
78	62	128	82	15.31	35.9	False
77	63	129	80	24.93	35.7	False
81	77	129	85	18.64	35.6	False
86	84	130	88	25.84	35.4	False
85	73	128	85	19.61	35.7	True
82	65	125	88	16.36	35.4	False
89	78	131	86	25.98	35.6	True
82	69	130	85	25.86	35.1	True
92	62	120	80	22.33	35.2	True
89	64	122	82	26.88	35.4	False
86	80	120	81	30.51	35.3	True
82	85	120	80	15.43	35.2	True
84	71	125	82	21.26	35.5	False
93	81	129	81	18.68	35	False
94	70	132	88	21.52	35.2	False
80	94	120	81	25.33	35.8	True
96	72	131	85	32.19	35.2	True



Figure 7 Correlation Heat Map of the dataset

Table 4: Interpretation of the correlation heatmap

Feature	Correlation with Y	Interpretation	Colour
HR	0.47	Moderate positive correlation	Light Red
BG	0.43	Moderate positive correlation	Light Red
SBP	0.43	Moderate positive correlation	Light Red
DBP	0.44	Moderate positive correlation	Light Red
BMI	0.30	Weak to moderate positive correlation	Pale Red
BT	0.10	Very weak positive correlation (nearly neutral)	Near White

The results of the performance of the MGNB model are presented using confusion matrix in table 5, which indicates that the model was able to classify 4 cases of non-heart disease correctly, and two cases of heart disease correctly. There was also no recoded cases of false negative or false positive. The accuracy was determined from this result as follows,

$$accuracy = \frac{TP+TN}{TP+TN+FP+F} = \frac{4+2}{4+2+0+0} 1.0 = 100\%.$$

Also, the area under curve (AUC) was obtained as shown in figure 7, indicating an outcome of 1.0 as shown in Figure 7.

These results of the training model indicates that the model performed very well on the dataset provided. This

was benchmarked with the performances of other models in table 6.

Table 5: Confusion Matrix

	Predicted: (False = 0) Non-Heart Disease	Predicted: (True = 1) Heart Disease
Actual: False (0)	True Negative (TN) = 4	False Positive (FP) = 0
Actual: True (1)	False Negative (FN) = 0	True Positive (TN) = 2

Table 6: Benchmarking the result

SN	MODEL	ACCURACY	AUC
1	Logistic Regression	50%	1.0
2	Decision Tree	75%	0.5
3	Random Forest	50%	1.0
4	SVM	25%	0.0
5	XGBoost	75%	1.0
6	GNB	100%	1.0

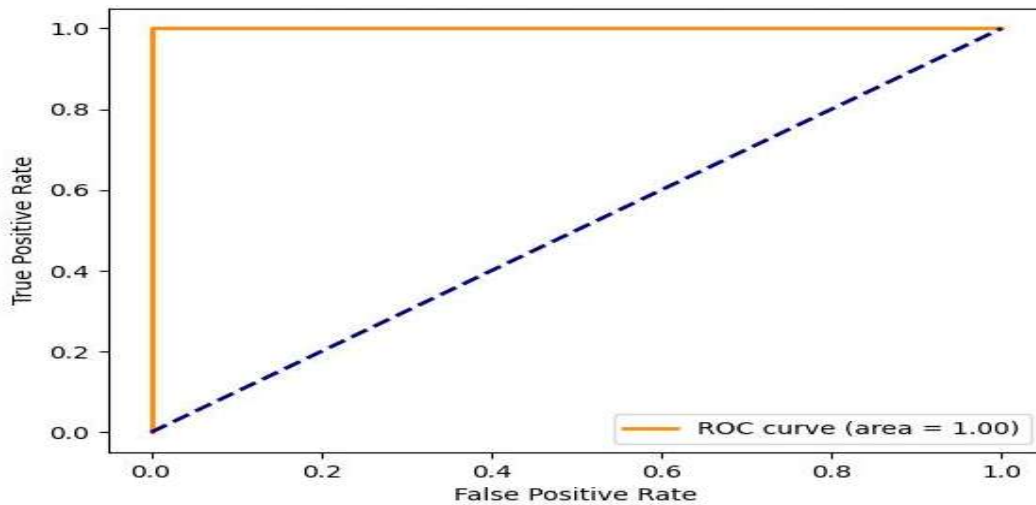


Figure 7 ROC curve of the training model

These results showed that GNB and XGBoost achieved significantly high performance in accuracy and AUC, suggesting their ability to do well with limited dataset. Other models in table 5 struggled with classification threshold. This can be attributed to the size of the dataset. Validating these results, the simulated data from Figure 2 was used on the MGNB, and the result showed that MGNB yielded 90.3% accuracy and AUC of 0.83. The drop in performance is attributed to the noise of data stream and latency. This result indicates great potential for real-world use of IoMT. Its ability to learn from streaming health information renders it extremely well-suited for real-time disease detection and continuous patient monitoring. Its lightweight aspect allows deployment in environments with limited computational resources, while its incremental learning capability addresses the problems of concept drift. However, the use of advanced preprocessing, hybrid modeling, and integration

with drift detection or privacy-preserving technologies could further enhance its performance and reliability.

V. CONCLUSION

This research addresses key challenges in IoMT-based healthcare with the design of a cloud platform that synergistically combines wearable technology, edge computing, and cloud infrastructure to facilitate real-time big data analytics and elastic deployment. The model analyses dynamic data streams with incremental machine learning, that is, the MGNB model, with a 90.3% prediction rate and an AUC of 0.83. These results demonstrate the model's capacity to generalize and withstand noise in both static and real-world environments and hence are highly well-fitted to patient-centric, low-latency healthcare systems. The results also indicate the framework to be able to use to enhance clinical judgment, enable early disease

detection, and enable continuous monitoring, particularly in resource-constrained or remote settings. Nevertheless, concerns of noise, data privacy, and secure transmission still linger. Future studies will focus on employing blockchain technology to enhance data security and trust and exploring more advanced machine learning techniques and feature engineering methodologies to further develop systems with higher accuracy and scalability.

AUTHOR CONTRIBUTIONS

Chukwuemeka Obasi: Conceptualization, Methodology, Validation, Writing – original draft, Writing

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