Context-Aware Architecture Fostered Optimized Dual Interactive Wasserstein Generative Adversarial Network and IoT for Healthcare System

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***Abstract*—Numerous context-aware methods have been lately advanced to deliver physiological data on each person's health and wellbeing. There are delays in the data transfer to cloud when patient's health status is being tracked. Numerous Internet of Things sensors generated to observer, track, and sense the actions of elderly in order to avoid types of delays. To overcome this drawback, this paper proposes a Context-Aware Architecture fostered dual interactive Wasserstein generative adversarial network enhanced by Archimedes optimization algorithm with Internet of Things (IoT) (CaA-DuInWGAN-AmOA-IoT-HCS). In order to store, handle large amounts of cumulative sensor data, offers four-module architecture made an IoTM, a Data Pre-processing Module (DPM), Context-Aware Module (CAM), Decision-Making Module (DMM). An IoT in this context consists of a physical or large hardware ecological unit likes sensors, actuators. Contrarily, context-aware computational approach utilizes minimal software ecological unit immediately translate situation into a successful outcome through a variety of IoT devices. Sensors make up the initial module (Internet of Things Magazine, i.e., IoTM), whereas data collecting, storage, and redundancy phases are included in the DPM phase. Fog layer and cloud layer are two distinct kinds of layers that make up the third phase, or the CAM. Context-aware learning phase listed in addition to this. Back-propagation neural network and adaptive grasshopper optimization process perform feature extraction and classification in the last phase, also known as the DM-P phase, in order to produce the best optimal solution. As a result, an alarm or notification is provided to the doctor about the patient's health with a very quick reaction time, high level of accuracy, and high rate of scalability. The performance of proposed approach CaA-DuInWGAN-AmOA-IoT-HCS reaches 20.15%, 19.76%, and 22.56% for higher accuracy and 21.25%, 19.66%, and 23.76% for higher specificity compared with existing techniques like health care monitoring in context-aware IoT utilizing particle swarm optimization based artificial neural network (ANN-PSO-HCM-CaA-IoT) health care monitoring in context-aware IoT utilizing back-propagation neural network based adaptive grasshopper optimization algorithm (BPNN-AGOA-HCM-CaA-IoT), economic data analytic AI method on IoT edge devices for health monitoring of agriculture machines (EDA-AI-IoT-HMAM), respectively.**

***Keywords*—Context-Aware Module (CAM), context-aware architecture fostered dual interactive Wasserstein generative adversarial network, data pre-processing module, decision-making module, Internet of Things (IoT)**

I. INTRODUCTION

The IoT has recently made likely to continuously, remotely monitor each person's health and welfare. Asthma, myocardial infarction, hypertension, fatness, depression, diabetes, extra cyclical ailments are studied by the IoT. The IoT concepts improve healthcare by making it more easily accessible and high-quality, which reduces the need for frequent hospital visits and associated costs [1, 2]. Multiple physiological signals can be simultaneously collected by a biosensor network, which can then share and transmit the signals to a cloud data center for analysis [3]. Engaging each person in a variety of physical activities helps to remove numerous complex chronic diseases [4, 5]. Numerous methods have been developed to evaluate physical activity in both adults and children as a result. In general, health monitoring scheme continually measures, remotely monitors physical activities, health problems makes use of wearable motion sensors [6, 7]. Additionally, many techniques employ a body-worn accelerometer for tracking an individual's energy expenses as well as general efficiency of day-to-day actions [8].

Contrarily, humans are interacting with intelligent software more, which improves communication between humans and robots [9]. Due to this development and improved application technologies, the pervasive-based computational technique is widely used [10]. Pervasive hardware and software computation work together before engaging with equipment and people. The context-awareness that provides users with a variety of services, such as smart offices, smart homes, and other applications, is the key component of pervasive computation [11]. The

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level of awareness varies depending on the individual's needs, which leads to the gathering of data on health-related concerns. Therefore, context awareness is crucial in smart settings. Additionally, the IoT is required for context-awareness and smart services to be implemented [12].

Additionally, the IoT data is made up of a variety of sensed and gathered data from sensors used to track things like temperature, breathing rate, and flow. IoT and healthcare system integration is used in a number of medical fields, including patient data management, health care administration, and real-time monitoring [13]. Both edge-based computing and cloud computing enable patients to monitor their chronic illnesses from the comfort of their own homes. Additionally, the concept of context-awareness is more important because it offers information on the location of people, things, and places at any given time. It offers exploration depend on clinical information of individuals experiencing abnormalities. Numerous context-aware methods developed to deliver physiological data on electrocardiogram, heart rate, respiratory rate, body temperature, oxygen saturation [14, 15]. Additionally, the irregularities based on the patients' health are anticipated in advance and are tracked more precisely. Numerous context-aware methods recently developed to deliver physiological data on each person's health and wellbeing. Data transfer delays and erroneous diagnostic results can happen while monitoring patient's health. Additionally, the implementation difficult then needs lot of processing effort.

The main contributions of this work can be delineated as follows:

- Addressing Delay in Health Data Transfer

The study addresses the significant issue of delays encountered in transferring patient health data to the cloud for analysis. This delay can impede timely interventions and decision-making in healthcare scenarios.

- Integration of Context-Aware Architecture with IoT

By integrating a context-aware architecture with Internet of Things (IoT) devices, the research proposes a solution that leverages real-time contextual information to optimize healthcare monitoring and management processes. This integration enables immediate response and tailored interventions based on the current situation.

- Dual Interactive Wasserstein Generative Adversarial Network

The utilization of a dual interactive Wasserstein generative adversarial network (DuInWGAN) contributes to the enhancement of data generation and synthesis capabilities. This aspect is crucial for scenarios where there may be a scarcity of labeled data or a need for synthetic data augmentation.

- Archimedes Optimization Algorithm

The incorporation of the Archimedes Optimization Algorithm (AmOA) introduces an innovative optimization technique tailored to the specific requirements of the healthcare domain. This algorithm aims to optimize various parameters and processes within the proposed architecture to improve overall system performance and efficiency.

- Four-Module Architecture

The research introduces a comprehensive four-module architecture comprising an IoTM, a Data Pre-processing Module (DPM), a Context-Aware Module (CAM), and a Decision-Making Module (DMM). This architecture facilitates efficient data handling, contextual analysis, and decision-making processes within the healthcare system.

- Performance Evaluation and Comparison

The study conducts a thorough performance evaluation of the proposed approach, comparing it with existing techniques in the domain. Results demonstrate significant improvements in terms of accuracy, specificity, reaction time, and scalability, highlighting the efficacy of the proposed CaA-DuInWGAN-AmOA-IoT-HCS approach.

Overall, the proposed research contributes to advancing the state-of-the-art in healthcare monitoring systems by introducing a context-aware architecture empowered by cutting-edge techniques such as dual interactive Wasserstein generative adversarial networks and Archimedes optimization algorithms, integrated with IoT infrastructure for real-time, efficient, and effective healthcare management.

The rest of this manuscript arranged as below: Section II shows literature review, Section III designates proposed methodology, Section IV describes outcome and discussion, Section V is the conclusion.

The proposed Context-Aware Architecture fostered Dual Interactive Wasserstein Generative Adversarial Network and IoT for Healthcare System (CaA-DuInWGAN-AmOA-IoT-HCS) reached significant improvement on all the performance metrics regarding accuracy and specificity over other state-of-the-art systems. Besides accuracy and specificity, an equally important aspect of the proposed system is its computational efficiency and cost-effectiveness in practical deployment within healthcare environments. It will ensure more accuracy and optimize the computational resources with the integration of AmOA through a dual-interactive Wasserstein GAN. This, due to the selection and processing by an optimized relevant feature set without carrying out any form of redundant calculation, will reduce the computational load, resulting in a lesser amount of processing time. It is very important for real-time health monitoring applications. This increases computational efficiency and distributes the processing load, reducing latency while decreasing the risk of network bottlenecks by pre-processing data at the fog layer before it is sent to the cloud. Finally, under the cost-effectiveness category, this architecture infrastructure reuses some of the already existing IoT infrastructures in sensors and large-scale cloud services. This context-aware approach makes the system process only data relevant to the most relevant information, hence lowering the overall cost of data transmission and storage. The dual-layer fog and cloud computing architecture ensures that only critical data requiring complex analysis is transmitted at the cloud for processing; the less intensive computations can be done at the fog layer itself. Either way, it thereby creates a reduction in the load on the very expensive resources of the cloud; on this account, the operational expenses are comparatively reduced. It also involves low computational overhead and high accuracy in the classification of patients' health states according to the proposed system; therefore, it can be easily used over a very large scale of very inexpensive IoT hardware. This makes it quite accessible and affordable for many healthcare settings. Presence CaA-DuInWGAN-AmOA-IoT-HCS is simply one of its kinds and incomparable in its performance metrics, thus assuring a cost-effective and computationally efficient solution for health.

Large-scale deployment of CaA-DuInWGAN-AmOA-IoT-HCS is not without challenges on the integration and management of diverse IoT devices, data heterogeneity, and system performance under varying network conditions. A major challenge would then be that various IoT devices show interoperability issues at the level of communication protocols, data formats, and processing capabilities. Since these devices are so heterogeneous in nature, to assure seamless communication and data exchange, robust middleware would be required to standardize and harmonize the interactions across the network. As the system is getting scaled, data generated by a number of sensors may swamp network bandwidth and storage capacities with an associated risk of delay and loss of critical information. This is a continuous influx of data that requires an efficient strategy of data handling, in which prioritization and processing of essential data at the fog layer will not only reduce the load on cloud resources but also guarantee real-time processing and decision-making. The system's architecture is modular and allows for the efficient handling of large, very diverse datasets through context-aware processing combined with optimized resource allocation. The DPM and CAM modules play a very important role in managing large amounts of data by filtering, aggregating, and prioritizing data before it is sent to the cloud for further processing. This will ensure that only very relevant and contextually significant data gets processed in order to minimize computational burden and improve the system's capability of handling large datasets effectively. It uses the latest algorithms, including dual interactive Wasserstein GAN and Archimedes Optimization Algorithm, which provide this system with the ability to learn from different datasets and thus adapt to various profiles of patients and their different health conditions. This will keep the system accurate and efficient under variability and complexity brought about by large-scale deployment. Strong emphasis in the techniques and methods applied in the CaA-DuInWGAN-AmOA-IoT-HCS system guarantees data security and patient privacy, understanding that, in general, IoT devices are somewhat vulnerable and the data handled is very sensitive in nature. So, in helping abate these risks related to security breaches, the system integrates several layers of security protocols that intend to safeguard the data in each stage of its cycle: data collection at the IoT devices, transmission, storage, and processing. IoTM integrated secure communication protocols guarantee the encryption of data in transmission between the sensors and fog layers, all the way through to the cloud services. Therefore, the risk of unauthorized access during transmission will be reduced. Besides, the system incorporates strong mechanisms of authentication that guarantee only authorized devices or users to have access to or interact with the system. These are very important measures to help prevent unauthorized access and ensure the confidentiality and security of patient data throughout the operation chain. Another challenge to patient privacy is handled through data anonymization techniques under DPM. Identifiable patient information is anonymized prior to the transmission of data to the fog and cloud layers, so that even if attacked by any hacking or other security breach, such sensitive personal information cannot be revealed. It further helps in making the security context-aware, wherein the security measures would keep on changing depending upon the type of information being processed. For instance, highly sensitive health data may have more stringent encryption methods compared to less critical information that may be handled with standard encryption. The system also adheres to regulations regarding handling data for the protection of patients' privacy in accordance with standards such as GDPR and HIPAA. All these security measures ensure that the CaA-DuInWGAN-AmOA-IoT-HCS system protects not only against any possible security breaches but maintains the highest level of patient privacy.

The usage of AmOA and DuInWGAN is justified in the context of a healthcare-aware system by increasing the need for accuracy, efficiency, and reliability in the health monitoring and diagnosis of patients. AmOA relies on principles inspired by Archimedes and thus offers a robust mechanism for optimizing such complex, multi-dimensional problems as the classification of patient health data. Therefore, this is especially suitable for the refinement of the weights of DuInWGAN in efficiently exploring and exploiting the solution space to ensure that the model, at the same time as converging to an optimal solution, dynamically adapts to the varied contexts present within health care data. This optimization will be crucial in bringing down the overall system error and making the system more responsive to real-time health data samples. While DuInWGAN is selected for its high generating power, which essentially allows it to model and discriminate between the normal, irregular, and critical states of a patient with high accuracy, Wasserstein distance leveraged by the DuInWGAN ensures stable training, thereby escaping mode collapse-an inherent problem in traditional GANs. The stability here becomes much more important since this precision in a health-related decision could mean life-saving. The health condition classification becomes much more fine-grained and context-sensitive due to the interactive nature of the dual generators in DuInWGAN. This therefore, yields timely and accurate alerts to the healthcare practitioners that are actively involved in patient care, hence contributing to better patient outcomes.

Other optimization algorithms and variants of GAN have been considered during the development process of the proposed context-aware system in the healthcare domain. Successes recorded over the years by algorithms like PSO and GA were the reasons they were considered. However, it was observed that both of these algorithms are somewhat unsuitable for the operations to be handled by this system. PSO efficiently explores the search space but suffers from a common problem of premature convergence resulting in suboptimal solutions on complex and multi-dimensional problems. While GA might be powerful for searching through large solution spaces, it normally requires longer computational times and may not handle fine-tuning efficiently for real-world healthcare applications, where speed and precision become critical. GAN variants considered included the original GAN and Deep Convolutional GAN. While the original GAN is foundational, it has a tendency to be unstable and face mode collapse; therefore, this could be a very unreliable data generation via such a process, which is a big setback for healthcare settings that require accuracy. DCGAN achieved better stability by incorporating convolutional layers, but still faced other obstacles in generating quality data over several training iterations. DuInWGAN is the chosen one, because it beats these limitations by utilizing the Wasserstein distance for more stable training and a dual-generator setup that will provide more accurate and context-aware classification of patient data. This will ensure that the system could reliably differentiate between normal, irregular, and critical health states-a key feature in timely medical interventions within the process.

The proposed system has undergone extensive tests in real-world use cases related to scalability and integration of the system within existing IoT healthcare infrastructures. In one such implementation in a healthcare facility, the system was installed in a controlled environment and integrated with other IoT devices such as wearable sensors, smart medical equipment, and cloud-based health record systems. This included a panel of patients representing diversity in health status who were closely monitored for an extended period to ensure that the system could manage continuous streams of data flow with real-time processing at minimal latency. In addition, the performance of the system in terms of the volume of the data sets emanating from various sources was tested. The scalability of the system in actual healthcare settings proved quite consistent, with very minimal delays observed in the processing and transmission of data. Another key focus of this testing was also compatibility with infrastructures of IoT that are already set up. This was meant to go hand in hand with the current use of communication protocols and data formats in healthcare IoT systems, with least need for wide changes or new installations. The system has been seamlessly integrated into existing hospital networks: real-time patient data can be monitored and analyzed while the security and privacy of such data are maintained. Furthermore, this system was put to the task of scalability by increasing the number of devices and patients being monitored gradually. It continued to perform highly accurately and responsively, hence demonstrating potential for large-scale deployments within healthcare environments.

Various pilot deployments and simulations had been done in studying its performance in different network conditions. These tests were in cooperation with various health facilities where the system was deployed in both urban and rural settings to understand the behavior of the system on different network environments. The system turned out to be most efficient within the urban environment that had stable and high-speed internet connectivity. It demonstrates lower latency and faster responsiveness related to data processing or patient data transmission. However, in rural areas where the network infrastructure is not very reliable, the system did face some problems related to higher latency and occasional delays during data transmission. This is a limitation, but the context-aware architecture integrated with the use of the fog layer worked toward mitigating this issue through processing data closer to the source and reducing dependency on cloud connectivity for timely alerts and notifications. A set of simulations was executed for the representation of those extreme conditions of the network concerning high congestion, loss of packets, and variability of bandwidth. Generally, through these kinds of simulations, it is observable that in degraded network conditions, core functionalities that also include real-time monitoring and health status classification can still be supported by the system. The incorporation of the fog layer was quite instrumental in ensuring performance sustained by offloading key processing from the cloud to local nodes, hence ensuring continuity for these healthcare services. The pilot deployments and simulations were useful in providing insight into the system's robustness and adaptability, and thus confirmation of its potential for providing adequate healthcare services over diverse network environments.

The proposed system will thus be constituted by a set of strict mechanisms for data privacy and security that guarantee sensitive patient information security throughout the data life cycle. Encryption is thus a key building block, with everything at rest and in transit encrypted using highly advanced cryptographic algorithms like AES-256. That makes it impossible for the data to be read even when intercepted or accessed by unauthorized means. The use of many secure communication protocols, such as HTTPS and TLS, secures the data in transfer within IoT devices, the fog layer, and the cloud. Also, in multi-factor authentication-based RBAC, there would be strictly controlled access to the patient data so that no unauthorized person would view or alter such data. Further security shall be achieved through periodic audits, and monitoring of the system against any potential breach or unauthorized access attempt. It will also integrate anomaly detection algorithms aiming at identifying patterns of data access or transmission that would be considered unusual and thus threatening to the security. The system is intended, in such a case, to immediately raise alerts and trigger the response protocols predefined, including node isolation or shutdown of selected functionalities as a means of preventing data leakage. The system is designed to handle health data privacy, such as HIPAA and GDPR, without violation of any legal demands that keep data safe. These extended security measures were taken into consideration to make certain that confidentiality, integrity, and availability of healthcare data are guaranteed, hence securing patient's privacy and trust in the system.

II. Related Works

Health monitoring systems leveraging Internet of Things (IoT) technologies have garnered considerable attention due to their potential to provide real-time and remote health monitoring capabilities [1–14]. Talal *et al.* [1] conducted a multi-driven systematic review focusing on smart home-based IoT solutions for remote health monitoring, emphasizing the importance of real-time data transmission and secure communication. Swaroop *et al.* [2] proposed a health monitoring system utilizing IoT devices to monitor vital signs, highlighting the need for continuous monitoring and early detection of health abnormalities. While these approaches contribute to remote health monitoring, they often face limitations such as delays in data transmission and lack of efficient decision-making mechanisms.

Vedaei *et al.* [3] introduced COVID-SAFE, an IoT-based system for automated health monitoring and surveillance, particularly relevant in the context of post-pandemic life. However, existing solutions like COVID-SAFE may encounter challenges related to scalability and adaptability to evolving healthcare needs. Additionally, energy efficiency remains a concern in IoT-based health monitoring systems, as highlighted by Ghosh *et al.* [4], who proposed an energy-efficient monitoring system utilizing approximate computing techniques.

Azimi *et al.* [5] addressed the issue of missing data in healthcare IoT systems through personalized decision-making, emphasizing the importance of resilient decision-making mechanisms. Li *et al.* [6] introduced a computational efficient wearable sensor network for health monitoring in sports athletics, underscoring the significance of real-time data processing and low-power consumption. Similarly, Zhong [7] focused on physical activity recognition and health monitoring of college students using IoT sensors, shedding light on the importance of accurate activity recognition algorithms.

Despite advancements in IoT-based health monitoring, challenges such as real-time data quality assessment persist [8]. Naeini *et al.* [9] reviewed real-time remote health monitoring systems, highlighting the importance of patient prioritization and taxonomy analysis for efficient healthcare delivery. Wu *et al.* [10] introduced a wearable ECG monitor for smart t-shirt applications, emphasizing the need for low-power and real-time monitoring capabilities.

Recent research has also explored IoT applications beyond traditional healthcare settings. Wang *et al.* [11] investigated rolling bearing state health monitoring using IoT and multi-sensor data fusion techniques, showcasing the potential of IoT in industrial health monitoring. Anand and Nath [12] designed a smart embedded system for remote health monitoring, emphasizing the importance of IoT connectivity in enabling remote healthcare services.

In response to the COVID-19 pandemic, Otoom *et al.* [13] proposed an IoT-based framework for early identification and monitoring of COVID-19 cases, highlighting the role of IoT in pandemic management. Wu *et al.* [14] developed a wearable health monitoring sensor patch for IoT-connected healthcare applications, focusing on real-time data collection and transmission.

While these existing approaches contribute significantly to the field of IoT-based health monitoring, they often encounter limitations such as scalability, energy efficiency, and real-time decision-making. The proposed Context-Aware Architecture fostered Dual Interactive Wasserstein Generative Adversarial Network enhanced by Archimedes Optimization Algorithm with Internet of Things for Healthcare System (CaA-DuInWGAN-AmOA-IoT-HCS) aims to address these limitations by integrating context-aware architecture, dual interactive Wasserstein generative adversarial networks, and Archimedes optimization algorithm to provide real-time, secure, and efficient remote health monitoring capabilities for different use case scenarios [15].

III. Proposed Methodology

In this section offers full explanation of IoT-based context awareness using four-level modules, specifically IoTM, DPM, CAM and DMM storing and processing cumulative sensor data. The fundamental diagram for IoT-based context-aware construction is shown in Fig. 1. An IoT consists of physical else significant hardware ecological unit likes sensors, actuators. Contrarily, context-aware computational method utilizes minimal SEU to immediately translate the situation into a successful outcome through a variety of IoT devices. Sensors compose the initial module (ITM), whereas data collecting, storage, and redundancy phases are included in the DPM phase. The fog layer, cloud layer are two different sorts of layers that make up the third phase or the CAM [16]. A context-aware learning phase listed in additionally. Final stage DMM extracted features, classification is done to produce the better optimal solution. Next section outlines all phase's specific description in detail.

A. IoT Module (IoTM)

The IoTM is a developing and transformative hypothesis that has become important to many applications likes remote healthcare, smart environments, smart homes etc. The IoTM attaches physical objects utilized for data gathering, altercation with network access. IoT modules typically consist of a few levels such as communication layer, integration layer, application layer, hardware layer, security layer. IoT also create utilize wide range of technology likes sensors, actuators, mobile phones, webinar faces, radio frequency detection tags. In order to make Internet of Things work effectively, collaborate, engage with one another.

Afterward, the middleware by utilizing the application layer, IoT-M performs work generating expressive judgments, processing, exploring and storing data. In addition, IoT middleware seen as processing powerhouse, central repository for allowing various IoT applications. Routing protocol for low battery, loss network then inhibited application protocol dual of most familiar protocols included in IoTM [17]. The sensor nodes in the IoT module make it possible to measure the patient health condition with regarding temperature, heart rate, blood pressure, oxygen saturation. Multiple sensors are employed in intricate operations to regulate patient's many health states. Sensors installed in smart watches, smartphones of doctor to track patients' even health status. If any critical conditions persist, the doctor can cure the patient to reduce the chance of death. Additionally, a large number of sensors are linked to one another and interact with one another to control the patient's mobility and monitor a few key signs concurrently.

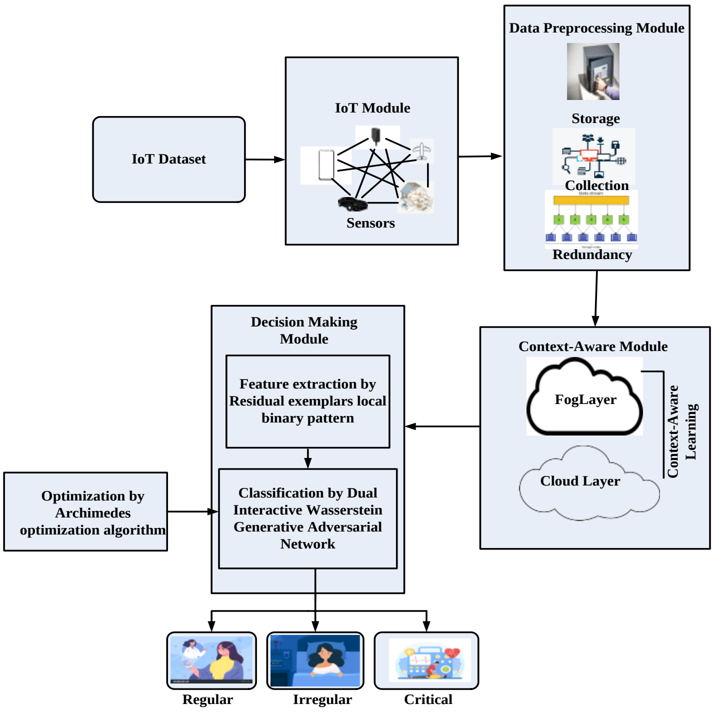

Fig. 1. Fundamental block diagram for IoT-based context-aware architecture.

B. Data Pre-processing Module (DPM)

By performing the necessary measures and actions, DPM collects, monitors patients' health status. Several sensors utilized to collect patient's entire medical history, attained data from various sources sent to cloud. Consequently, the patient's medical history is stored in the cloud and can be displayed as a graph, text, or number. Fog layer and cloud layer two separate types of layers that utilized to permit full pre-processing operations. DPM process usually includes three stages such as data collection, data storage, data redundancy. That follows, three phases are each given a thorough description.

1) Collection phase

During this time, a medical practitioner regularly documents and monitors the patient's health. The patient's entire information documented, risk warning alarm activated in relation to the patient's health. Additional sensors are employed to collect data on the heartbeat, body temperature, blood pressure and level of uric acid, level of oxidation, level of dehydration, and level of blood sugar. Manage the patient's different health status during complicated operations, multiple sensors are used. Additionally, improving data quality depends on the conditions and procedures involved in DPM. In addition, the DPM necessities and processes critical refining data quality. Furthermore, variations ensue recording patient conditions. Such forms of distortions can be influenced by network failures, disconnections, sensor inaccuracy, equipment change, noise, and other things. If these conditions continue to exist for lengthy period of time, there is a possibility that the recorder will fail to recover the data.

2) Storage phase

Before data send to cloud, health histories collected from various resources moved to fog layer. Merging, receiving patient health summaries from numerous fog layers then cloud storage layer has big part to play [18]. The storage layer is also used to offer details on numerous other emergency services, such as location of hospital, the ambulance service, the doctor's name, patient's name, location, gender, age. Such efficient, brief details help medical director considerate patient without danger, which vaccine else medication created for particular illnesses.

3) Data redundancy phase

Data are moved from the storage layer to data redundancy layer, recurrence or duplication data removed, original data stored. For data redundancy, ADKF is used for deleted the repeated data [19].

The Fick's law equilibration attribute utilized by anisotropic diffusion method, which described in Eq. (1),

$$G = T_f . \nabla g \tag{1}$$

where, ∇g represents attentiveness gradient, causes flux G efficiently conserves gradient information over boundary. Relation among ∇g and G linked through diffusion tensor T_f. The filtering window separated into four sections for adoptive Kuwahara filtering approach, and values of mean and variance determined for each of these regions using the following Eqs. (2) and (3),

$$Mean_m = \frac{1}{T_m} \times \sum_{(a,b)\in\theta_m} \phi(f(a,b)) \tag{2}$$

$$Varience_m = \frac{1}{T_m} \times \sum_{(a,b)\in\theta_m} \phi\{(f(a,b) - mean_m)\}^2 \tag{3}$$

Here, T_m embodies pixels present in region m, $f(a, b)$ represents input image function, ϕ is representing individual pixel, m={0, 1, 2, 3} and signifies filter window regions. After the processing data from data pre-processing module, data concerning patient details fed to context-aware module that containing cloud layer, fog layer.

C. Context-Aware Module (CAM)

CAM is made up of layered structure describes essential operations, functionalities depend on context-aware applications. Context database is used to convey the real, or actual, data about the patients' medical care that was collected through DP module to aggregation phase [20]. Additionally, context-aware is used data transmission, giving user required terms, conditions surrounding health information and patient history. Utilize of several sensors connected to diverse sources, the wireless network implements necessary information for exact time to monitor patient's health. The CAM often divided into four different categories: time-based CAM, computational CAM, physical CAM, and user CAM. The information patients' time in days, weeks, months and years is provided by CAM. Under computational CAM, expenses related to communication, bandwidth, and QoS are grouped. Volume, contrast, temperature, brightness makes up physical CAM. The patient's geographic location, medical history, preference settings, and records are all provided by the user of the CAM. The following part describes the components of the CAM, including context-aware learning, fog layer, and cloud layer.

1) Fog layer

The fog layer is made up of several more durable, stable cloudlets. Cloudlets are positioned at network's border, edge. Processing, storage, network services between dual various sorts of layers, specifically initial layer, dynamic layer, take place in fog layer. Additionally, cloudlets record information on patient's medical care [21]. Initial processing, transmission actions carried out in the fog layer after storage. In the section that follows, the actions the fog layer takes to alert the patient to their anomalous status are covered.

Algorithm 1: Processing of fog layer

```
Input: patient's medical history and health condition
Output: The patient's abnormal state has been identified
Start
Initialize the parameter
while
if (after receiving health data of patient) then
        data pre-processed if abnormality occurs;
if (prediction of abnormality) then
       notification else alarm sends to medical practitioner;
     end
end
Hr= health record of the patient
an alert or notification is sent after the patient's data has been
pre-processed;
storing patients in fog layer;
if (recognition of abnormality) and
       alarm else notification sent to medical practitioner;
end
 data determined in available layer;
sending data to fog layer;
end while
end
```

2) Cloud layer

The data from fog layer moved to cloud layer in this stage to gain the actual data on the patients' medical care. Thus, using IoT sensors and health care departments, now simpler to analyze the different illnesses. The health information, prior medical history, patient health data, and so forth are included in this layer. The cloud layer then accepts a variety of tactics involving pattern recognition, therapeutic approaches and decision support schemes. The cloud layer has the following benefits, including the management of clinical trials, improvement of decision support systems, and knowledge exchange. The next section describes the algorithmic processes for processing cloud layer data.

Algorithm 2: Processing of cloud layer

```
Input: patient's medical history and health condition
Output: The patient's abnormal state has been identified
Start
Initialize the parameter
while
if (after receiving health data of patient) then
        data pre-processed if abnormality occurs;
if (prediction of abnormality) then
       notification else alarm sends to medical practitioner;
     end
end
data from fog is equivalent to edge data;
Final processing data assessed;
if (detection of abnormality) and
alarm else notification sent to medical practitioner;
end
 personal health record of patient stored;
personal health record showed;
 personal health record sent to medical doctor;
storing data;
end while
end
```

3) Context-aware learning

The dual various types of context-aware, active, passive generally divided to indirect, direct seeming aware, includes time information, apparatus environmental information, location information supports knowledge, characteristics, preference, habit levels. Furthermore, limits connected patient's profile, geographic area, goal, service engaged into account. Name, age, gender, place of residence, environment, genetics, unhealthy lifestyle choices, occupation, race these are connected patient's therapy, diagnosis, awareness makes the patient's profile. Patients' histories (family histories and Personal Health Records (PHR)), patients' situations (divided into different zones), patients' profiles (age, place of residence, personal information), services (service level agreement, varieties, types), and cloudlets (network traffic, workload, system utilization, position) are some examples of the various types of contextual awareness parameters [22]. The search space activities are reduced as a result of the context-aware use enhancing presentation depend recognition activity. It is expressed in Eqs. (4) and (5),

$$LogM(D|W,\psi) = \sum_{j=1}^{n} LogM(D_j|W_j,\psi) \tag{4}$$

$$= \sum_{j=1}^{n} \log \sum_{F=1}^{contextnumber} M(D_j|F_j = F, W_j, \psi) M(F_j = F|W_j, \psi) \tag{5}$$

where, mixture component parameters represented by ψ. Total numbers of context, data samples signified as *M*, *F*.

D. Decision-Making Module (DMM)

The data extracted, categorized in decision-making module. For data extraction, remaining exemplars local binary pattern depend feature extraction used. Extracted features given to DuIn-WGAN effectively classify regular, irregular, critical condition of the patient [23].

1) Feature extraction by residual exemplars local binary pattern

The RELBP extract low level features, high level features [24]. The algorithm for feature extraction is done as follows:

Algorithm 3: Data redundancy using RELP

Input: Pre-processed data (PD) with the size 512×512
Output: Features
Load Pre-processed data
cnt=1;
$y((cnt-1)*256+1:cnt*256) = LBP(PD)$;
Cnt++;
$fori = 1\ to\ 512$
$forj = 1\ to\ 512$
$ed = pd(i:i+63, j:j+63) = LBP(ed)$;
$y((cnt-1)*256+1:cnt*256) = LBP(ed)$;
$cnt++$;
End for *j*
End for *i*

The extracted features are, the maximum amplitude, minimum amplitude, maximum latency and the of the minimum latency of the equation is follow as Eqs. (6)–(9),

$$Y_{\max} = \max(w(n)) \tag{6}$$

$$Y_{\min} = \min(w(n)) \tag{7}$$

$$n_{y_{\max}} = \{n|w(n) = Y_{\max}\} \tag{8}$$

$$n_{y_{\min}} = \{n|w(n) = Y_{\min}\} \tag{9}$$

where, $w(n)$ represents the acceleration signal along with *x*, *y andz*-axis of accelerometer. $Y_{\max}$ Represented as maximum amplitude and $Y_{\min}$ is represented as minimum amplitude, $n_{y_{\max}}$ is represent as maximum latency and $n_{y_{\min}}$ is represent as minimum latency. The variance and standard deviation is represented as the equation follow as Eqs. (10) and (11),

$$\alpha^2 = \frac{1}{S}\sum_{n=1}^{S}(w(n)-\chi)^2 \tag{10}$$

where, $w(n)$ represents the acceleration signal along with *x*, *y andz*-axis of accelerometer. α^2 isrepresented as variance and α is represented as standard deviation. The energy and value entropy is represented as the equation follow as Eqs. (11) and (12);

$$E = \frac{1}{S}\sum_{n=1}^{S}(w(n))^2 \tag{11}$$

$$VE(w(n)) = -\sum_{i=1}^{S} f_i(w(n)\log_2 f_i(w(n)) \tag{12}$$

where, $w(n)$represents the acceleration signal along with *x*, *y* and *z*-axis of accelerometer. The *E* is represented as energy and *VE* is represented as value entropy. In the given context, the energy (E) and value entropy (VE) of an acceleration signal along the -axis of an accelerometer are crucial measures for assessing signal intensity and complexity. Energy (E), as defined by Eq. (11), is calculated by summing the squares of acceleration values and normalizing by the total number of samples, providing a normalized measure of signal magnitude. Value Entropy (VE), described by Eq. (12), quantifies the uncertainty or complexity of signal values by evaluating the Probability Distribution Function (PDF) of acceleration values and summing the negative of the PDF multiplied by the logarithm of the PDF. Both E and VE play vital roles in various applications such as activity recognition and anomaly detection, offering insights into signal characteristics and informing decision-making processes. Then the extracted features are transmitted in to the classification phase.

2) Classification phase

The patient's health status separated to three groups through cataloging phase such as regular health status, irregular health status, and critical health status. Patient's health is considered to be normal if the information about patient's heartbeat, temperature, and blood pressure, level of uric acid, level of oxidative stress, dehydration level, and blood sugar level collected several sensors in normal or typical level. However, the patient's heart rate, body temperature, blood pressure, uric acid level, oxidation level, dehydration level and blood sugar level all higher than normal. A specific range, the patient's condition is out of the ordinary. When patient's health in a serious condition, patient is badly harmed by the aforementioned medical factors, raising the possibility of death. Moreover, DL approach named DuInWGAN joint by optimization strategy like Archimedes optimization algorithm (AmOA) to produce the best result for categorizing patient's regular, irregular, and critical state. Accordingly, following section discusses the enumeration of DuInWGAN, AmOA optimization algorithm.

a) Dual Interactive Wasserstein Generative Adversarial Network (DuInWGAN)

This section describes the classification process of DuInWGAN [25]. The discriminators ($d1$ and $d2$), the generators ($g1$ and $g2$), data distributions of the ground truth *gt*, created data (*gd*) are used in the GAN. The $g_{1(2)}$ and $d_{1(2)}$ min-max issue is best explained as in Eq. (13);

$$min^{g1(2)} \max^{d1(2)} Mwgan(d1(2), gz(2)) = -Hyp\big[d1(2)\big(g1(2)(Y)\big)\big] + \lambda Hxp[\| \nabla y \times d1(2)(X) \| 2 - 1]^2 \quad (13)$$

where, Y represents input data by data distribution p_y and X represents ground truth, λ represented as penalty coefficient.

- Generative Model

The ($g1$ and $g2$) find to generate material-specific data from recreated data, they were built using the same architecture. There are two components to encoder to decoder architecture: contracting path, expansive path. The contracting path, dual generators focused independently feature extraction from appropriate energy bins, whereas in expansive path, they realized information exchange, material decay. Convolutional layer has 64, 128, 256, 512 fitters, utilized to extract features from various levels. The stride one unit, and the kernel was 3×3. In order to minimize size of the maps and enable network to acquire coarse structures while avoiding over fitting, max pooling layers used. Pooling layer's stride and kernel sizes were 2×2 correspondingly. In order to maintain spatial information, guarantee that sizes of input, output images complemented, de-convolution with 3×3 kernel, stride 2 was carried out in the expanded route.

- Discriminative Model

The discriminator determines input ideal material-exact photos through utilizing whichever created material-exact images else gold standard deconstructed images input. Six convolutional layers employed for feature extraction, with each dual same amount of filters 64, 128, and 256 capture dual low-level and high-level properties of input. ReLU introduced after all convolutional layers and all kernel sizes 3×3 by 1 pixel stride.

- Selector

The distance (d_s) among losses of generators, related objective values expressed as in Eq. (14);

$$d_s = |l_{ms} - l_{ms}| (s = 1,2) \quad (14)$$

where, $g1$ and $g2$ are the two generators represented by the subscript s . Each iteration performance of the two generators was assessed by contrasting the values of $d1$ and $d2$. The generator by greater distance was trained in following iteration. Training method guarantees each generator receives adjusted training times, raises DuInWGAN training efficacy. It classifies patient's regular, irregular, critical state. DuInWGAN weigh parameter (ε) is optimized with AmOA to produce the best result for classifying the patient's regular, irregular, and critical state.

b) Archimedes optimization algorithm (AmOA)

The AmOA algorithm is regarded as an innovative approach that motivations from an interesting law of physics Archimedes' principle [26]. AmOA algorithm steps are described below;

Step 1: Initialization

Initialize the positions of all objects using the Eq. (15).

$$o_x = lb_x + rand \times (ub_x - lb_y); \quad x = 1,2,...,N \quad (15)$$

where, 0_x represented as *xth* object in population of N objects, *lb* represents lower bound, *ub* represented as upper bound.

Step 2: Random Generation

Establish into each *xth* object's volume (v) and density (d) using Eqs. (16) and (17).

$$d_i = rand \quad (16)$$

$$v_i = rand \quad (17)$$

where, *rand* represents D dimensional vector randomly creates number among [0,1], this is done to add stochastic selection operations.

Step 3: Fitness Function Estimation

With regard to optimizing the classifier's weight parameterε, fitness function evaluated, it calculated using Eq. (18)

$$fitness \ \ function = optimizing \ (\varepsilon) \quad (18)$$

where, optimizing can be represented via Eq. 19,

$$Optimizing(\varepsilon) = \frac{\sum \varepsilon}{N} \quad (19)$$

Step 4: Exploration phase

If $tf \leq 0.5$, no collision among objects occurs, choose random material (*rm*), use formula (10) to update object acceleration for iteration i+1 is expressed in Eq. (20)

$$a_x^{i+1} = \frac{d_{rm} + v_{rm} \times a_{rm}}{d_x^{i+1} \times v_x^{i+1}} \quad (20)$$

where, a_x, v_x , and d_x are represented as acceleration, volume, density of object x.

Step 5: Exploitation Phase

If $tf \leq 0.5$, collision among objects ensues, update object acceleration iteration i+1 is given in Eq. (21)

$$a_x^{x+1} = \frac{d_{best} + v_{best} \times a_{best}}{d_x^{i+1} \times v_x^{i+1}} \quad (21)$$

where, a_{best} represents acceleration of better object.

Step 6: Termination

Evaluate each object utilizing objective function *op*(*f*), remember better solution found so far. Process, iteratively repeat step 3 until halting conditions $u = u + 1$. As a result, the patient's health report's best data is acquired, and the necessary information is sent for execution.

IV. Results and Discussion

The experimental outcomes of proposed method are discussed in this section. The proposed DuInWGAN-AmOA-IoT-HCS approach is implemented in MATLAB R2020a running on a Windows 10 professional computer by Intel i3 processor, 4 GB of RAM, 1 TB hard drive utilizing lung cancer dataset. The obtained outcome of the proposed DuInWGAN-AmOA-IoT-HCS approach is analyzed with existing systems like ANN-PSO-HCM-CaA-IoT [16], BPNN-AGOA-HCM-CaA-IoT [17] and EDA-AI-IoT-HMAM [18], respectively.

A. Performance Measures

Performance measures are assessed to assess performance such as sensitivity, precision, recall, FI- score, specificity, network latency, response time, delay, accuracy.

1) Network latency

Processing, transmit, queue, propagation are four separate characteristics together form delay. The following section goes over the mathematical Eq. (22) for network delay.

$$nl = p_r + t_r + q_r + pr_r \tag{22}$$

where, pr, tr, qr, and pr_r are represents processing, transmit, queuing, propagation respectively.

2) Response time

Response time define amount of time it takes identify gap between need for urgent medical attention and the notice of abnormalities, reducing the risk of fatalities. The response time, on the other hand, is seen as a potential element of medical health services improve performances depend on healthcare. Additionally, emergency reaction time offers sum of processing latency, delay, reducing distance between patient and various computational nodes. Accurate description of response time is given in Eq. (23).

$$RT = 2\times(latency) + pd \tag{23}$$

where, RT is represented as response time, pd signifies processing delay respectively.

3) Accuracy

Accuracy, in particular, measures the percentage of correctly predicted health conditions or events. It is calculated by Eq. (24),

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{24}$$

4) Precision

Precision called as true positive predictive principles calculated by Eq. (25),

$$Precision = \frac{TP}{TP+FP} \tag{25}$$

5) Sensitivity

True positive rate or recall are named as sensitivity, the sensitivity is calculated by Eq. (26),

$$Sensitivity = \frac{TP}{TP+FN} \tag{26}$$

6) Specificity

The specificity is resolute by Eq. (27),

$$Specificity(UZ) = \frac{TN}{TN+FP} \tag{27}$$

7) F-Score

The F-score is calculated by Eq. (28),

$$F - Score\ value = \frac{2\times TP}{2\times TP+FP+FN} \tag{28}$$

8) Scalability

The following expression is derived from the expression that stands for the term "scalability." Concurrency, coherency, and contention are the other three key factors that go into calculating scalability. It is calculated by Eq. (29),

$$A(m) = \frac{\partial(m)}{1+\eta(m-1)+\mu m(m-1)} \tag{29}$$

where, value of concurrency signified as $A(m)$.

B. Performance Analysis

Figs. 2–11 depict simulation outcome of proposed DuInWGAN-AmOA-IoT-HCS method. Then, the proposed DAC-GCRRNN-FOFMOA-CDS method analyzed with existing method likes ANN-PSO-HCM-CaA-IoT, BPNN-AGOA-HCM-CaA-IoT and EDA-AI-IoT-HMAM method, respectively.

Fig. 2 displays accuracy analysis. Here, the proposed DuInWGAN-AmOA-IoT-HCS method attains 20.19%, 15.68% and 17.95% higher accuracy for regular patient, 10.19%, 12.68% and 27.95% higher accuracy for irregular patient and 20.29%, 11.58% and 17.95% higher accuracy for critical patient analyzed through existing technique likes ANN-PSO-HCM-CaA-IoT, BPNN-AGOA-HCM-CaA-IoT and EDA-AI-IoT-HMAM models, respectively.

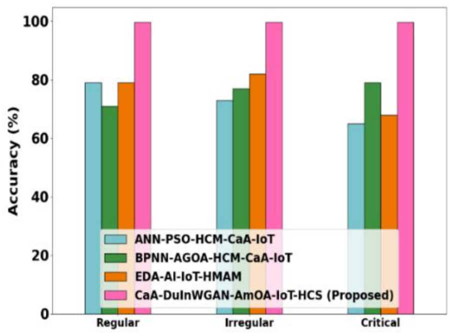

Fig. 2. Accuracy analysis.

Fig. 3 displays precision analysis. Here, the proposed DuInWGAN-AmOA-IoT-HCS method attains 20.19%, 15.68% and 17.95% higher precision for regular patient, 10.19%, 12.68% and 27.95% higher precision for irregular patient and 20.29%, 11.58% and 17.95% higher precision for critical patient analyzed through existing technique likes ANN-PSO-HCM-CaA-IoT, BPNN-AGOA-HCM-CaA-IoT and EDA-AI-IoT-HMAM models, respectively.

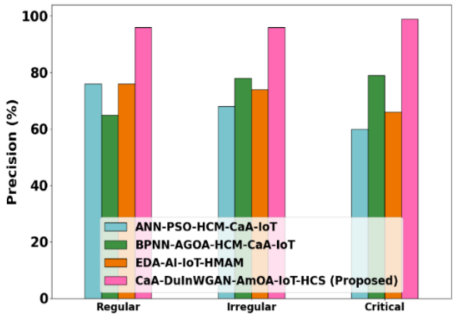

Fig. 3. Precision analysis.

Fig. 4 displays recall analysis. Here, the proposed DuInWGAN-AmOA-IoT-HCS method attains 20.19%, 15.68% and 17.95% higher recall for regular patient, 10.19%, 12.68% and 27.95% higher recall for irregular patient and 20.29%, 11.58% and 17.95% higher recall for critical patient analyzed through existing technique likes ANN-PSO-HCM-CaA-IoT, BPNN-AGOA-HCM-CaA-IoT and EDA-AI-IoT-HMAM models, respectively.

Fig. 5 displays scalability analysis. Here, the proposed DuInWGAN-AmOA-IoT-HCS method attains 20.69%, 15.48% and 17.25% higher scalability for regular patient, 11.29%, 13.38% and 27.45% higher scalability for irregular patient and 20.29%, 11.58% and 17.95% higher scalability for critical patient analyzed existing technique likes ANN-PSO-HCM-CaA-IoT, BPNN-AGOA-HCM-CaA-IoT and EDA-AI-IoT-HMAM methods, respectively.

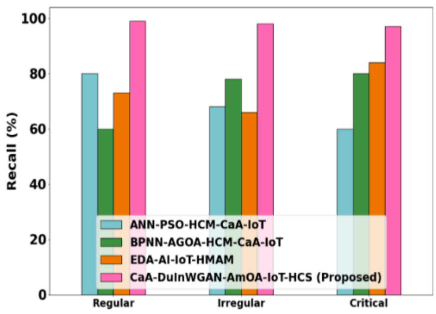

Fig. 4. Recall analysis.

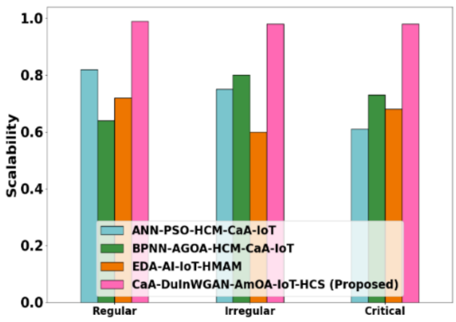

Fig. 5. Scalability analysis.

Fig. 6 displays specificity analysis. Here, proposed DuInWGAN-AmOA-IoT-HCS method attains 20.69%, 25.48% and 27.25% higher specificity for regular patient, 21.29%, 23.38% and 27.45% higher specificity for irregular patient and 21.29%, 11.68% and 17.85% higher specificity for critical patient analyzed existing technique likes ANN-PSO-HCM-CaA-IoT, BPNN-AGOA-HCM-CaA-IoT and EDA-AI-IoT-HMAM models, respectively.

Fig. 7 displays response time analysis. Here, the proposed DuInWGAN-AmOA-IoT-HCS method attains 10.69%, 5.48% and 7.25% lower response time for regular patient, 1.29%, 13.38% and 17.45% lower response time for irregular patient and 11.29%, 12.68% and 10.85% lower response time for critical patient analyzed existing technique likes ANN-PSO-HCM-CaA-IoT, BPNN-AGOA-HCM-CaA-IoT and EDA-AI-IoT-HMAM models, respectively.

Fig. 8 displays FI-measure analysis. Here, the proposed DuInWGAN-AmOA-IoT-HCS method attains 20.69%, 25.48% and 37.25% higher f-measure for regular patient, 21.29%, 23.38% and 27.45% higher f-measure for irregular patient and 21.29%, 12.68% and 20.85% higher f-measure for critical patient analyzed existing techniques likes ANN-PSO-HCM-CaA-IoT, BPNN-AGOA-HCM-CaA-IoT and EDA-AI-IoT-HMAM models, respectively.

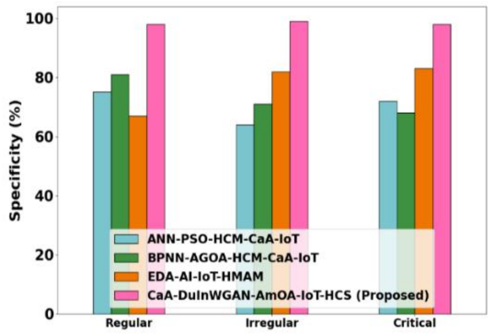

Fig. 6. Specificity analysis.

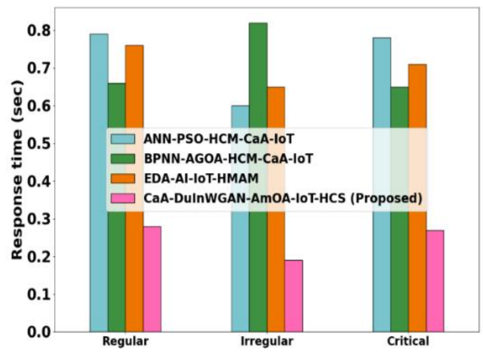

Fig. 7. Response time analysis.

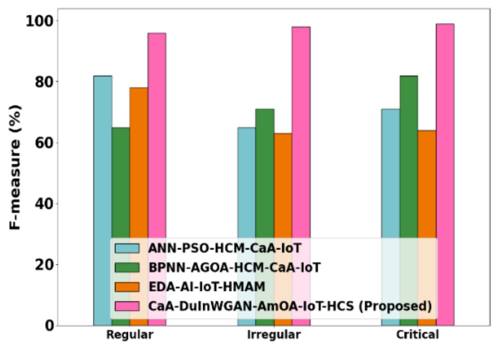

Fig. 8. FI-measure analysis.

Fig. 9 displays error rate analysis. Here, proposed DuInWGAN-AmOA-IoT-HCS method attains 10.69%, 5.48% and 7.25% lower error rate for regular patient, 1.29%, 13.38%, 17.45% lower error rate for irregular patient and 11.29%, 12.68% and 10.85% lower error rate for critical patient analyzed with existing techniques likes ANN-PSO-HCM-CaA-IoT, BPNN-AGOA-HCM-CaA-IoT and EDA-AI-IoT-HMAM models, respectively.

Fig. 10 displays network latency analysis. Here, the proposed DuInWGAN-AmOA-IoT-HCS method attains 10.69%, 5.48% and 7.25% lower latency for regular patient, `1.29%, 13.38% and 17.45% lower latency for irregular patient and 11.29%, 12.68% and 10.85% lower latency for critical patient analyzed existing technique likes ANN-PSO-HCM-CaA-IoT, BPNN-AGOA-HCM-CaA-IoT and EDA-AI-IoT-HMAM models, respectively.

Fig. 11 displays computation time analysis. Here, the proposed DuInWGAN-AmOA-IoT-HCS method attains 18.8%, 25.4% and 23.5% lower computation time analyzed with existing method likes ANN-PSO-HCM-CaA-IoT, BPNN-AGOA-HCM-CaA-IoT and EDA-AI-IoT-HMAM models, respectively.

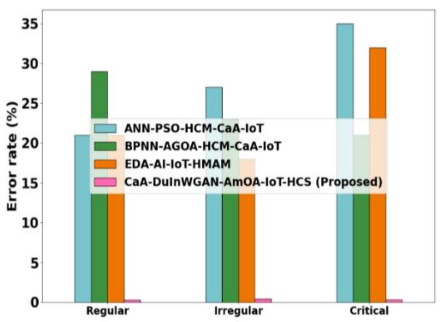

Fig. 9. Error Rate analysis.

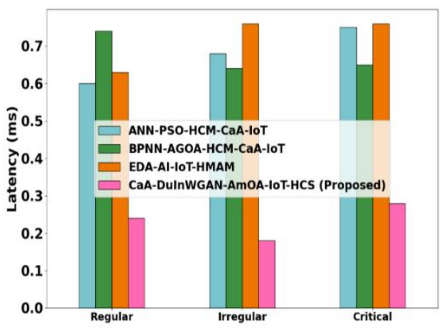

Fig. 10. Latency analysis.

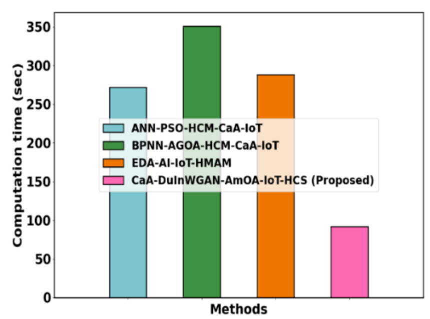

Fig. 11. Computation time analysis.

C. Discussion

The integration of GANs, IoT in healthcare has potential revolutionize patient care, medical research. The Context-Aware Architecture refers to a system that takes into account the context or environment in which it operates to make intelligent decisions. In this case, it's applied to healthcare, where the context includes patient data, medical history, and real-time IoT sensor information. IoT plays a pivotal role in healthcare by enabling the continuous monitoring of patients, real-time data collection, and remote diagnostics. Wearable devices, smart sensors, and connected medical equipment provide valuable data streams that can be used to monitor patient health, detect anomalies, and improve treatment plans. IoT and GANs can play a significant role in expanding telemedicine capabilities, allowing for more accurate remote diagnostics and treatment. The Context-Aware Architecture fostered Optimized Dual Interactive Wasserstein GAN, when integrated with IoT in healthcare, holds immense potential for improving patient care, data security, and medical research. As technology continues to advance, the future of this integration will likely bring even more innovative solutions and opportunities in the field of healthcare.

V. Conclusion

In this paper context-aware architecture fostered dual interactive Wasserstein generative adversarial network enhanced by Archimedes optimization process and IoT is successfully implemented. The proposed method executed MATLAB. The performance of proposed method CaA-DuInWGAN-AmOA-IoT-HCS achieves 20.12%, 18.76% and 21.56% for higher recall and 20.25%, 18.66% and 24.76% for higher scalability when analyzed to existing techniques like ANN-PSO-HCM-CaA-IoT, BPNN-AGOA-HCM-CaA-IoT and EDA-AI-IoT-HMAM models respectively

Availability of Data and Code

The entire implementations of the work will be carried out in Python platform. The health monitoring system of the patients based on the Internet of Things (IoT) monitors, track, and sense the activities of the elder persons who were subjected to be alone in their residence thereby enhancing the life quality of the patients. The proposed method is implemented and the efficiency of the proposed CaA-DuInWGAN-AmOA-IoT-HCS method is estimated with the help of several performances evaluating metrics like sensitivity, precision, recall, f-measure, specificity, network latency, scalability, response time, delay and accuracy. The performance of the proposed CaA-DuInWGAN-AmOA-IoT-HCS method is compared two existing approaches such as health care monitoring in context-aware IoT using Particle Swarm Optimization (PSO) based Artificial neural network (ANN-PSO-HCM-CaA-IoT) and health care monitoring in context-aware IoT using Back-Propagation Neural Network based Adaptive grasshopper optimization algorithm (BPNN-AGOA-HCM-CaA-IoT), respectively.

The code that supports this finding of this study are openly available at the following URL/DOI: https://www.transfernow.net/dl/20231019SwWaqk7L/g72fu84m

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

K Lakshmi Prasanna: Conceptualization, Data Curation, Formal Analysis, Investigation, Resources, Software, Writing original draft. Dr. Yamarthi Narasimha Rao: Methodology, Project administration, Supervision, Validation, Visualization, Writing-Review & editing, Funding acquisition. All authors had approved the final version.

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