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A Safe and Reliable Internet of Things and Fog-Based Intelligent Cascaded deep learning model for Intensive Care Units

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Abstract: Internet of Things (IoT) is a network of sensors and actuators that connect actual things and give them the power to react instantaneously and intelligently to shifting and changing situations in their surroundings. In an emergency, fog computing has been utilised to create a framework for increasing user experience and service robustness. Real-time processing is achieved by connecting devices linked to the IoT to the network's perimeter. Fog edge computing's scattered nature and closeness to end users can increase IoT service quality and response times. Our foundation for providing patients with a more intelligent healthcare experience includes fog computing, the IoT, and machine learning. The implementation of Blockchain technology ensures the framework's full and comprehensive security. Cancer, cardiovascular disease, and diabetes are the most frequent types of chronic illnesses that impact individuals worldwide. These illnesses may affect patients of various ages. Due to the wide range of symptoms that people with heart disease may exhibit, it can be difficult to accurately diagnose them. As intelligent wearable technologies proliferate, fog computing and IoT-based diagnostics have gained importance. A novel technique that employs computers at the edge, in the fog, and in the cloud to provide rapid and precise results has been developed. It is crucial to extract cardiac features from data to gain valuable information. Furthermore, data collecting gives insight into the process of extracting characteristics based on a range of parameters. After the data has been collected and processed by the diagnostic system analyses it is fine-tuned here utilizing the Galactic Swarm Optimization (GSO) approach for it to operate at its peak performance level. It was found to be 97.99 percentage points more accurate than the other four models. Several comparative effectiveness studies have shown that the proposed technique outperforms established procedures.

Keywords: Internet of Things, Cascaded deep learning model, Convolution Neural Network, Healthcare, Cloud Computing, Blockchain, Fog computing.

I. INTRODUCTION

It is essential to identify a substitute for the current healthcare system, in the alternative approach, patients' health is closely monitored to keep infectious illnesses under control and avoid their spread to others [1]. Radio frequency technologies were used in the construction phase to provide the infrastructure that allows ordinary networking performance [2]. The dynamic and connection-aware programmes may be customised to meet the specific needs of each individual user. In response to worries about the technology's future, designers of Network-on-a-Chip systems have had to adjust their attention to ensure that their products are entirely trustworthy. Because of the routing algorithms, certain routers may become obsolete much faster than others, thereby limiting the system's lifetime. As a result, the amount of data that may be transmitted across the network will be limited. According to this study, life expectancy is analogous to a finite resource that may be decreased over time. Every router has a unique parameter known as a "lifetime budget" that reflects how much work it can perform

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in each amount of time. We devised a test to maximise lifespan by sending flits along the path with the greatest bang for their buck. As a result, the degree to which the reliability of a router's lifetime fluctuates is highly dependent on the routing strategy used. This is because they have a profound, fundamental link with one another. Dynamic programming was used to develop a routing strategy that considers lifespan. This strategy takes into consideration the overall cost of an item during its lifetime. A dynamic programming network technique is presently being deployed to tackle this problem of linear complexity. You can communicate with any of the network-connected devices by using channels on which you are confident. Because of the exponential increase in the number of easily available IoT services, it is now important to develop new approaches to manage the fluctuating availability, data-creating characteristics, and diverse device characteristics of IoT devices [2-3]. Intelligent health cards are required to deliver intelligent medical treatment. At the same time, it protects patient information privacy while assuring patient safety. To put it another way, electronic health records stored on smart cards are vulnerable to a wide range of threats and assaults. Abuse by business insiders and online criminal activity are only two of the numerous possible risks and threats that an organisation may face. To provide adequate safety, the suggested architectural design makes use of a decentralised intelligent e-health gateway. Because the gateway is dispersed, it is feasible to hack medical sensor nodes established by end users. As a result, patients' lives are jeopardised. People may be hesitant to use Internet of Things-based health care solutions due to concerns about privacy and data security, as well as unethical uses of personal information. The greatest hurdle that the Internet of Things must overcome is the preservation of user privacy in a future when all linked gadgets communicate data in real-time. If the connection you are using to complete the procedure is not secure at any point, the information you have provided might be accessed by a third party. When working with such massive amounts of data in real-time, there is always the possibility of errors. This applies to both long- and short-range transmission. It is conceivable to deliver personalized services in a smart city context [4], the structure of this facility allows for regular breathing exercises for senior persons and people suffering from Alzheimer's disease. The architecture will notify users if they do not complete their breathing workouts or do not perform them at all. There are many smart cities all around the world, and our framework can connect them all. As a result, individuals living in more evolved civilizations will be able to make use of the benefits that contemporary technology provides. The architecture, on the other hand, has the disadvantage of being unable to cover a vast geographical region and can only focus on the basic components of a smart city; also, it has not been tested.

In today's modern economy, the usage of the internet enables the on-demand availability of service resources to clients. Because addressing these expectations is critical, cloud computing and fog computing have received a lot of attention [5]. These study areas are becoming increasingly significant in several situations, including the academic and professional worlds. Cloud computing is not an acceptable alternative for any application that demands immediate replies due to the large delay in response time. The current scenario necessitates a solution since it is difficult to locate a suitable site to store this volume of data without exhausting all of the capacity of the existing computer systems. Massive data sets may be difficult to protect in the storage sector. Maintaining the infrastructure needed to securely store and retrieve digital data might become costly. This has been a significant contribution, particularly in recent years, to the extraordinary growth of these technologies. Because it can alleviate and increase network capacity constraints, low latency, security and privacy, as well as mobility. Frameworks for

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cloud computing have grown in importance in recent years because they enable the development of new applications by providing a robust and trustworthy infrastructure and service [6]. Using cloud-based computer services can bring a variety of advantages. To begin, it reduces the amount of energy utilised while simultaneously cutting the network's reaction time and latency. It has been established that QoS restrictions in real-world fog conditions face two of the most challenging and critical challenges: latency and reaction time.

This is the most critical application to consider when considering "fog computing" and real-time outcomes in the healthcare business. Using fog computing to transfer resources closer to patients is one strategy to improve healthcare safety by bringing them closer together [7]. The researchers aimed to develop this more complicated imaging by combining the results of single-spectrum CT scans with a deep learning system. After being trained on dual-energy CT scans, the team's technique delivered exact estimates with a relative error of less than 2%. Using the photos, the algorithm was trained to achieve this. The researchers arrived at this result by using these images to train the algorithm. As a result of this, the lowest possible latency may be realised. Patients who display early indications of a serious heart problem may now be able to obtain therapy more quickly because of these procedures. The turnaround time is substantially longer due to the intricacy of the data and the necessity of getting it properly because current research has been taught using very huge datasets, it is possible to attain very high levels of accuracy by utilizing the many types of deep learning. According to the most recent methodology [8], data on people's health is collected in two ways, most notably for those with cardiovascular disease. Devices connected to the internet of things acquire file input data. Using the network, patients' medical records may be retrieved at a pace of up to 250 gigabytes per minute. Applications that operate with large amounts of data must use resources from both the cloud and the edge. Edge computing is a sort of distributed information technology architecture in which user data is managed as near to the point where it was created as is technically practicable. After "smart devices of IoT networks" have gathered and aggregated data, cloud servers or edge nodes are employed to store and analyse it [9], this paradigm may be useful to other users as well.

Deep learning has been demonstrated to be particularly successful in several scenarios needing mixed-modality data, and as a result, its use is becoming more common [10]. It is feasible to significantly increase the overall performance of machine learning algorithms by utilising ensemble learning. The ultimate outcomes are projected using this strategy. Random subsets of data are fitted to and assessed to train the estimator. As a result of the randomization of the data, these estimators are more able to reduce variation than a single estimator. The advancement of contemporary deep learning algorithms has made it possible to accurately anticipate and categorise healthcare data [11].

Because of the intricacy of its neural networks, deep learning is often used in healthcare applications. These applications need a substantial amount of computer resources as well as time for training and analysis. The absence of existing methods for achieving accurate accuracy rates in real-time may be a hurdle to the adoption of IoT applications in particular industries, such as healthcare and other critical professions [12]. In the healthcare industry, end-user acceptance of IoT technology is sometimes insufficient. Learning how to make the most of the internet of things is one of the most difficult difficulties in providing high-quality medical care to patients. Numerous studies have provided insightful new perspectives on the IoT's potential in healthcare. Despite this, additional research and analysis into the factors that drive IoT

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adoption are required. The purpose of this study is to collect information from many sources about the factors that influence doctors' decisions to use IoT apps in healthcare. This research looks at the literature very carefully to figure out what is important, then collects, sorts, and summarises the results. It is now feasible to combine cutting-edge deep learning ensemble models with cutting-edge edge computing to achieve exceptionally accurate results for real-world applications. As a result of this, cutting-edge research may be undertaken. The model developed focuses on deploying this technique as soon as possible to assist patients suffering from heart disease in making the numerous decisions that are needed of them.

The following is a shortened summary of the smart healthcare paradigm's most significant contribution: (1) The researchers propose a novel method for forecasting heart disease that takes use of IoT and fog computing. To achieve its learning objectives, the system employs a metaheuristic-based deep learning model. (2) The procedure of gathering a large amount of information about an individual using traditional medical equipment to learn about their medical history and other problems. (3) It is worth noting that the GSO algorithm was used in an automated diagnosis system for heart disease with optimised CNN to optimise certain parameters and achieve maximum performance. A diagnosis of cardiac disease is feasible using this procedure.

The remaining components are given in the table below the section 2 focuses on related work, and section 3 the proposed model. In Section 4, we will investigate the results and section 5 shows the conclusion.

2. Related Work

Researchers oversee creating the "IoT-enabled ECG monitoring system." The gadget employs the "Pan Tompkins QRS detection" technology developed by the two researchers. "Dynamic and statistical features" were utilised as a last stage in the categorization of cardiac arrhythmia sickness. This model, which was created to estimate the risk levels for a range of heart illnesses, used ECG signals as its major data source. Primary care providers were able to diagnose cardiac abnormalities in their patients in a timely way while retaining a high degree of accuracy by using this strategy. Cardiovascular disease is the main cause of death in every region of the world. As a result, assessing whether a patient has a cardiac issue may be difficult and requires a thorough grasp of the disease's pathogenesis. These models can aid in the early identification and prevention of cardiovascular disease. Despite the tremendous amount of research that has been undertaken in this sector, the accuracy of identifying cardiovascular disease remains rather low. Even though IoT has been around for a while, this is still the case with each passing year, the IoT becomes more intertwined into our daily lives [13-15]. As a result, its importance in the context of remote monitoring systems is becoming more obvious. There is a wide range of remote monitoring systems available, some of which are intended to monitor healthcare facilities, others to track assets or cars, and still, others to manage parking lots. There is a significant amount of research being conducted in several different areas, two of which are in the realm of medical technology and the question of how to integrate newly developed electronic technology into the process of giving care to patients, figure 1 shows the picture of an intensive care unit where attendants and doctors are taking care of patients.

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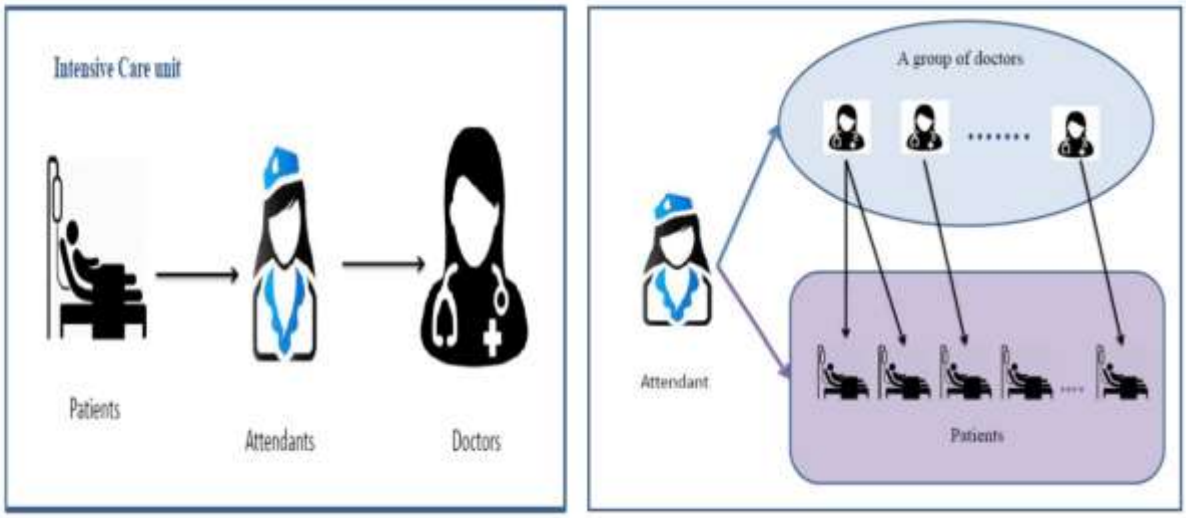

Figure 1. An Intensive Care Unit

A bus tracking system based on a present path is a simple yet elegant approach, when a particular length of time has passed, a smartphone application will display the location on an LED display screen. This will take place automatically. Students who attend large educational institutions, such as colleges and universities, will benefit greatly from this technique. A method for properly managing keys inside an Intelligent Transportation System, which may be accessed here ITS systems will be able to safely swap keys with one another thanks to Blockchain technology [7]. Concerns include a lack of control over who gets access to and uses data. A piece of equipment capable of determining whether poisons are present in water would be extremely useful in the fight against pollution [9] discusses the several ways that may be used to monitor water. Each sensor has the capability of measuring a wide variety of variables, including temperature, humidity, and PH. The data acquired by sensors can be transferred to a base station to allow for continuous monitoring of the water's quality[10]. A variety of sensors were used to acquire measurements of the subject's heart rate, ECG, and other vital indications.

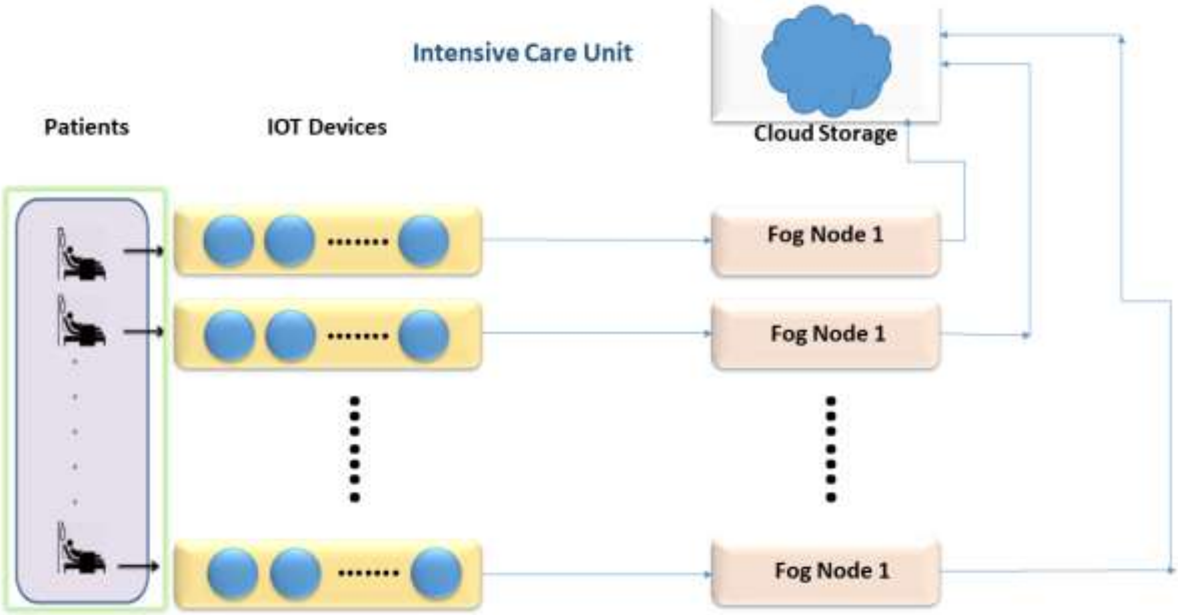

Figure 2. Internet of Things and Clouds Role in Treatment

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Patients in intensive care units may be examined at any time of day or night and from a variety of places thanks to the information gathered by the sensors shown in figure 2. According to [16-19], patients in intensive care units should be forced to undergo service disruptions. The employee in charge of a specific intensive care unit (ICU) receives data in real-time thanks to technology that allows data to be acquired and supplied remotely. Taking measurements of blood pressure (both systolic and diastolic), the fluctuation of the heart rate, the activity of brain waves, and the oxygen saturation of the blood are some of the physiological signals.

A new framework called HealthFog to build this system, a method known as integrated ensemble deep learning on a decentralized network of edge computers. This framework was developed to aid in the automated detection of cardiovascular diseases utilizing mobile applications in "real world" settings. This way of delivering medical care has been running as a fog service by keeping a watch on the medical records of cardiac patients and obtaining information with the use of IoT devices[20-23]. The studies used a fog-inspired integrated cloud architecture known as FogBus to evaluate the performance of the proposed model in terms of execution time, accuracy, jitter, latency, network bandwidth, and power consumption. Because of its adaptive design, HealthFog was able to fulfill the demands of a diverse set of users and complete a diverse set of fog computing use cases. End users benefited from the transition in various ways, including improved service quality and more realistic estimates.

By combining the Internet of Things with a "Deep Learning Modified Neural Network," a cutting-edge framework for patient monitoring. This approach will assist cardiac patients all around the world. This paradigm is comprised of three procedures: authentication, encryption, and categorization [24-25]. The SHA-512 algorithm and the substitution cipher were used to authenticate the legitimacy of the medical center where the heart patient was being treated in the first portion of the operation. A "patient's body" was surgically implanted with a sensor device connected to the Internet of Things once more, and data was promptly transferred to the cloud. Before being "securely transferred to the cloud," the data, which may have included "patient id," "doctor id," and "hospital id," was encrypted using the Advanced Encryption Standard. This was done to protect the privacy of the information. After the data was encrypted, the DLMNN classifier was used to create the categorized findings, which were then separated into abnormal and normal groups. In the great majority of cases, the most common diagnostic procedure has been to check the patient's heart for abnormalities. In order to make data more secure while reducing processing times, researchers compared the results of their experiments to those of traditional encryption and decryption methods.

An IoMT technique for the identification of cardiac disease utilizing "Modified Salp Swarm Optimization (MSSO) and an Adaptive Neuro-Fuzzy Inference System (ANFIS)," which improved the search efficiency of the Levy fly method. Previously, information on the probability of cardiac illnesses was collected by reviewing medical records. This type of occurrence occurs significantly less frequently nowadays. Health indicators include blood pressure readings, cholesterol levels, chest pain, age, and gender (BP). To arrive at its diagnosis, ANFIS employed a multi-pronged strategy that combined gradient-based learning with other, more traditional sorts of educational methodologies [26-28]. However, it is possible for this method to become trapped in a rut, never progressing beyond the bare minimum on a local level. The MSSO approach was used to fine-tune the ANFIS learning parameters, and the results were exceptional. When the MSSO-ANFIS model is compared to other ways of doing things, positive results have been found.

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A "Modified Deep Convolutional Neural Network" (MDCNN) to provide an Internet of Things framework for online detection of cardiac problems. Researchers were able to compare the data they acquired since the patient wore both the ECG monitor and the smart watch at the same time. The data collected by the sensors was sent into an MDCNN, which discovered any anomalies in the data. The model was compared to deep learning neural networks and logistic regression. The results of the tests showed that the newly built MDCN was more accurate at predicting cardiovascular disease than its predecessor.

The "Enhanced Deep Learning Assisted CNN (EDCNN)" to help improve prognosis for patients with heart disease. This EDCNN model was built with advanced approaches such as multi-layer perceptron's and regularization learning. It was decided to use only a subset of the system's capabilities to assess its overall performance rather than try to use them all at once. As a result, classification algorithms have been found to perform well in terms of processing speed and accuracy. The IoMT architecture for "decision support systems" was utilized to assist in building the proposed model, which would allow medical practitioners all around the world to identify "heart patient's information in cloud" scenarios [29]. It has been assessed how probable it is that a person may develop heart-related difficulties using tried-and-true methodologies. Based on the results of the experiment, the generated model could be made better by tweaking the EDCNN network's hyperparameters to reach the required level of precision and accuracy.

After gathering information from patients both before and after the onset of heart disease, Patients were interviewed for this information over a period of years. The High-Order Boltzmann Deep Belief Neural Network, commonly known as HOBDBNN, was frequently utilized to manage patient data given by the medical institution. This level of speed was achieved due to the exact processing of complex data, which served as the foundation for the characteristics. The model's performance because of these efforts was evaluated using a range of quantitative measures, including the ROC curve, the loss function, the sensitivity, specificity, and the f-measure. Thanks to advancements in IoT-based analysis and the HOBDBNN approach, heart illness may now be recognized fast, easily, and correctly. Because of this, the total number of deaths caused by heart disease has gone down.

Cyber-physical localization infrastructure serves as the foundation for their identification technique. For decision-making, the model employs an "adaptive neuro-fuzzy inference system." This has allowed for the earlier detection of high-risk people with coronary heart disease than was previously achievable. The need to collect this data more rapidly pushed the development of this approach. This approach may be used to assess an individual's risk of developing heart disease and categorize that risk as high, medium, or low. If an abnormality in the ECG readings was identified, alarms were sent to both the user's mobile device and the healthcare practitioner's mobile device. These interventions might improve the accuracy and timeliness of patient health monitoring [30]. The results of the simulation show that the model made is a good way to estimate risk levels in the shortest amount of time.

"Internet of Things-enabled EKG monitoring system" to evaluate the acquired ECG data. To retrieve and evaluate the statistical characteristics, the "Pan Tompkins QRS detection" method was utilized. This was done to get the features of dynamic movement. The "dynamic and statistical features" were then added into the classification step of the heart arrhythmia predicting technique [31-33]. The ECG signals have been the primary focus of research on the relative odds of developing heart disease. If primary care doctors used this method, they might be able to tell more quickly and accurately which of their patients are at risk for heart disease.

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The cardiovascular system is primarily responsible for human mortality. Given this, cardiac prognosis is critical. However, diagnosing cardiac disease is difficult and requires extensive data collection. The IoT has found extensive adoption in a range of medical systems as a direct result of the pervasive collection of sensor data for the purpose of diagnosis and prognosis of cardiac ailments [34]. Numerous researchers have attempted to enhance heart disease diagnosis over the years, but most of their attempts have been futile. The results of this study show that new ways must be found to use the internet of things in healthcare to reliably predict cardiac problems early on.

3. Proposed Work

In this part, we'll talk about how we think intelligent healthcare will evolve in the future. Critical care units are launched in almost every hospital to provide treatment to patients whose lives are in urgent danger. The acquired and processed data are derived from the patients' numerous biometric features. This mechanism can notify the proper authorities if a patient need assistance before proceeding with anything further, a framework must be built. Models are also available because the medical industry generates a large amount of data, new computer models have been created to provide users with resources that are both low-latency and energy efficient. These frameworks are also known as "edge computing" and "fog computing." When it comes to the disadvantages of fog computing, longer reaction times and less precise findings are prevalent. The IoT, fog computing, and cloud computing are examples of cutting-edge technologies that boost network bandwidth, latency, privacy, and security while also delivering better communication, processing, and data storage options. Cloud computing and fog computing can help enhance the performance of applications that demand low latency or real-time updates. For this work, we chose fog computing because of its potential to manage cardiac patient data at edge devices or fog nodes with more processing capability. Delay, reaction time, and latency are all decreased when Internet of Things devices are placed close to edge devices rather than in cloud data centres. The time it takes for data to travel from the edge network to the core network is the primary cause of network latency. A network architecture in which multiple nodes converge on a central location (data centres). The network's "edge," or most exterior layer, and its "core," or most central layer both contribute significantly to overall delay and delay variability. Where would you look for the items listed below? Following that, models for both the edge and core networks are created to estimate and forecast latency.

Waiting periods vary greatly amongst networks, ranging from nearly none to many minutes. This article investigates the novel concept of sensor-based edge networks and their possible applications. The term "Edge Sensor Network" refers to the logical expansion of a conventional network caused by the Internet of Things devices. Users must first connect to the DCN in order to access cloud computing services. Current systems are hampered by slow reaction times, increased workloads, excessive resource use, and excessive energy consumption, even though a diverse variety of cardiac patients require treatment. Figure 3 depicts a visual depiction of the proposed architecture, which may be seen for further information. The number of layers in the cascaded CNN model determines the threshold value for entropy loss. When the procedure begins, the input data are delivered to the CNN's convolution layer [20-24]. These computations are based on the characteristics of both the data and the signal. Following the conclusion of the convolution layer's processing, the pooling layer will take control. If the quantity of entropy lost is equal to or more than the threshold, the totally linked layer will have just one CNN. If this is not the case, the pooling layer's output will feed the network's

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subsequent input layer. A CNN is regarded to be a single network if the entropy loss is less than 0.4. As a result of their joint efforts, the linked layers eventually deliver classified results. The notation shown above depicts the value that forms the threshold. As a result, both the entropy loss and the threshold value have a role in selecting the number of networks that must be trained. Throughout the CNN optimization process, not only the network layers but also the hidden neurons and the activation function, are considered. As a result, the GSO algorithm has a much higher recognition rate than the industry average. Figure 3 depicts a convolutional neural network architecture constructed with the assistance of GSO.

Each buried neuron layer's activation function, commonly known as AF, may be personalized. The parameters are used by CNN in its processes, it is thought that five to two hundred and fifty neocortices are buried. The CNN's activation function is based on the Sigmoid, Tanh, Rectified Linear Unit, or Leaky ReLU function, depending on which is applicable. It is very helpful as the final component of the convolutional layer since it increases output nonlinearity, making it extremely favorable. The ReLU method outperforms other algorithms because it employs fewer neurons than other techniques [35-39], one of the causes behind this is as follows. It achieves convergence six times faster than combining the rates of the sigmoid and tanh activation functions. In the absence of a gradient, the Leaky ReLu method is used.

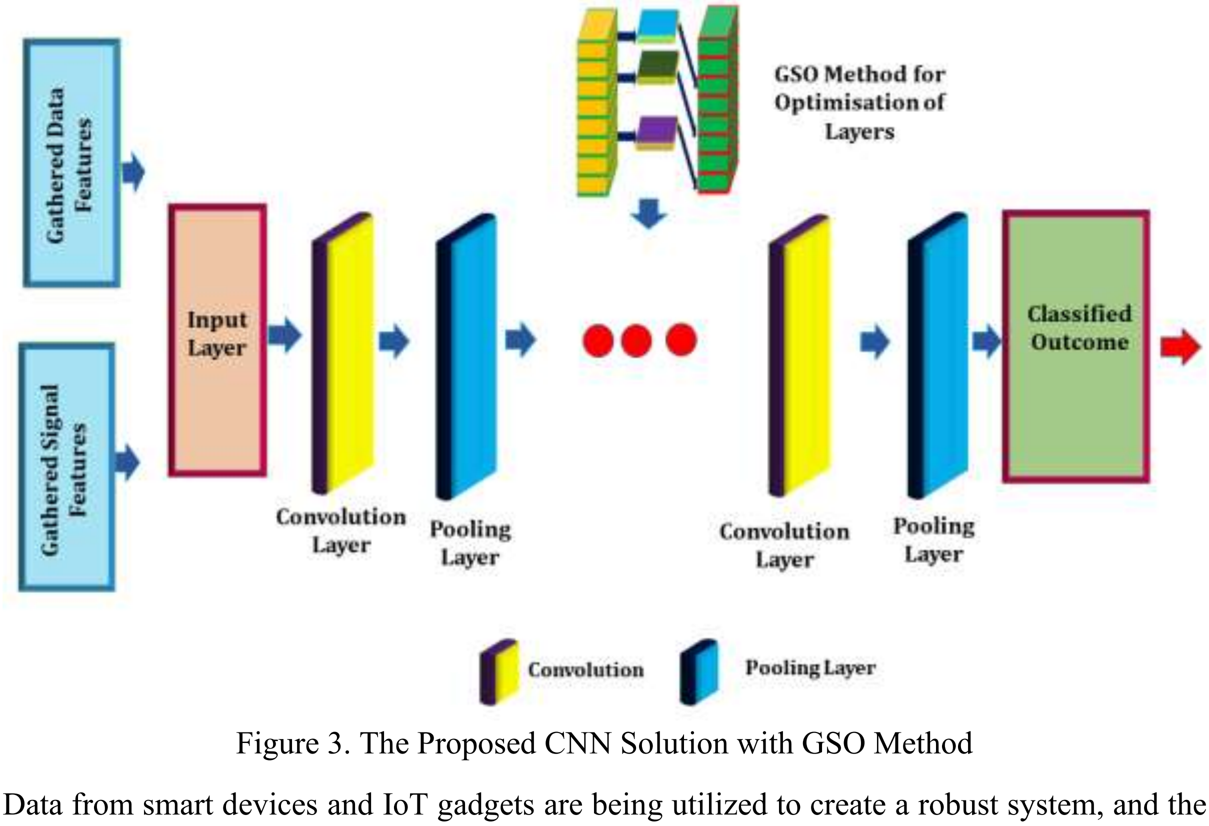

Figure 3. The Proposed CNN Solution with GSO Method

Data from smart devices and IoT gadgets are being utilized to create a robust system, and the health of cardiac patients may be followed using this method. Surgically implanted sensors, environmental monitoring sensors, and activity sensors are examples of "hardware components." The body may provide a wealth of information, ranging from activity level to blood pressure to breathing rate to electroencephalogram (EEG) to electromyogram (EMG) to ECG. Following that, a side-by-side comparison of the two is performed. As a result, FogBus is important to the planned intelligent system for detecting heart problems early. The three primary components of the FogBus are the cloud data centre, worker nodes, and broker nodes. Using the information gathered during this stage of the diagnostic procedure, an enhanced

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convolutional neural network (CNN) is employed to identify whether the patient has cardiac disease. The GSO approach is used to optimise the cascaded network's layers as well as the activation function of the CNN and hidden neurons to get the best possible outcomes. The diagnostic paradigm for heart disease seeks to minimise prediction loss as measured by mean square error to the greatest degree possible. As a result, gathering output classes that may be classed as normal or abnormal is one option for improving the system's warning and protection capabilities.

Algorithm 1

A part of the GSO pseudo code is as follows:
1. The initial step is to initiate the network connection process. Find out how many nodes will be used for the input, output, and hidden layers of the network.
2. The beginning value of the weights, which might range from -0.5 to 0.5, must be set in the second stage.
3. Describe the PSO parameters in operational terms (c1, c2, w, r1, r2).
4. Develop a whole new population.
5. The horde will be split into smaller groups.
6. Regarding each cluster individually:
Always remember to place each particle in the finest possible location the sub-member swarms compute the deviations of the new velocities from the particles' new locations as well as determines the new velocity of the particles, the best job is always a new job if the most recent mistake is better than the most brilliant one.
7. The current state If the newly discovered error eventually proves to be better than the greatest in the world, the status will be changed to "the finest in the world."
a movement that starts at the beginning and circles back on itself.
8. Reclaim your place atop the most important list.
9. This will cause some of the best athletes in the world to join the super swarm right away.
10. Always consider where each particle will be most effective (galactic-best).
11. At this point, it is critical to computing the velocity of each particle.
12. Learn everything you can about your new position.
13. Check the distance between the new and old locations.
14. For us to be able to say so, this new error must be more serious than the prior one.
15. The best thing that has happened since the discovery of bread is that this latest mistake is worse than the last one.
16. Restore the operation in the first place.
17. The last step is to develop a diagnosis.

The intelligent heart disease prediction system that was built is referred to as a "fog service." This system processes data generated from smart devices and IoT devices efficiently. In this technique, FogBus is utilised to give services for the prediction of cardiac disorders. FogBus is a platform for the deployment and development of hybrid cloud and fog environments. When programmes use this technology, they may interact with one another without relying on the operating system in which they are running. These sensors, dubbed "healthcare sensors with gateway devices," are linked together so that fog worker nodes may receive data and jobs from them. Broker nodes are responsible for starting tasks and maintaining fog resources. A security manager can use techniques such as encryption, authentication, and blockchain technology to guarantee that the environment is both resilient and trustworthy. Furthermore, the proposed

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FogBus would leverage HTTP RESTful APIs to ensure that cloud environments could be smoothly integrated and connected.

The smart healthcare paradigm proposed involves several hardware and software components. In this part, both software and hardware will be dissected. As a starting point, we can consider sensors that collect data to be "environmental," "activity," and/or "medical." An ECG sensor is one of several medical instruments that include an ECG. Glucose and oxygen level sensors, respiration rate sensors, and temperature sensors are examples of other sensor types. Following that, the data is sent to gateway devices like smartphones, tablets, and desktop PCs. In addition to gathering data from a variety of sensors and processing the requests to the broker nodes for processing before any data can be delivered, the request input module must receive a "task request from gateway devices." Only then may the information be sent. In addition to guaranteeing secure connections between various components, a security management module may monitor and govern security. By protecting freshly received data against harmful alterations and unauthorized access, data integrity and system dependability may be increased. Data protection is the practice of safeguarding data from dangers such as unauthorized access, hostile user behavior, and device failure. The phrase is frequently used in ordinary conversation. People who are concerned about the security of their personal information are becoming increasingly common as people's dependence on computerised information systems grows. A few other operational disciplines are inextricably linked to the security of sensitive information. Information security may be jeopardized at any stage throughout the processing phase, depending on how each of these actions is carried out. This applies to both data transit and data input, as well as display, sequence management, and user guiding. But many applications must deal with problems, the most important of which is the need to protect user privacy. Without arbitration, the "resource management" job of the broker node would be incomplete. Based on the output, which is the load statistics of all worker nodes in the cluster, this module selects which worker nodes will be used to offer real-time jobs. The worker nodes send the results of their work to the gateway devices. The gateway devices route data to the worker nodes, which process it. In addition to speeding up data processing, the cloud-based data centre functions as an economical and effective storage option. When developing the model, the model considered the resources available in a cloud data centre. The fog infrastructure can withstand some delays as data processing volume grows, but it will ultimately run out of capacity. Feature extraction would be included as part of the planned intelligent healthcare system. Following that, a side-by-side comparison of the two is performed. Based on qualities detected in databases or cloud storage facilities for data, an appropriate prescription for medical tests and drugs can be issued automatically. In this method, the patient may be able to save some time and effort. The resource manager is comprised of two modules: arbitration and task management. The resource management system is made up of two parts. The arbitration module, which maintains task queues and job requests for data processing, may be used to mediate disputes between users. You may manage vast volumes of information by using the task management system. Workload management also includes the scheduling of cloud and fog resources, as well as the processing of queued workloads. The arbitration module handles cloud and fog resource scheduling. The broker, cloud data centre, fog worker node, or any of these three organisations can use fog computing's "arbitration module" to determine which piece of data they need to receive to fulfil their purpose. Broker nodes include modules like this one. It is feasible to distribute work among several devices to provide the greatest possible performance and load distribution.

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3.1 Scalability of the Framework

After the feature extraction step is complete, a CNN is used to train the deep learning module, which uses the dataset to identify "data points." It is the responsibility of the resource managers, who are also accountable for reducing the amount of data that is received from gateway devices, to generate a forecast that makes use of this data to provide superior support for the company's clientele. The patient's situation is finally disclosed as a long wait comes to an end.

3.2 Obtaining Data and Information

The suggested model was evaluated using data that was originally obtained by hand. Glucose sensors are vital pieces of medical equipment used to monitor diabetes patients' blood glucose levels. Diabetes types 1 and 2 are typically thought to be the most common. Blood glucose monitoring is the only way to diagnose cardiac problems. Diabetics are at risk for heart disease because their blood glucose levels are abnormally high, causing neuron and blood vessel damage. Diabetics are also more likely to develop heart disease than non-diabetics, even at a younger age. Slow breathing was shown to be adversely associated with heart rate variability (HRV), with HRV differentiations being substantially lower during slow breathing than during quick breathing. In contrast to quick breathing, slow breathing has a negative relationship with HRV. To identify whether there is a problem with the heart, a test that analyses the pace of breathing must be performed. A thermometer, often known as a temperature sensor, utilizes the patient's body as a reference to determine interior temperature. When the internal temperature of the body rises, the heart and blood flow more rapidly throughout the body. This needs a detailed investigation of the issue.

Sensors like this one are widely used in medical and biological applications. An EMG is required to provide a thorough picture of the health of nerve cells and muscles. Microvolts are typically used to represent the value of an EMG signal, which may range from 0.1 to 0.5 millivolts. ECG sensors are used to determine the heart's rhythm and rate: This information is widely utilized in diagnosing irregular heartbeats, enlarged hearts, coronary artery disease, and other disorders that may lead to heart failure. The use-case scenario includes patients in the critical care unit, their caregivers, and the attending physicians for those patients. Figure 1 shows how the procedure works. It is advised that only a few physicians collaborate under the supervision of an attendant. The primary role of the attendant would be to give appropriate medical care to all the physicians' patients. Figure 4 depicts interactions between the attendant, the patients, and the medical experts. The concept of fog computing offers the potential to provide a framework for social relationships between edge-based Internet of Things devices. Fog computing is mostly based on virtualization, which makes it possible to make fake things that can stand in for real Internet of Things devices.

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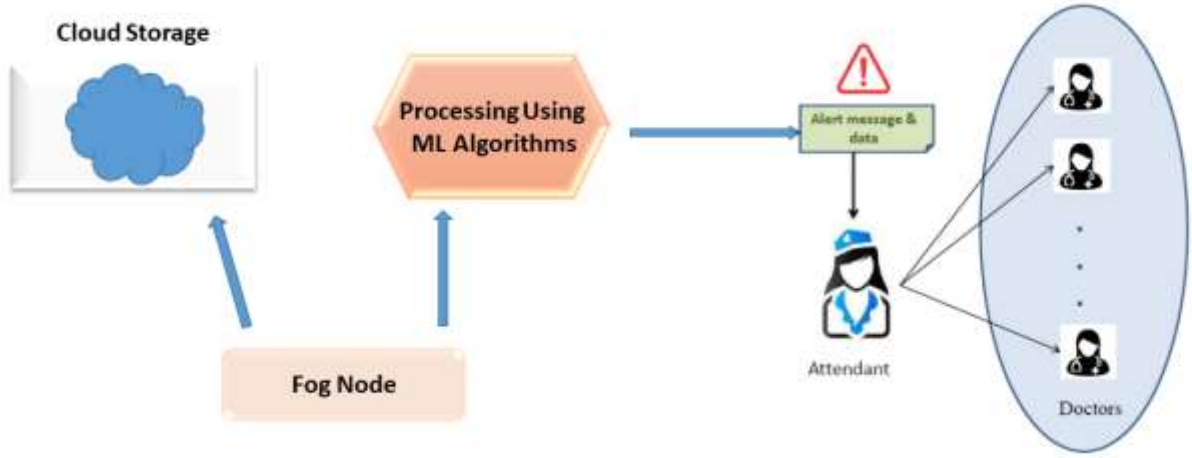

Figure 4. Fog Node and Processing of Data using Machine Learning

At any given moment, a patient in critical care may have more than one caregiver. Attendants oversee the patients' medical treatment and connect them with the appropriate medical professionals. The use of Internet of Things-connected devices allows for real-time data collection. The therapy delivered in an ICU necessitates the use of several monitoring equipment's. Several medical tools in the critical care unit can monitor the biometric parameters of patients getting therapy.

1. While doing continuous monitoring, the monitor displays the patient's temperature, ECG, blood pressure, and heart rate. In addition, the patient's oxygen saturation level is shown. Additional measurements, such as pressure in the central veins, pressure in the pulmonary arteries, and cardiac output, can be taken if the patient so wants. The data is relayed to the fog devices via clever devices. Real-time data is often only kept on fog devices for a short period of time, typically three to four hours. Figure 5 depicts a graphical depiction of the technique, which may be explored further by following this link.

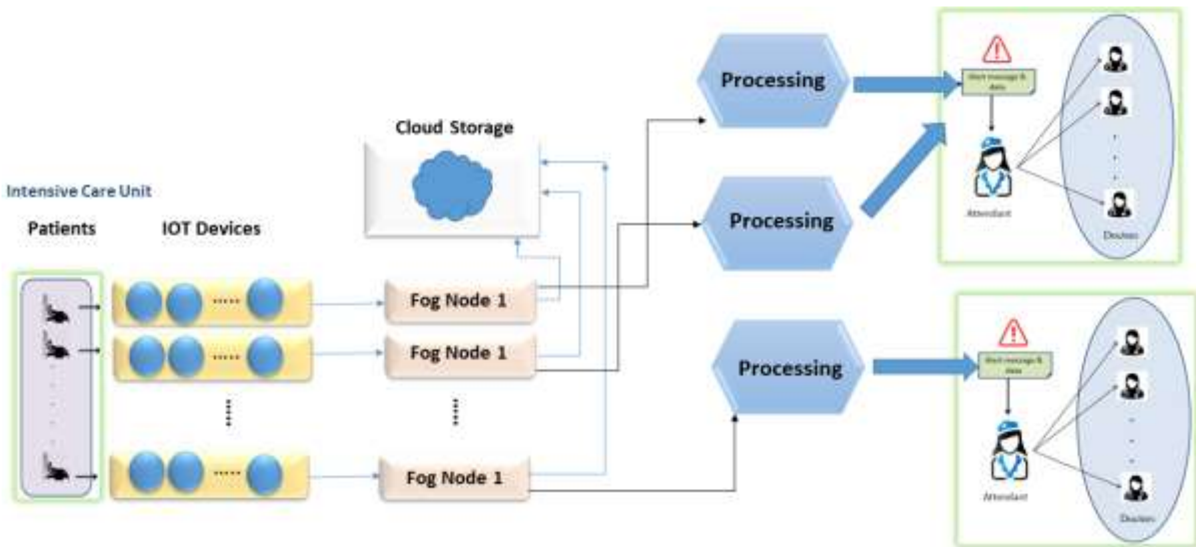

Figure 5. Processing of Data Through Multiple Fog Nodes

2. Due to the use of high-tech equipment, fog devices may be able to gather and transmit the patient's physiological indicators. These judgments may be based on the results of machine learning. Every fog device has the capacity to save a maximum of three hours of data. This

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enables the devices to analyze and determine if the physiological signs received in real-time indicate that the patient needs the attention of an attendant. As a result, it is now possible to examine and analyze physiological information in real-time. The attendant will receive a notification on their smartphone if the physiological signs and the true need for medical treatment are met. The alert will not only serve as a gentle reminder to keep a careful check on the patient, but it will also offer the most up-to-date information on the patient's physiological markers. It is the attendant's job to tell the attending physician if the patient is in a position that puts their life at risk. This technique is depicted visually in Figure 6, which may be found on this page.

3. Using blockchain technology to secure the flow of data, as soon as blockchain technology was established, efforts were made to use it to safeguard IoT devices. These attempts have been continuing since the invention of technology. Even though further research is required, several potential solutions have been presented. Using blockchain technology, our team has developed a whole new security system.

Almost every piece of monitoring equipment in modern critical care units can be linked to the internet and remotely monitored. A unique identification offers information about the manufacturer for each Internet of Things device launched in the last several years, including the model number and run number. Memory that is unchangeable in any form is required for the Internet of Things devices that we propose. On an Internet of Things device, a temperature-resistant memory can be used to store a private key and a public key that can be used to authenticate device ownership. This may be done to ensure that the device is indeed owned by the designated user. If desired, these keys can be used to demonstrate ownership of the device in the issue. The public key for every approved Internet of Things device is now widely available to the public. Because of technological advancements, it is now possible to check the validity of the digital signature attached to each data packet transferred from an Internet of Things device to a fog-based device. If fog devices have access to the Blockchain's public key, they will be able to verify the accuracy of the data they gather.

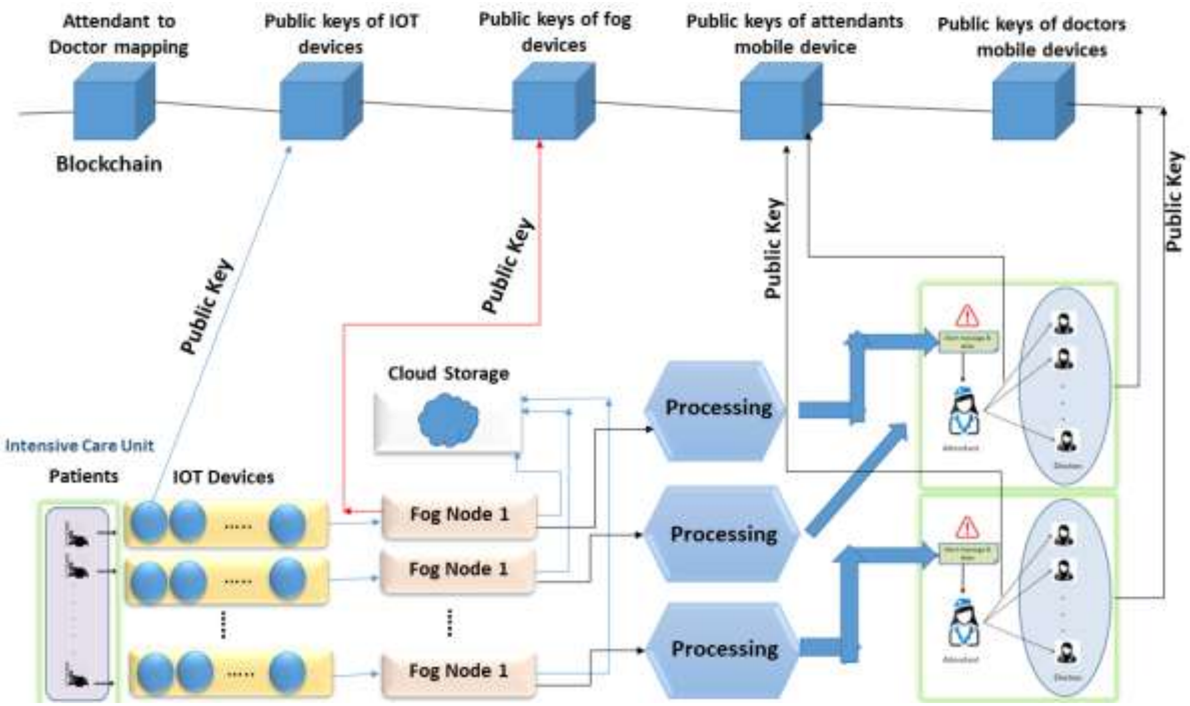

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Figure 6. Blockchain and Fog Nodes Integration for Security

A private and public key pair is assigned to each fog node, as well as the mobile devices used by attendants and physicians, in a manner like this. Only when the data from fog nodes can be validated can a digitally signed warning message reach mobile device. This must be handled by mobile devices. A digitally signed warning message cannot be transmitted to a mobile device that is not connected to the Internet. After that, fog nodes will be able to send and receive messages. A public key stored on the blockchain will be used to authenticate an alert message sent to guests' mobile devices. Check that the message has not been tampered with in any way. With this technique of communication, ensure that the message is received in its entirety.

A similar digital signature is used to digitally sign the alarm messages so that they may be transferred from the attendant's phone when the phone's private key is utilized. To validate the legality and completeness of the message conveyed by the doctor's mobile device, the receiver must be able to access the public key kept on the doctor's mobile device. The proposed framework technique is split down into its component elements and illustrated in this section.

IoT gadgets that are connected to the internet in intensive care units, IoT-connected equipment capture real-time patient data. Using this framework, you may provide unique IDs to a set of Internet of Things devices that conform to the "IOT XY" structure. This is how the patient's identity number, denoted by X, and the Internet of Things device's identification number, designated by Y, are represented. This will allow the proper patient to be paired with the corresponding set of IoT devices. As a result, the ID "IOT 21" is used to identify the patient's first Internet of Things device, and the patient referred to in this statement is the one who was placed in bed number 2.

As previously mentioned, every piece of hardware connected to the internet of things will be supplied with a pair of private and public Elliptic Curve (EC) keys. This contrasts with the Blockchain, which stores all private keys. On the other hand, the Blockchain stores both the public key PbK IOT XY and the transaction's one-of-a-kind identifier, which is written as "IOT XY," for every single transaction. Because the identification of "IOT XYunique" is recorded on the Blockchain, it is not susceptible to modification. This protects the data by limiting access to just those individuals who have been granted permission to view or alter the data. The goal of this section of the essay is to offer a short explanation of, as well as an illustration of, the possible functioning of the framework that we have described, if it were really put into reality.

What caused the fog? In "fog computing," a data source and cloud service distribute data, processing, storage, and application workloads. This sort of setup is also known as "cloud computing." This type of system is commonly referred to as "hybrid cloud computing." This sort of setting is commonly referred to as "fog computing." The many elements that make up this environment are referred to as fog nodes. The data pertaining to each individual patient is kept and processed in a fog node that was developed expressly for the purpose of completing these tasks in the fashion that we have indicated. Each fog node has its own distinct identity, beginning with the prefix "F x," which helps to distinguish it from the others. In addition, each fog device keeps a private key and a public key for an elliptic curve in its internal memory. The fog node "F X" is the unique identifier for the public key PbK F X, which is kept in a temperature-resistant memory area. The blockchain also keeps track of the public key PbK F X. By storing both keys in the same location, you can assure their protection. To digitally sign

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the message broadcast by the fog device, an Elliptic Curve Signature Algorithm (ECDSA) application was employed [13].

In accordance with the previously established paradigm, CNN [26] is used in the process of predicting the cardiac state. It not only processes the signals, but it also processes the data. This enhancement was made possible thanks to the cooperation of GSO. As a result, cardiac abnormalities might be diagnosed more easily, and the key aim is to maximize prediction rate while minimizing the error rate. CNN is built by superimposing several CNN methods on top of one another. "CNNs" is an acronym for feed-forward neural networks that contain convolutional, pooling, and fully connected layers. CNNs are usually referred to by the abbreviation "CNN." CNN uses features like pooling, weight sharing, and a more localized perspective to demonstrate the specific structure of its organization. To produce a feature map, a convolution kernal is initially applied to a relatively small rectangular section of the input data, and then local perception is considered throughout the process. This operation is performed at this location. Everything happens in the space inhabited by the info that has been presented to us. A convolution kernel's weight-sharing function allows you to distribute biases and weights in a way that is unique to each feature map. There are several ways available for limiting the quantity of data received from a feature map, such as using a descending sampling approach or pooling [37-40]. The maximum pooling method and the average pooling method both function by assigning a single value to all the feature map's small regions. The maximum or average value of the map determines this value. Following that, the data is compressed to the smallest amount possible while retaining the integrity of the extracted properties (or attributes).

The output of the network layers is finally reduced to a vector with a single dimension after a sequence of convolutional and max-pooling layers. When a new input is introduced to an existing network that is already connected, this procedure begins. The final product is the result of a method that has been divided into several phases or levels. Each layer, as well as the totality of the connections, is used at each stage of the categorization process. Previous research has shown that CNNs with smaller convolution kernels perform better in image recognition. This was demonstrated in both training and inference. The convolution kernel, with a size of one, employs cross-channel aggregation to minimize the number of parameters and the dimensionality of the problem. This reduces the reliability of the identification process, which is a disadvantage. Furthermore, there are issues with overfitting and fading gradients that must be addressed.

The calculation in the fog node does not begin until the patient has been transported to the critical care unit, which takes another two to three hours. This is according to the research we proposed. While doing so, a machine learning model is built using the physiological signal data collected during the early morning hours. Throughout this procedure, the model's constraints are also considered [29-30]. The same amount of time is spent on analysing the model to see if it meets the requirements. As soon as the model is trained, a newly formed fog node will begin receiving input indicating "attention required" or "attention not required." This initial step must be performed for subsequent stages to be carried out in a manner appropriate to the category into which they fall.

Data is stored in fog nodes for a maximum of three hours after it is sent there. A Raspberry Pi 3 may be converted into a fog node, allowing it to interface with other IoT devices and sensors.

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The most recent three-hour data period is gathered to feed the machine learning model with the most recent three hours' worth of data. The model will be updated every three hours beginning in a few minutes. Because this is the case, you may continue to use the previously trained model even while new training is taking place. This is because the prior instruction was effective. Due to the reduced time necessary for re-training, two distinct models will be working concurrently. Following the completion of the refresher training, the older version will be phased out in favour of the current one. Everything relating to the fog mode has been upgraded successfully, and it is now assured to remain secure for the foreseeable future.

If a person is healthy, their biometric data should all be within the permissible limits for their respective categories. It is exceedingly harmful for a patient's heart rate to fall below the recommended range of 70 to 110 beats per minute, which is equivalent to 20 to 30 beats per minute. Life-threatening heart rates are below 50 or above 120, Blood pressure functions as an engine to pump blood through a person's circulatory system. This picture can help to explain blood pressure. In this case, the unit of measurement is millimetres of mercury, which is represented by two numbers (mmHg). The systolic blood pressure reading is represented by the first number on a blood pressure scale, sometimes known as the top number. It is possible for a person's blood pressure to reach this level if they have a considerably faster heart rate than normal. This is the sole feasible outcome in each one of these scenarios. It is the lowest level of blood pressure that a person's heart can sustain when at rest between beats, which is known as diastolic pressure. This is the lowest amount of blood pressure that a human being blood pressure may achieve. This is the very lowest blood pressure level that can be obtained. The diastolic blood pressure is indicated by the second number in the blood pressure measurement. This number can be seen at the bottom of the blood pressure measurement. A healthy blood pressure range is between 120 and 80 millimetres of mercury (120/80); thus, a healthy person should have a reading that falls somewhere in that range. When a person is young (between the ages of 20 and 30), their blood pressure should be between 150 and 100 over 100 (150/100), also written as 150 over 100. When a man is in the middle of his life, a blood pressure measurement between 150 and 100 millimetres of mercury (150/100) is considered normal. A person's blood pressure is often measured using a variety of criteria, including age, gender, and race. Patients with a systolic blood pressure of more than 200 mmHg are more likely to suffer a stroke. When a patient's systolic blood pressure is less than or equal to 90 millimetres of mercury, hypotension is diagnosed.

The quantity of oxygen in the blood is referred to as "saturation of oxygen in peripheral capillaries" (abbreviated as "SpO2"). It is also known as "peripheral capillary saturation." Sp02 represents oxygenated haemoglobin as a proportion of total blood haemoglobin, which includes both oxygenated and non-oxygenated haemoglobin. The symbol does not represent nonoxygenated haemoglobin (haemoglobin containing oxygen). If the Sp02 is in outstanding condition, expect to receive between 95% and 100% of the original purchase price. Because Sp02 was not damaged in any manner, we may presume that this is accurate. If a patient's oxygen saturation level falls below 70%, medics must act promptly; however, if the level falls below 50%, the patient is dead. If your SpO2 level is less than 70% of normal, seek emergency medical assistance.

A person's core temperature is affected by their age, the amount of physical activity they engage in each day, and the time of day. In contrast, a person's body temperature remains generally stable throughout his or her life. According to most doctors and other medical experts, a healthy

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individual should have a body temperature of 98.6 degrees Fahrenheit (37C). According to the findings of several research, a person's body temperature can range from 97 to 99 degrees Fahrenheit on average. If a patient's temperature is determined to be outside of this range, he or she must receive emergency medical attention as quickly as possible.

Depending on the circumstances, any of these factors can function as either an independent or a dependent variable in an analysis. A system was developed to allocate computing resources among the fog nodes and to make decisions using machine learning algorithms while keeping the previously stated constraints in mind. As a rule, we recommend adopting the Naive Bayes Classifier classification strategy for two-class categorization. In this technique, physical signals are presumed to be independent variables. We have chosen this path because we are confident in our capacity to tackle the difficulties ahead. As a result, it is acceptable to recognize body signals that do not act in tandem. When physiological data do not behave as entirely independent variables, we recommend logistic regression as a classification strategy. However, there are a few negatives to consider. For example, logistic regression requires that the independent variables have little to no multi-collinearity. This implies that there should be little connection between the variables. Logistic regression also involves the assumption that the independent variables are linear. Because the processing is done on fog devices, which have restricted capabilities, various categorization techniques can be used. Therefore, the procedure should not necessitate a large amount of computing power. To avoid employing deep neural networks, for this reason, one should do so at all costs. In the healthcare industry, data gathering techniques such as questionnaires, in-person patient interviews, and medical record checks are often used. Today, the majority of data collection occurs online, and numerous programs are used during a single market study.

4. Results

Blockchain, one of the most advanced technologies of our time, is being employed in a variety of industries. One of these worries is the internet of things.

A. Authorization

Only mobile devices, IoT equipment, and fog gadgets certified by the appropriate medical authorities will be kept on the Blockchain. Because Blockchain is immutable, an external entity cannot change the list of allowed devices. As a result of this development, contraband devices are now much easier to discover.

B. Authentication

Every data packet received from an Internet of Things device is validated by a fog device. Each data packet is digitally signed using the IoT device's private key. As a result, the transaction's public key may be used to validate its legality. Transaction validation is the process of assessing whether or not a transaction meets the conditions for being considered legitimate. Before transactions are added to the distributed ledger, they are checked by validators to make sure they meet the protocol's rules.

C. The claim's non-repudiation

Nonrepudiation does not exist if someone cannot say that they signed a communication while keeping their private key confidential. This is because non-repudiation requires that this not occur. Our technique includes the use of a digital signature, which provides non-repudiation.

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D. Sincerity

Using the approach, we've recommended; that a digital signature is appended to each message and data packet sent between devices. A digital signature is a mathematical method that may be used to confirm the authenticity of a digital document, computer programme, or communication. Digital signatures are becoming more common. It works the same way as a real-world signature or stamp, but in the digital world, and it adds another layer of security. A digital signature may be used to authenticate both the data and the communication. The bulk of digital signatures uses hashing technique. To complete the verification method, the sender must provide confirmation that they signed the correct hash over the contents.

4.1 The efficacy of classifiers

A "heart disease prediction model" comprised of many classifiers, NPV (probability) and F1-scores (precision and accuracy) are the values (specificity). By adjusting the "learning percentages," current classifiers may evaluate the smart heart disease, prediction model. This validates the idea. For all performance criteria, the proposed model has a higher prediction rate and a lower error rate. This method is more accurate than DNN (95.09%), RNN 94.77%), LSTM (94.55%), WOA (95.92) and the proposed Model (97.99%). On every performance metric, the proposed model beat the others, resulting in a promising smart heart disease prediction model. On all performance metrics, the proposed model beat all other classifiers.

Table 1. Traditional Methods are being used to compare the smart healthcare model with the Proposed Model

Measures	**Deep Neural Networks**	**Recurrent Neural Network**	**Long short-term memory**	**whale optimization algorithm**	**The Proposed Model**
Accuracy	0.9509	0.9477	0.9455	0.9592	0.9799
Sensitivity	0.9473	0.9375	0.9309	0.9537	0.96594
Specificity	0.9565	0.9579	0.959	0.9047	0.9836
Precision	0.95599	0.95679	0.95766	0.92259	0.99088
False Positive Rate	0.0657	0.0643	0.063	0.0975	0.0386
False Negative Rate	0.0749	0.0847	0.0893	0.0085	0.076278
Net Present Value	0.9565	0.9579	0.959	0.9047	0.9836
False Discovery Rate	0.066208	0.065409	0.064565	0.099633	0.029345
F2-score	0.95064	0.94696	0.9446	0.96042	0.96836
Matthew's correlation coefficient	0.99275	0.98449	0.97923	0.99988	0.99945

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Tables 1 investigates the efficacy of the suggested smart healthcare paradigm, which makes use of IoT-assisted fog computing. Smart healthcare is more efficient and yields better results than earlier methods. The model employs cutting-edge technology.

5. Conclusion

This research suggests intelligent medical care based on the edge, fog, and cloud computing. To collect model data, many types of equipment were used. This was done to understand more about those characteristics. With fog computing and IoT, smart healthcare has been a success. Complex optimization, feature selection, and classification algorithms may improve heart disease prediction soon. This also benefits real-time programs because to our suggested design, patients in the intensive care unit may now be better and more securely monitored. The suggested model has a greater prediction rate and a lower error rate for all performance criteria. DNN, RNN, LSTM, WOA, and the suggested model are all more accurate than this technique (95.09 percent) (97.99 percent). It was found that the suggested model outperformed the competition on all performance metrics, making it a viable tool for early detection of heart disease in the population at large. On every metric, the suggested model outperformed the competition. The approach helps everyone in the critical care unit, not only the physicians and patients. IoT sensors capture real-time physiological data and send it to fog nodes for analysis. This information is then analyzed. When assessing whether a certain patient needs immediate attention from a caregiver, nodes in the fog using several machine learning methods. The attendant is informed if the reaction is good or negative. Any additional requirements that the patient may have will be communicated to the doctor in charge of the case by the attendant. The usage of blockchain technology provides the system's complete security. One flaw in the design is that it expects all patients would be seen by the same doctor, which isn't always the case. Aside from that, the framework must be implemented, and this concept must be researched further.

Dataset

The dataset has been collected through the tweepy library using Python and it will be provided on request.

Conflicts of Interest

No potential conflict of interest was reported by the authors.

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