



## Secure Honeynet Cloud IoT Model and Machine Learning based Smart Healthcare System with Urban Management

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### Abstract

Smart health is becoming an increasingly sensitive field because to the growing use of a variety of Internet of Medical Things (IoMT) devices as well as apps. IoMT is a well-liked technique for developing smart city solutions that eventually improve critical infrastructures, such smart healthcare. Numerous IoMT devices in smart cities employ Bluetooth technology for short-range communication because it is adaptable and resource-efficient. This research proposes novel method in urban planning in smart public healthcare system utilizing ML algorithms. The smart healthcare system is developed based on secure honeynet cloud IoT model. Here the input smart healthcare-based health monitoring data is collected and processed for missing value removal and noise removal. Then this data classified and optimized using recurrent Bi-LSTM temporal Gaussian model with whale swarm particle colony optimization. Experimental analysis is carried out in terms of detection accuracy, precision, data integrity, throughput, recall, latency. Proposed technique obtained 96% of Detection accuracy, 97% of Precision, 95% of Throughput, 88% of RECALL, 94% of LATENCY.

**Keywords:** Secure honeynet; Cloud IoT model; Machine learning algorithms; Health monitoring; Particle colony optimization

### 1. Introduction

Health is without a doubt most important part of existence. A rise in diseases and population expansion in recent years has led to a huge need for improved healthcare systems, which in turn calls for a large number of clinical resources and even hospital personnel. Since traditional healthcare systems are unable to meet needs of all people due to their high cost and limited accessibility, it presents a significant challenge to the outstanding services that computerized

health systems provide to both patients and hospital workers. Early in the 1990s, medical advancements were made; field was seen to be fully developed in terms of treatment [1]. Agile treatment, appropriate early patient servicing, remote delivery and monitoring of healthcare services, prompt response to emergency situations are only a few examples of ways that healthcare systems have changed since then. The requirement for new, effective equipment to provide patients with the greatest care was the main obstacle faced as the medical field developed. Using IoT and evolutionary technologies can help solve this problem. The use of IoT in medical field has grown in popularity, following contemporary strategies such as smart gadgets, smart cities, and smart regions. In order to enhance quality of therapy and conduct primary illness evaluation, it has been imperative in recent years to digitize generated data with assistance of healthcare institutions. Reducing risk factors and organizing hospital data in best possible way are two most important tasks [2]. By providing the acquired medical data, a descriptive insight is produced based on the significant diagnosis with clinical data, improving effectiveness of medical systems and identifying performance. These days, the healthcare sector makes use of several cutting-edge methods, such as blockchain, augmented reality, virtual reality, and robotics. According to reports, big data is a popular strategy in the medical industry, which includes numerous significant datasets that seem to be too big and difficult for medical professionals to calculate and understand with conventional methods. The iterative approach improves outcomes and boosts the efficiency of using medical data [3]. However, key healthcare services, like primary illness identification, prevention, and enhanced disease control, are very challenging to deliver due to the inverted age pyramid, rapid population expansion, and paradigm shift. As a result, a given dataset's volume makes it impossible to do the computation with big data quality. Accurate outcomes and the resolution of complicated health problems are two other uses for machine learning. For the machine learning models to function well, the most multifaceted and correct data must be produced. IoMT has an impact on medical devices and healthcare items that save useful data in order to produce massive amounts of data for machine learning algorithms [4]. Below are a few of the machine learning algorithms' drawbacks. It might need a lot of processing power, and its accuracy is only mediocre. A data-driven security framework is not necessary. It is unable to foresee unidentified attacks. However, they have been negatively impacted by the growing amount and complexity of medical data, which are resolved with DL methods [5].

## **2. Literature review**

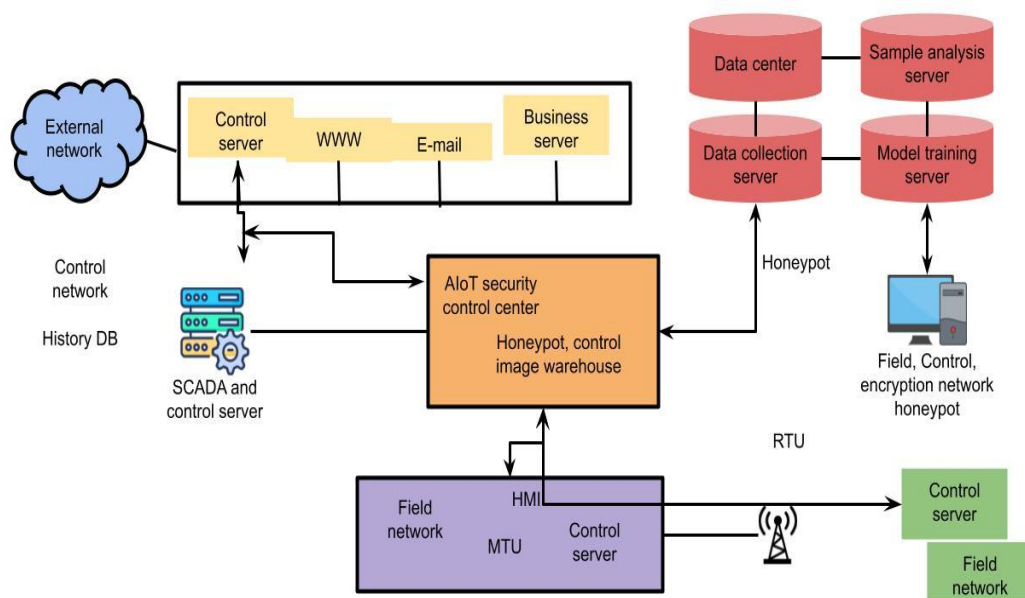
Importance of IoT as well as ML in creating a data-centric smart environment has been the subject of numerous recent research. Work [6] examined privacy and security concerns with IoT applications in smart cities and found solutions. In [7], the authors examine smart city systems in their entirety and talk about how a smart healthcare system works for the healthcare industry and interacts and cooperates with smart city infrastructure. Authors also evaluate a number of case studies as well as offer suggestions for leveraging smart healthcare technologies to create a more potent, integrated, efficient system. [8] conducted a thorough survey study outlining IoT technology for smart cities as well as the key elements as well as characteristics of a smart city. Writers also discussed the difficulties and real world experiences that implementers worldwide encounter. In order to make smart cities smarter in terms of data collection, privacy, security, public safety, disaster management, energy consumption, quality of life, author [9] carried out a thorough analysis of various methods as well as applications of collaborative drones with IoT that are used recently. A thorough evaluation of use of ML techniques for big data analysis in intelligent healthcare methods was provided by Work [10].

Authors also listed several benefits and drawbacks of the existing methods, with a focus on the research problems in this field. Author proposed a paradigm for an intelligent health monitoring method based on fog computing [11]. By addressing fundamental issues with a clinic-centric healthcare system, the suggested architecture intends to transform it into an intelligent patient-centric healthcare system. An accuracy of 86% is demonstrated by a method for identifying heart illness that combines interval type-2 fuzzy logic with rough sets-based attribute reduction using the chaotic firefly method. An 88.7% performance accuracy is demonstrated by a ML hybrid method that predicts heart disease [12] by merging random forest (RM) and linear method (LM) techniques [13]. A  $\chi^2$  statistical model is recommended for feature refinement in a smart system for detecting heart disease, whereas a DNN is recommended for classification jobs. The model achieves 91.57% accuracy, 93.12% specificity, and 89.78% sensitivity, respectively [14]. Method for determining risk level for heart disease is provided that is based on adaptive weighted fuzzy rules. The accuracy of this genetic algorithm-based automatic diagnostic system for fuzzy models, which uses a modified dynamic multi-swarm particle optimisation technique, is 92.3% [15]. The authors [16, 17] had implemented a heart disease prediction using ML methods. They have considered some measures to minimize incidence of chronic diseases in patients. Age, sex, zodiac sign, daily cigarette consumption, and additional medical information serve as inputs, which are subsequently modeled for predictive analysis. The prediction of heart conditions is one of the most formidable

challenges in the medical sector today. Currently, heart disease affects one individual for every four persons. A substantial volume of data is analyzed in healthcare sector with ML.

### 3. Proposed smart healthcare system based on secure honeynet cloud IoT model

As seen in Fig. 1, we created overall system architecture. Standard IIoT architecture is expanded by three components in our concept. Here are the specifics. 1) Security Control Centre for AIoT (ASCC). Situational awareness, security threat monitoring, and honeynet control are the main duties of the ASCC. Below is an explanation of the three nodes that comprise the ASCC. a. Honeynet control master, or HCM. HCM is primarily in charge of overseeing and communicating with HoneyNet nodes: HoneyNet is made up of separate devices that are all part of a larger HoneyNet system. The HCM is in charge of setting up HoneyNet's infrastructure, deploying honeypot, starting or stopping it, uploading logs. b. HIW stands for HoneyNet Image Warehouse. Managing and storing honeypot photos is mostly the responsibility of the HIM. c. The Monitor Server. Situational awareness and threat detection make up the other component. To identify risks on real data, the server makes use of a DL model that has been developed by the data center's model training server.



**Figure 1.** Proposed secure honeynet cloud IoT model

2) HoneyNet. Finding various dangerous apps and malicious behaviors in AIoT is HoneyNet's primary purpose. Three kinds of honeypots listed below are all part of HoneyNet. a. Honeypot for Enterprise Networks (ENH). Finding and capturing harmful code and behaviors within company network is the primary responsibility of the ENH. b. Honeypot for Control Networks (CNH). The CNH is principally in charge of identifying and capturing harmful code, inappropriate behaviours, and malicious instructions within control network. c. Field Networks Honeypot (FNH). Finding and recording hostile activity and malicious instructions within field network is primarily responsibility of FNH. 3) The data centre, or DC. The DC's main responsibility is to collect data from HoneyNet, including malicious activity, malicious instructions, and malicious code, and then preprocess this data to produce training samples. Produced samples are utilized to train a CNN DL method. As explained below, DC consists of two primary nodes. a. Server for Data Collection (DCS). DCS is primarily in charge of gathering information and restoring source logs that the honeypot has erased. The Hadoop Distributed File System is where the gathered data is kept. c. The SAS, or Sample Analysis Server. SAS is primarily in charge of compiling and combining the logs that different honeypots have gathered. Along with data features, important details are collected, including ports, numbers, attacker IP addresses, attack pathways, requested content, vulnerability fingerprints, malicious sample server IP addresses. b. MTS, or Model Training Server. Training modules are the main responsibility of MTS.

### 4. Recurrent Bi-LSTM temporal Gaussian model with whale swarm particle colony optimization (RBTG-WSPCO)

For practical monitoring in the event of medical emergencies such as diabetes, heart attacks, asthma, and so on, IoT-connected devices are essential. These medical gadgets can be utilized for clinical operations and workflow management in the healthcare sector due to their remote locations. To guarantee that patients receive quality care, they use sensors and other connected equipment. Two advantages of the big data analytics approach are the ability to forecast preventable diseases and epidemics as well as improve quality of healthcare. In order to make an informed decision about a health condition, data is also analyzed, patterns are found, and those patterns are learned using deep structured architectures and expert systems. This lowers risk and guarantees patient safety by accurately detecting at the appropriate time.

The provided text segment or sentence,  $s = \{s_1, s_2, \dots, s_n\}$ , can be regarded as a token sequence. An LSTM unit using embedding  $x_t$  of every token  $s_t$  as input produces the hidden state  $h'_t$ , which is determined by Equation 1. In this case,  $h'_t$  records both the information of token  $s_t$  and its predecessors. Another LSTM unit computing in opposite direction also generates a counterpart  $h''_t$  of  $h'_t$  to collect information of its successors. All of the tokens' final representation sequence,  $h = \{h_1, h_2, \dots, h_n\}$ , is created by first concatenating  $h'_t$  and  $h''_t$ , reducing dimension to  $n$  ( $h$ ) via a compositional operation. It is possible to formulate this process as

$$h_t = \tanh(W_1 \cdot (h'_t \oplus h''_t) + b_1)$$

According to the borders of the target entities, we split the token representation sequence  $h$  into five sections in the next step: before, former, middle, latter, and after. We generate five representations that correspond to the five parts by applying the four standard pooling functions (max, min, average, and std) to the token representations of each part, respectively. The previous entity representation  $r$  former, for instance, can be calculated by

$$r_{\max} = \max_{1 \leq k \leq K} h_{kj}$$

$$r_{\min} = \min_{1 \leq k \leq K} h_{kj}$$

$$r_{\text{avg}} = \frac{1}{K} \sum_{1 \leq k \leq K} h_{kj}$$

$$r_{\text{std}} = \sqrt{\sum_{1 \leq k \leq K} h_{kj}^2}$$

$$r_{\text{former}} = r_{\max} \oplus r_{\min} \oplus r_{\text{avg}} \oplus r_{\text{std}}$$

where it is presumed that the former entity begins at first token and finishes at  $K$ th token.  $j$ -th element of  $k$ -th token representation vector is indicated by symbol  $h_{kj}$ .  $j$ -th components of representation vectors produced by respective pooling functions are shown by symbols  $r_{\max j}$ ,  $r_{\min j}$ ,  $r_{\text{avg} j}$ ,  $r_{\text{std} j}$ . In order to choose relation type with highest probability, output layer lastly computes probabilities of each relation type.  $i$ -th relation type  $R_i$ 's probability is calculated by

$$p(R_i) = \text{softmax}(R_i) = \frac{e^{w_{2i} \cdot x_{\text{penut}}}}{\sum_{j=1}^{|R|} e^{w_{2j} \cdot x_{\text{penut}}}}$$

where  $w_{2i}$  is the output layer's  $i$ -th row of parameter matrix  $W_2$ . Covariance matrix should capture the similarity between data points and is only dependent on the input attributes. The covariance design is extremely important when the data are structured, meaning they show a specific structure. Scaled anisotropic Gaussian kernel function is a popular and incredibly adaptable kernel function.

$$k_1(\mathbf{x}_i, \mathbf{x}_j) = \text{vexp} \left( - \sum_{f=1}^F \frac{(x_i^f - x_j^f)^2}{2\sigma_f^2} \right) + \sigma_n^2 \delta_{ij}$$

The hyperparameters gathered in  $\theta = \{v, \sigma_1, \dots, \sigma_F, \sigma_n\}$  thereby fully parameterize this covariance. We use the squared exponential as the stationary covariance operating on time variable  $z(t) = [\cos(t), \sin(t)]^T$ , which is mapped to a 2-D periodic space, as described in

$$k(t_i, t_j) = \exp\left(-\frac{\|\mathbf{z}(t_i) - \mathbf{z}(t_j)\|^2}{2\sigma_t^2}\right)$$

which results in the periodic covariance function that follows:

$$k(t_i, t_j) = \exp\left(-\frac{2\sin^2[(t_i - t_j)/2]}{\sigma_t^2}\right)$$

where  $\sigma_t$  is a hyperparameter that must be estimated and characterizes the periodic scale. The seasonal trend's exact periodicity is unclear, so we adjust this equation by adding a squared exponential component to allow for a degradation away from exact periodicity, i.e.,

$$k_2(t_i, t_j) = \gamma \exp\left(-\frac{2\sin^2[\pi(t_i - t_j)]}{\sigma_t^2} - \frac{(t_i - t_j)^2}{2\sigma_d^2}\right)$$

where the period has been set at one year,  $\gamma$  indicates the magnitude,  $\sigma_t$  indicates the periodic component's smoothness, and  $\sigma_d$  indicates the periodic component's decay time. Consequently, our final covariance can be written as

$$k([\mathbf{x}_i, t_i], [\mathbf{x}_j, t_j]) = k_1(\mathbf{x}_i, \mathbf{x}_j) + k_2(t_i, t_j)$$

While the exploitation phase oversees the local search, exploration phase guarantees that design space is searched worldwide by randomly choosing beluga whales. Furthermore, BWO modifies beluga whale postures by considering the possibility of whale falls. Beluga whales are considered search agents due to BWO's population-based technique. Every beluga whale represents a possible solution that is altered throughout optimization procedure. The search agents' positions are based on the beluga whales' pair swim, beluga whale positions are updated as follows:

$$\begin{cases} X_{i,j}^{T+1} = X_{i,p_j}^T + (X_{r,A_1}^T - X_{i,p_j}^T)(1 + r_1)\sin(2\pi r_2), & j = \text{even} \\ X_{i,j}^{T+1} = X_{i,p_j}^T + (X_{r,A_1}^T - X_{i,p_j}^T)(1 + r_1)\cos(2\pi r_2), & j = \text{odd} \end{cases}$$

Two random values,  $r_1$  and  $r_2$ , are utilized to improve random operators throughout exploration stage. Accurately locating the global optima is substantially aided by WSA's strong local search capacity and good population diversity preservation. WSA updates a whale  $X$ 's position based on its "better and nearest" whale  $Y$  using following formula.

$$x_i^{t+1} = x_i^t + \text{rand}(0, \rho_0 \cdot e^{-\eta \cdot dX,Y}) * (y_i^t - x_i^t)$$

The ultrasonic source's intensity,  $\rho_0$ , can be set to 2 in practically all situations. The natural constant is represented by  $e$ . The attenuation coefficient is denoted by  $\eta$ . Euclidean distance between  $X$  and  $Y$  is denoted by  $dX,Y$ . A random number generated uniformly between 0 and  $\rho_0 \cdot e^{-\eta \cdot dX,Y}$  is indicated by  $\text{rand}(0, \rho_0 \cdot e^{-\eta \cdot dX,Y})$ . When guided by its "better and nearest" whale, which is positioned locally, a whale would travel randomly and favorably; when guided by that whale, which is placed relatively far away, it would travel randomly and unfavorably, according to Equation 10. Each particle records where its most recent peak performance, or  $pbest$ , occurred.  $Gbest$  represents swarm's best performance to date. Following definition applies to current velocity of  $i$ th particle's  $d$ th dimension at iteration  $t$ :

$$v_i^d(t) = w \times v_i^d(t) + c_1 \times \text{rnd} \times (pbest_i^d - x_i^d(t-1)) + c_2 \times \text{rnd} \times (gbest^d - x_i^d(t-1))$$

$$v_i^d \in [-v_{\max}, v_{\max}]$$

$\text{Rnd}$  is a random function in interval  $[0,1]$  in formula above.  $W$  is the inertia weight, while the positive constants  $c_1$  and  $c_2$  stand for the social and personal learning components, respectively. Local exploitation and global exploration are balanced by inertia weight. With  $v_{\max}$  as a predetermined boundary value, velocity is limited to  $[-v_{\max}, v_{\max}]$  range. Resolution of search regions between current as well as target positions is determined by the value of  $v_{\max}$ . In each dimension,  $v_{\max}$  should be set between 10 and 20 percent of the variable's dynamic range. The following formula is used to determine a particle's new position:

$$x_i^d(t) = x_i^d(t-1) + v_i^d(t)$$

Length of a solution is determined by multiplying number of clusters by the dataset's dimensions. When assessing value of clustering, objective function is specified as

$$f = \frac{\sum_{k=1}^{N_c} \sum_{i=1}^{N_s} \min \|X_i - C_k\|^2}{\sum_{k,j=1; k \neq j}^{N_c} d(C_k, C_j)}$$

where  $\|X_i - C_k\|$ ,  $N_c$  = number of centers, and  $N_s$  = sample sized( $C_k, C_j$ ) = distance between center  $k$  and center  $j$ , and  $2 =$  distance between sample  $i$  and center  $k$ . The intra-cluster distance is calculated as the sum of all pairwise distances between cluster sites and cluster center. A lower value for  $f$  indicates that clusters should be compact, with cluster centers widely separated, for the best clustering. Every variable is scaled prior to clustering. In general, the following formula can be used to linearly scale each variable to the interval  $[0,1]$ :

$$x^{new} = \frac{x - \min(x)}{\max(x) - \min(x)}$$

where  $\min(x)$  and  $\max(x)$  are the variable  $x$ 's minimal and maximum values,  $x^{new}$  represents variable  $x$ 's scaled value. The pheromone-particle's inferior solutions are swapped out for better ones from  $K$  new particles and  $M$  new ants. Main difference between sequential as well as parallel techniques is how they update pheromone particle database.

**5. Experimental analysis**

**Simulation setup-** A PC with an Intel Core i5-8300H CPU running at 2.3 GHz, a GeForce GTX 1050 GPU, 8 GB of RAM, Windows 10 as operating system was utilized to carry out the experiment. The Python Software Foundation developed Python 3.6, the programming language, and the NVIDIA Corporation developed CUDA 10.2.

**Dataset description-** The two standard datasets—the "Mhealth dataset" and the "UCI-HAR dataset"—from which the necessary dataset for health monitoring is gathered are described in detail below.

**Mhealth dataset:** It contains recordings of ten volunteers' bodily motions and vital signs taken while they were engaging in specific physical activities. In order to capture the "acceleration, rate of turn, and magnetic field orientation," sensors are affixed to various body parts.

**UCI-HAR dataset:** A smartphone is attached to the waist of 30 participants, and their bodily activity are monitored while they execute six distinct actions: "walking, walking upstairs, and walking downstairs, sitting, standing, and laying."  $BD_{cld} v$  represents the collected data from two datasets, where  $v = 1,2,\dots, V$  and  $V$  represents the total quantity of health data collected.

"Pima Indians Diabetes Database (PIMA)"- "<https://www.kaggle.com/uciml/pima-indians-diabetes-database>: access date: 2022-02-03" is the source of this dataset. According to the specific diagnostic calculations, this is used to focus on the people who have diabetes. The instances were selected from the large database using a variety of restrictions. This dataset includes multiple outcomes of medical predictor variables along with a single target variable.

**6. Comparative analysis**

**Table 1:** Comparative analysis for MHEALTH dataset

Technique	Detection accuracy	Recall	Precision	Throughput	Latency
RFNN	74	75	70	73	71
STFNN	80	78	76	79	82
RBTG-WSPCO	90	85	88	91	89

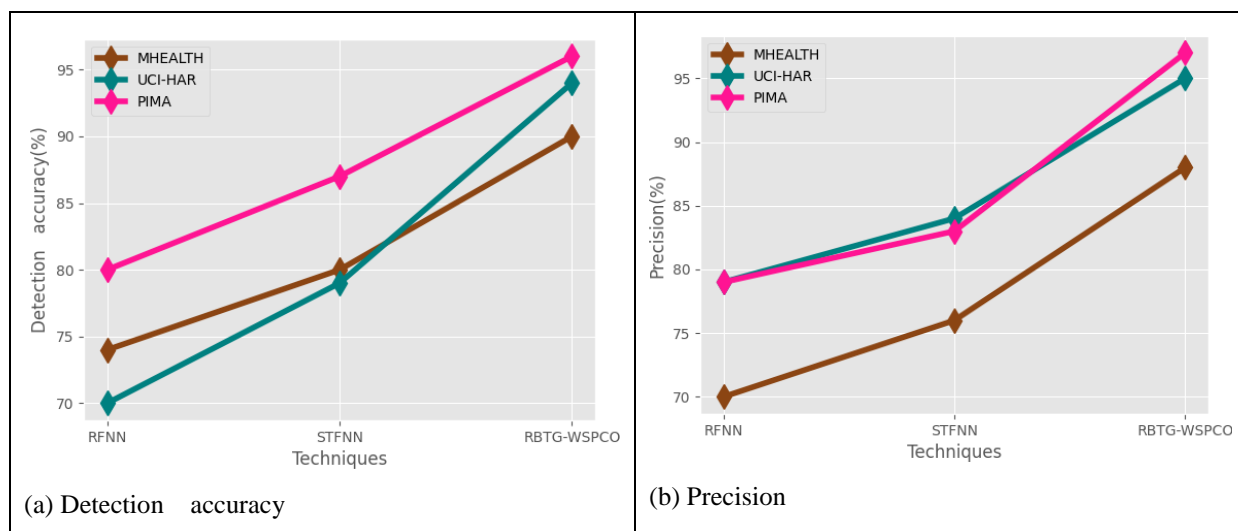
**Table 2:** Comparative analysis for UCI-HAR dataset

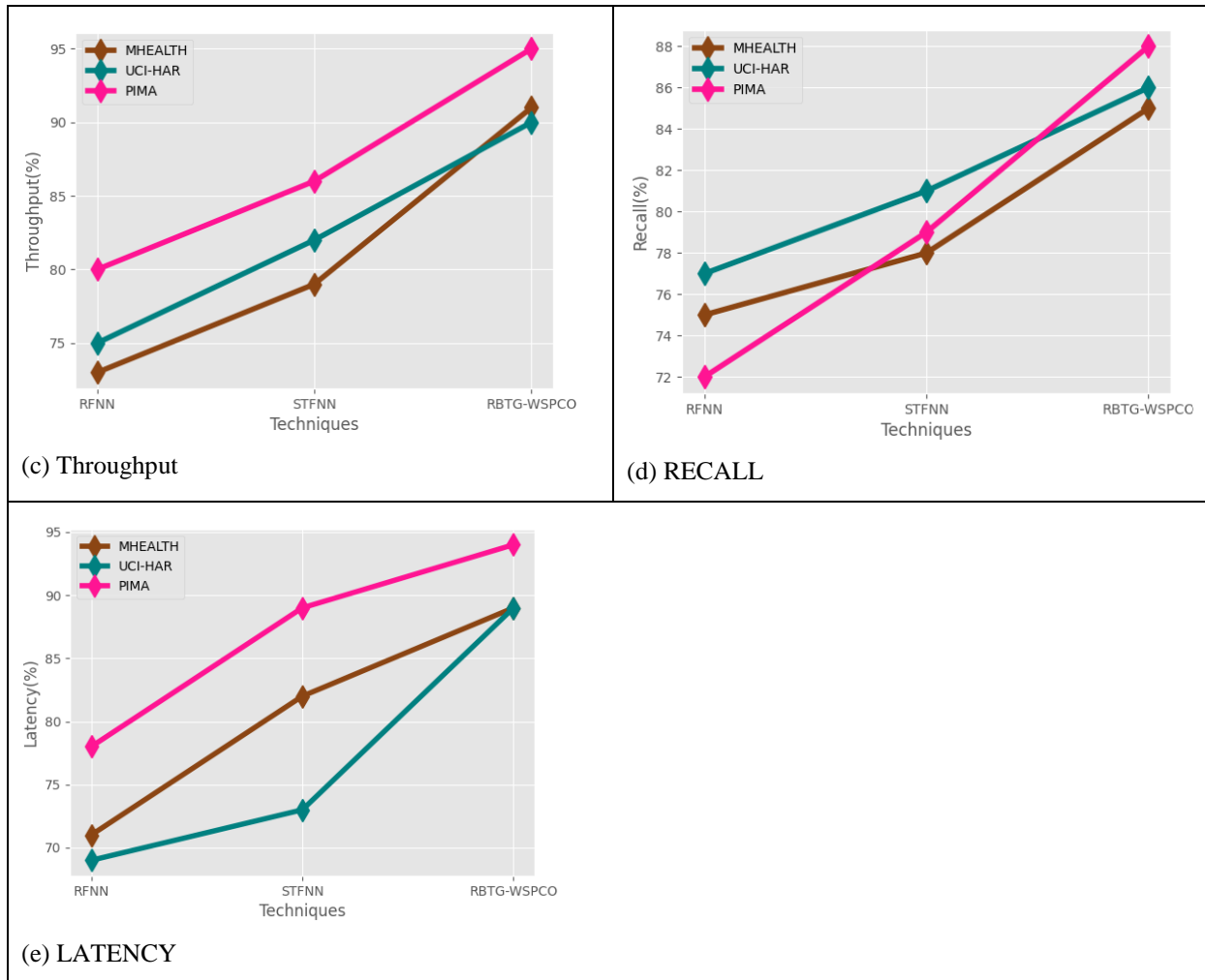
Technique	Detection accuracy	Recall	Precision	Throughput	Latency
<b>RFNN</b>	70	77	79	75	69
<b>STFNN</b>	79	81	84	82	73
<b>RBTG-WSPCO</b>	94	86	95	90	89

**Table 3:** Comparative analysis for PIMA dataset

Technique	Detection accuracy	Recall	Precision	Throughput	Latency
<b>RFNN</b>	80	72	79	80	78
<b>STFNN</b>	87	79	83	86	89
<b>RBTG-WSPCO</b>	96	88	97	95	94

Table-1-3 shows Comparative analysis based on various smart health monitoring dataset. Dataset analyzed are MHEALTH, UCI-HAR, PIMA dataset in terms of Detection accuracy, RECALL, Precision, throughput, Latency.





**Figure 2.** Comparative analysis for smart health monitoring dataset in terms of (a) Detection accuracy, (b) Precision, (c) Throughput, (d) RECALL(e) LATENCY

Figure 2 (a)- (e) shows comparative analysis for smart health monitoring dataset. Here the proposed technique attained Detection accuracy 90%, Precision 88%, Throughput 91%, RECALL 85%, and LATENCY 89%. While existing RFNN attained Detection accuracy of 74%, Precision of 70%, Throughput of 73%, RECALL of 75%, LATENCY of 71%; STFNN attained Detection accuracy of 80%, Precision of 76%, Throughput of 79%, RECALL 78%, LATENCY of 82% for MHEALTH dataset. The proposed technique obtained 94% of Detection accuracy, 95% of Precision, 90% of Throughput, 86% of RECALL, 89% of LATENCY. existing RFNN attained Detection accuracy of 70%, Precision of 79%, Throughput of 75%, RECALL of 77%, LATENCY of 69%; STFNN attained Detection accuracy of 79%, Precision of 84%, Throughput of 82%, RECALL of 77%, LATENCY of 69% for UCI-HAR dataset. For PIMA dataset proposed technique obtained 96% of Detection accuracy, 97% of Precision, 95% of Throughput, 88% of RECALL, 94% of LATENCY. existing RFNN attained Detection accuracy of 80%, Precision of 79%, Throughput of 80%, RECALL of 72%, LATENCY of 78%; STFNN attained Detection accuracy of 87%, Precision of 83%, Throughput of 86%, RECALL of 79%, LATENCY of 89%.

### 7. Discussion

The suggested system is extremely important for healthcare data analysis and monitoring. By precisely monitoring and forecasting physical activity and health patterns, this cutting-edge system significantly improves the quality of healthcare, especially for the elderly, enabling early treatments and ultimately leading to better patient outcomes. Additionally, by reducing needless hospital stays and treatments, it lowers costs. It is a flexible solution due to its capacity to scale to various scenarios and adjust to changing healthcare data. Furthermore, study's contributions to

optimization and ensemble learning techniques set the standard for further healthcare monitoring research, and its intuitive visualisations facilitate data-driven decision-making. In summary, this solution is a revolutionary strategy that will have a significant impact on data analysis and healthcare, leading to better patient care, lower expenses, and more advancements in field's research.

## 8. Conclusion

In a smart public health system, this study proposes a novel approach to urban design through machine learning algorithms. The smart healthcare system was developed based on the secure honeynet cloud IoT paradigm. The input data has been collected and processed using smart healthcare-based health monitoring to eliminate noise and missing information. To classify and improve this data, we next employed a recurrent Bi-LSTM temporal Gaussian model with whale swarm particle colony optimization. An ensemble of DL techniques takes a lot of time and processing resources to train and maintain because to their computational complexity. This could be problematic for organizations with limited computing resources or for real-time applications. As a result, compared to current healthcare monitoring systems, the suggested IoMT-based solution based on four datasets is more effective. Here are some examples of this work's shortcomings. There is a possibility of a data privacy issue when more data is being collected. Without a secure connection, data such as private health information and medical records can be compromised. In order to gather data, the system needs a lot of bandwidth and storage space. Latency and communication amongst healthcare organizations may also be problems. This performance will be expanded in future work by combining the hybridised heuristic method with the ensemble technique. Additionally, privacy of data that is not focused on in this work is considered a future study.

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