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Urban Planning Based Sustainable Public Healthcare System using Machine Learning Algorithms

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Abstract

Growing use of a wide range of Internet of Medical Things (IoMT) devices and apps makes smart health an increasingly vulnerable area. One popular method for creating smart city solutions that benefit vital infrastructures over time, such smart healthcare, is IoMT. Because Bluetooth technology is flexible and uses few resources, it is used for short-range communication by many IoMT devices in smart cities. This research proposes novel technique 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.

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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 and prompt response to emergencies are only a few examples of the ways that healthcare systems have changed since then. The requirement for new, effective equipment to provide patients with the greatest care was 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 technologies, such as blockchain, augmented reality, virtual reality, and robotics. According to reports, big data is a popular strategy in 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. Methodology

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. Since traditional methods do not yield the best results for security as well as safety critical methods, authors frequently utilise graph theory to correct flaws that are discovered. 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 and characteristics of a smart city. Writers also discussed the difficulties and real world experiences that implementers worldwide encounter. Author [9] conducted a comprehensive analysis of different approaches and uses of collaborative drones with IoT that are employed recently in order to increase smartness of smart cities in terms of data collection, privacy, security, public safety, disaster management, energy consumption, quality of life. Work [10] offered a comprehensive assessment of application of ML methods for large data analysis in intelligent healthcare methods.

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 system 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. A machine learning hybrid approach that combines random forest (RM) and linear method (LM) algorithms to predict heart disease [12] shows an 88.7% performance accuracy. A 91.0% accurate integrated decision support technique for heart failure risk prediction includes an artificial neural network for classification tasks with a fuzzy analytic hierarchy methodology for feature weighting [13]. In a smart system for detecting heart illness, it is recommended to utilise a $\chi 2$ statistical model for feature refinement and a deep neural network for classification tasks. 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 utilizing ML algorithms. 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). ASCC's primary responsibilities are situational awareness, security threat monitoring, and honeynet control. Three nodes that make up te ASCC are explained below. a. HCM, or honeynet control master. The HCM is primarily in charge of overseeing and communicating with HoneyNet nodes: Honeypot 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 Honeypot 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.

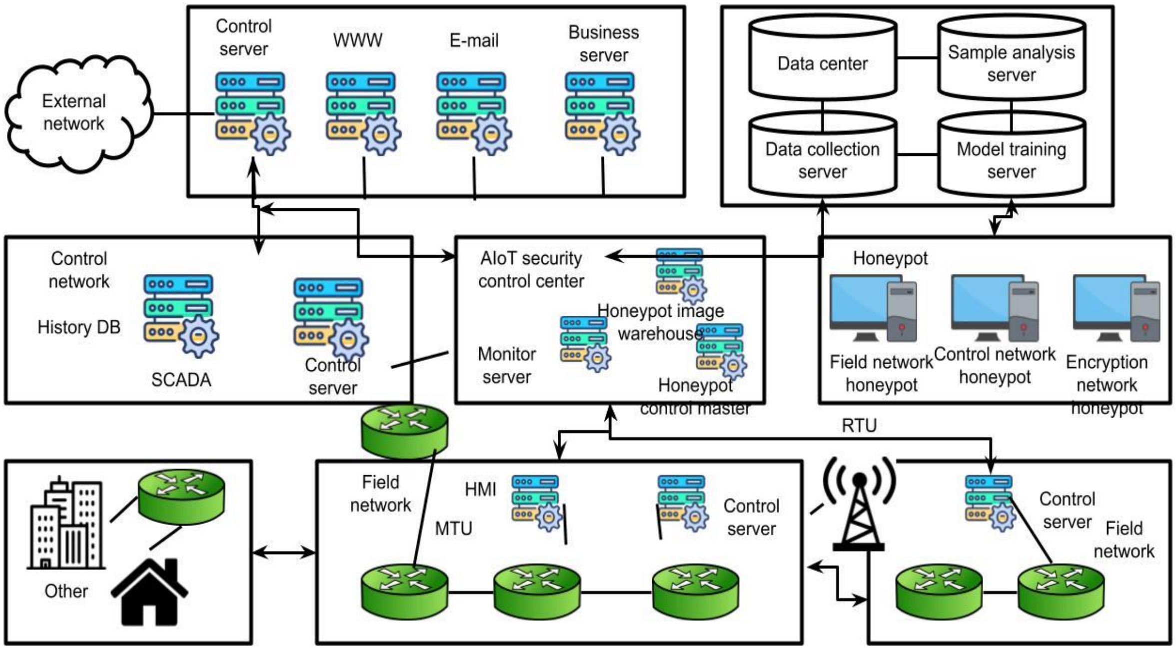


Figure1. Proposed secure honeynet cloud IoT model

2) HoneyNet. Finding various dangerous apps and malicious behaviours 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 as well as capturing harmful code and behaviours 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 the control network. c. Field Networks Honeypot (FNH). FNH is principally responsible for identifying and documenting hostile activities as well as malicious instructions in field network. 3) The data centre, or DC. DC's main responsibility is to collect data from HoneyNet, including malicious activity, malicious instructions, and malicious code, and then pre-process this data to produce training samples. Produced samples are used to train a CNN DL method. As explained below, the 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. The 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, and malicious sample server IP addresses. b. The MTS, or Model Training Server. Training modules are the main responsibility of MTS.

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

For practical monitoring in the event of medical emergencies such diabetes, heart attacks, asthma, and so on, IoMT-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 = {s1, s2,..., sn}, can be regarded as a token sequence. An LSTM unit using embedding xt of every token st as input produces the hidden state h ′ t, which is determined by Equation 1. \ 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 = {h1, h2,..., hn}, is created by first concatenating h ′ t and h ″ t, reducing the 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

$$r_{\underset{j}{\max}} = \max_{1 \leqslant k \leqslant K} h_{k_j}$$

$$r_{\underset{j}{\min}} = \min_{1 \leqslant k \leqslant K} h_{k_j}$$

$$r_{avg_j} = \frac{1}{K} \sum_{1 \leqslant k \leqslant K} h_{k_j}$$

$$r_{std_j} = \sqrt{\sum_{1 \leqslant k \leqslant K} h_{kj}^2}$$

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

where it is presumed that the former entity begins at first token and finishes at Kth token. j-th element of k-th token representation vector is indicated by symbol hkj. j-th components of representation vectors produced by respective pooling functions are shown by symbols rmaxj, rminj, ravgj, rstdj. In order to choose relation type with highest probability, output layer lastly computes probabilities of each relation type. i-th relation type Ri's probability is calculated by

$$p(R_i) = \text{softmax}(R_i) = \frac{e^{w_2 \cdot x_{penut}}}{\sum_{j=1}^{|R|} e^{w_j j \cdot x_{penut}}}$$

where w2i is the output layer's i-th row of parameter matrix W2. 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.

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

where F is number of features, σf is a dedicated parameter that controls spread of relations for every specific feature f, v is a scaling factor, xf i is feature f of example xi, σn is noise standard deviation parameter, which is usually considered to be independent as well as identically distributed. The hyperparameters gathered in θ = {ν, σ1,...,σF, σn} 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

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

which results in the periodic covariance function that follows:

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

where σt 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.,

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

where the period has been set at one year, γ indicates the magnitude, σt indicates the periodic component's smoothness, and σd indicates the periodic component's decay time. Consequently, our final covariance can be written as

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

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:

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

Two random values, r1 and r2, are used to enhance 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.

$$x_i^{t+1} = x_i^t + \mathrm{rand}(0, \rho_0 \cdot e^{-\eta \cdot d_{\mathbf{X},\mathbf{Y}}}) * (y_i^t - x_i^t)$$

where y t i is i-th element of Y's position at t iteration, x t i and x t+1 i are i-th elements of X's position at t and t+1 iterations. The ultrasonic source's intensity, ρ0, can be set to 2 in practically all situations. The natural constant is represented by e. The attenuation coefficient is denoted by η. Euclidean distance between X and Y is denoted by dX,Y. A random number generated uniformly between 0 and ρ0 · e −η·dX, Y is indicated by rand 0, ρ0 · e −η·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 the swarm's best performance to date. Let pbestd i be previous optimal position of dth dimension that ith particle came across, let gbestd be best position of dth dimension. Following definition applies to current velocity of ith particle's dth dimension at iteration t:

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

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

Rnd is a random function in interval [0,1] in formula above. W is the inertia weight, while the positive constants c1 and c2 stand for the social and personal learning components, respectively. Local exploitation and global exploration are balanced by inertia weight. With vmax as a predetermined boundary value, velocity is limited to [−vmax,vmax] range. Resolution of search regions between current and target positions is determined by the value of vmax. In each dimension, vmax 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

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

where ||Xi − Ck||, Nc = number of centers, and Ns = sample sized(Ck, Cj) = 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. Inter-cluster distance between clusters is determined by distance between centers. 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]:

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

where min(x) and max(x) are variable x's minimal and maximum values, xnew 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.

4. 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." BDcld v represents the collected data from two datasets, where ν = 1,2,...., 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.

5. Comparative analysis

Table 1: Comparative analysis for MHEALTH dataset

Method	**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

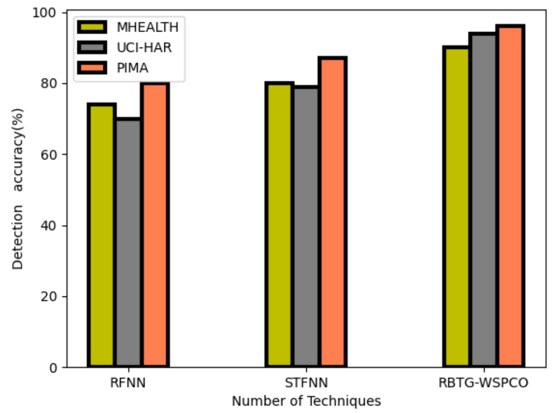
Table 2: Comparative analysis for UCI-HAR dataset

Method	**Detection accuracy**	**Recall**	**Precision**	**Throughput**	**Latency**
RFNN	70	77	79	75	69
STFNN	79	81	84	82	73
RBTG-WSPCO	94	86	95	90	89

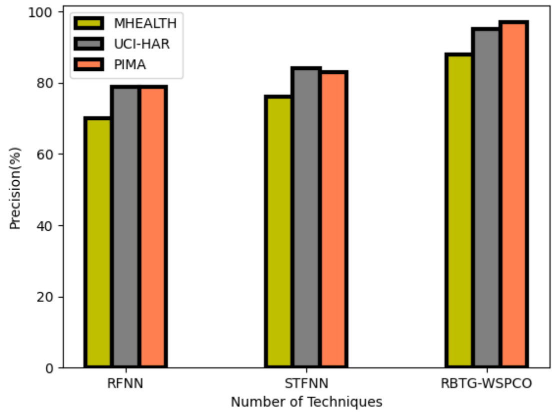
Table 3: Comparative analysis for PIMA dataset

Method	**Detection accuracy**	**Recall**	**Precision**	**Throughput**	**Latency**
RFNN	80	72	79	80	78
STFNN	87	79	83	86	89
RBTG-WSPCO	96	88	97	95	94

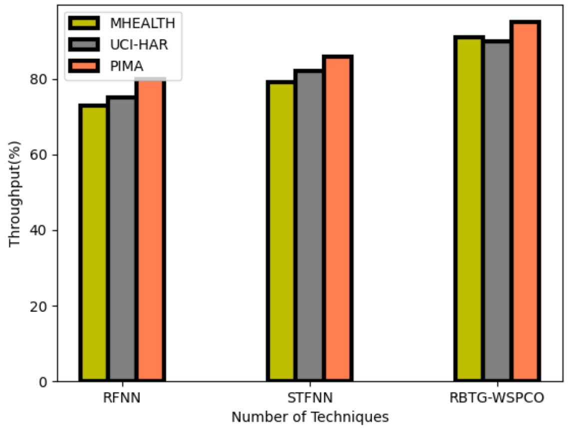
Table 1-3 shows Comparative analysis based on various smart health monitoring dataset. Dataset analysed are MHEALTH, UCI-HAR, PIMA dataset in terms of Detection accuracy, RECALL, Precision, throughput, Latency.



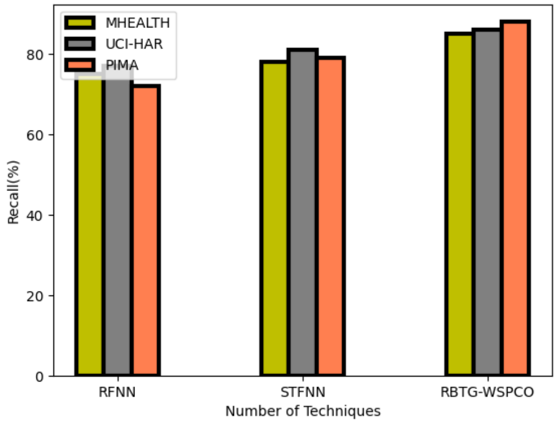
(a) Detection accuracy



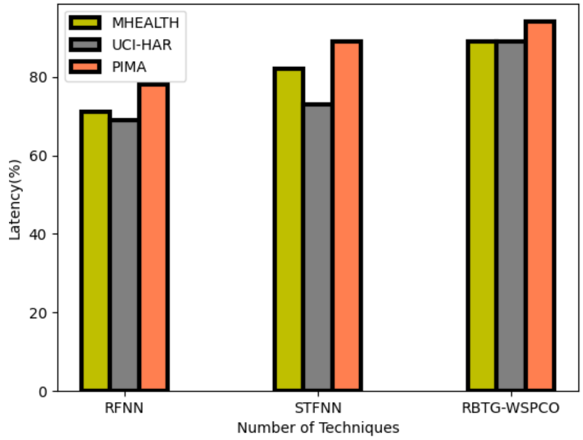
(b) Precision



(c) Throughput



(d) RECALL



(e) 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%.

6. 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 optimisation and ensemble learning techniques set the standard for further healthcare monitoring research, and its intuitive visualizations 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.

7. Conclusion

Using machine learning algorithms, this study suggests a fresh approach to urban design in a smart public healthcare system. Based on the secure honeynet cloud IoT model, the smart healthcare system was created. To remove missing values and noise, the input data from smart healthcare-based health monitoring has been gathered and processed. We then used a recurrent Bi-LSTM temporal Gaussian model with whale swarm particle colony optimisation to classify and optimise this data. An ensemble of DL methods are computationally complex to train as well as maintain, requiring a large amount of time and processing power. This could be problematic for organisations 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 organisations may also be problems. This performance will be expanded in future work by combining the hybridized 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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