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# A Novel Approach of Cloud Computing Network for Authentication and Security Enhancement of IoT Enabled Cancer Forecasting System

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**Abstract:** Recently, a variety of approaches have been employed to address a broad spectrum of real-world issues; these methodology cover a variety of areas, including healthcare systems. Previous researchers concentrated on health-care monitoring software. It had several shortcomings, such as poor health-care data storage, time, expense, and processing complexity. This paper proposes a unique IoT-enabled and secured clinical monitoring paradigm to address these issues. Initially, implant several sensors to gather information on vital indicators like body temperature fluctuation. Phone numbers, marital status, heart rate deviation, residence, name, age, and blood pressure are among the patient's health information. The IoT medical sensor dataset is used in this investigation. During pre-processing, extra unnecessary attributes are removed, resulting in data size reduction and normalization. A convolutional neural network supporting the classification of cancer sickness that is based on the improved teaching-learning optimization (CNN-ITLO) method. The CNN-ITLO model ascertains whether or not the patient is cancer-prone based on the sensor input. The management of the hospital receives the gathered data after which it is analyzed. Lastly, the homomorphic encryption approach is used to encrypt and store the patient's data on the cloud. The Java platform will be used to carry out the recommended work. According to the experiment results, the suggested method performed better than current cutting-edge practices.

***Keywords***: *Cloud computing, Internet of Things, Cancer prediction, Improved teaching learning optimization, Convolutional neural network and Homomorphic encryption.*

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# 1. INTRODUCTION:

Healthcare monitoring, which links multiple devices and collects data, is one of the most prevalent IoT applications.

Numerous illnesses, including cancer, skin conditions, heart disease, chronic renal disease, and others, are predicted by the usage of IoT devices [1]. It is important in a variety of fields, including hospital administration, E-healthcare, IoT-enabled transportation, smart cities, and so on. Sensors can be used to store, gather, and interpret data in a variety of ways. Variations in blood pressure, heart rate, and the operation of human body parts are predicted by a variety of sensors [2]. The organization of IoT is made up of animals or humans, items, mechanical with propelled equipment, and linked prepared gadgets. Healthcare monitoring, which links multiple devices and collects data, is one of the most prevalent IoT applications [3]. Numerous illnesses, including skin conditions, heart disease, chronic renal disease, breast cancer, and more are identified by the usage of IoT devices [4]. It is crucial in many domains, such as E-healthcare, smart cities, hospital management, and transportation facilitated by the Internet of Things. Sensors can be used to store, gather, and interpret data in a variety of ways. Numerous sensors forecast fluctuations in blood pressure, heart rate, and the operation of bodily parts. The Internet of Things is composed of humans and/or animals, objects, mechanical devices with propulsion, and networked prepared devices.

For example, if the driver has a problem, the sensors will sound a warning and the vehicle will be equipped. IP addresses are allocated to each IoT group, as well as the ability to go data crosswise the system. The Internet of Things (IoT) heralds a major and improved information age [5]. An extra link between the IoT sensors is established via a web of things cloud service. Compute a cloud figure and show the different IoT points of interest that are intermixing [6]. The need for scalable, energy-efficient, cost-effective, real-time healthcare systems that can control people's vital signs is increasing. Virtually analyzes the information and uses the cloud's storage capacity. The Industrial Internet of Things (IIoT) envisions connectivity, which entails data flow. Big data is used to determine emerging patterns or major trends. Several unstructured information items are in various formats as of a variety of sources [7]. The data generated by the linked plant is enormous. The convergence of IoT with Cloud Computing provides additional networking capabilities, scalability, processing, and storage. Cloud computing is used to deliver infrastructure services and applications to a large number of stakeholders [8]. In addition, the healthcare sector has benefited from the employment of numerous cutting-edge artificial intelligence data mining techniques that provide massive data and real-time processing. Existing approaches do not specify any attack detection model, and they have transmission delay, insufficient medical information, misdiagnosis, increased computational complexity, and other issues. This paper presented a new approach for healthcare monitoring in IoT environment. This article's main contribution is summarized as follows:

- Various sensor devices collect patient-specific information such as heart rate variation, blood pressure, past history, phone number, marital status, residence, age, and name. Pre-processing includes data size reduction and standardization, as well as the removal of duplicated or superfluous information.
- To extract characteristics for cancer prediction and diagnosis, the convolutional neural network based improved teaching learning optimization (CNN-ITLO) model is utilized. The

homomorphic encryption approach is used for safe communication, and the encrypted data is accumulated on the cloud.
The article is structured as follows: Section 2 lists related works, and Section 3 lists the suggested model. Section 5 concludes the paper, and Section 4 examines the outcome.

## 2.RELATED WORK:

An IoT-based big data system for the healthcare industry is connected to a wearable sensor developed by Muthu et al. [9]. To gather patient data from IoT devices, regression methods using Generalize approximation Reasoning foundation Intelligence Control (GARIC) were employed. To train the data (electroencephalogram), a combination of deep Boltzmann belief network and artificial intelligence (AI) was utilized. The findings of the experiment demonstrated that greater accuracy might be attained with shorter training times and higher processing costs. For hospitals and other medical institutions, Lakhan et al. [10] suggested segmenting and scheduling deep neural network (DNN) based apps using IoT-assisted mobile fog clouds. This design uses less energy and produces more accurate results. However, they only examined difficult mobility elements in a dynamic context, which resulted in increased delay and service cost.

Attia et al. [11] proposed an IoT-blockchain architecture based on the hyperledger (IoT-BH) model for healthcare monitoring applications. In the design phase, the IoT-BH model was verified by concrete examples, and only a small number of completed features were made public. Fabric Hyperledger was chosen as the foundation for the IoT-BH architecture, and various blockchain technologies were investigated. This model gave improved accuracy at a lower cost of computation, but it resulted in delayed transmission and misdiagnosis. For COVID19 monitoring systems, Kallel et al. [12] recommended an IoT fog cloud based architecture. The enhancement of the business development replica and notation made it possible to model IoT-aware business processes (BPMN). Additionally, the experimental research revealed improved results in terms of overall system dependability, computing time, and data integrity guarantees. However, when the system's production time, dependability, and security improve, the total performance suffers.

In order to handle a lot of data, Elhoseny et al. [13] presented a novel method for optimizing the selection of virtual machines (VMs) in cloud-IoT health services applications (NOVMs) in integrated industrial 4.0. Particle Swarm Optimizer (PSO) and Parallel Particle Swarm Optimization (PPSO) are combined to optimize VM selection. CPU utilization, turnaround time, and waiting time are the three primary variables used to assess how quickly requests from stakeholders are carried out. Gupta et al. proposed an energy-efficient fog-cloud based structure (EEFCS) [14]. Because of the heavy demand, cloud data centers' energy usage has often increased. The testing results showed that there was a shortage of adequate medical information, as well as maximum resource allocation and storage, enhanced system efficiency, data processing speed with improved task scheduling. This EEFCS lowered latency, energy usage, and delay when compared to cloud. This architecture is devoid of any security mechanisms that would make the system more complicated.

## 1. Proposed Methodology:

IoT is the real network enabled by technology. With the use of wireless communications for sensors, IoT may connect mobile objects and distant places. Computer equipment and inexpensive storage are helpful. An Internet of Things-based paradigm for health care monitoring supplements the internet on health sensor items. The proposed workflow diagram is shown in Figure 1. It is the doctor's responsibility to manage the massive amount of data. Patients' health is anticipated by their doctors, and they need to use this previous data [15, 16]. The CNN-ITLO algorithm was utilized to forecast cancer disease, with the health-care reports serving as the input. The data is encrypted using a homomorphic encryption technique, resulting in encrypted data authentication. In the following part, the general proposed model is delineated

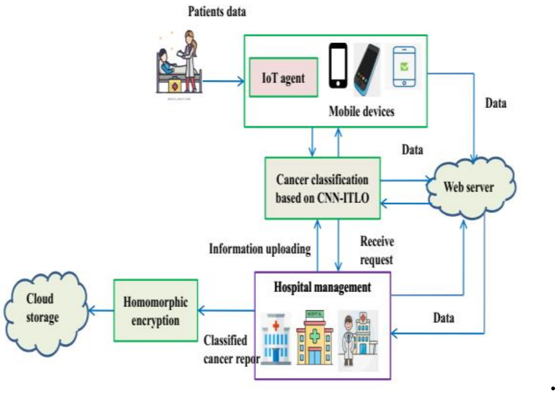


**Fig 1:** Proposed workflow diagram

## 1.1 Data acquisition:

Different sensors in the human body are used to track changes in blood pressure and temperature. These acquired data, which are presumed to be clinical data, are stored in any local processing system. The mammography or blood test report is detected after the variation in blood cells. These sensors gather a variety of essential characteristics [17, 18]. It ensures cancer prevention in the approaching days by sending pre-alerts. These critical criteria are used to classify the various types of cancer disorders in this study.

For cancer prediction, sensing devices and basic healthcare equipment are used. Mobile applications are used to register each patient data. The system generates a unique identity number for future authentication, and each registered patient receives services. Following the basic check-up list, keep track of each patient's fundamental information [19]. Use a local server compatible with multiple local networks (Wi-Fi and LTE services) for data transfer and initial storage. Link the IoT-based device sensing features and SQ light database to the local server. Both structured and unstructured data have been collected. Cloud storage security is achieved using a variety of security-procedures.

**Pre-processing:**

In an IoT medical sensor dataset, replacing missing features, eliminating redundancy, and XY normalization are the three main steps in the pre-processing stage. There are 1314 missing variables in the IoT medical sensor dataset [20]. These characteristics are switched and the maximum number of repeated attribute values is used. Change the specific characteristic of the missing value. Swap the values if a patient has many identical values for various attributes.

The features that are unnecessary or redundant are eliminated, resulting in a reduction in data size and data normalization.

### 1.2 Cancer disease classification:

The Improved Teaching Learning Optimization (ITLO) algorithm, which is based on Convolutional Neural Networks (CNNs), is used in this part to classify cancer diseases. ***Convolutional Neural Network:***

One of the most popular varieties of neural networks is CNN. At the ultimate stage, one or more fully connected layers—which comprise alternate, convolutional, and pooling layers—adhere to the CNN architecture [21]. An important part of this architecture is the convolutional layer. Using the input, a convolutional layer determines whether feature sets are present. This layer compresses the set of convolutional kernels. Figure 2 depicts the general structure of CNN. A convolutional neural network's operation is expressed in Equation (1).

Gck(U,M)=aJ,QIaJ,Q×IckiU,M

(1)

The $I_c$ is an instance of the input vector Ic J,Q and the $k^{th}$ kernel of the $c^{th}$ layer is Ikc U,Mderived from this equation. Through a thick layer, the inputs from the earlier phases are accepted. All previous layer outputs are assessed [22]. A non-linear amalgamation of specified features is made for classification purposes.

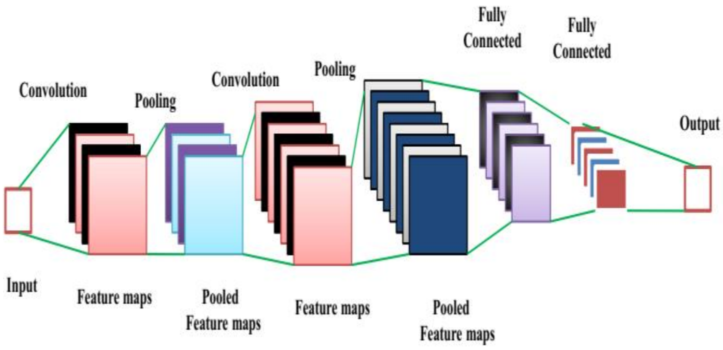


**Figure 2:** General CNN model

The output mapping is explained in the equation below.

$$. \ G_c^k = \left[G_c^k(1,1),....., G_c^k(m,n),...., G_c^k(U,M)\right] \quad (2)$$

The pooling layer is positioned between two convolutional layers and the vector size is reduced without sacrificing relevance. The associated data of the receptive domain region is compiled. The ith kernel is used to determine the cth layer of the pooled feature map.. Various pooling operations are calculated with the help of $DP_s$

### *1.2.1 Teaching Learning based Optimization (TLO) algorithm:*

The superior student in a realistic class takes into account just one student. The student has the ability to learn actively and is a good self-learner. In the real education-knowledge state of things, the improved teaching-learning-based optimization (ITLO) technique shows a faster convergence rate and better solution quality when compared to the TLO method [23]. The ITLO algorithm contains two key stages: teaching and learning. The ITLO algorithm is explained in the following section.

**A. *Teaching phase:***

The way a teacher affects their students served as the model for the conventional TLO algorithm. Think about two instructors instructing distinct subjects in two distinct classrooms. Teacher T1 performs better than Teacher T2 and produces the best results. A person's mark can be improved during the instructor phase of the TLO by using their mark [24]. Regard the kth students as superior when their fitness value for the minimum optimization problem is less than the mean. Equation (3) takes into account the best people as well as the knowledge acquired from independent research.

$$Z_{new,k} = \left(Z_{old,k} + (random - 0.5) \times 2 \times \left(Z_{mean} - Z_{old,k}\right)\right) \times \lambda_1 + D \times \lambda_2, \quad , \quad if \quad F\left(Z_{old,k}\right) > F\left(Z_{mean}\right) \tag{3}$$

$$Z_{new,k} = Z_{old,k} \times M + \left(Z_{best} - Z_{old,k}\right) \times random, \quad if \quad F\left(Z_{old,k}\right) < F\left(Z_{mean}\right) \tag{4}$$

Consequently, the mean fitness value has decreased relative to the preceding fitness value. At first, the teacher imparts knowledge to the student. The mean and the inertia weights mark are $M$ and $z_{mean}$ . Teachers boost the student's knowledge in the first stages. The updating mechanism is depicted in Equation (4).

$$M = \lambda_s - \left(\lambda_s - \lambda_e\right) \times \frac{Itr}{Max_{Itr}} \tag{4}$$

Where,

$$\lambda_1 = \sin\left(\frac{\pi}{2} \times \frac{Itr}{Max_{Itr}}\right) \tag{5}$$

$$\lambda_2 = \cos\left(\frac{\pi}{2} \times \frac{Itr}{Max_{Itr}}\right) \tag{6}$$

There are as many iterations as possible in this present iteration $Max_{Itr}$ . In a linear method, decrease the inertia weight from to [25]. In the initial steps, the ITLO algorithm is allowed to modify the inertia weight procedure in order to explore the search spaces. The inclusion of and accelerates the rate of convergence.

**B. *Learning phase:***

Maintain all of the students fitness values in ascending order following the instruction period. Consider the top partially of the first-year scholars and the remainder of the second-year students. The first group members are looked down upon by the superior students. Update the first and second class results using equations (7) and (8).

$$\begin{aligned} &IF \quad F\left(Z_{old,k}\right) > F\left(Z_{neighbour}\right) \\ &\qquad Z_{new,k} = Z_{old,k} + \left(Z_{neighbour} - Z_{old,k}\right) \times \cos\left(\frac{\pi}{2} \times \frac{Itr}{Max_{Itr}}\right) \\ &ELSE \\ &\qquad Z_{new,k} = Z_{old,k} + (random - 0.5) \times 2 \times \left(Z_{UL} - Z_{LL}\right) \\ &STOP \end{aligned} \tag{7}$$

$$Z_{new,k} = Z_{old,k} + \left(Z_{best} - Z_{old,k}\right) \times \cos\left(\frac{\pi}{2} \times \frac{Itr}{Max_{Itr}}\right) \tag{8}$$

In the $k^{th}$ iteration, it randomly selects $Z_{neighbour}$ one of the learners $Y_j$ . If the $Z_{neighbour}$ has a lower fitness value than the $Z_j$ student receives knowledge from $Z_{neighbour}$ . Depending on this process, increase the rate of convergence and population diversity. For the second class members, the half learners and teacher have a large disparity.

### *1.2.2 CNN-ITLO algorithm for cancer classification:*

The benefits of CNN are discussed in the preceding section, and they include greater dimensionality reduction, computational efficiency, automatic feature detection, and so forth. However, lower classification accuracy necessitates more training data, more processing costs, and so on. To address these challenges, researchers suggested the Improved Teaching Learning Optimization (ITLO) technique for hyper parameter optimization of CNN, resulting in cancer illness classification and prediction. Using the suggested CNN-ITLO, extract the characteristics from the blood test report prior to classification. As a result, the features of the normal and abnormal patients are retrieved. The CNN-ITLO model's flow diagram is shown in Figure 3.

Improving CNN parameters in terms of batch size, convolutional layer count, filter count, and feature map counts is the main objective. To integrate the parameter optimization, initialize the CNN by applying the ITLO approach. Each solution is used to complete CNN training, and the ITLO method is used to optimize these CNN parameters and select optimal parameters [26, 27]. Based on ITLO algorithm, increase population variety in the last steps to prevent being trapped in a local optimum. The important role enhances the student's knowledge. Two inertia weights enhance the analysis's convergence rate and solution quality.

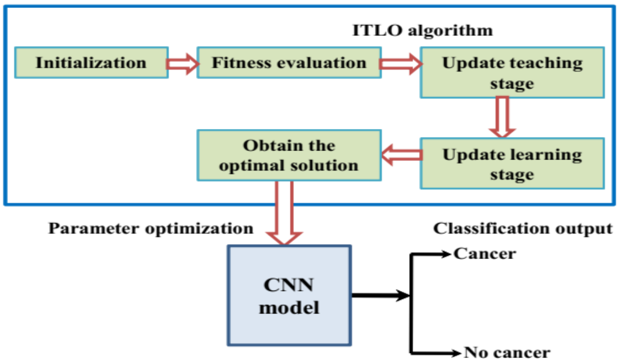


**Figure 3:** Cancer prediction using

The CNN-ITLO model performs both feature extraction and classification. CNN receives the pre-processed health records as input, and ITLO works together to adjust or optimize the hyperparameters of the network, such as the number of convolutional layers, number of filters, number of feature maps, and batch size. The CNN-ITLO model ascertains the presence of cancer in the patient data. The CNN-ITLO model assesses the patient's propensity for cancer based on the sensor data. After that, the Hospital Management receives the results for review. Acquire the patient's test findings and save them in the cloud. IoT sensors gather the parameters, and the associated sensory data is saved on the cloud [28, 29]. Get the cancer patients' data periodically during the testing intervals.

### 1.3 Homomorphic Encryption model for secure communication:

Homomorphic encryption is a kind of encryption so as to permits users to do computations on encrypted data without first decrypting it [30]. Outsourced and encrypted data is authorized to be processed in commercial cloud environments. A homomorphic encryption model is used by the data owner to encrypt their data. Various encryption algorithms are used, and the optimal strategy is selected based on how well it can outperform in terms of computational cost and system security. The homomorphic encryption protocol for data privacy is explained as follows:

***Key Generation:*** Let's have a look at the $M = u \cdot v$. The two largest primes that are independent of each other are $u$ and $v$. As a result, $x/u = x/v = -1$ is the A non-residue is chosen by the legendre symbol y. In conclusion, the public, private keys are $(M, x)$, as well as the Jacobi sign is $x/M = +1$.

### 1.3.1 Encryption and decryption:

To encrypt the message with $d$ and choose a non-zero random number like $R \in Z_M^*$. In the end, the cipher-text ($c$) seems like this:

$$c = R^2 \cdot x^d \mod M \qquad (9)$$

Following the cancer classification, this part develops a homomorphic encryption model for data privacy, such as forensic picture security. This method is well-suited for encrypting data bit by bit, and further plaintext results can be obtained by decrypting the ciphertext. If not, the homomorphic encryption yields a plaintext of 0 or 1, which they can easily identify and reject. At minimum, the malevolent user tampers with the outcome. It makes computations on encrypted data possible without requiring decryption, and the subsequent framework is activated if the client decodes the result, which is stored in the encrypted data [31].

Secure communication is made more secure by the support for both encryption and decryption. The cloud storage of this encrypted cancer data enhanced the efficiency of the healthcare system [32]. We are employing OTP-based authentication to take security a step further, allowing insurers, research parties, and registered physicians to access patient data. Next to verification procedure is completed, the diagnostic procedure begins stands on the preset data development. The Internet of Things (IoT)-based image sensors capture high-resolution images from multiple cloud servers in between different cancer disease groups that are already cloud-stored. Medications can be found, prescribed, and diagnosed by licensed doctors. This information is launched to patients by SMS and a health examination app.

In this stage, patients are given with a variety of services, either directly or indirectly. Health check psychoanalysts, doctors, and insurance companies are 3 main service providers, and they treat and care for patients. The data collected is used to explore treatment, diagnostic approaches, and developing ailments. The scientific team will study the critical metrics and issue precautionary alarms. Any amended or new illness data is refreshed or updated in the cloud database by the team. As a result, the accuracy of auto diagnostic improves. The service providers are a group of insurance professionals. They gave benefits and hospitalized care if the condition was determined to be critical.

## 2. Investigational Results:

The proposed paradigm is based on the JAVA programming language and platform. The performance of the suggested approach is tested in this phase using a healthcare IoT model, and the proposed methods are compared to current works in terms of some performance measures [33, 34]. The parts that follow provide a thorough explanation of the proposed methods' analyses. Parameters used in this investigation are delineated in Table1.

**Table 1:** Metrics used in this investigation

| Metrics | Values |
|---|---|
| Maximum number of epochs | 50 |
| Leaning rate | 0.05 |
| Mini batch size | 30 |
| Momentum | 0.9 |
| Dropout rate | 0.2 |
| Optimizer | TILO |
| Number of students | 50 |
| Number of teachers | 2 |
| Number of iterations | Maximum |

The IoT enabled datasets are used in this paper. The patient health record is delineated in Table 2, which describes different patients with their unique id, zip code, age, gender and the type of disease.

To evaluate the effectiveness of the suggested form, performance metrics such as accuracy, specificity, sensitivity, and false positive rate are employed.

The ratio of accurate examples to all instances participating in the testing method is checked using a standard performance form termed accuracy. Equation (10) is used to determine the precision.

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP} \tag{10}$$

**Table 2:** Example of patient record

| Name | Unique Id | Zip Code | Age | Gender | Disease |
|---|---|---|---|---|---|
| JESSY | 0978 | 8874 | 55 | Female | Lung cancer |
| MARY | 0009 | 6787 | 24 | Female | Liver cancer |
| SUBIN | 0758 | 5675 | 34 | Male | Blood cancer |
| RAM | 0097 | 3241 | 38 | Male | Melanoma |
| REETA | 0987 | 9776 | 44 | Female | Liver cancer |

Specificity is the real negative proportion that may be precisely defined as negative and represented in equation (11).

$$Specificity = \frac{TN}{FP + TN} \tag{11}$$

The genuine positive fraction correctly classified as positive is known as specificity or recall, and it is represented as follows:

$$Sensitivity = \frac{TP}{FP + TP} \tag{12}$$

Where,

$TP$ is the genuinely positive class in which the model's prediction of cancer and the patient's actual diagnosis of cancer coincide.

*TN* is the truly negative class has happened means the patient is cancer-free, and the model does not forecast malignancy.

*FP* is the rate of false positives. A false positive class indicates that although the model predicts cancer, the patient does not have the disease.

*FN* is the false negative rate. This was a true negative class that occurred. For example, if a patient has cancer, the model will not predict cancer.

The CNN-ITLO model's performance in relation to the number of epochs is shown in Figure 4. Figures 4(a) and (b) show the display of accuracy and loss with regard to the number of epochs. The effectiveness of the suggested approach was shown by these graphs. When it comes to dengue fever prediction, the suggested CNN-ITLO representation shows better training and testing accuracies with lower training and testing loss values. As a result, the CNN-ITLO model approach is ideally suited for predicting cancer disease.

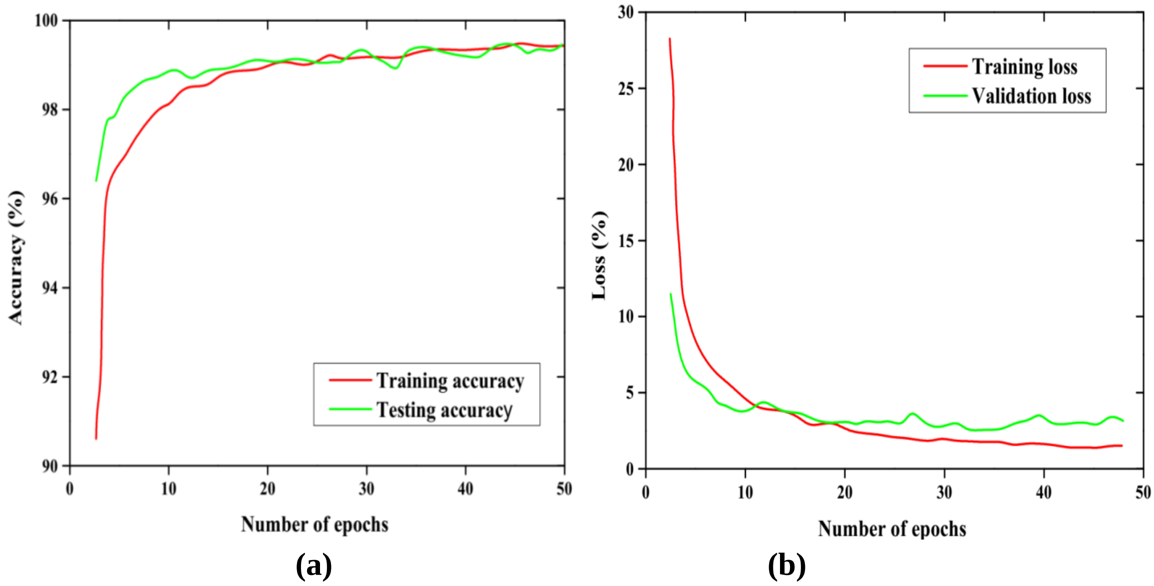


**Figure 4:** Proposed CNN-ITLO algorithm performance analysis, (a) Accuracy and (b) Loss

In addition, for the planned and current efforts, several performance metrics are assessed with IoT medical sensors datasets, as shown in Figure 5. To evaluate the performance of GARIC [9], DNN [10], IoT-BH [11], and NOVMs [12], current works were used. The accuracy, false positive and true positive rate of proposed CNN-ITLO algorithm is superior to GARIC [9], DNN [10], IoT-BH [11] and NOVMs [12].

Table 3 outlines the state-of-the-art outcome of secure communication. Here, we have chosen, Symmetric algorithm DES, Asymmetric Encryption Scheme, Asymmetric ABE and Homomorphic encryption model. From this analysis, the homomorphic encryption demonstrated higher security strength and the cryptographic resistances than other Symmetric algorithm DES and Asymmetric Encryption Scheme, Asymmetric ABE. This table evidence that the security rate and cryptographic resistance is higher for the homomorphic encryption and it is less for the other methods.

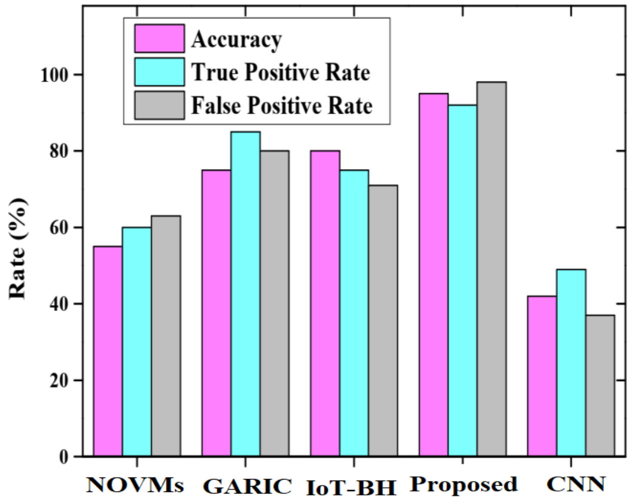


**Figure 5:** Evaluation criterion performance based on IoT sensor datasets

**Table 3:** State-of-art result of secured communication

| Techniques | Security Strength | Cryptographic Resistance |
|---|---|---|
| Symmetric algorithm DES (S-DES) | 92 | 112 |
| Asymmetric Encryption Scheme (AES) | 452 | 612 |
| Asymmetric ABE (A-ABE) | 110 | 367 |
| Homomorphic encryption (Proposed) | 521 | 779 |

Figure 6 shows how the suggested work performs in comparison to other state-of-the-art works in terms of the false-positive rate. To analyze the performance consider, GARIC [9], IoT-BH [11] NOVMs [12] and proposed method. The false-positive rate has been analyzed by considering the various attacks known as DoS, Probe, R2L, U2R, and normal classes. It is clear from the figure that the suggested method has a lower FPR than the other strategies.

To evaluate the usefulness and reliability of the Symmetric algorithm DES (S-DES), Asymmetric Encryption Scheme (AES), Asymmetric ABE (A-ABE), and Homomorphic encryption (HE) models, experiments were carried out to estimate encryption accuracy, as shown in Figure 7. The A-ABE algorithm's encryption accuracy is 58 percent, and it fluctuates depending on the transmission data. However, the encryption accuracy of the AES algorithm is 44%, besides, the encryption accuracy of S-DES is 48% and the proposed HE is 90%. As a result, the suggested ABE outperforms all previous systems in terms of encryption accuracy.

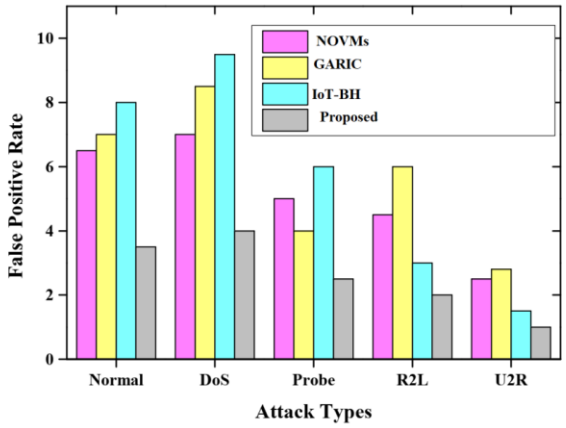


**Figure 6:** Comparative analysis based on the false positive rate

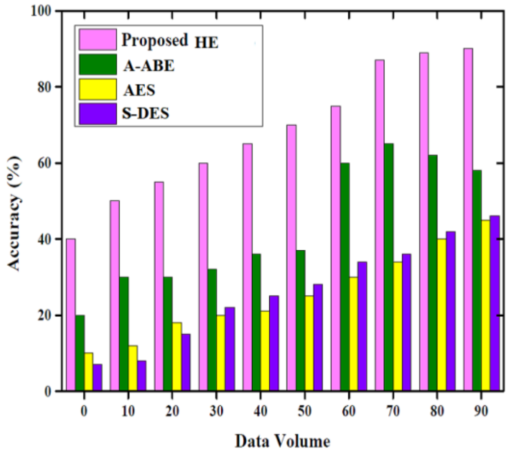


**Figure 7:** Comparative analysis based on the encryption accuracy

Figure 8 compares the proposed work's performance in terms of false-positive rate to that of other state-of-the-art works. Consider GARIC [9], IoT-BH [11], NOVMs [12], and the proposed technique for analyzing performance. The false-positive rate has been investigated using the DoS, Probe, R2L, U2R, and regular classes of attacks. The projected method have a lower FPR than the other approaches, as seen in the figure.

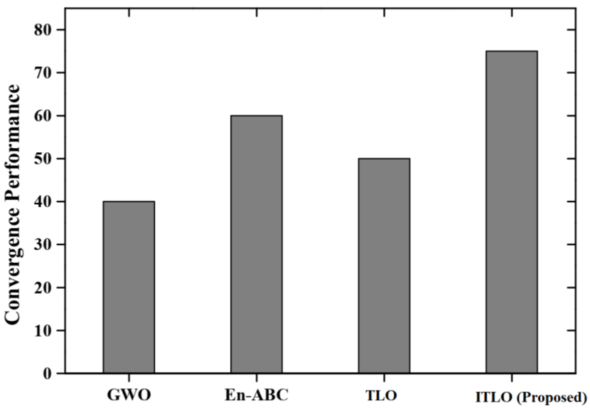


**Figure 8:** Comparative analysis based on the convergence

**Table 4:** Security analysis of state-of-art methods

| Methods | Security Level 60 (bits) | Security Level 120 (bits) | Security level 160 (bits) |
|---|---|---|---|
| Symmetric algorithm DES (S-DES) | 729 | 1211 | 2078 |
| Asymmetric Encryption Scheme (AES) | 1010 | 2043 | 3042 |
| Asymmetric ABE (A-ABE) | 510 | 1022 | 1538 |
| Homomorphic encryption (Proposed) | 1245 | 3501 | 4010 |

Table 4 tabulates the security analysis of contemporary techniques. Furthermore, the strongest of the security level of Homomorphic encryption (Proposed) has been evaluated and compared with the Symmetric algorithm DES (S-DES), Asymmetric Encryption Scheme (AES) and Asymmetric ABE (A-ABE). In contrast, AES is an asymmetric public key algorithm that combines encryption and decryption techniques; the encryption key is private, or secret, while the decryption key is public.

After completing the evaluation of encryption time it is a must to analyze the time complexity for the above-said algorithms. Figure 9 time complexity of different algorithms. For this investigation, the S-DES, A-ABE, AES and proposed HC models are taken. It may be inferred from the figure that the suggested work is simpler than the other works.

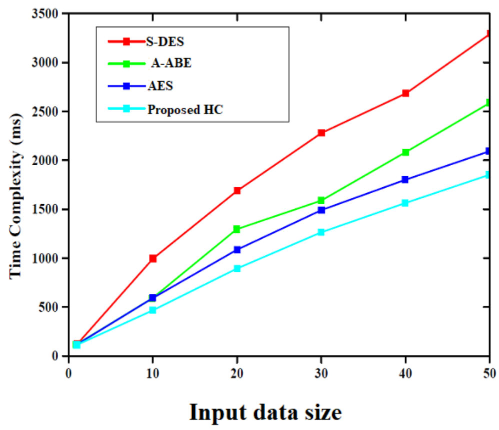


**Figure 9:** Comparative analysis of time complexity

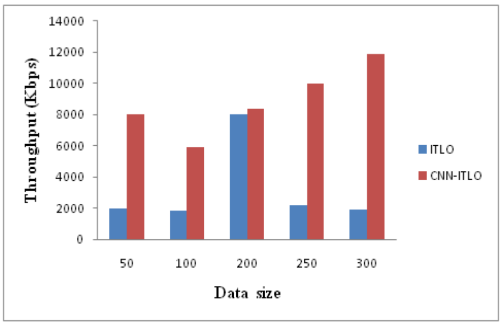


**Figure 10:** Comparative analysis of time complexity

The throughput performance for different data sizes is displayed in Figure 10. This study validates the performance of the proposed approach. Between fifty and three hundred megabytes of data are processed using the ITLO and CNN-ITLO algorithms. In terms of throughput, the proposed CNN-ITLO technique performs better than the current ITLO model.

Figure 11 depicts a comparative examination of overall categorization performance. This study employs a assortment of state-of-the-art approaches, including GARIC [9], IoT-BH [11], NOVMs [12], DNN [10], and the suggested method, which includes sensitivity, specificity, and accuracy metrics. This experiment yielded results of 90 percent specificity, 80 percent sensitivity, and 92 percent accuracy. The suggested strategy, however, outperforms existing state-of-the-art methods such as GARIC [9], IoT-BH [11], NOVMs [12], and DNN [10] in terms of overall classification performance.

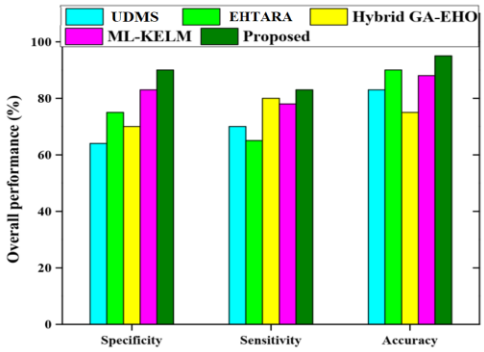


**Figure 11:** State-of-art assessment of general classification performance

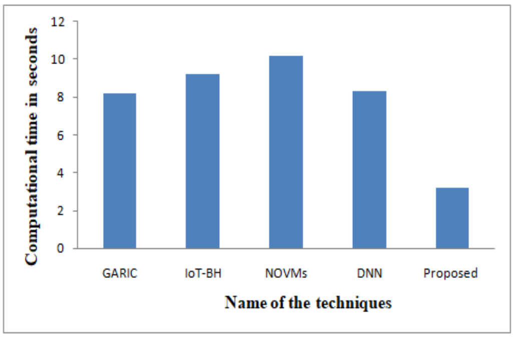


**Figure 12:** Comparative analysis of computational time

In terms of computing time, Figure 12 illustrates the state of the art at the moment. The proposed method's computation time is compared with existing approaches like DNN [10], GARIC [9], IoT-BH [11], and NOVMs [12]. The new approach computes in 3.2 seconds, compared to the previous methods that took longer. In comparison to other procedures, it is less costly.

## 3. Conclusion:

This paper presents CNN-ITLO model for cancer prediction based the IoT enabled clou computing. Because Cloud Computing and IoT are so closely intertwined, IoT is thought to be a great study topic when combined with Cloud Computing. The application of IoT and cloud computing to e-healthcare systems, namely cancer sickness prediction, is the main topic of this study. The proposed paradigm is based on the JAVA programming language and platform. IoT is used to collect and analyze data about cancer patients, and before it is stored in the cloud, the patients' private information is encrypted using the homomorphic encryption technique. Data from a blood test for a tumor patient was encrypted and subsequently expanded using an Internet of Things-based cancer prediction engine. Enhancing the security and adaptability of accessing stored cancer patient data is the primary goal of this project. According to the experimental analysis, the suggested approach presents itself better than the state-of-the-art research, which include DNN, GARIC, IoT-BH, and NOVMs.

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