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Cloud Computing Based Network Analysis in Smart Healthcare System with Neural Network Architecture

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Abstract

The recent progressions in Artificial Intelligence (AI), the Internet of Things (IoT), and cloud computing transformed the traditional healthcare system into a smart healthcare system. Medical services can be improved through the incorporation of key technologies namely AI and IoT. The convergence of AI and IoT renders several openings in the healthcare system. In machine learning, deep learning can be considered a renowned topic with a wide range of applications like biomedicine, computer vision, speech recognition, drug discovery, visual object detection, natural language processing, disease prediction, bioinformatics, etc. Among these applications, medical science-related and health care applications were raised dramatically. This study develops a Cloud computing-based network analysis in the smart healthcare systems with neural network (CCNA-SHSNN) architecture. The presented CCNA-SHSNN technique assists in the decision-making process of the healthcare system in a real time cloud environment. For data pre-processing, the CCNA-SHSNN technique uses a normalization approach. Secondly, the CCNA-SHSNN technique applies the autoencoder (AE) model for healthcare data classification in the CC platform. At last, the gravitational search algorithm (GSA) is used for hyperparameter optimization of the AE model. The experimental outcomes are determined on a benchmark dataset and the outcomes signify the outperforming efficiency of the CCNA-SHSNN technique compared to existing techniques.

Keywords: Smart healthcare; Diagnosis; Medical data classification; Cloud computing; Neural network

1. Introduction

The Internet of things (IoT) has been created from the interconnection of inserted PC frameworks to the interconnection of smart sensor gadgets. Be that as it may, it will in general open up issues like limited handling limits and low stockpiling limits in the climate of a brilliant city. Meanwhile, cloud figuring gives capacity and quick handling. In this way, IoT-cloud combination is expected to manage profoundly testing wise medical services [1]. The center idea of savvy medical care frameworks was consistently understanding reconnaissance and ongoing contact. Nonetheless, the requirement for a mental framework with IoT-cloud innovation offers patient-focused and top notch savvy medical care for minimal price increments. The utilization of human-like knowledge into clever well-being structures is opportune with artificial intelligence (AI) and deep learning (DL) methods [2]. As of late, IoT and cloud innovation have made critical upgrades and have conveyed smart medical care administrations continuously. With IoT-cloud coordination, a gigantic interest in a shrewd and smart medical care framework gives a consistent and quick reaction. DL and AI can improve mental way of behaving and direction. High level electronic applications and developments are accessible to savvy city partners notwithstanding brilliant sensor gadgets. By the by, it is trying to find or access clinical experts and emergency clinics in a climate of a savvy city. Frequently basic patients need a quick reaction and pressing thoughtfulness regarding saving their life [3]. Thus, information recorded from patients should be moved and deciphered with the insignificant postponement, and the outcomes should be adequately exact to be involved by clinical experts for starting assessment. In this manner, a keen medical care framework is required that can settle the above challenges utilizing the innovation and administration accessible in a climate of a savvy city. Fig. 1 represents the backbone of smart healthcare system.

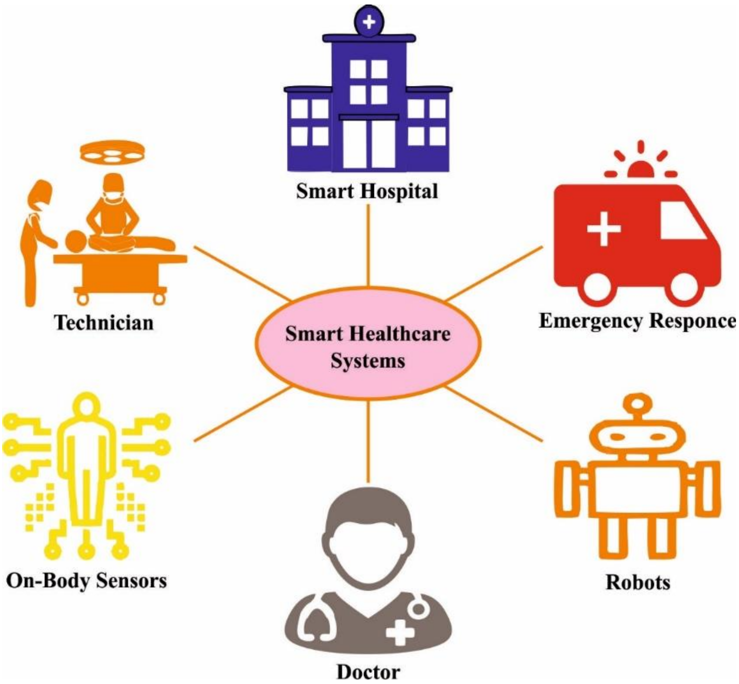

Fig. 1. Backbone of smart healthcare system

The medical care industry is additionally one of the quickest extending markets with extraordinary requests. It offers fundamental administration to patients, yet it additionally contributes critical benefits to the wellbeing area. In view of specialized progressions, we want a medical services framework with a shrewd dynamic limit [4]. Numerous analysts have additionally endeavoured to consolidate mental conduct in the advancement of clever IoT systems. Considering that medical care structures are multimodal and include wise direction, mental way of behaving is turning out to be progressively significant. IoT-depended applications grow the limits of medical services and worked even at home for essential infection expectations and expand the patient's lifetime [5]. Such spaces are basically applied to give energy-viable, least expense, most extreme fulfilment as well as lower inactivity administrations for medical services members. Huge conventional brilliant wellbeing observing techniques rely on the cloud climate. This model is utilized to advance the wellbeing data created from IoT gadgets to the cloud through the Internet and gives the demonstrative reports accomplished utilizing DL move toward utilized in the cloud [6]. Sadly, it is lacking in medical care administrations where low idleness is one of the fundamental credits. Consequently, the medical services emotionally supportive network needs a clever handling procedure with delay-delicate observing which must be brilliant and stable administration.

As of late, edge registering and haze processing were expected as appropriate procedures to inspect the information sources from different uses of the medical care area. Likewise, portable edge registering is an arising model that is applied right now for multi-access outer observing methodologies [7]. Despite the fact that the models can give ideal results, it has the impediments of postponement and identification rate in sending the medical care dataset through the framework. The use of neural network (NN) depended on number juggling handling on wellbeing dataset calculation isn't reasonable to accomplish powerful outcomes concerning dependability and energy use. It is one of the essential examinations in the clinical area of numerous entrance actual checking framework, that generally focuses on diminishing individuals' fitness based risk factors [8].

A portion of the works have suggested that telehealth modules are applied generally, yet it gives no best outcomes, and information based strategies are applied for foreseeing the multimodal modifications of physiology. This strategy achieves most extreme prescient worth, with higher precision and the illness determination can't be performed as expected because of the presence of difficulties [9]. Brilliant medical services frameworks are prescient and can choose and interface with the climate. Likewise, they can be energy free and networked. Medical services experts will benefit from the joining of miniature sensors and miniature actuators in items to all the more likely to treat and deal with patients in the clinics and at home which was unrealistic before [10]. The pressing requirement for unavoidable and pervasive continuous admittance to patients' information from anyplace and from any computerized gadget is fundamental for legitimate finding and therapy method that prompts accomplishing great clinical benefits.

This study develops a Cloud computing based network analysis in smart healthcare systems with neural network (CCNA-SHSNN) architecture. The presented CCNA-SHSNN technique assists in the decision making process of the healthcare system in real time cloud environment. For data pre-processing, the CCNA-SHSNN technique uses normalization approach. Secondly, the CCNA-SHSNN technique applies autoencoder (AE) model for healthcare data classification in CC platform. At last, the gravitational search algorithm (GSA) is used for hyperparameter optimization of the AE model. The experimental outcomes are determined on the benchmark dataset.

2. Related works

Nasser et al. [11] devise an intellectual medical system that compiles IoT-cloud technologies. It will use smart connection nodes and DL for smart executives out of viewpoint revering smart cities. In [12], the authors advanced a clever typical for the finest mission agenda of Hybrid Moth Flame Optimization (HMFO) for cloud computing (CC) combined with IoHT atmosphere on e-medical mechanisms. The HMFO assurances even source tasks and boosted quality of services (QoS). The method can be qualified by the Google clustering data such that it would the examples of in what way a work remains arranged in cloud and the qualified HMFO perfect stands employed to list the works practically.

In [13], a Rooted Elliptic Curve Cryptography including Vigenere Cipher (RECC-VC) positioned safety improvement on the IoMT remains planned to attract security. First, it uses Exponential K-Anonymity algorithm (EKA) to preserve secrecy. Then, an innovative Improved Elman Neural Network (IENN) was projected to examine the data compassion level. The GMCO was denoted to weight apprising in the IENN. Lastly, a fresh RECC-VC stays projected to upload the data strongly for server. Farid et al. [14] suggest innovative individuality supervision outlines for IoT and CC -related tailored medical schemes. The projected outline custom many encoded biometric traits for completing verification. It uses an amalgamation of central and joined individuality admittance methods in addition to biometric related incessant validation. This outline will use a combination of photoplethysmogram (PPG) and ECG signals once execution validation. Also trusting over the exclusive credentials features of the operators' biometric traits, the refuge of the outline stays authorized via the practice of Homomorphic Encryption (HE). The HE usage permits affected role data to break scrambled after actuality treated or examined in the cloud.

Venkatasubramanian [15] runs a key to monitor high-risk MHF grounded on IoT beams, data analysis-related extraction features, and a smart arrangement related to the Deep Convolutional Generative Adversarial Network (DCGAN) method. Several medical pointers like uterine tonus of maternal, heart rate, blood pressure, and oxygen saturation were checked uninterruptedly. Numerous figure bases yield great volumes of data in diverse ratios and formats. The keen well-being analytics mechanism suggests toward excerpt numerous structures and quantity non-linear and linear scopes. Singh et al. [16] recommend an IDS related to the behaviour belief of the Smart Medical Device (SMD) i.e., the Medical Smart Phone (MSP). The hope price of the MSP or SMD is assessed via diverse behaviour structures through the beta standing method. A customary decisive rule related to the animatedly totalled trust grade was projected on checked the node's invasive close and attentive peers' procedure.

3. The Proposed Model

This study developed a new CCNA-SHSNN model for data classification in the cloud enabled healthcare system. The presented CCNA-SHSNN technique assists in the decision making process of the healthcare system in real time cloud environment. Fig. 2 demonstrates the overall process flow of CCNA-SHSNN system.

3.1. Normalization

For data pre-processing, the CCNA-SHSNN technique uses normalization approach. Standardization (z-score) and normalization (min-max scaling) were 2 traditional approaches for feature scaling [17].

$$Standarization = \frac{x - \mu}{\sigma} \tag{1}$$

Here, z denotes the standard values, x signifies the original values of feature instance, was average or mean of the values, and denotes the standard deviation. Standard deviation can be utilized in the method which uses the Standard Scaler approach from the scikit learn library. Therefore, feature scaling has been applied in this work.

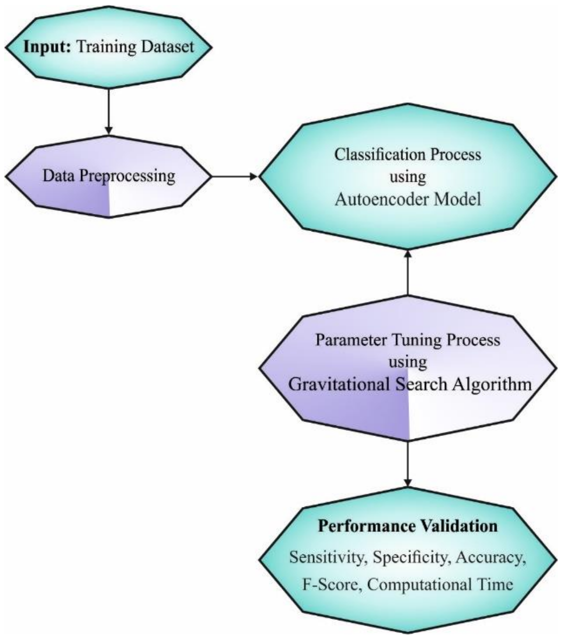

Fig. 2. Overall process of CCNA-SHSNN approach

3.2. Data Classification in Cloud environment

Here, the CCNA-SHSNN technique applies AE model for healthcare data classification in CC platform. AE is the conventional technique used in ML and DL algorithms for extracting features, involving a three layer architecture of input, hidden and output layers. It assumes unsupervised learning and takes the input dataset as the learning target that is utilized for compressing the dimensionality of the input dataset and is trained by comparing the difference between original dataset and the reconstruction dataset for making the input and output for obtaining the data representation in lower dimension without any loss of accuracy.

In the study, SAE is utilized for extracting EF feature, where neuron has a sparse constraint mechanism and the activation function is a sigmoid function range within [0,1] that is given below [18].

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{2}$$

Assume $X = \{x_1, x_2, \cdots, x_{n-1}, x_n\}(x_j \in R^{(m)})$ indicates the data samples, whereby n represents the quantity of information and m indicates the dimensionality of features. The encoder network employs the sigmoid activation function for encoding the input layer x to accomplish the hidden layer h. Next, the decoder network decodes the hidden state for obtaining the output vector $\hat{x}$. The decoding function $g(h)$ and encoding function $f(x)$ are given below:

$$h = f(x) = f(W_1 x + b_1) \tag{3}$$

$$\hat{\chi} = g(h) = g(W_2 h + b_2) \tag{4}$$

Now, W_1 indicates the weight from the input to the hidden layers, W_2 indicates the weight from the hidden to output layers, b_1 and b_2 represents the bias terms of hidden and the output layers, correspondingly.

The key concept of SAE is to develop a sparse penalty term into the loss function for limiting the activation of neurons in the hidden layer. For the provided neuron, if the output is closer to one, then its activation level is higher. On the other hand, the activation level is lower when it is closer to 0. Consider the output of $j\text{-}th$ neurons in the hidden state as $h_j(x^{(i)})$, where the average activity is represented in the following:

$$\hat{\rho} = \frac{1}{m}\sum_{i=1}^{m} h_j\left(x^{(i)}\right) \tag{5}$$

In Eq. (5), $\hat{\rho}$ denotes the sparsity variable, and to decrease the activation of neurons, that value is predictable to converge to 0, KL scatter is presented as a penalty term such that $\hat{\rho}$ converged to the constant ρ closer to 0, and the difference between the two is formulated in the following equation:

$$KL(\rho \| \hat{\rho}_j) = \rho \log \frac{\rho}{\hat{\rho}} + (1-\rho)\log \frac{1-\rho}{1-\hat{\rho}_j} \tag{6}$$

The loss function of AE usually has the form of Eq. (7). With the summary of KL scatters, the loss function of SAE is formulated as follows:

$$L = \sum_{i=1}^{m} \frac{1}{2} \|x_i - \hat{x}\|^2 \tag{7}$$

$$L_{SAE} = L + \beta \sum_{j=1}^{k} K\,L(\rho \| \hat{\rho}) \tag{8}$$

whereas β indicates the weighting factor of sparse penalty term.

3.3. Parameter Tuning

Lastly, GSA is used for hyperparameter optimization of the AE model. In this work, search space of the problem can be regarded as a multi-dimension scheme using diverse results in the search space [19]. In the study, all the points in the problem is an exclusive resolutions to resolve the challenges. The aim is to compute all the solutions as a natural, heavier mass produces best solution for the problem. Now, a set of elements is deliberated as search agents. This conformation creates the problem that only motion laws and gravitation govern. According to the unique situation of the recommended technique, the Law of Motion and Gravitation law is described in the following:

Gravitation law: all the particles in problem attract another particle towards them. The quantity of these forces is proportionate to the gravitation properties and inverse to the distance amongst those elements.

Laws of Motion: The actual velocity of all the particles is equivalent to the amount of constant of the preceding velocity of the particles and variation of the velocity. Variation in acceleration and velocity is equivalent to the imposed force on the particles separated based on the mass of the gravitation.

A sequence of m particles considering the search space. Considering the location of all the particles and solution to the problem. In Eq. (9) evaluates the location all the particles in the problem and it is expressed in the following equation.

$$x_i = \left(\chi_{i,}^{l} \chi_i^d, \dots \chi_i^D\right) \tag{9}$$

In the study, a force $F_{ij}^{d}(t)$ is forced from the i to j particles in the d dimension direction at t time. The quantity of these forces is calculated from Eq. (10) where $G(t)$ indicates the constant gravitation at t time, $R_{ij}(t)$ shows the distance among i, and j particles at time, and s shows a smaller value. M_i and M_j indicates the mass of i and j particles, correspondingly.

Eq. (11) is utilized for calculating the Euclidean distance amongst the elements.

$$F_{ij}^{d}(T) = \frac{G(t) \times M_i(t) \times M_j(t)}{R_{ij}(t) + \varepsilon} (\chi_j^d(\tau) - \chi_i^d \tag{10}$$

$$R_{ij}(T) = \|X_i(T), X_j(T)\|_2 \tag{11}$$

The force $F_i^d(t)$ on the i particle is equivalent to the overall amount of the forces of another particle of the model forced towards the time and direction of t and d correspondingly. In these equations, f_{ij} indicates the force among i and j particles, r_j denotes the radius of j particles

$$F_i^d(T) = \sum_{j=1}^{m} r_j\, f_{ij}^{d}(T) \tag{12}$$

The acceleration of particles towards the d dimension at t time is demonstrated as $a_i^d(t)$ and it is accomplished as follows.

$$a_i^d(\tau) = \frac{F_i^d(T)}{M_i(T)} \tag{13}$$

The velocity of all the particles is computed by calculating the coefficients of the existing velocity and acceleration of the particles. The novel location of the i particle at d dimension is acquired as follows.

$$V_i^d(t+1) = r_i \times V_i^d(t) + a_i^d(t) \tag{14}$$

$$X_i^d(t+1) = r_j \times X_i^d(t) + V_i^d(t+1) \tag{15}$$

Whereas r_i and r_j indicates the uniformly distributed arbitrary number within (0, 1). For adjusting the gravitation constant Eq. (16) was employed.

$$G(t) = \beta^{-a\frac{1}{T}} \tag{16}$$

Now, α indicates a positive constant, and T denotes the amount of iterations. In another word, T represents the system life.

4. Experimental Assessment

This section inspects the performance validation of the CCNA-SHSNN model in smart healthcare system.

Table 1 provides overall classification outcomes of the CCNA-SHSNN model on HD dataset.

Fig. 3 reports comparative results of the CCNA-SHSNN model on HD dataset with 2000 samples. The figure implied that the CCNA-SHSNN model has reached improved performance under each metric. For instance, in terms of $accu_y$, the CCNA-SHSNN model has resulted in higher $accu_y$ of 96.88% while the k-NN, NB, SVM, and DT models have reached lower $accu_y$ of 88.72%, 89.96%, 84.67%, and 92.92% respectively. Meanwhile, in terms of F_{score}, the CCNA-SHSNN approaches have resulted in higher F_{score} of 96.88% while the k-NN, NB, SVM, and DT techniques have reached lower F_{score} of 88.72%, 89.96%, 84.67%, and 92.92% correspondingly.

Table 1 Comparative analysis of CCNA-SHSNN approach with recent algorithms under HD dataset

Heart disease related Dataset					
Measures	**CCNA-SHSNN**	**k-NN**	**NB**	**SVM**	**DT**
No. of Instance = 2000					
Accuracy	96.68	88.72	89.96	84.67	92.92
Sensitivity	96.77	87.06	89.71	94.63	91.04
Specificity	96.93	85.19	87.66	87.35	88.61
F-Score	97.68	86.94	90.30	91.87	93.49
No. of Instance = 4000					
Accuracy	97.20	93.11	88.71	89.55	87.88
Sensitivity	97.02	88.13	95.54	84.08	91.91
Specificity	98.59	84.51	87.87	91.61	86.14
F-Score	98.75	90.52	95.53	95.88	90.72
No. of Instance = 6000					
Accuracy	98.14	84.58	84.24	92.88	93.51
Sensitivity	98.51	90.00	84.10	84.60	94.64
Specificity	97.32	91.67	87.55	88.24	91.28
F-Score	97.80	95.86	88.95	88.91	93.45

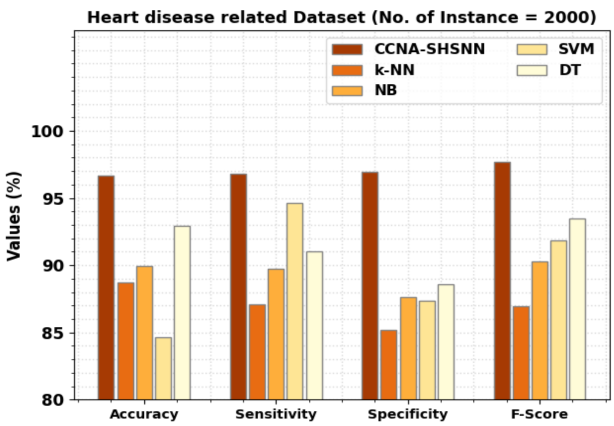

Fig. 3. Comparative analysis of CCNA-SHSNN approach under HD dataset with 2000 samples

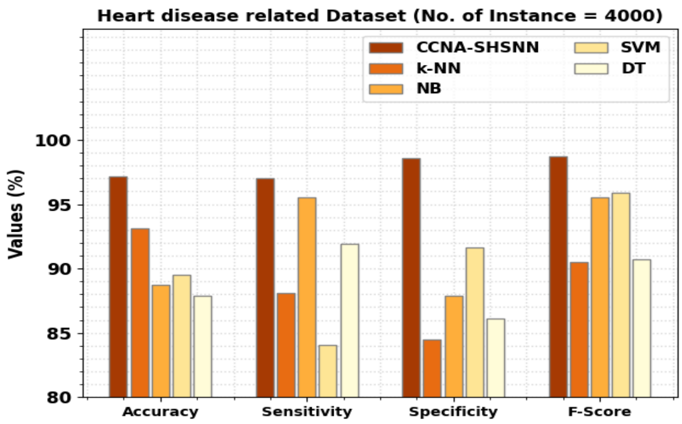

Fig. 4. Comparative analysis of CCNA-SHSNN approach under HD dataset with 4000 samples

Fig. 4 reports brief results of the CCNA-SHSNN model on HD dataset with 4000 samples. The figure implied that the CCNA-SHSNN method has reached improved performance under each metric. For example, in terms of $accu_y$, the CCNA-SHSNN model has resulted in higher $accu_y$ of 97.20% while the k-NN, NB, SVM, and DT approaches have reached lower $accu_y$ of 93.11%, 88.71%, 89.55%, and 87.88% respectively. In the meantime, in terms of F_{score}, the CCNA-SHSNN model has resulted in higher F_{score} of 98.75% while the k-NN, NB, SVM, and DT algorithms have reached lower F_{score} of 90.52%, 95.53%, 95.88%, and 90.72% respectively.

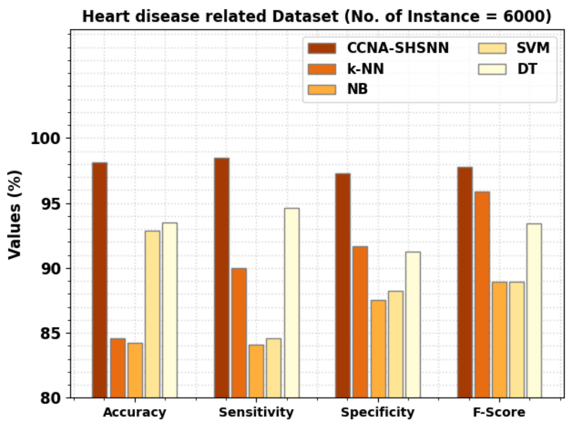

Fig. 5. Comparative analysis of CCNA-SHSNN approach under HD dataset with 6000 samples

Fig. 5 reports relative results of the CCNA-SHSNN approach on HD dataset with 6000 samples. The figure implied that the CCNA-SHSNN model has reached improved performance under each metric. For example, in terms of $accu_y$, the CCNA-SHSNN model has resulted in higher $accu_y$ of 98.14% while the k-NN, NB, SVM, and DT techniques have attained lower $accu_y$ of 84.58%, 84.24%, 92.88%, and 93.51% correspondingly. Meanwhile, in terms of F_{score}, the CCNA-SHSNN model has resulted in higher F_{score} of 97.80% while the k-NN, NB, SVM, and DT models have reached lower F_{score} of 95.86%, 88.95%, 88.91%, and 93.45% correspondingly.

Table 2 delivers overall classification outcomes of the CCNA-SHSNN approach on Infectious dataset. Fig. 6 reports detailed results of the CCNA-SHSNN technique on HD dataset with 2000 samples. The figure implied that the CCNA-SHSNN model has reached improved performance under each metric. For example, in terms of $accu_y$, the CCNA-SHSNN approach has resulted in higher $accu_y$ of 98.32% while the k-NN, NB, SVM, and DT techniques have reached lower $accu_y$ of 84.37%, 89.99%, 91.46%, and 93.96% correspondingly. In the meantime, in terms of F_{score}, the CCNA-SHSNN model has resulted in higher F_{score} of 97.95% while the k-NN, NB, SVM, and DT approaches have reached lower F_{score} of 90.26%, 93.16%, 94.25%, and 93.25% correspondingly.

Table 2 Comparative analysis of CCNA-SHSNN approach with recent algorithms under Infectious dataset

Infectious Dataset					
Measures	**CCNA-SHSNN**	**k-NN**	**NB**	**SVM**	**DT**
No. of Instance = 2000					
Accuracy	98.32	84.37	89.99	91.46	93.69
Sensitivity	97.83	86.68	91.05	95.14	94.96
Specificity	98.12	89.22	89.40	89.20	90.71
F-Score	97.95	90.26	93.16	94.25	93.25
No. of Instance = 4000					
Accuracy	97.98	87.83	89.58	92.65	95.83
Sensitivity	97.57	84.49	90.73	91.90	88.46
Specificity	97.38	88.90	93.12	85.03	84.96
F-Score	98.03	92.64	91.55	93.90	89.03
No. of Instance = 6000					
Accuracy	98.74	87.67	87.77	88.96	89.28
Sensitivity	97.03	92.39	90.70	87.46	86.66
Specificity	97.14	85.91	89.84	87.96	87.65
F-Score	98.00	88.47	90.62	88.12	95.31

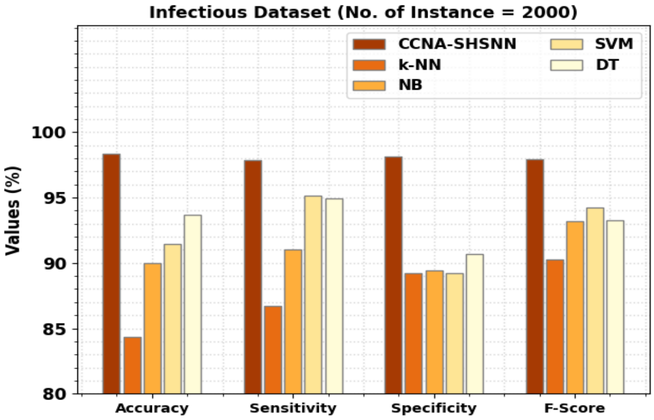

Fig. 6. Comparative analysis of CCNA-SHSNN approach under Infectious dataset with 2000 samples

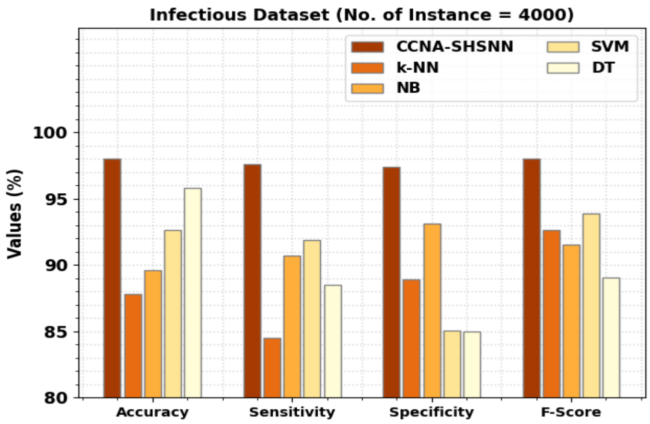

Fig. 7. Comparative analysis of CCNA-SHSNN approach under Infectious dataset with 4000 samples

Fig. 7 reports brief results of the CCNA-SHSNN model on HD dataset with 4000 samples. The figure implied that the CCNA-SHSNN technique has reached improved performance under each metric. For instance, in terms of $accu_y$, the CCNA-SHSNN model has resulted in higher $accu_y$ of 97.98% while the k-NN, NB, SVM, and DT approaches have reached lower $accu_y$ of 87.83%, 89.58%, 92.65%, and 95.83% respectively. For the meantime, in terms of F_{score}, the CCNA-SHSNN algorithm has resulted in higher F_{score} of 98.03% while the k-NN, NB, SVM, and DT models have reached lower F_{score} of 92.64%, 91.55%, 93.90%, and 89.03% correspondingly.

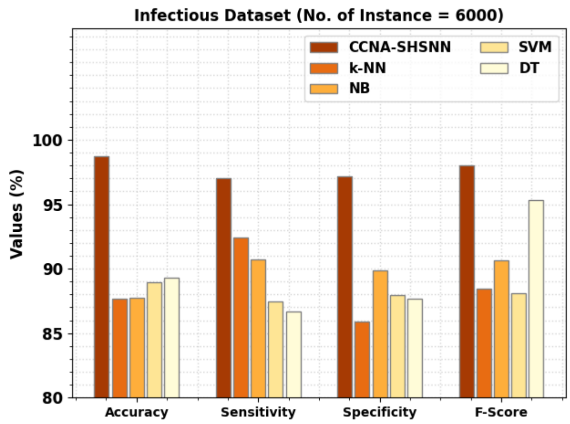

Fig. 8. Comparative analysis of CCNA-SHSNN approach under Infectious dataset with 6000 samples

Fig. 8 reports comparative results of the CCNA-SHSNN model on HD dataset with 6000 samples. The figure implied that the CCNA-SHSNN approach has reached improved performance under each metric. For example, in terms of $accu_y$, the CCNA-SHSNN model has resulted in higher $accu_y$ of 98.74% while the k-NN, NB, SVM, and DT models have reached lower $accu_y$ of 87.67%, 87.77%, 88.96%, and 89.28% respectively. Meanwhile, in terms of F_{score}, the CCNA-SHSNN model has resulted in higher F_{score} of 98% while the k-NN, NB, SVM, and DT techniques have reached lower F_{score} of 88.47%, 90.62%, 88.12%, and 95.31% correspondingly.

5. Conclusion

This study developed a new CCNA-SHSNN model for data classification in the cloud enabled healthcare system. The presented CCNA-SHSNN technique assists in the decision making process of the healthcare system in real time cloud environment. For data pre-processing, the CCNA-SHSNN technique uses normalization approach. Secondly, the CCNA-SHSNN technique applies AE model for healthcare data classification in CC platform. At last, GSA is used for hyperparameter optimization of the AE model. The experimental outcomes are determined on benchmark dataset and the outcomes signify the outperforming efficiency of the CCNA-SHSNN technique compared to existing techniques. In future scopes, advanced DL models can be applied.

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