International Journal of Data Informatics and Intelligent computing (IJDIIC)
Vol.2, No.1, March 2023, pp. 32~41
DOI: 10.59461/ijdiic.v2i1.45

Cloud Computing with Artificial Intelligence Techniques for Effective Disease Detection

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Article Info

Article history:

Received February 24, 2023
Revised March 17, 2023
Accepted March 20, 2023

Keywords:

Cloud computing
Artificial intelligence
Medical field
Whale optimized
fuzzy neural network
Internet of Things

ABSTRACT

With the current rapid advancement of cloud computing (CC) technology, which enabled the connectivity of many intelligent objects and detectors and created smooth data interchange between systems, there is now a strict need for platforms for data processing, the Internet of Things (IoT), and data management. The field of medicine in CC is receiving a lot of attention from the scientific world, as well as the private and governmental sectors. Thousands of individuals now have a digital system due to these apps where they may regularly obtain helpful medical advice for leading a healthy life. The use of artificial intelligence (AI) in the medical field has several advantages, including the ability to automate processes and analyze large patient databases to offer superior medicine more quickly and effectively. IoT-enabled smart health tools provide both internet solutions and a variety of features. CC infrastructure improves these healthcare solutions by enabling safe storage and accessibility. We suggest a novel Cloud computing and artificial intelligence (CC-AI) premised smart medical solution for surveillance and detecting major illnesses to provide superior solutions to the users. For disease detection, we suggested AI-based whale optimization (WO) and fuzzy neural network (FNN) (WO-FNN). Patients' IoT wearable sensor data is gathered for detection. The accuracy, sensitivity, specificity, and computation time are evaluated and compared with existing techniques.

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1. INTRODUCTION

World medical services are about to transform due to a fundamental change in digital technology from conventional medicine to intelligent medicine. Modern tools are used in intelligent medicine to make it simple to explore patient data, connect people with services and entities, and manage and respond to changes in the medical setting. Individuals, medical experts, associations, and authorities are just a few of the entities in the medical sector that are connected through smart treatment. Cloud computing (CC), artificial intelligence (AI), the internet of things (IoT), and sensors technology all of which are developing rapidly help to accomplish this. The evolution of the rapidly developing, ground-breaking idea termed smart treatment is significantly influenced by these innovations [1]. Health systems are evolving and becoming more contemporary owing to the development of IoT and CC technologies and prominent companies are increasingly embracing cloud technology in professional medical care. The United States created a cooperative care system to make it simple for patients to obtain scattered medical data. The US Secretary of State is partnering with all Scripts and MicroHealth to develop a cloud-based healthcare system for the administration of its worldwide digital health data. The ministry of state's medical and administrative personnel will have simple availability to the individuals' hospital history owing to this technology. Both patients and healthcare providers will gain from this. The use of IoT gadgets in the medical sector is expanding. The IoT and CC innovations are being incorporated into healthcare solutions by medical professionals in Europe and Asia[2]. The idea of a digital society is not novel given that more residents are relocating to urban areas. The foundation of a digital town is the transformation of the medical field via improved efficiency, decreased costs, and a renewed emphasis on patient welfare. A thorough grasp of the various digital city systems is necessary for the implementation of CC and AI for remote healthcare (RH) observation platforms. These platforms take the shape of supporting techniques, apparatus, platforms, concepts, layouts, application cases, and software products. The fundamental way that the CC-based RH platform uses AI is to collect various records and information. On the contrary hand, a variety of medical sector delivery models and medical outcome assistance tools contain AI techniques that are widely utilized to develop analytical depictions. Medical outcome support tools thoroughly consider each element before recommending a specific course of therapy, lifestyle recommendations, and care plan to individuals. The software employed supports healthcare activities and analyzes bodily functions such as blood sugar, respiratory rate, and pulse rate[3]. All of the equipment used in the medical sector has been automated as a result of modern technology improvements. These technological innovations make life easier and more pleasant. People thus employ a variety of gadgets in their everyday lives, such as wearable sensors. A novel way to gather medical data for effective health monitoring is made possible by wearable sensors and virtual communities. But utilizing wearable sensors to continuously monitor patients produces a lot of medical data. These tools may be used to keep a close eye on the person in real-time. It helps to monitor the patients and detect the disease. Earlier disease detection is very essential to treat patients [4]. Remote healthcare observation is a kind of telehealth that entails utilizing digital health technology to gather and transmit patient wellness information to their medical team. For preventive therapeutic practice and to include the patient's families in a children's treatment, RH may be used to collect and show longitudinal patient-generated medical information. For many years, gathering remote information has been regarded as the pattern of treatment for various severe illnesses. However, the widespread use of RH in medicine has been restricted by software restrictions, shortages in connectivity to the Web and technological equipment, a lack of technical education, inadequate payment, and other issues [5]. Hence, we presented a novel technology cloud computing and artificial intelligence (CC-AI) based technique for detecting disease in remote monitoring and improving healthcare services.

Researcher [6] claimed that creating a detection model using risk variables might offer an effective way to detect breast cancer. Techniques for machine learning (ML) have been used to improve the effectiveness of earlier detection. They suggested using support vector machines (SVM) together with additional trees, a much-randomized tree classification, to diagnose breast cancer at an earlier stage depending on hazard variables. SVM was utilized to determine the breast cancer grade whereas the additional-trees classification was employed to eliminate unnecessary data. In [7] aimed to create computer-aided detection (CAD) to distinguish between regular function and Alzheimer's disease (AD). The majority of the older strategies created a system or classification to categorize the brain images after using image processing approaches for preparation and characteristic retrieval. The identification rate of earlier approaches was significantly impacted by the recovered characteristics as a consequence. To solve this problem, a new and improved CAD system built on a convolutional neural network (CNN) is developed that can distinguish between those with normal cognitive function and those suffering from AD. CNN uses several layers and prediction nodes to cause the slow-level prediction. Reseacher [8] focus on the enhancement of survivorship estimation for individuals with osteosarcoma. The Kaplan-Meier assessment is a popular statistical method utilized for this aim. The improvement of patient experience and economic management now depends on life prediction. They offer an alternate survivorship evaluation that makes use of genetic algorithms and K-nearest neighbor (KNN). To maintain all of the trained information, KNN needs a lot of storage. Researcher [9] created a method that uses a tumor segmentation technique to remove problematic tumor tissue. Then, characteristics based on surface and structures are used to describe breast lesions. Initial and second-order data are included in the retrieved characteristics. Utilizing compound feature vectors, a combination of Ml techniques is used to identify breast cancer. Different ML methods are unable to appropriately manage the enormous amount of multi-feature information on diabetic illness. Focusing on deep ML and information-fusing viewpoints, a smart healthcare classification method for a diabetic condition is developed. They can reduce the needless strain on system processing power by using data fusion. The aggregate ML system is then taught to detect diabetes [10]. Using the wristband photo plethysmography (PPG) data and fundamental biological indicators, a non-invasive diabetes mellitus recognition method is developed to make the diagnosis of the condition simple. To minimize the amount of input information, a hybrid feature selection approach (Hybrid FS) is suggested[11]. Researcher [12] suggested a hybrid decision support system that, when used in conjunction with the patient's clinical characteristics, may help in the early diagnosis of cardiac disease. To deal with the missing data, the researchers employed the multivariate restoration by chained formulas approach. The choice of appropriate characteristics from the provided database was made using a mixed feature selection approach that combines the Genetic Algorithm (GA) with recurrent attribute removal. These existing techniques have numerous drawbacks like low detection accuracy, high computation energy, sensitivity to large datasets, more detection time, and high error rate. To tackle these drawbacks we proposed a CC-AI-based technique WO-FNN for effective disease detection. Medical infrastructures are crucial because they directly impact people's lives. Many people are developing chronic illnesses. These illnesses, which account for more than 2/3 of all fatalities globally, make up the majority of dangers to public health. Together with population expansion, the prevalence of chronic diseases has grown. As a result, hospitals cannot manage all patients. These disorders need regular hospital visits for medication and observation, adding to the workloads of both hospitals and patients. Additionally, chronic illnesses need specialized residential services to satisfy patients' demands and provide therapeutic plans. The remote healthcare monitoring system satisfies these objectives by efficiently monitoring patients and detecting diseases.

2. METHOD

The growth of the medical industry will transform every part of people's lives because of the growth of smart gadgets, AI, and CC. In this research, CC-AI based WO-FNN is recommended as a means to improve the speed and efficiency of healthcare services, as well as the quality of treatment provided to patients. The proposed workflow is presented in figure 1.

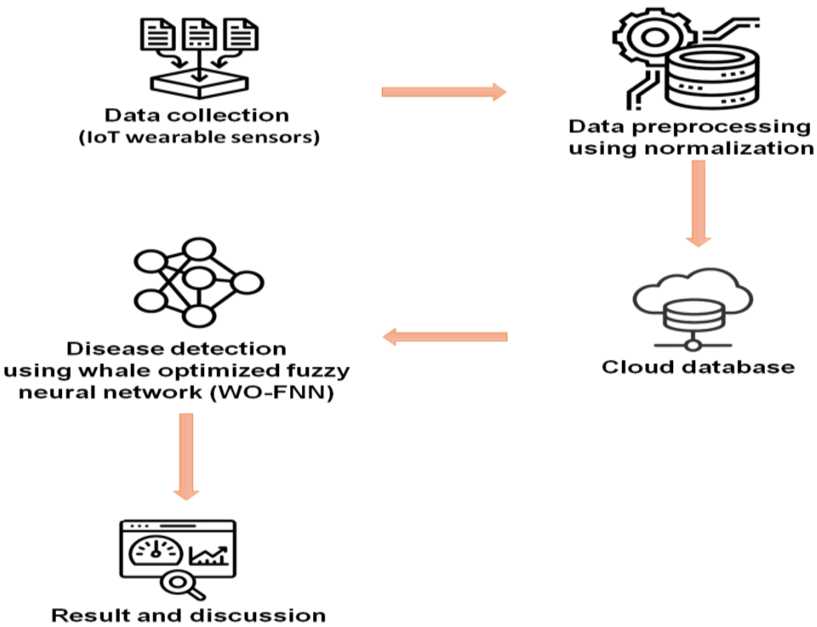

Figure 1. Proposed flow

2.1. Data collection

Possible disease indications derive from wearable sensors. Heart rate, respiration percentage, physical behavior, body temperature, oxygen saturation amount, cough problems, and tension are all measured using a variety of sensors. The wearable gadgets that may be used to identify and track patients, including accelerometer, thermometer, Global positioning system (GPS), electrocardiogram (ECG), and oxygen saturation. Sensors transmit the biological readings to the cloud, where further computation and research forecast the patients' conditions [13].

2.2. Data preprocessing using normalization

Preprocessing is the process of transforming raw data into a form that computers can interpret and analyze as part of the data extraction and research process. Data from the real world, including text, images, videos, and other forms, are mixed. In addition to being difficult, it lacks a logical framework and is filled with errors and contradictions. Statistical normalization is the process of transforming information from any regular probability into a conventional regular probability with an average of 0 and a single deviation.
Equation 1 defines statistical normalization.

$$a_i = \frac{u_i - \varepsilon}{\sigma} \tag{1}$$

where $\varepsilon = \frac{1}{N}\sum_{i=1}^{N} u_i$ ε is the average of n instances for a property with value 1, and σ is the standard variation which is shown in equation 2.

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(u_i - \varepsilon)} \quad (2)$$

Furthermore, the data set must have a regular probability if statistical normalization is to be used; specifically, the center limitation theorem states that there must be a high number of samples (N) in the database. The number of the property is not scaled into [0,1] via statistical normalization. Rather, it distributes 99.9 percent of the characteristic's instances into [-3, 3].

2.3. Cloud database

The suggested scheme used a variety of healthcare data types while determining recommendations. Meanwhile, IoT systems gather health information for numerous patients from several faraway locations for evaluation. For evaluation, this information should be kept on a server. It is difficult to preserve and manage such a big amount of information. The cloud infrastructure offers enough area for preserving this significant amount of information. Hadoop can scale and preserve this huge amount of information. Additionally, a major difficulty in a cloud system is information protection. Cloud utilizes a protected storage technique to store health information for this function. The purpose of this safe preservation technique is to safeguard health information. The two stages of the safe preservation operation are the safe preservation stage and the recovery stage.

2.4. Disease detection using whale optimized fuzzy neural network (WO-FNN)

This section provides a detailed explanation of a recently developed illness detection model. This study proposes a novel artificial intelligence-based WO-FNN for detection that is built on fuzzy rules and a neural network. The main benefit of the suggested identification technique is that it can quickly categorize records based on time limitations while choosing contributing attributes. This approach frames rules using a triangle membership function. The parameters that were extracted from the IoT device data are used for disease detection. Based on the characteristics that were gathered, the categorization separates the data into groups. The method of FNN architecture includes the development of fuzzy rules utilizing an IF-THEN structure. To do this, FNN are trained to create the foundation and follow elements of the fuzzy IF-THEN rules for identifying systems in the best manner feasible. The research uses IF-THEN rules of the Takagi-Sugeno-Kang (TSK) kind. These regulations have a soft preceding portion and a severe ensuing component.

Thus B_1 is A_{1i} and B_2 is A_{2i}

$$v_i \ is \ \sum_{j=1}^{n} d_{ji}B_j + p_i \quad (3)$$

Equation 3 illustrates how the TSK-type fuzzy system, which has the format described above, reflects non-linearities with linearization. In this instance, c_1 and c_2 are the program's inlet and outlet data, correspondingly. j = 1,..., n is the count of intake data, and i = 1,.., p is the count of regulations. d_{ji} and v_i are coefficients, while aij and aij are source fuzzy subsets. The FNN has six levels in all. The distribution of the c_1 (j= 1,..., n) intake data takes place at the initial level. The subsequent level has elements for participation. Single nodes so represent a separate data word. As a result, for each intake data point reaching the system, the participation extent at which an intake value belongs to a fuzzy system is determined. The research uses the Probabilistic participation function to define interaction data.

$$\mu 1_i(B_j) = x^{-(c_i - x_{ji})^2/\sigma_{ji}^2}, j = 1, \dots, n, i = 1, \dots, k, \quad (4)$$

where x_{ji} and σ_{ji}^2 are the size and feature, correspondingly, of the Stochastic probability density distributions which are shown in equation 4. The intake parameter's involvement criteria for the ith term is $\mu 1_i(c_j)$. The total quantity of incoming data is n, and the total quantity of the fuzzy system is k. (3rd concealed neuronal).

$$\mu_i(B) = \prod_j \mu 1_i(B), j = 1, \dots, n, \ \ i = 1, \dots., k, \quad (5)$$

The third layer is, in fact, a regulatory layer. The number of nodes and regulations in this instance are equal. As a result, the rules are identified by the letters K1, K2,..., and Kk. The method stated in equation 5's definition of the k-norm min (AND) technique is utilized to determine the outcome of the data from this layer.

$$v_i = \sum_{j=1}^{n} B_j \omega_{ji} + q_i \tag{6}$$

The incoming data for the fifth layer is provided by the j(x) data above. The fourth layer is the one that comes after. It contains n monotonic processes. Equation 6 establishes the values of the results of the rules.

$$v1_i = \mu_i(B).v_i \tag{7}$$

The 3rd layer's result values are doubled by the 4th layer's result data in the subsequent fifth layer. The jth node's result is computed as in equation 7.

$$c_r = \frac{\sum_{i=1}^{k} \omega_{ir} v1_i}{\sum_{i=1}^{k} \mu_i(x)} \tag{8}$$

The FNN detected final data are identified in the 6th layer, which is represented by equation 8, as follows. After the section best optimal result should be identified by whale optimization. The procedure of WO-FNN is shown in figure 2.

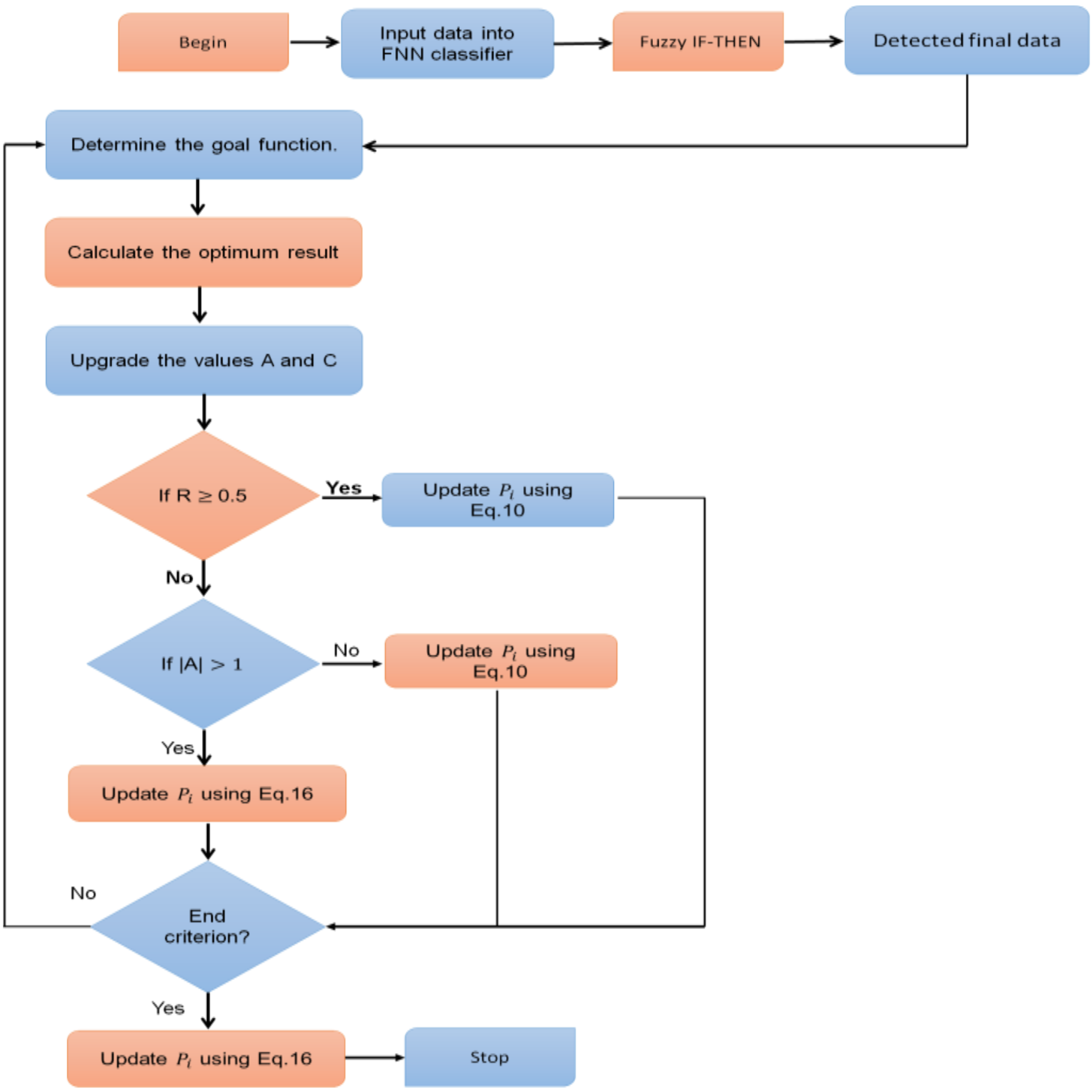

Figure 2. Procedure of WO-FNN

An innovative dynamic method is the whale optimization algorithm. WO mimics the foraging behavior of enormous whales. The humpback whales are known to use a specific predatory strategy known as bubble-net eating, in which whales capture a bunch of tiny fishes close to the substrate. They travel toward food in a decreasing circle while producing characteristic bubbles along a spiraling path. Two steps comprise the whale optimization process. Utilizing the bubble loop assault strategy, the initial step is expropriation, in which the target is surrounded. The next process, known as exploration, involves the selection of prey at random. The hunt circumstance may be found by the whale optimization to surround them. Since the ideal hunt site has not yet been established, the desired food is assumed to be the current best position or to be close to it in the whale technique. Likewise, the optimal result will be detected. These mathematical equations 9 and 10 describe this outcome:

$$\vec{D} = \left|\vec{A}.\vec{P}^{*} - \vec{P}(c)\right| \tag{9}$$

$$\vec{P}(a+1) = \vec{P}^{*}(t) - \vec{b}.\vec{D} \tag{10}$$

where c denotes the present cycle, $\vec{P}$ is the position variable, and P^{*} is the position variable of the optimal result. a and b are regarded as component variables. A and B are represented by equations 11 and 12 below.

$$\vec{A} = 2\vec{a}.\vec{R} - \vec{a} \tag{11}$$

$$\vec{B} = s.\vec{R} \tag{12}$$

where decreases from 2 to 0 by loop phase, and R is a randomized vector generated with constant dispersion in the [0, 1] range. Solutions to equation 10 should be verified at the place of the optimum responses (prey). A is lowered using the given equation 13 in WO to achieve the shrinking surrounding action in a trap.

$$a = 2 - r\frac{2}{MaxIter} \tag{13}$$

where r is a recurring integer and MaxIter is the number of repetitions that are allowed in total. To replicate the spiral-shaped path, the space between the finest searching (P^{*}) and a searching factor (P) is determined. Then, a spiraling equation 14 is created as follows to provide the nearby searching agent position:

$$\vec{P}(t+1) = D'.e^{fl}.cos(2\pi C) + \vec{P}^{*}(r) \tag{14}$$

where C is a chance number in the range [1, 1], f is a fixed, the ith whale's area, and the food is all taken into account. Equation 15 is used to determine the optimum solution (prey).

$$D' = \left|\vec{P}^{*}(r) - \vec{P}(r)\right| \tag{15}$$

As was previously noted, humpback whales move concurrently in a spiraling and shrinking circle surrounding their food, likewise, repetition is done until getting an optimal solution. Throughout the optimization procedure, there is a 50% chance that one of the two processes will be chosen to imitate the other which is denoted in equation 16, where R is a random integer in the range [0, 1].

$$\vec{P}(r+1) = \begin{cases} Diminishing\ enclosing & \big(Eq.(13)\big)\ (R < 0.5) \\ Spiraling\ route & \big(Eq.(14)\big)(R < 0.5) \end{cases} \tag{16}$$

3. RESULTS AND DISCUSSION

In this part, the effectiveness of the suggested illness detection in remote healthcare is examined. Accuracy, sensitivity, specificity, and computation time are among the performance criteria used for evaluation. Convolutional neural network (CNN), Deep-learning Diabetic Retinopathy (DeepDR), Extended Kalman Filter with Support Vector Machine (EKF-SVM), and Bagging Ensemble with K-Nearest Neighbor (BKNN) are the methods used for comparison.

3.1. Accuracy

Figure 3 displays the accuracy of the proposed and conventional technologies. Table 1 shows the findings of the accuracy of the proposed and conventional technologies. The model's accuracy may be calculated by dividing the total number of detections by the number of accurate illness detections, which includes both real positive and negative outcomes. The degree to which a forecast is close to the genuine value is referred to as accuracy. As a gauge of the accuracy of the detection, the ratio between the predicted value and the actual value was calculated. When compared to other approaches now in use, the suggested method offers a (95%) of accuracy in illness detection.

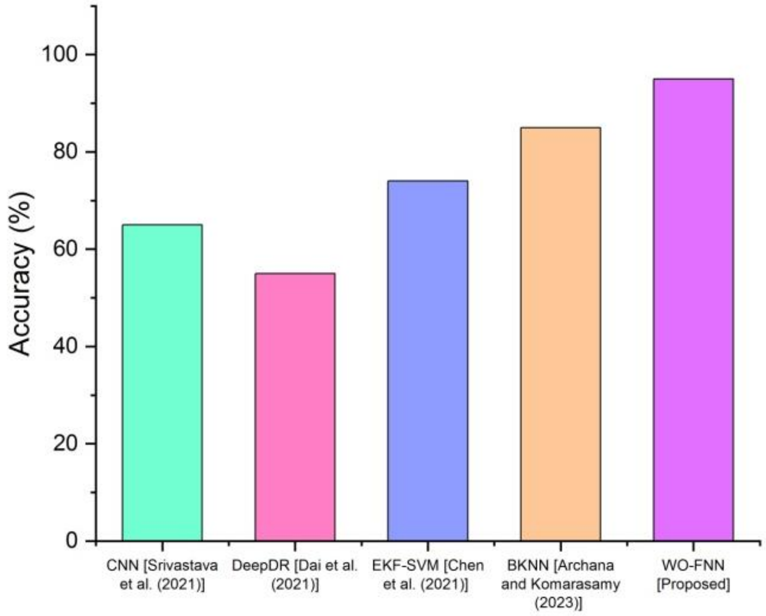

Figure 3. Accuracy of the proposed and conventional technologies

Table 1. Findings of accuracy

Methods	Accuracy (%)
CNN [Srivastava et al. (2021)]	65
DeepDR [Dai et al. (2021)]	55
EKF-SVM [Chen et al. (2021)]	74
BKNN [Archana and Komarasamy (2023)]	85
WO-FNN [Proposed]	95

3.2. Sensitivity

Figure 4 displays the sensitivity of the proposed and conventional technologies. Table 2 shows the findings of sensitivity of the proposed and conventional technologies. The effectiveness of a diagnostic technique to accurately detect people with an illness is known as sensitivity. If the diagnostic technique shows that the individual has the disorder then the technique is reliable. It shows that the sensitivity is (98%) in the proposed technology.

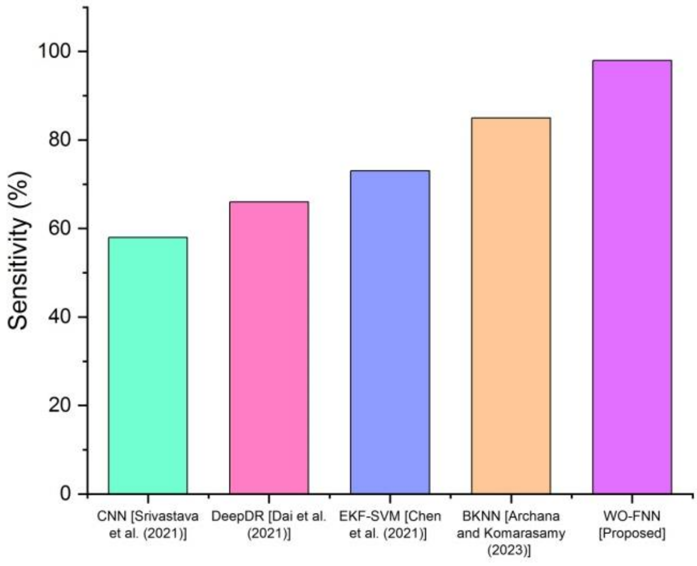

Figure 4. Sensitivity of the proposed and conventional technologies

Table 2. Findings of sensitivity

Methods	Sensitivity (%)
CNN [Srivastava et al. (2021)]	58
DeepDR [Dai et al. (2021)]	66
EKF-SVM [Chen et al. (2021)]	73
BKNN [Archana and Komarasamy (2023)]	85
WO-FNN [Proposed]	98

3.3. Specificity

Figure 5 displays the specificity of the proposed and conventional technologies. Table 3 shows the findings of specificity of the proposed and conventional technologies. Specificity refers to a method's capacity to appropriately recognize individuals who do not have the sickness being examined. If the individual is not suffering from the disease and the result comes out negative. It indicates the efficacy of the method. The comparisons show that the specificity is (95%) in the proposed method, which proves that the proposed technique is reliable.

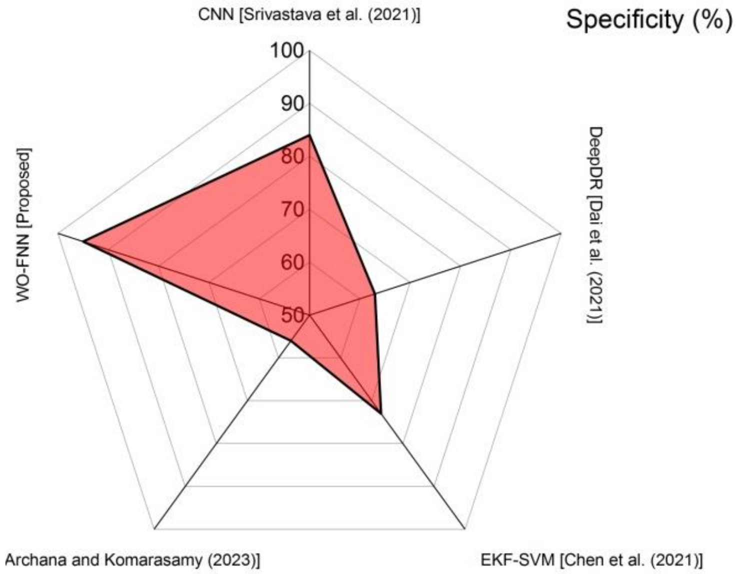

Figure 5. Specificity of the proposed and conventional technologies

Table 3. Findings of specificity

Methods	Specificity (%)
CNN [Srivastava et al. (2021)]	84
DeepDR [Dai et al. (2021)]	63
EKF-SVM [Chen et al. (2021)]	73
BKNN [Archana and Komarasamy (2023)]	56
WO-FNN [Proposed]	95

3.4. Computation time

Figure 6 displays the computation time of the proposed and conventional technologies. Table 4 shows the findings of the computation time of the proposed and conventional technologies. The amount of time needed to perform a computational operation is known as computation time, also referred to as processing time. It is possible to think of the time needed to do a computation as a reflection of the analysis itself since it is inversely correlated with the number of times the associated rules must be applied. It demonstrates that the suggested method executes illness detection in less time (65%).

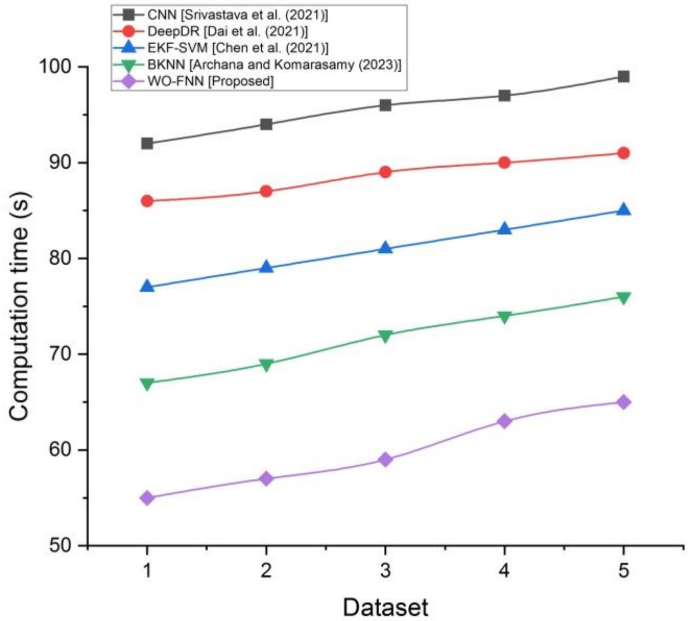

Figure 6. Computation time of the proposed and conventional technologies

Table 4. Findings of computation time

Dataset	Computation time (s)				
	CNN [Srivastava et al. (2021)]	DeepDR [Dai et al. (2021)]	EKF-SVM [Chen et al. (2021)]	BKNN [Archana and Komarasamy (2023)]	WO-FNN [Proposed]
1	92	86	77	67	55
2	94	87	79	69	57
3	96	89	81	72	59
4	97	90	83	74	63
5	99	91	85	76	65

4. CONCLUSION

The development of innovative wearable devices, cloud computing, and artificial intelligence concepts have benefited the healthcare industry. These innovative advancements are essential for directly improving the quality of life for those suffering from sickness. Early disease detection may result in more successful treatments and extended survival times for patients. These CC-AI technologies provide people access to remote health monitoring for the diagnosis and treatment of diseases. To achieve effective detection, we suggested using a technology called whale optimized fuzzy neural network (WO-FNN), which is based on CC-AI. The research makes use of a dataset from wearable sensors. Statistical normalization is used to preprocess the data. Performance criteria including accuracy (95%), sensitivity (98%), specificity (95%), and computation time (65s) are evaluated. The techniques considered for comparison include Convolutional Neural Network (CNN), Deep-learning Diabetic Retinopathy (DeepDR), Extended Kalman Filter with Support Vector Machine (EKF-SVM), and Bagging Ensemble with K-Nearest Neighbor (BKNN). The results show that the suggested approach is effective in detecting diseases remotely. Future versions of the suggested system might include innovative technology for faster detection.

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