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Design of intelligent IoT for smart healthcare monitoring system using optimal neural network (IONN) model

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***Abstract*---**One of the most important aspects of human life is health. Every society is paying more attention to and implementing technology in the areas of health and healthcare. In the healthcare sector, Artificial Intelligence (AI) is frequently employed to deliver quick and reliable results. Early disease predictions assist doctors in making timely decisions to save patients' lives. The Internet of Things (IoT) is assisting AI applications in healthcare by acting as a catalyst. The data of the patients is gathered by IoT sensor, and the data is analysed using machine learning algorithms. The IONN model, an innovative and intelligent healthcare monitoring system based on modern technologies such as the IoT, optimization techniques, and machine learning, is introduced in this study to detect various

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diseases early and precisely. For people who reside in rural places, this system gives a low-cost solution. The accuracy of the proposed IONN model has enhanced by 4% to 15% when compared to existing approaches. Furthermore, as compared to ANNs that use the BPN algorithm, the IONN model reduces the overall training time by 15% to 52%. Based on the results, the proposed IONN model performs well in terms of training time and accuracy when diverse healthcare datasets are used for training.

***Keywords*---**design intelligent, IoT, smart healthcare, IONN.

Introduction

One of the most important aspects of human life is health[1]. Every society is paying more attention to and implementing technology in the areas of health and healthcare. Despite significant disparities between developing and metropolitan countries, access is a critical issue in rural health all around the world. Persons in rural areas of developing countries have poorer health than people in developed countries. As a result of the Internet's new revolution, IoT is swiftly gaining ground as a new study topic in healthcare[2]. Health-care platforms that integrate IoT, wearable devices, mobile Internet and AI to allow users to enter health records and link people, resources, and organisations are referred to as smart intelligent healthcare[3]. Through health care, the IoT is gradually connecting doctors and patients. In IoT-enabled healthcare systems, machine learning and deep learning algorithms, among other AI technologies, are now frequently deployed. Machine learning is an artificial intelligence technology that allows an AI system to automatically learn from its environment and utilise that knowledge to make intelligent judgments. Early disease predictions assist doctors in making timely decisions to save patients' lives. IoT is assisting AI applications in healthcare by acting as a catalyst. The use of IoT in healthcare reduces emergency wait times, makes inventory, staff, and patient tracking easier, improves drug management power, makes monitoring and reporting easier, sends emergency notifications to doctors, lowers costs, and allows for faster illness diagnosis. It's tough to care for a patient for 24 hours at home, and it's even more difficult to remember to give medicine on time, but IoT devices can simply monitor the patient for 24 hours and send an alarm or message notice for medicine. IoT is a network of numerous connected devices that can communicate across a computer network. Patients' data is gathered by IoT sensors via this global network, and patient data is analysed using machine learning techniques. Early, accurate, timely, and simple predictions are made using machine learning algorithms.

In this study, the IONN model, an innovative and intelligent healthcare monitoring system based on modern technologies such as IoT, optimization techniques, and machine learning, is introduced. This system is capable of sensing and processing patient data via a medical decision support system. For people who reside in rural places, this system gives a low-cost solution. The following is a list of the proposed work's main contributions:

1. For improving training and testing speed, the best features are chosen by implementing an ant colony optimization (ACO) algorithm
2. Using optimal features, Human health is classified using the IONN model which is an intelligent healthcare monitoring system using IoT, optimization techniques and machine learning.
3. Evaluate the developed healthcare IONN model's performance in various real-time multiple health databases.
4. Compare the developed healthcare IONN model's performance to that of other recently developed models.

The remaining work is divided into the subsequent groups. Section 2 represents previous work in this domain, while Section 3 represents proposed framework. In Section 4, the experimental results and discussion are presented. The work is concluded in Section 5.

Literature Review

As per the literature survey, machine learning[4][5] deep learning algorithms[6][7][8][9][10], Cloud Computing[11], Fuzzy Logic[12] and 5G network[13] are all extensively employed in IoT-enabled healthcare systems, according to the literature. A model for detecting lung cancer that integrates the computational intelligence with IoT and while inflicting the smallest amount of environmental damage is being developed[14]. Based on the heuristics-based Greedy Best First Search (GBFS) method, a new hybrid machine learning model to optimize the lung cancer dataset has been developed. A random forest classifier, on the other hand, aids with lung cancer patient classification based on their symptoms. Using deep learning techniques, Xingdong et al suggested an IoT-enabled real-time smart healthcare system for sports. The suggested system makes use of portable medical devices to gather various signals from the human body and then applies various deep learning algorithms to extract useful data[7]. Information may now be transmitted more quickly and securely due to technologies like cloud computing and IoT. Sensors in IoT and cloud computing supply data and information on the patients' status, which is subsequently fed into the LSTM deep neural network via cloud computing and IoT. On the basis of trained input data, the LSTM Deep Neural Network generates a model with neural structure of input, hidden and output layer. The generated model is then used by the system to remotely classify and monitor the health of patients' by obtaining information about their situations for categorization and evaluation[15]. Smart Patient Monitoring and Recommendation (SPMR) is a novel framework based on Deep Learning (DL) and Cloud-based analytics[6]. Modern technologies such as AI, IoT, and cloud computing are included into the concept. Rasha et al demonstrated a data science strategy for continuous patient monitoring that combined IoT and cloud computing. Human healthcare is classified using a backtracking search-based deep neural network (BS-DNN). Based on IoT and neural network techniques, a decision-support healthcare system has been developed by a number of researchers[4][5]. In wearable Internet of Things (IoT) Edge sensors, a lightweight neural network is employed for system level power conservation and real-time electrocardiogram (ECG) anomaly detection. In the proposed network's hybrid design, Multi-Layer Perceptrons (MLP) and Long Short Term Memory (LSTM) cells are utilised [5]. A hybrid deep neural network technique has been proposed for a novel binary spring search (BSS) algorithm based on group theory (GT) to address the security challenges in transferring health data[9]. For the 5G network, J. Lloret presented a framework for creating smart e-health monitoring systems[13].

Smart Healthcare Monitoring **System Architecture**

The architecture of Intelligent IoT for smart Healthcare Monitoring System using optimal neural network (IONN) model is show in the Figure 1.

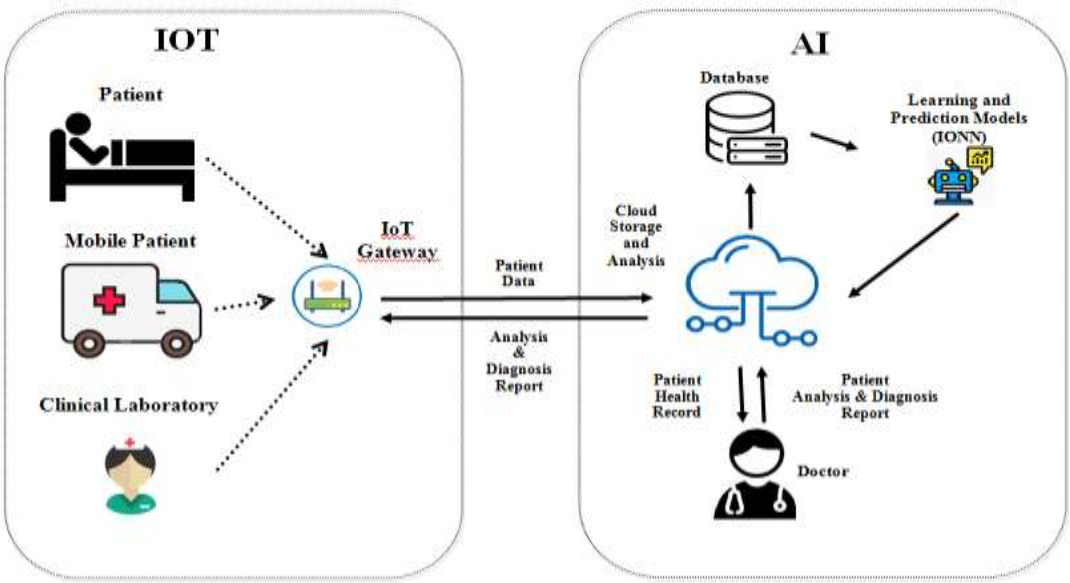

Figure 1: Architecture of Smart Healthcare **Monitoring System**

Data Collection

To acquire patient data, IoT devices such as implanted and external sensors are used. Internal data is collected through implanted sensors integrated in patients' bodies, while environmental and external data is collected by the eternal sensor. Patients, whether at home or in the hospital, are equipped with easily available low-cost IoT sensors to record patient data. These IoT sensors collect health data from patients and send it to an IoT agent for analysis. In the event that a patient arrives to a clinic or laboratory but no doctors are available, all resources are available. The patient data was collected by the medical support team. If a patient lives in a remote region or is extremely far away from a hospital, IoT sensors are used to collect patient data and deliver it to doctors in real-time so that they can receive better care. To collect patient data, these three sensors are connected via an Arduino board.

Learning and Prediction Process

After collecting data, the data is transmitted to fog server in IoT Cloud for further analysis. The communication and networking devices will manage the above transmission. The fog server analyzes the stored data using IONN algorithms. Various machine learning algorithms, such as optimization and classification algorithms, were employed to analyse and categorise the collected data in the developed IONN model to distinguish between healthy and diseased people.

The research investigation has been carried out using a three-layer feedforward neural network with several layers[16][17]. In the proposed neural network topology, N neurons serve as input, P neurons serve as hidden, and O neurons serve as output. The number of neurons in the input layer corresponds to the training dataset's properties. Because the defined neural network is fully integrated, the neurons in the previous layer are linked to each neuron in the following layer.

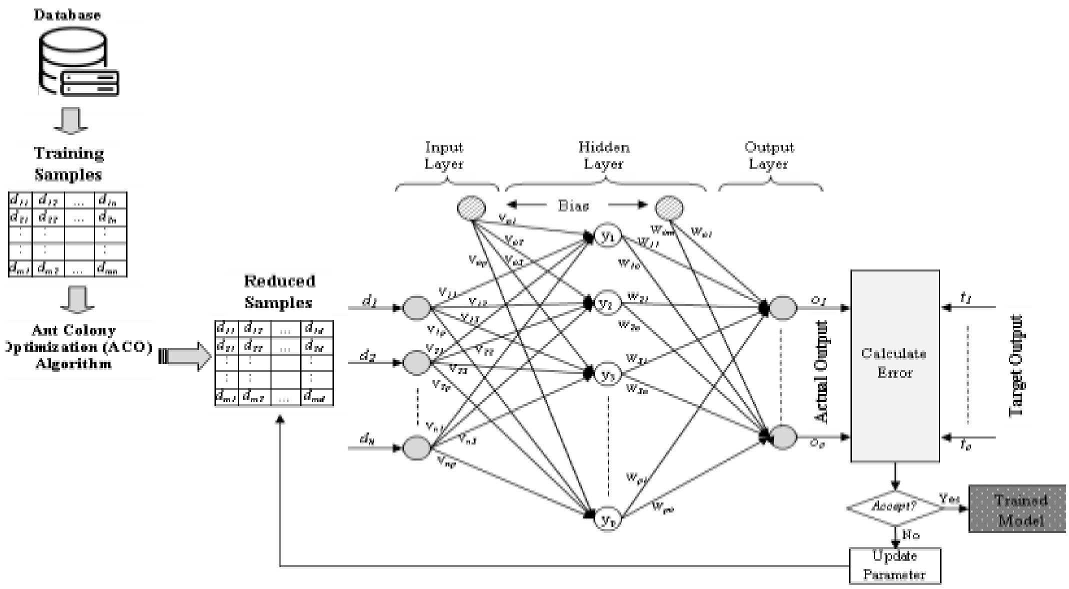

Figure 2. Proposed IONN Framework

The proposed IONN algorithm's working principle is as follows:

Pseudocode: IONN Algorithm
Input: Training dataset of size M × N
Output: Fully trained Network

```
(1) Initialize all ACO and NN parameters
(2) Initialize necessary parameters and pheromone trials;
(3) while not termination do:
(4)        Construct Ant Solutions by generating population
(5)        Calculate fitness values associated with each ant;
(6)        Find best solution through selection methods;
(7)        Update pheromone trial;
(8)  end while
(9) Repeat until the terminating condition is satisfied {
(10)            For every pattern in training dataset D {
(11)                // Forward Propagation
(12)                For each layer in the network
(13)                    For every node in the layer
(14)                        Calculate the weighted sum of the inputs to that node
(15)                        Apply the activation for that node
(16)                // Backward Propagation
(17)                For each node  in the output layer
(18)                    Compute the error value
(19)                For each layer in the hidden layer
(20)                    For each unit in the hidden layer
(21)                        Compute the error value
(22)                        Update the weight of each node based on error value
(23)            }
(24)      }
```

After analysis, the data is sent to a fog server in the IoT Cloud for storage, where it will be accessed by clinicians for early diagnosis. With the information provided, the doctor will assess the health of the patient and advice on the next steps to ensure the best possible treatment.

Results and Discussion

The outcomes of several classification methods like ANN and IONN are examined in this section. Four real-world healthcare datasets from the UCI Machine Learning Repository, including Breast Cancer, Liver Disorders, SPeCT Heart and Thyroid Disease, are used to test the proposed IONN model [18]. The description about all the datasets is tabulated in Table 1. Implementation work is carried out at : processor with Intel Core i5-3210M , CPU M60 @ 2.50 GHz in Python.

Table 1. Dataset Properties

Dataset	Number of Features	Number of Samples	Number of Classes	Classification Type
SPeCT Heart	22	267	2	Binary
Liver Disorders	7	345	2	Binary
Breast Cancer Wisconsin (Diagnostic)	32	569	2	Binary
Thyroid Disease	21	7200	3	Multiclass

The performance metrics used to evaluate the performance of all the classifiers are Training Time and Accuracy. Training Time is defined as total time consumed by the classifier for training process. Accuracy is defined as the overall performance of the classifier which is calculated as

$$\text{Accuracy} = \frac{\text{Total number of correctly classified samples}}{\text{Total number of samples in testing dataset}} \times 100$$

The current ANN model and the proposed IONN model, which utilises all training data to boost training accuracy, are both trained using the ten-fold cross validation technique[19]. The results of various learning models for training different datasets, such as ANN and IONN for the entire fold in tenfold cross validation are summarised in Tables 2, 3, 4, and 5. The accuracy of the proposed IONN model is improved by 4% to 15% when compared to existing approaches. In addition, as compared to ANNs that use the BPN algorithm, the IONN model decreases the overall training time by 15% to 52%.

Table 2. SPeCT Heart Dataset Comparison Results

SPeCT Heart Dataset			ANN		IONN	
Sample Size	Fold Number	Epoch	Training Time (in Sec)	Accuracy (%)	Training Time (in Sec)	Accuracy (%)
267 × 22	1	4184	55.2815	77.78	45.8896	96.29
	2	3776	60.2228	70.37	49.6698	92.59
	3	3500	60.8562	81.48	41.2144	88.89
	4	3577	58.2967	77.78	48.9555	96.3
	5	3584	57.9872	81.48	46.5869	85.19
	6	4322	58.0272	92.59	45.6088	88.89
	7	3609	57.6815	77.78	40.1506	96.29
	8	3724	64.5597	70.37	42.8866	88.89
	9	4040	63.9545	70.37	42.4150	96.29
	10	4433	55.8795	92.59	44.0447	85.19
Average:			**59.2747**	**79.2590**	**44.7422**	**91.4810**

Table 3. Liver Disorders Dataset Comparison Results

Liver Disorders Dataset			ANN		IONN	
Sample Size	Fold Number	Epoch	Training Time (in Sec)	Accuracy (%)	Training Time (in Sec)	Accuracy (%)
345 × 7	1	1711	57.5946	85.71	51.2677	88.57
	2	1576	52.2091	80	40.5391	88.57
	3	1031	54.8913	77.14	42.1614	97.14
	4	1032	63.9694	85.71	30.7403	85.71
	5	1833	38.9431	80	27.5838	85.71
	6	1003	61.2509	88.57	41.9189	94.29
	7	1787	66.5168	80	31.1594	97.14
	8	2364	52.7261	82.86	33.8099	97.14
	9	1646	59.2738	77.14	40.8019	77.14
	10	1990	54.3109	85.71	39.3367	97.14
Average:			**56.1686**	**82.2840**	**37.9319**	90.8550

Table 4. Breast Cancer Dataset Comparison Results

Breast Cancer Wisconsin (Diagnostic) Dataset			ANN		IONN	
Sample Size	Fold Number	Epoch	Training Time (in Sec)	Accuracy (%)	Training Time (in Sec)	Accuracy (%)
569 × 32	1	5897	101.3862	75.44	40.2151	96.49
	2	4273	96.3294	89.47	49.2392	94.74
	3	5762	88.9225	80.7	48.2829	98.45
	4	4572	109.3300	80.7	44.4864	98.24
	5	4662	103.9083	84.21	47.0797	87.72
	6	4838	91.6944	77.19	45.6125	94.74
	7	4262	85.7959	73.68	40.5711	82.46
	8	5820	105.4725	87.72	48.3197	92.98
	9	4869	106.1723	77.19	46.9036	98.45
	10	4918	81.9943	75.44	49.6860	98.24
Average:			**97.1006**	**80.1740**	**46.0396**	**94.2510**

Table 5. Thyroid Disease Dataset Comparison Results

Thyroid Disease Dataset			ANN		IONN	
Sample Size	Fold Number	Epoch	Training Time (in Sec)	Accuracy (%)	Training Time (in Sec)	Accuracy (%)
7200 × 21	1	8243	76.8685	85.97	42.8393	99.17
	2	7735	65.1968	90.83	48.9908	98.89
	3	7694	65.0659	83.89	40.8197	92.08
	4	8227	59.4530	87.5	46.1169	92.92
	5	7649	104.6218	90.69	41.0860	90.42
	6	8438	96.8537	84.31	46.9502	93.33
	7	6724	100.1059	92.92	40.3543	93.33
	8	7607	65.3292	89.03	48.2854	97.36
	9	7972	64.1432	90.97	46.1815	98.75
	10	8284	61.2684	88.33	48.1625	97.5
Average:			**75.8907**	**92.0800**	**44.9787**	**95.3750**

Figure 3 illustrates how much time various algorithms like ANN and IONN spent on training at each training fold.

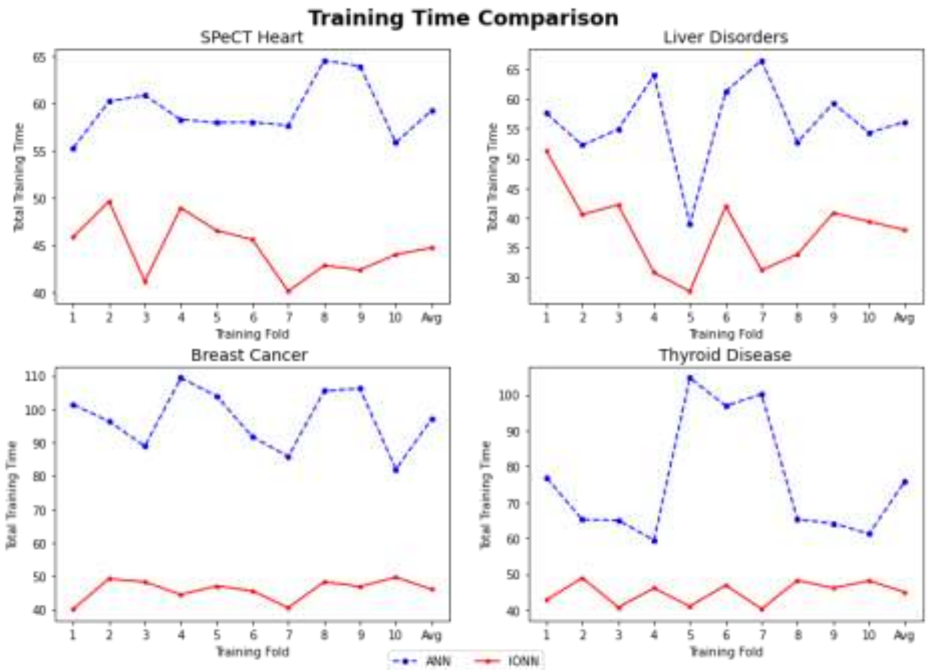

Figure 3. Comparison of Training Time

According to Figure 4, the IONN model takes less time to train than the ANN model for all of the datasets provided in Table 1. For evaluating SPeCT Heart datasets, compared to the ANN model, the IONN model took 15% less time to train. For evaluating Liver Disorders datasets, compared to the ANN model, the IONN model took 19% less time to train. For evaluating Breast Cancer Wisconsin (Diagnostic) datasets, compared to the ANN model, the IONN model took 52% less time to train. For evaluating Thyroid Disease datasets, compared to the ANN model, the IONN model took 31% less time to train.

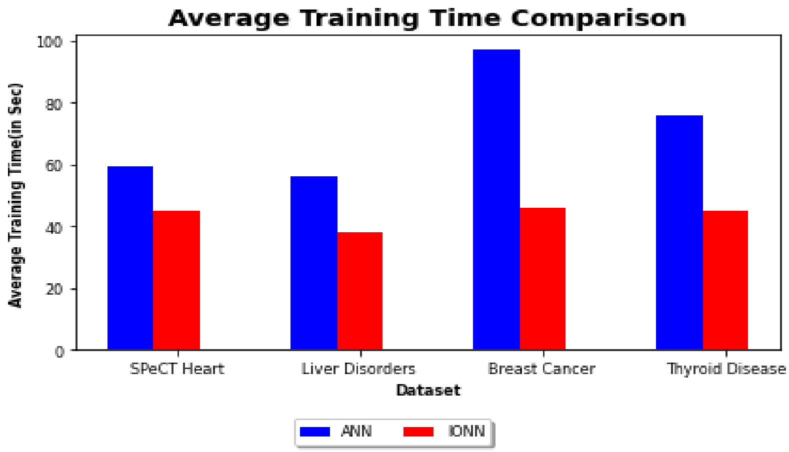

Figure 4. Average Training Time Comparison

Figure 5 shows that while training the dataset provided in Table 1, the IONN model gets a greater accuracy percentage than the ANN model for all datasets. For evaluating SPeCT Heart datasets, the IONN model outperformed the ANN model by 14%. For evaluating Liver Disorders datasets, the IONN model outperformed the ANN model by 10%. For evaluating Breast Cancer Wisconsin (Diagnostic) datasets, the IONN model outperformed the ANN model by 15%. For evaluating Thyroid Disease datasets, the IONN model outperformed the ANN model by 4%.

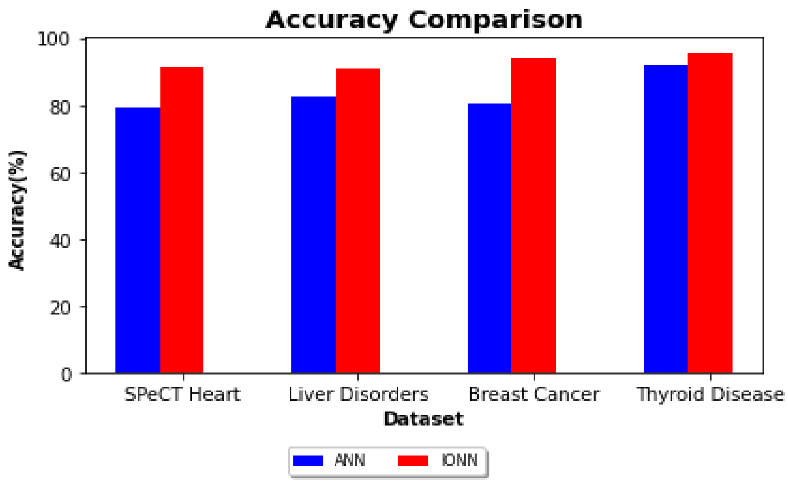

Figure 5: Accuracy Comparison

The IONN model's accuracy is compared to that of other existing machine learning models which is shown in Table 6. The accuracy of the IONN model for the SPeCT Heart Dataset is 13%, 8%, 5%, 1%, and 2% higher than ANN, NB, k-NN, SVM, and DT, respectively. The accuracy of the IONN model for the Liver Disorders Dataset is 9%, 21%, 17%, 14% and 21% higher than ANN, NB, k-NN, SVM and DT respectively. The accuracy of the IONN model for the Breast Cancer Dataset is 15%, 4%, 1%, -1% and 1% higher than ANN, NB, k-NN, SVM and DT respectively. The accuracy of the IONN model for the Thyroid Disease Dataset is 4%, 14%, 14%, 12% and 15% higher than ANN, NB, k-NN, SVM and DT respectively.

Table 6. Accuracy Comparison of various classifiers with different dataset

Dataset	ANN (%)	NB (%)	k-NN (%)	SVM (%)	DT (%)	IONN (%)
SPeCT Heart Dataset	79.26	84.2	87.12	91.37	90.27	91.48
Liver Disorders Dataset	82.28	70.11	74.05	76.9	70.82	90.86
Breast Cancer Wisconsin (Diagnostic) Dataset	80.17	90.37	94.11	96.22	93.84	94.25
Thyroid Disease Dataset	92.08	81.9	82.36	83.56	81.34	95.38

These tables show that the proposed IONN model performs well in terms of training time and accuracy when diverse healthcare datasets are used for training. The drawback identified in this study is that the parameters used in optimization and machine learning algorithms must be fine-tuned in order to improve the IONN model's performance.

Conclusions

In this study, the IONN model, an innovative and intelligent healthcare system based on modern technologies such as the IoT, optimization techniques, and machine learning, is offered. The developed healthcare monitoring system's performance was assessed using performance measures like accuracy and training time, and it was compared to various classification algorithms including ANN, NB, k-NN, SVM, and DT. According to the results, the suggested IONN model performs well in terms of training time and accuracy when diverse healthcare datasets are used for training. In the real world, the suggested training algorithm can resolve any type of classification problem encountered. The drawback identified in this study is that the parameters used in optimization and machine learning algorithms must be fine-tuned in order to improve the IONN model's performance. Many parameter tuning strategies can be used to overcome the above constraint. As a future research, a more thorough analysis of these variables has the potential to produce even better results.

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