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Online clinical decision support system using optimal deep neural networks

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HIGHLIGHTS

- IoT with a cloud-based clinical decision support system is proposed for chronic kidney disease (CKD).
- Optimal Deep Neural Network (DNN) classifier for the prediction of CKD is proposed.
- Particle swarm optimization was used for the selection of the optimal feature subset.
- The proposed DNN classifier outperforms the compared methods for the diagnosis of CKD.

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ABSTRACT

The Internet of Health things (IoHT) has numerous applications in healthcare by integrating health monitoring things like sensors and medical devices for remotely observe patient's records to provide smarter and intelligent medicare services. To avail best healthcare services to the users using the e-health applications, in this paper, we propose an IoT with cloud based clinical decision support system for the prediction and observance of Chronic Kidney Disease (CKD) with its level of severity. The proposed framework collects the patient data using the IoT devices attached to the user which will be stored in the cloud along with the related medical records from the UCI repository. Furthermore, we employ a Deep Neural Network (DNN) classifier for the prediction of CKD and its level of severity. A Particle Swarm Optimization (PSO) based feature selection method is also used to improve the performance of DNN classifier. The proposed model is validated by employing the benchmark CKD dataset. Different classifiers are employed to compare the performance of the proposed model under several classification measures. The proposed DNN classifier alone predicts CKD with an accuracy of 98.25% and is further enhanced to 99.25 by PSO-FS method. At the same time, the improved classification performance is verified with higher values of 98.03 specificity, 99.25 accuracy, 99.39 F-score and 98.40 kappa value respectively.

1. Introduction

Internet of Things (IoT) is a recent technology which aims to design and interlink the Internet-connected Things using computer networks. IoT defines that it is efficient to use more number of less powerful gadgets like wrist band, refrigerator, umbrella, etc. rather than the use of few powerful computing gadgets like computers, tablets and mobile phones [1,2]. Nowadays, some of the objects like room freshener, air conditioner are programmed by the micro controller to provide more sophistication in the day to day life activities. So, the interlinked gadgets or objects has the ability of powerful transmission and computation ahead of the requirements of less computation gadgets like low power electric lamp, umbrella and interlink buildings also by the use of computer networks. These interesting gadgets in IoT [3] have the scientific reasoning capability to perform the allocated task with no necessity of a name as well as humans. The term "Ubiquitous

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computing" is different from IoT since IoT works on a different range of Internet connections. The term "Things" or objects in the real environment has the capability to get many input from human or a living things and converts the received data to the Internet for gathering and processing data. For instance, a sewing machine can calculate the leftover threads, number of stitches done and also number of stitches can do. It is done by the use of sensing devices to save the performance shown by the objects in a predefined time interval. The "Actuators" can also be utilized in the sensor for displaying the output to the external world by interlinking the objects in the environment. A sewing machine can also raise an alert when no more threads are present and needs to be replaced.

IoT and Cloud Computing are beneficial in both ways when these two are integrated to develop an application [4]. A monitoring framework can be developed by the combination of these IoT and cloud to monitor the patient data efficiently even at the remote areas which will be very useful for the medical practitioners. In most of the cases, IoT technology is always sustained with the cloud platform to improve its effectiveness in terms of effective resource usage, storing data, processing and computational capabilities. Additionally, cloud computing gains benefit from the IoT by expanding the scope for handling the present world and also for delivering various new services dynamically. The integration of IoT and cloud based services performs well than the traditional cloud based services. Some of the recent application areas in healthcare, military, consumer electronics and banking sections make use of this integration. Among the different applications, medical and healthcare are the two promising research fields to the rapid developments in the medical gadgets and sensing devices [5]. Since the medical expenses are increasing and many new diseases are also exists globally, it is mandatory to convert the healthcare facilities from a hospital to the person-centric platform. In this paper, we focused on a clinical decision support system in online by the utilization of the sensing abilities of IoT gadgets for the prediction of the presence of serious disease in a user. In our framework, an IoT and cloud based Clinical Decision Support System (CDSS) is presented by the use of computational sciences. By the use of IoT gadgets in healthcare, successive measures are employed to gather data such as frequently changing health parameters over a time period and presence of various abnormal situations in fixed time duration. Additionally, IoT gadgets and healthcare sensor readings are used efficiently to diagnose the disease with the severity level in a particular time period. The personal healthcare services using IoT and cloud help us to live a healthy life at a cheaper cost. So, efficient healthcare framework is needed to diagnosis the diseases by the use of medical IoT gadgets.

As a massive amount of data is being created by the IoT gadgets in the medical field, data science can provide a significant way to make IoT applications more intelligent. The data science is a multidisciplinary field which incorporates data mining, machine learning (ML) and other approaches to identify patterns and new directions from the data [6]. ML algorithms are significant in the CDSS even in situations to handle a massive quantity of data. The process of employing data investigation methods to specific area involves defining data types like velocity, variety, and volume. The conventional data investigation techniques include neural network (NN) model [7], classification schemes, clustering methodologies and also employing efficient approaches. The data can be created from different sources with specific data type, and it is essential to develop methods which can manage the different features of data. In IoT, a massive quantity of sources can create the required data in real time with no issue of scalability, velocity and for determining the better models. These different issues create number of chances in the new developments. In this paper, we have gathered the medical data directly from the patient using IoT devices as input data. The gathered data will be saved in the cloud platform in a secured manner and can be retrieved by the use of new healthcare applications. Next, we employed an ML algorithm using Deep Neural Network (DNN) to carry out the learning tasks of mapping data into two classes like 'Normal' and the 'Abnormal.' DNN learns the categories steadily by incrementing it using the hidden layer architecture, initially representing the low-level categories like letters then slightly higher level categories like words and then higher level categories like sentences.

Since chronic kidney disease (CKD) dataset involves various features, it may degrade the classification performance due to the presence of unwanted features. To resolve this, feature selection methodologies are introduced to select the required features and eliminate the unwanted features thereby the computation time will be minimized with better classification performance. The feature selection problem can be mapped as a combinatorial optimization problem, and the function selection is a dataset. The design variables are the addition (1) or the elimination (0) of the features. A comprehensive selection of features would assess numerous combinations (2^N, where N indicates the number of features). For achieving better feature selection results at a faster rate, optimization algorithms like Ant Colony Optimization (ACO), particle swarm optimization (PSO) algorithm, genetic algorithm (GA), simulated annealing, etc., are used. PSO algorithm shows much resemblance with the other optimization algorithms particularly GA. Each algorithm starts with the swarm of arbitrarily created population and searches for an optimal solution using random approaches. The major benefit of the PSO algorithm over other algorithms is that it does not involve operators like a crossover, mutation, and so on. However, the particle itself updates concerning its internal velocity. Also, it is easier to implement, fast convergence and requires less number of parameters to alter when compared to other algorithms. So, in this study, we have employed the PSO algorithm to select the required number of features. The PSO algorithm considers all particles as features in the instances, and the best particle will be considered as a chosen feature.

This paper introduces a new framework for CDSS to predict and identify the presence of CKD. Several studies [8–10] reported that CKD is one of the significant diseases which increase the mortality rate globally where the recent statistics revealed that 2.5 to 11.2% people are affected by CKD across UK, Asia, Australia, and North America. Notably, in the US, 27 million are suffered by the presence of CKD. Moreover, the available CKD prediction models are based on the conventional statistical techniques, and it may result in less accurate performance [11]. Presently, various offline disease prediction and diagnosis model were developed using the medical data. But, the massive amount of patient data created by the IoT gadgets can be investigated on the cloud rather than on the constrained memory and computational resources of the mobile devices.

Contribution of the paper

In this paper, we propose an IoT with cloud based clinical decision support system for the prediction and observance of CKD with its level of severity. The proposed framework collects the patient data using the IoT devices attached to the user which will be stored in the cloud along with the related medical records from the UCI repository. Furthermore, we employ a Deep Neural Network (DNN) classifier for the prediction of CKD and its level of severity. A Particle Swarm Optimization (PSO) based feature selection method is also used to improve the performance of DNN classifier. The proposed model is validated by employing the benchmark CKD dataset. Different classifiers are employed to compare the performance of the proposed model under several classification measures. In overall, the contribution of the paper is summarized as follows:

- Presents an IoT with Cloud based framework for CDSS
- Gather the related medical data from the UCI repository as well as the patient data from the IoT medical sensors from the patient's body
- Present a DNN classifier for the identification of CKD
- Present a PSO based feature selection technique to reduce the feature subset
- Validate the performance of the proposed model in terms of different classification measures over other classifier models

Organization of the paper

The remaining portion of the paper is arranged as follows: Section 2 surveys the recent IoT based healthcare models along with some data mining techniques for IoT healthcare. Section 3 explains the proposed work in a detailed manner, and the results are validated in Section 4. At the end of the paper, in Section 5, the conclusions are drawn with future enhancements.

2. Related works

In this field of study, many researchers have done their work for the past five years which include [12–17]. In [18], a detailed review of medium access control (MAC) layer protocols employed in IoT with a brief discussion of such protocols is grouped (by short and long distance coverage). [19] focused on a detailed review of machine learning techniques employed for IoT and Intrusion Detection for computer network security. This work performs a recent as well as elaborated research works which deal with numerous intelligent techniques and their applied intrusion detection architectures in computer networks. [20] presented an extensive survey of IoT based methods for healthcare and ambient-assisted living (IoHT). [21] provides a complete survey of related work, discovering the variations among the present Internet and IoT-based systems, and offering a detailed study of the difficulties and future scope on IoT middleware. [22] investigates the cloud of things (CoT) architectures and platforms, as well as the implementation of CoT in the circumstance of smart healthcare. Consequently, this paper also discusses some relevant difficulties present in CoT. Also, it concentrates on energy efficiency with an in depth analysis of the latest works in the area of study. [23] introduced an anomaly detection-based Optimum-Path Forest (OPF) classifier in the abovementioned context. The results are compared with one-class support vector machines and multivariate Gaussian distribution. Above all, [17] commenced a novel structure by employing cloud and IoT technology to monitor the level and diagnosing the disease. This is majorly employed to calculate the probability of the seriousness of the disease. To take care of the student's health, this structure has been built. Here, a methodical healthcare data which is student view has been created by the use of benchmark UCI repository and also sensing devices are employed to forecast different diseases which are affected severely to the student. Different classification techniques are employed to predict the existence of different diseases based on some measures like F-measure, specificity and sensitivity. The experimental results ensured that the model is better than the previous ones. [24] introduced new energy models which are operating in a dedicated cloud based IoT platform. These models have been used to analyze the videos captured by the camera connected to the vehicles. This model is validated on the real testbed for particular applications and performs the simulations by the popular simulator to observe the improvement with the use of IoT devices.

A review is made [25] on Cloud and IoT technologies along with their challenges related to security. Also, the contributions of the cloud to the IoT platform are also discussed. In the end, a demonstration is made to explain the significance of cloud in the improvement of IoT functions. [26] developed a new multi-layer cloud model to enable the effective and continuous interaction and interoperation over the heterogeneous services given by different dealers in smart homes. Additionally, ontology has been employed in the study to solve the heterogeneity issues presented in a layered cloud environment. [27] designed novel 3-tier architecture to store a massive amount of sensor data. Initially, Tier-1 focuses on the process of data gathering from various sources. Next, Tier-2 dealt with the massive quantity of sensor data storing in the cloud servers. Finally, in tier-3, a new prediction model is developed to predict heart diseases. [28] devised a new scheme mainly developed for Cloud to manage the real time IoT data and technical data which is not related to IoT. [29] developed a capable Cyber Physical System architecture to support multiple sites and multiple products manufacturing. [30] presented a smart method in the car camera system which makes use of mobile cloud computing model for deep learning. It identifies the objects from the recorded videos during driving and decides the specific portion of the video that has to be saved in the cloud to conserve the local storage space of the system. It has three phases to train, recognize and gather data.

In [31], a new cloud based distributed ML approach for machinery prognostics are developed. They have employed random forest (RF) classifier to predict the tool wear in the dry milling functions. Besides, the RF algorithm has been presented by the use of MapReduce and implemented on the Amazon Cloud. They ensured that the RF method could identify the disease accurately. [32] have done a case study to monitor the voice pathology of people by utilizing cloud and IoT. A new local binary pattern based detection model is also presented to detect the voice pathology in the monitoring model. This model attains better classification performance over the existing methods. [33] discussed the fundamentals of IoT with its appropriate applications which are already exists in the direction of u-healthcare. [16] devised a new technology in the body area sensor network based on the IoT gadgets in the human body. In this model, the patient can be continuously observed by the use of compact and lightweight sensor networks. The need for security is also considered in the design of healthcare model. An online healthcare monitoring model is proposed in [34] which have the capability to analyze the patient health data to negotiate the occurrence of death. It gathers the related patient data which is needed for investigation by the sensing and healthcare devices. Security mechanisms like watermarking and signal enhancements are also intergraded into the model eliminate the clinical errors and a variety of identity thefts. [14] discussed about the different methods exists to develop applications' in the domain of m-healthcare. The applications like website developer and the application developer are employed for the monitoring of patient's health conditions in remote areas. [35] presented a people centric sensing model for elder and people with disabilities. The intention of this model is to give a service based emergency response during the patient's abnormal conditions. [13] presented an efficient and distributed model to minimize the risks associated in the IoT based healthcare platform. Additionally, the recent advancements present in the IoT healthcare domain are also discussed. [12] developed an intelligent model named as neuro-fuzzy temporal knowledge representation model to predict and diagnose different deadly diseases. [36] developed an intelligent and optimized fuzzy based classifier for the medical diagnosis. [37] presented a new online

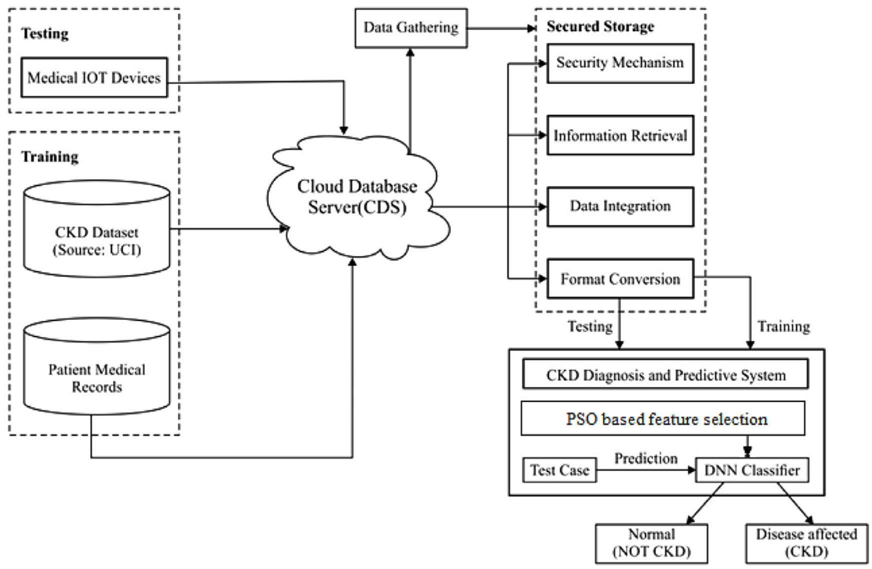

Fig. 1. Overall system architecture.

healthcare monitoring framework to monitor the heart patient using mobile phones and wearable sensors. [38] devised a new monitoring model to provide emergency situations in monitoring service utilizing the context of motion tracking disease patients.

The reviewed healthcare applications present an environment to billions of user to receive information about their health in a periodical manner for a good healthy life. Though the existing models use various disease prediction and diagnosis models, most of the work concentrated on the offline mode of data examination. In this paper, the usage of IoT devices and cloud computing in the medical field has introduced various features of these applications.

3. The proposed model

3.1. System architecture

The overall architecture of the proposed model is given in Fig. 1. The main elements in the proposed model are IoT gadgets embed in the patient, benchmark CKD dataset, patient medical records, cloud database server (CDS), Data gathering module, Security mechanism, CKD diagnosis, and disease prediction module. The wearable IoT medical gadgets are assumed as IoT gadgets which are placed in the patient body. The benchmark CKD dataset from the UCI Repository is used. The medical dataset contains the past details of the patient's data which are gathered from the hospitals. These datasets are saved in the CDS. The data gathering module has the role of gathering essential data from the CDS. The security mechanism recollects the data from the data gathering module. These data will be saved in the secured manner by the use of various levels of information retrieval, data integration and format conversion. The secured data will be again saved in the CDS and it will be retrieved upon demand. The essential data will be saved in the CDS for flexible access. CKD diagnosis and disease prediction module uses DNN classifier for the identification of CKD. During the training phase, the healthcare data from the patient medical records as well as CKD dataset is used to train the DNN classifier.

During the testing phase, DNN classifier classifies the patient data in online and it will be classified into normal (non-CKD) and disease affected (CKD) with its severity level. The proposed IoT with cloud based CDSS model operates on three levels. In the first level, required data will be gathered from various sources such as IoT gadgets, benchmark CKD dataset, and the patient medical records. In the second level, the gathered data will be saved in the CDS in a secured manner. The final third level is used to predict the presence of CKD with the level of severity. This level identifies the level of severity by the use of DNN with the data from medical records. These three levels are discussed in the following subsections.

3.2. Data gathering

The proposed framework contains three variant kinds of data. In this level, the healthcare data of the patient will be gathered by the use of wearable IoT gadgets which is operating by sensors as shown in Fig. 2. The wearable gadgets are placed on the human body to collect the specific patient healthcare data regularly in a particular time duration. In general, the IoT gadgets in the patient body checks every sensed healthcare data whether it is normal or not. When the healthcare data crosses the normal values, then an alert will be raised and sent to the doctors and also to the data gathering for further processing. The proposed CDSS model employs 4G mobile networks for transmitting the sensed healthcare data to the CDS. Moreover, the CKD dataset from UCI repository is also employed to map with the real data which is generated by the IoT devices. Also, patient medical records are employed to map the actual data generated by the individual patient's data.

3.3. Security mechanism on CDS

The proposed framework contains three types of data to make decisions. The three types of data include the data collected by IoT gadgets from the patient body in real time, CKD dataset and the real records of the patients which have been gathered to analyze the severity level of the CKD. These three kinds of data have to be stored in a database for further investigation. Also, the storing and handling the massive quantity of data is also a crucial process. The cloud platform gives enough space to store a large amount of data. This data is saved in the Hadoop environment with scalability. Besides, the security of the stored data is also critical in the cloud platform. To achieve this, a security mechanism is also provided to store healthcare data. The intention of this proposed security mechanism is to secure healthcare data efficiently. The

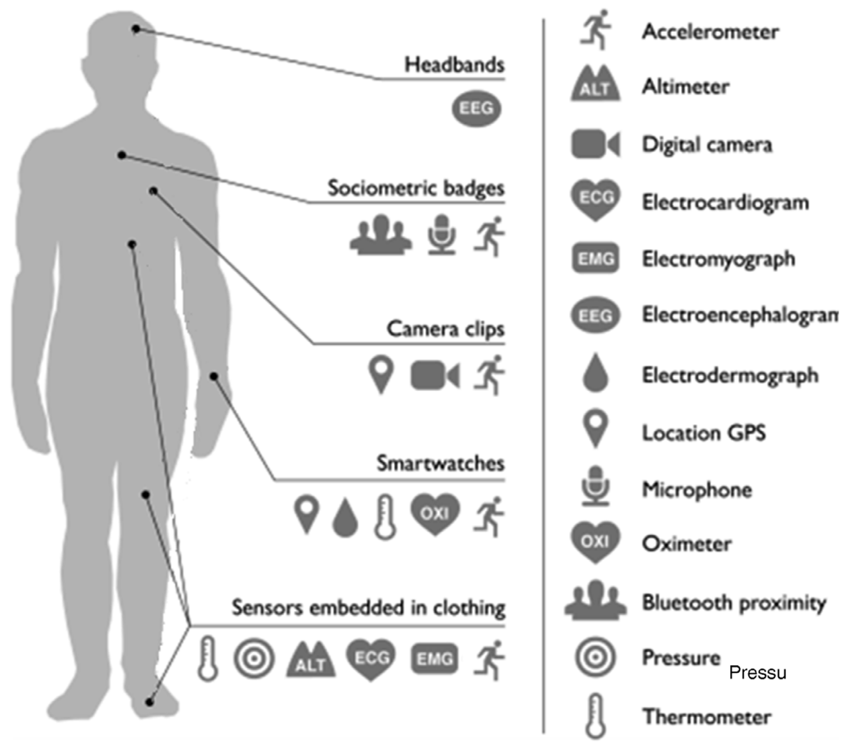

Fig. 2. IoT sensors connected to human.

secured storage mechanism operates in two stages: a secured storage stage and information retrieval stage.

The process involved in the secured storage mechanism is explained as follows: The patient's healthcare data will be read as input and data hiding operation takes place on the input data. Then the ASCII values are determined for the healthcare data, and the transformed ASCII numeric values will be arranged as a matrix. The primary attributes in the first table data are encrypted by AES algorithm, and the sensitive attributes are encrypted by DES algorithm.

For the information retrieval process, the primary key values in the encryption process are read. Then the primary key values are concatenated which exists in the two tables after the data integration process. Then, the decryption process for the primary key values takes place by employing keys and algorithms. Next, the subtraction operation takes place on all the elements available in the particular rows and columns for getting the original values from the summation values. Next, the resultant values and forwards it to the data integration process. Once all the data is integrated, the respective data is transformed into a format which is compatible to carry out the CKD diagnosis and prediction system. After the conversion of the data to the .csv format, then the respective data is applied to the next level for predicting the existence of CKD.

3.4. PSO based feature selection

Due to the presence of unwanted and noisy features, the classification performance will be reduced. The main intention of feature selection is to eliminate the noisy features and rule out unwanted features. PSO algorithm is a commonly used feature selection tool which identifies the optimal characteristics using local and global searching of features in the feature search space in an iterative way. In PSO, swarm comprises of a collection of random particles, which moves around the solution space of the problem by updating through iterations for an optimum solution and go till convergence is attained. A process of PSO based feature selection is shown in Fig. 3.

Here, n represents the number of random particles is selected initially from the features space. Every particle has c parameters that are attained, and their respective random velocities form a position matrix $X[n, c]$. Now, the threshold should be chosen for the first round of selection of these random velocities and its respective positions by the following functions, $V[i, j] = e(X[i, j])$ where $1 \leq i \leq n$ and $1 \leq j \leq c$ and it is assumed to be 0.5 for this work. The velocity of the ith particle is defined as $V_i = (v_{i1}, v_{i2},..v_{ic})$ and its corresponding state is defined by $X_i = (x_{i1}, x_{i2},..x_{ic})$. When the recently determined velocity is higher than the threshold value (0.5), then this velocity and its location is chosen for the subsequent iterations. It is expected that, after every iteration, the recognition rate of the disease with the recently chosen features from the features space. Therefore, the success rate is computed by an objective function called as a fitness function in PSO. The minimum distance function is utilized here as a fitness function for this work. In this situation, minimum distance classifier focuses on local and global information of the features.

The fitness function is validated for every particle in the swarm, and a comparison is made with the best previous (pbest) result for that particle and to the fitness of the best particle (gbest) among all particles in the swarm. Once the two best values (pbest and gbest) are identified, the particles begin to update the velocity and positions based on the Eqs. (1) moreover, (2), respectively.

$$V_i\,(t+1) = w \times V_i\,(t) + c_1 \times ud \times [pbest_i\,(t) - X_i\,(t)] + c_2 \times ud \times [gbest\,(t) - X_i\,(t)] \quad (1)$$

$$X_i\,(t+1) = X_i\,(t) + V_i\,(t+1) \quad (2)$$

Where, $i = 1, 2, \ldots, n$, and n is the population size, 'ud' is another random number lies in [0,1], c_1 and c_2 are cognitive and social parameters, respectively. The first term in Eq. indicates the inertial

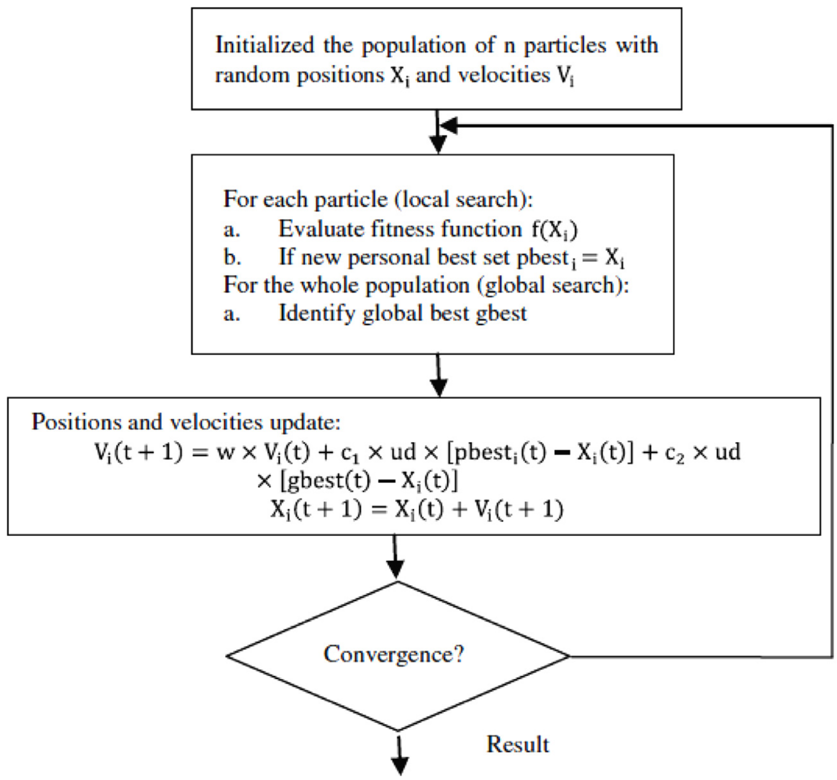

Fig. 3. The overall process of PSO based feature selection.

component, the second term defines a cognitive component, and a third term represents the social component, respectively. The inertia weight w is a control parameter which balances the search algorithm between exploration (=0.15) and exploitation (=1); the second element is the 'cognitive' section representing the local knowledge of the particle itself; the third component is the 'social' part, representing the cooperation among the particles. The steps will be repeated till the process exceeds the stopping criterion. It is identified that 30 thirty iterations are enough for the identification of the optimum features from the features space, which results in a better success rate.

3.5. DNN based CKD diagnosis and prediction system

In this section, the proposed DNN based diagnosis and prediction system for the identification of CKD and also determines the severity level. The proposed model makes decisions on healthcare data. The benefit of this model is the selection of significant attributes and the classification of medical records depending upon the time limitations for making decisions effectively.

Artificial Neural Networks (ANN) is a computational intelligence technique stimulated from the network of biological neurons for resolving prediction problems, natural language processing and drug identification and so on. A DNN is a neural network (NN) with a definite level of complexity, a neural network with multiple layers. DNN uses a complicated mathematical model for processing the data in a complex manner. DNN with multiple layers intrinsically combines the feature extraction and classification process into a signal learning body and builds a decision-making function. These types of NN have attained success in complex domains for the identification of patterns in recent years. In general, DNN comprises an input layer for the raw descriptors X_l, L hidden layers, and an output layer for the data prediction. An overview of the proposed DNN is illustrated in Fig. 4.

The DNN is developed by the use of TensorFlow framework [39], the tf.contrib.learn.DNNClassifier deep learning library from Google, in the Python programming language. Presently, none of the conventional methods constructs an optimal NN with a proper number of layers and neuron count for every layer. So, a DNN is constructed by performing a wide set of trials. In every trail, the manual configuration of DNN takes place by modifying the following parameters: number of hidden layers, the activation function, number of learning steps and, for every hidden layer, the number of neurons making up the layer. For every manual configuration, the validation of the classification accuracy takes place over the testing set. After this difficult manual stage, the best classification performance is attained with a DNN composed of 7 hidden layers, with five, ten, thirty, fifty, thirty, ten and five neurons, respectively. The DNN Classifier class employed here generates all the neuron layers, using the ReLU (Rectified Linear Unit) activation function. From the Eq. (3) of the function, it is seen that the DNN is simpler and effective. The output layer depends upon the softmax function, and the cost function is the cross entropy. The rectifier is an activation function represented in Eq. (3):

$$f(x) = x^{+} = \max(0, x) \tag{3}$$

Where x is the input to a neuron. It is also called as ramp function which is similar to the half-wave rectification process in electrical engineering. A unit utilizing the rectifier is termed as a Rectified Linear Unit (ReLU). A smooth approximation to the rectifier is the analytic function:

$$f(x) = \ln[1 + \exp(x)] \tag{4}$$

Which is called the softplus function. The rectifier and softplus functions are illustrated in Fig. 5.

During the prediction process, a new representation of the raw descriptors is filtered from the hidden layers as follows:

$$X_{t+1} = H(W_l X_l + B_l), \qquad l = 1, \ldots, L \tag{5}$$

where W_l and B_l represents the weight matrix and bias for the lth hidden layer, and H is the related activation function, which

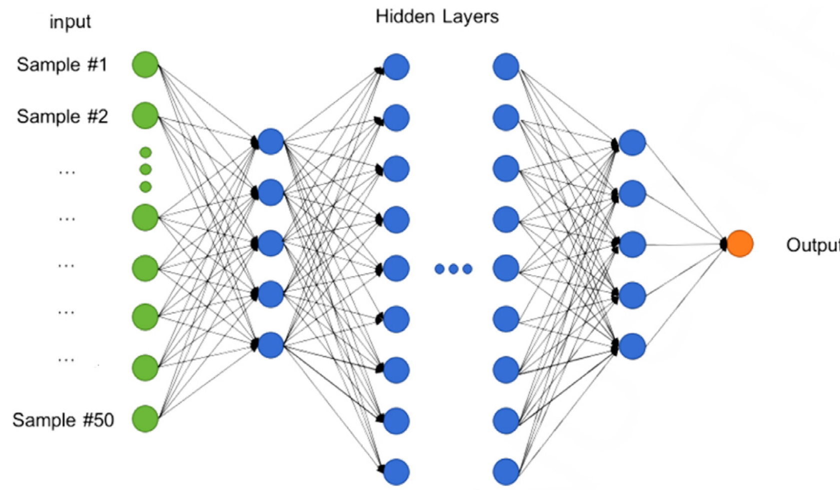

Fig. 4. DNN Architecture.

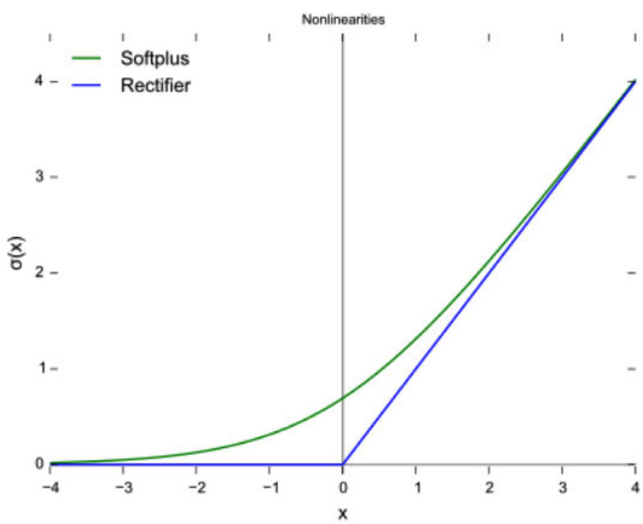

Fig. 5. Plot of the rectifier near x = 0.

is chosen to be a rectified linear unit (ReLu). The pseudo-code explaining the steps of DNN is given below:

- load the training and testing set of CKD dataset
- construct the classifier utilizing tf.contrib.learn. DNNClassifier Google library based on the chosen manual configuration, i.e., number of hidden layers, activation function, number of learning steps, and, for every hidden layer, neuron count for making up the layer;
- fit the model utilizing the classifier.fit function;
- estimate the accuracy of the DNN in the training set utilizing classifier.evaluate function;
- compute the prediction of the DNN in the testing set utilizing the classifier.predict function;
- assess the classification results of the DNN in the testing set using the confusion matrix;
- validate the classification results of the DNN on the entire CKD dataset.

4. Performance evaluation

For assessing the classification results of the DNN classifier on the applied CKD dataset, a set of experiments are carried out. The proposed model has been implemented using Python programming and Amazon web services (AWS). For experimentation, the parameter used is batch size:8, learning rate: 0.02, epoch or step size: 10000, score threshold:0.7, minimum dimension: 600 and maximum dimension: 1024. Moreover, the parameters involved in the PSO algorithm is provided in Table 1. The details of the dataset, performance measures and the results are discussed in the following subsections.

Table 1
Parameter setting.

Parameter	Value
Swarm size	20
Max. velocity	4 ms
Min. velocity	4 ms
Initial momentum weight	1.0 Ns
Final Momentum weight	0.4 Ns
Stopping criteria	Max. iteration (i.e. 600)

Table 2
Dataset description.

Detail	Value
Dataset name	CKD
Source	UCI
# of instances	400
# of attributes	24
# of class	2
CKD/NON_CKD	250/150

4.1. Dataset details

The proposed model is validated by employing the benchmark CKD dataset from the UCI repository [40]. The details of the dataset are tabulated in Table 2.

The CKD dataset holds a total of 400 instances, 25 attributes and two classes namely CKD and Non-CKD. From the total of 400 instances, 250 instances come under the class of CKD whereas the remaining 150 instances come under the class of Non-CKD. We have used 10-fold cross validation technique for assessing the performance of the presented model. In this case, a total of 40 instances are employed for testing, and the remaining 360 instances are employed for training purposes. This procedure of splitting the dataset for training and testing will be reiterated up to ten times.

4.2. Measures

For highlighting the classification results of the proposed model using DNN classifier, a set of performance measures [41] used are include false positive rate (FPR), false negative rate (FNR), sensitivity, specificity, accuracy, area under curve (AUC), F-score, Mathew Correlation Coefficient (MCC) and kappa value. Before defining the classification measures, the concept of a confusion matrix is defined. A confusion matrix is a 2 × 2 matrix, comprises of 4 elements namely true positive (TP), true negative (TN), false positive (FP) and false negative (FN). Based on the confusion matrix, classification measures are defined.

FPR is used to compute the possibility of wrongly rejecting the nullhypothesis for a specific test. It is represented in Eq. (6).

$$\mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{FP} + \mathrm{TN}} \tag{6}$$

FNR is used to compute the conditional probability of a positive test result given an instance that was not present. It is the ratio of a number of false instances classified adequately as negative and the total number of actual correctly classified instances. It is represented in Eq. (7).

$$\mathrm{FNR} = \frac{\mathrm{FN}}{\mathrm{FN} + \mathrm{TP}} \tag{7}$$

The sensitivity indicates the number of actual positives which are correctly classified as positives and is represented in Eq. (8).

$$\text{Sensitivity} = \frac{\mathrm{TP}}{\mathrm{TP} - \mathrm{FP}} \tag{8}$$

Specificity indicates the number of actual negatives which are correctly classified as negatives and are represented in Eq. (9).

$$\text{Specificity} = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}} \tag{9}$$

Accuracy is the most widely used classification performance metric. It represents the percentage of correctly classified instances and is measured in percentage (%). For better classification performance, the classification accuracy should be closer to 100% and is defined in Eq. (10).

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

F-score determines the accuracy of the testing process. It is an average measure which makes use of both precisions and recalls set and is expressed in Eq. (11).

$$\mathrm{F} - \text{Score} = \frac{2\mathrm{TP}}{2\mathrm{TP} + \mathrm{FP} + \mathrm{TN}} \tag{11}$$

MCC is considered as a balanced metric utilized in situations when the classes are of various sizes and are expressed in Eq. (12).

$$\mathrm{MCC} = \frac{(\mathrm{TP.TMN} - \mathrm{FP.FN})}{\sqrt{(\mathrm{TP} + \mathrm{FP})\,(\mathrm{TP} + \mathrm{FN})\,(\mathrm{TP} + \mathrm{FP})\,(\mathrm{TN} + \mathrm{FN})}} \tag{12}$$

Kappa coefficient value (K)

Kappa computes the level of agreement between two classifications in which it classifies N items into C mutually exclusive categories.

$$\text{Kappa Test} = \frac{\text{Observed Agreement} - \text{Expected Agreement}}{100 - \text{Expected Agreement}} \tag{13}$$

where, Observed Agreement = % (Overall Accuracy)

Expected Agreement = (%(TP+FP)* %(TP+FN)) + (%(FN+TN)* %(FP+TN))

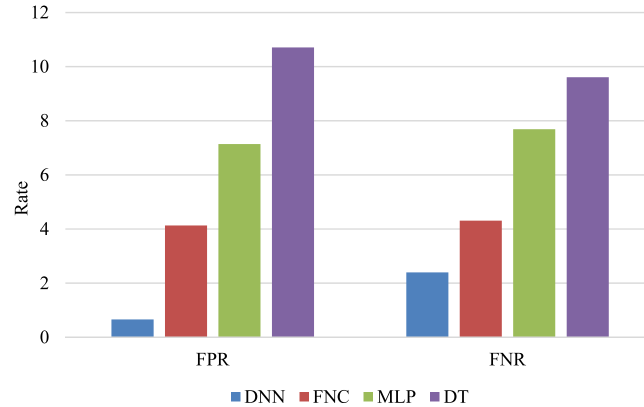

Fig. 6. Comparison of classifiers results in in terms of FPR and FNR.

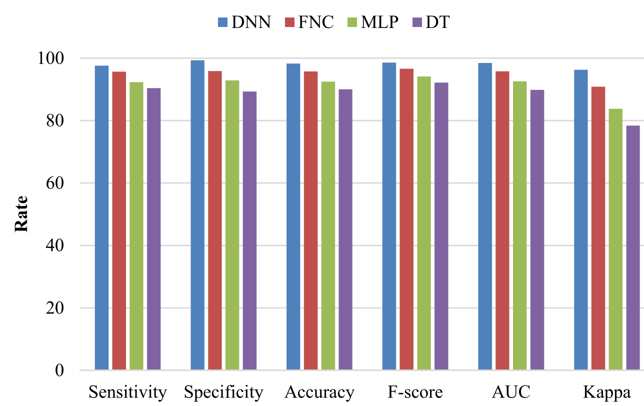

Fig. 7. Comparison of classifiers results in in terms of various measures.

4.3. Results and discussion

Table 3 provides the experimental results of proposed DNN classifier, the fuzzy based neural classifier (FNC) [42], multi layer perceptron (MLP) and decision tree (DT) in terms of different measures such as FPR, FNR, sensitivity, specificity, accuracy, F-score, AUC, MCC and kappa value. Fig. 6 shows the comparative results of proposed DNN and other classifier in terms of FPR and FNR. To attain better classifier results, the value of FPR and FNR should be as low as possible. From this Fig., it is evident that among the compared methods, the highest FPR and FNR value of 10.71 and 9.61 is attained by the DT classifier. This value implies that the DT classifier showed the worst performance. Next, the FNC manages to perform well than the other classifiers MLP and DT except for the proposed DNN classifier. Also, it is apparent that the DNN classifier attains the lowest value of FPR and FNR with a value of 0.66 and 2.4 respectively.

Fig. 7 shows the obtained experimental results of different classifiers in terms of six measures namely sensitivity, specificity, accuracy, F-score, AUC and kappa value. Of all these measures, the values should be as high as possible, i.e., closer to 100. The classifier with the highest value is considered as the better classification algorithm. Interms of sensitivity, Fig. 7 shows that the DT classifier shows poor results with the lowest value of 90.38 whereas the MLP attains a value of 92.30. Moreover, FNC tries to achieve maximum performance with a sensitivity value of 95.68. However, it showed only inferior results to the proposed DNN classifier. From the sensitivity values, it is apparent that DNN classifier is the better one than the compared methods.

On measuring the classifier results in terms of specificity, the order of better performance of the different classifiers is

Table 3
Performance evaluation of CKD using DNN with various classifiers.

Classifier	FPR	FNR	Sensitivity	Specificity	Accuracy	F-score	AUC	MCC	Kappa
DNN	0.66	2.4	97.60	99.33	98.25	98.58	98.47	0.96	96.29
FNC	4.13	4.31	95.68	95.86	95.75	96.63	95.77	0.91	90.87
MLP	7.14	7.69	92.30	92.86	92.50	94.11	92.58	0.83	83.78
DT	10.71	9.61	90.38	89.28	90.00	92.15	89.84	6.78	78.37

Table 4
Performance evaluation of Chronic Kidney Disease using DNN with PSO-DNN.

Classifier	FPR	FNR	Sensitivity	Specificity	Accuracy	F-score	AUC	MCC	Kappa
DNN	0.66	2.4	97.60	99.33	98.25	98.58	98.47	0.96	96.29
PSO-DNN	1.96	0	100	98.03	99.25	99.39	99.02	0.98	98.40

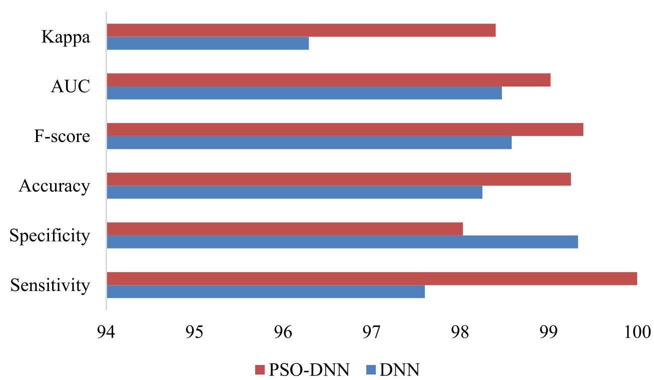

Fig. 8. Comparative analysis of DNN with and without feature selection.

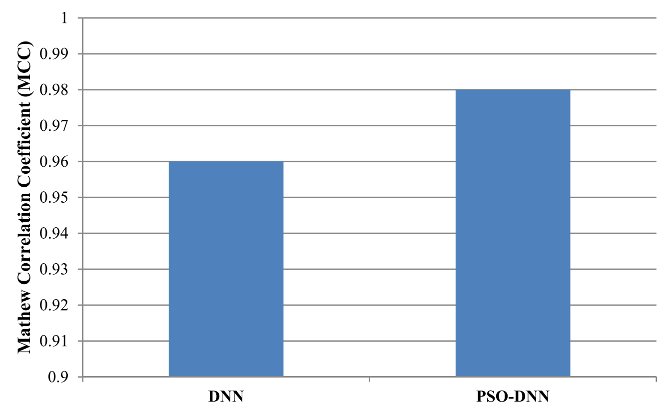

Fig. 9. Comparative analysis of DNN with and without feature selection in terms of MCC.

DNN, FNC, MLP, and DT. The classifier DT which appears last in the sequence indicates the poor classifier performance and DNN classifier which appears first in the sequence implies effective classification performance. Next, the classification accuracy is an important metric, and the DNN classifier obtains a maximum classifier accuracy of 98.25 whereas the DT classifier attains a minimum accuracy of 90.00. Similarly, the lowest value of F-score obtained by DT indicates the worst classification performance with a value of 92.15. At the same time, the classifiers MLP and FNC showed competitive performance with the F-score value of 94.11 and 96.63 respectively. Interestingly, the DNN classifier attains an F-score of 98.58, which is higher than all the compared ones. Likewise, DNN classifier provides better AUC with a value of 98.47. The classifier results in terms of kappa value indicated that the DT fails to show superior results whereas DNN showed excellent performance over the compared classifiers. From the overall results, it is perhaps interesting that the DNN classifier is found to be superior to FNC, MLP and DT on the applied CKD dataset in terms of various classification measures.

To further enhance the classifier performance of the DNN classifier, a feature selection process can be employed. The results obtained by DNN classifier with and without PSO based feature selection are tabulated in Table 4 and are shown in Fig. 8.

From the table values, it is indicated that the sensitivity value of DNN is 97.60 and it reaches the maximum value of 100 when the PSO based feature selection is included. The specificity, accuracy, F-score and kappa values without feature selection are 99.33, 98.25, 98.58 and 96.29 respectively. At the same time, the classification performance is improved with higher values of 98.03 specificity, 99.25 accuracy, 99.39 F-score and 98.40 kappa value respectively. In addition, the MCC value before feature selection is 0.96 which is increased to 0.98 by the use of feature selection technique. The comparative results of DNN with and without PSO based feature selection are shown in Fig. 9. From the above tables and discussion, it is verified that the classification results of DNN are improved by the use of PSO based feature selection methodology.

To further investigate the efficiency of the proposed method, a comparison is made with the recently proposed method [36]. The accuracy of the compared model in predicting CKD is 97.8%. However, the proposed DNN classifier alone predicts CKD with an accuracy of 98.25% and is further enhanced to 99.25 by PSO-FS method.

From the above results and discussion, the essential points are noted as

- DNN classifier attains the lowest value of FPR and FNR with a value of 0.66 and 2.4
- DNN classifier obtains a maximum classifier accuracy of 98.25
- The specificity, accuracy, F-score and kappa values without feature selection are 99.33, 98.25, 98.58 and 96.29 respectively
- The specificity, accuracy, F-score and kappa values with feature selection are 98.03, 99.25, 99.39 and 98.40 respectively
- The proposed DNN classifier alone predicts CKD with an accuracy of 98.25% and is further enhanced to 99.25 by PSO-FS method.

From the above tables and figures, it is apparent that the proposed model is efficient on the detection of CKD. At the same time, it is observed that the proposed model is compatible with detecting the CKD on the cloud platform. The DNN model has enhanced classification rate due to the characteristics of PSO based feature selected. The proposed RS-CNN model can be easily embedded in real-time applications to effectively detect the presence of CKD remotely at a faster rate.

5. Conclusion

This paper has presented an IoT with Cloud based CDSS framework and implemented for the prediction of CKD with its level of severity. This paper provides a systematic scheme for the CKD, and the relevant healthcare data is created by the use of UCI Repository dataset. In addition to that, the medical sensors are utilized to gather data from the CKD affected patients and maintained as the patient records. We employed an ML algorithm using DNN to carry out the learning tasks of mapping data into two classes like 'Normal' and the 'Abnormal'. The use of PSO based feature selection significantly enhances the classifier results with the classification accuracy of 98.25 whereas the accuracy is only 99.25 prior to the feature selection process. The experimental results validate the performance of the proposed model in terms of different classification measures over other classifier models. In the future, the proposed model can be improved by the inclusion of clustering methodologies to reduce the complexity and encryption standard for achieving better security on the CDS.

Declaration of competing interest

One or more of the authors of this paper have disclosed potential or pertinent conflicts of interest, which may include receipt of payment, either direct or indirect, institutional support, or association with an entity in the biomedical field which may be perceived to have potential conflict of interest with this work. For full disclosure statements refer to https://doi.org/10.1016/j.asoc.2019.105487.

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