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Heart Diseases Diagnosis Using Chaotic Harris Hawk Optimization with E-CNN for IoMT Framework

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In the current state of medical research, the diagnosis of heart disease has become a challenging medical objective. This diagnosis is dependent on a thorough and accurate review of the detailed medical test results and medical background of the patient. With the aid of the internet of things (IoT) and the huge advancements in the field of deep learning, researchers aim to produce intelligent monitoring systems that assist physicians in both predicting and diagnosing disorders. In this context, this work proposes a novel prediction model based on deep learning and Internet-of-Medical-Things for the efficient and real-time diagnosis of heart disease. In this work, data from the Cleveland dataset is used for training the proposed model and further the data that is gathered from the sensors in the IoMT environment is used for testing the prediction capability of the model. Chaotic Harris Hawk optimization algorithm is employed for the feature extraction from the data and these extracted features are further passed on to the classification stage where Enhanced Convolutional Neural Networks are utilized to classify whether the patient is affected by heart disease or not. In order to evaluate the performance of the proposed model, it is compared with the Machine learning models such as Support Vector Machine with Ant Colony Optimization(SVM-ACO), Random Forest with Particle Swarm Optimization(RF-PSO), Naive Bayes with Harris Hawk Optimization(NB-HHO), K Nearest Neighbor with Spiral Optimization (KNN-SPO). Moreover, the proposed model is compared against deep learning architectures such as VGG-16, ResNet, AlexNet, ZDNet. Further, the proposed model also outperforms two existing works taken from the literature, Faster R-CNN-ALO, and MDCNN-AEHO, with a higher accuracy of 99.2%.

KEYWORDS: Heart disease prediction, Convolutional neural networks, Deep learning, Optimization algorithms, Internet-of-Medical Things.

1. Introduction

The World Health Organization (WHO) reports that cardiovascular disease causes 18.3 million deaths annually, making it one of the world's top causes of mortality. The main causes of heart disease include a number of harmful behaviors, including high blood pressure, obesity, a rise in triglyceride levels, and blood cholesterol [13]. Heart disease risk factors include sleep issues, increased heart rate, bloated legs, and, in certain cases, weight gain of 1 to 2 kg each day [4]. The right diagnosis is challenging because all these symptoms are typical of many illnesses that will cause death in the near future. Smart healthcare offers medical systems that connect patients, companies, and individuals to health evidence and resource connections via IoT, activity trackers, and high-speed internet access. Some of the smart healthcare networks utilized in disease diagnosis, and clinical science include the Internet of Things, Artificial Intelligence, data analytics, cloud computing, 5G, and beyond technologies [26].

In addition to IoT, the Internet of Medical Things (IoMT) is very important in the healthcare industry for time prediction and diagnosing chronic illnesses, as was earlier mentioned. When it comes to making a diagnosis and making a prognosis for many illnesses, the amount of information needed by the healthcare industry, security considerations, processing speed, and information accuracy is crucial [10]. Previous studies have employed machine learning-based algorithms to boost the accuracy of patient data and address these issues. IoMT is a brand-new network-based method for integrating medical equipment and its applications to healthcare IT platforms. Through the development of intelligent sensing devices, smart gadgets, and cutting-edge lightweight routing algorithms, IoMT offers medical diagnosis without human assistance [22]. IoMT-based healthcare includes enhanced chronic illness management, remote monitoring, ingestible sensor monitoring, smart hospitals, and more.

With the world's expanding population in the modern era, a better healthcare system is the key obstacle. The goal of the Internet of Medical Things (IoMT) is to offer a more advanced and widespread system for health monitoring [19]. The Internet of Medical Things (IoMT) enables device-to-device (D2D) communication by unifying surgical equipment with Wi-Fi technology. The time required for microservices was the most difficult problem in recent decades. As a result of modern technological advancements, even three-dimensional videos can be downloaded intermittently. Acquired large amounts of data can be measured accurately with less delay. Also, the device resource allocation capabilities are improved and give heterogeneous networks faster speeds. The Internet of Things (IoMT) is made up of a variety of heterogeneous networks, including Wi-Fi and Bluetooth as well as ZigBee [30]. The core component of the IoMT technology, with its exceptional efficiency and dependability, is Device-to-Device communication. Minimal latency, high bandwidth, and resilience are the key characteristics of an intelligent healthcare system, and these qualities are crucial for an accurate and successful diagnosis and consultation [3]. The crucial period assessment is the most important factor to take into consideration for applications in emergency healthcare. Through IoT-driven wearable electronics, extremely dependable, delay-tolerant data exchange and distribution was made possible.

In recent years, machine learning has become increasingly used in the healthcare sector to analyze huge data for early disease prediction, resulting in an improvement in the standard of healthcare [20]. Complex health problems can be resolved using machine learning, which also produces reliable outcomes. One of the main industries where machine learning has proven useful is the healthcare sector. The functionality of machine learning algorithms is greatly influenced by the creation of precise and complex datasets [6]. IoMT makes it possible for healthcare organizations and goods to exchange real-time data, thus producing a large amount of data for machine learning. Huge volumes of research information and patient cases are now available. Research can be done to employ computer technology for patient identification and precise disease diagnosis in order to stop the mortality due to these diseases. There are several open sources for acquiring access to patient records [18].

Artificial Intelligence (AI) and machine learning (ML) are now widely acknowledged to play important roles in the healthcare sector, and a variety of ML and DL models can be used to categorize and diagnose illnesses or forecast outcomes [12]. It is simple to do a thorough examination of genome data using several machine-learning methods. In the current digital era, the healthcare industry produces a lot of patient data. Manual management of these data is challenging for doctors, but IoT can manage the generated data very effectively [11]. IoT generates massive amounts of data and is capable of diagnosing illnesses using computer algorithms in order to apply various ML techniques to the generated data. For the initial prediction of heart illness in relation to IoT, an ML technique is suggested in [12].

Large amounts of medical data collected by the IoT are managed and supervised by cardiac image processing techniques derived from DL. A unified DL and IoT platform called Deep IoMT is in charge of accurately extracting cardiac imaging data from common equipment and devices. To make healthcare more accessible and inexpensive, wearable technology must be reliable (i.e., have a longer battery life), energy-efficient, and valid. A new effective strategy based on the consciously enhanced efficient-aware approach (EEA) of self-adaptive power control is suggested in [24] to reduce energy consumption while enhancing validity and battery life. A new standard DL-IoMT framework (DL-based layered architecture for IoMT) has also been developed for remote cardiac imaging of elderly patients.

In the partitioning clustering techniques, a dataset is divided into groups according to the particular measure taken into account as a fitness function [16]. This function has a bigger influence on the nature of constructing these groups. The partitioning procedure is transformed into an optimization problem once the right fitness function is chosen. In this case, partitioning is carried out in N-dimensional space by either optimizing the frequency or decreasing the distance between the patterns. An appropriate choice of optimization algorithm is also essential to build a highly predictive model. In this work, a novel deep learning approach combined with optimization algorithms to make predictions on data collected from the IoMT framework is proposed.

The main contributions of this work are as follows,

- a To present a novel hybrid heart disease prediction system with an Internet-of-Medical Things framework. the novelty of the work lies in selecting optimal features using a metaheuristic framework.
- b To implement a meta heuristic-based optimization algorithm, Chaotic Harris Hawk optimization algorithm, to extract insightful features from the complex healthcare data
- c To make predictions using Enhanced Convolutional Neural Networks on real-time data collected through the IoMT framework.

The remainder of the paper is organized as follows. Section 2 discusses the works related to heart disease prediction in the existing literature. Section 3 focuses on the proposed hybrid deep model detailing the different phases involved in the architecture. Section 4 discusses the results obtained on executing the proposed models. Section 5 compares the performance of the proposed model against existing models. Section 6 concludes the work.

2. Related Works

This section presents the existing works for heart disease diagnosis using the Internet-of-Things, Internet-of-Medical Things, Machine learning, and Deep learning algorithms.

Many researchers have been continually engaged in this subject as a result of recent developments in machine learning and medical data processing. Data on cardiac illnesses, which have attracted the interest of many academics, are among the most difficult medical data. Recursive neural networks (RNN) and decision trees (DT) were claimed to have achieved the best results in [8, 23], where a variety of machine learning algorithms were investigated for the prediction of cardiac disorders. In [20], a neural network with a convolution layer was employed for categorizing clinical data that was unbalanced. For greater accuracy in classifying unbalanced data, this work employs a double-step strategy that includes feature weighting based on the minimum relative shrinkage and screening activator (LASSO) and then identifying essential features based on a secret ballot.

In order to examine people with heart failure, Abdel-Basset et al. [31] presented a system that utilized IoT and digital diagnosis, using data from numerous sources. At first, users' smartphones used Bluetooth technology to collect data from the body sensors concerning heart failure symptoms, which were then sent by a sophisticated gateway to a central repository. Clinicians divided the patients into various groupings based on the symptoms they exhibit [27]. Finally, the Internet of Medical Things (IoMT) and the multi-criteria strategic planning (MCSP) methodology were used to quickly and cheaply diagnose, monitor, and treat heart problems. The results of the experiential assessment supported the high-level system's performance [25].

An extensible three-layer framework was suggested by Kumar and Gandhi [3] for processing and storing enormous amounts of mobile sensing data. Layer 1 was in charge of gathering the data from the integrated sensor devices. In order to efficiently store the integrated Sensor data in a virtualized environment, Layer 2 used Apache HBase. In order to create the logistic-regression-based prediction system for heart disease, Layer 3 used Apache Mahout. Finally, to identify the important clinical markers of heart disease, an operating characteristic analysis was performed [21].

A computer-aided diagnosis paradigm for the recognition of cardiac disease was introduced by Al et al. [3]. The data were split into training and test datasets after texture features had been normalized. The trained data was then subjected to sampling and feature evaluation using a statistical framework. The framework used the same subset of features for testing the data that it had used for training [27]. A network used the training data with fewer characteristics to do training. Using the test data, the trained model's performance was evaluated.

An IoMT-based server design was proposed by Gupta et al. [9]. The system used embedded equipment sensors rather than smartphones or wearable sensors to store the values of the fundamental health-related indicators. This architecture made use of XML Web services to facilitate quick and safe data transfer [1]. It can appear that the total response between the local database server and the data center is nearly in line with the increase in users.

A function for identifying the ideal weights based on population heterogeneity and tweaking parameters was introduced by Vijayashree and Sultana [28]. Additionally, an objective function for particle swarm optimizations (PSOs) using support vector machines was created using the framework that was described (SVMs). Six distinguishing characteristics for classifying heart illness were identified using the PSO-SVM feature selection algorithm: gender, maximal pulse rate, fasting blood glucose level, resting Electrocardiogram, multiple main arteries, and aerobic activity angina [9]. The effectiveness of the proposed PSO-SVM system was compared to that of a number of other techniques. It has been demonstrated that the suggested methodology outperforms the alternatives.

Though several works exist in the literature for heart disease prediction using Machine Learning and Deep Learning algorithms [29, 14], it has been employed to standard datasets collected from repositories. In this work, a real-time prediction of heart disease is proposed based on the data collected through sensors from the IoMT framework. In addition to this improved optimization algorithm such as Chaotic Harris Hawk is used in combination with Enhanced Convolutional Neural Networks for classification purposes.

3. Proposed Methodology

The proposed methodology comprises four phases as depicted in Figure 2. In the first phase, the data is collected through the sensors placed in the patient. The Cleveland dataset is used to train the model and the real-time data obtained from the IoMT framework is used for testing purposes and to make predictions. In the second phase, the data obtained is preprocessed in order to prepare the data for making it parsable by the model. In the third phase, Chaotic Harris Hawk Optimization (C-HHO) is applied for the feature selection process, and in the fourth phase, the classification of heart disease is implemented using Enhanced Convolutional Neural Networks (E-CNN).

The classification is carried out through training and testing processes. The dataset used in the proposed work is taken from the UCI Machine Learning Repository. This repository hosts several datasets from VA Long Beach, Switzerland as well as Cleveland. The Cleveland dataset is employed for the diagnosis of heart disease in this work. This dataset consists of 303 instances and almost all the data in this dataset are complete in nature. Preprocessing of the Cleveland dataset will be performed during the training phase. After this, the feature selection is executed using the C-HHO algorithm followed by the classification using E-CNN on the selected features. During the testing phase, real-time data collected from the sensors through Narrow Band IoT is tested using the proposed model to classify whether the patient is affected or not by heart disease. For the affected patients, an immediate alert is transmitted to the healthcare professional to take necessary action to treat the patients.

3.1. Data Collection Phase

This layer involves the Internet of Medical Things Framework for the data collection process. The architecture of the IoMT framework is depicted in Figure 1**.** The acquisition layer is used to gather data from the objects placed on the patients where signals are acquired and converted for medical analysis. The access layer is responsible to transmit the acquired data to the network layer using technologies like Wi-Fi, Zigbee as well as Bluetooth. The network layer is one of the most important layers in the IoMT framework. This layer is responsible for the synchronous transfer of data using mobile networks and other heterogeneous networks. The application layer is the layer in which the analysis of the data and management of data takes place in order to aid intelligent decision-making and predictions. From this layer, the data is taken for preprocessing, feature selection, and classification purposes.

Figure 1

IoMT framework

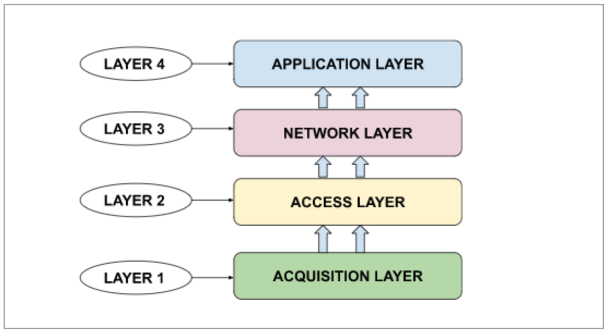
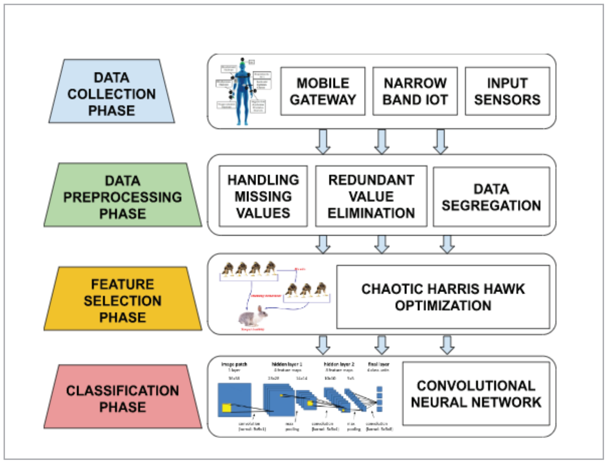


Figure 2

Proposed Architecture



3.2. Data Preprocessing Phase

This is the initial stage in which three important tasks are executed for the preparation of the data before forwarding it to the next phase which is feature selection.

Task 1: Handling Missing Values

The missing values in certain attributes are replaced by the values that are present for the corresponding records by analyzing the whole dataset. There were missing values for attributes such as cholesterol and blood pressure in the Cleveland dataset. The missing values in these attributes are replaced by suitable values by analyzing the records of all patients based on the age attribute. The records with maximum matching values are chosen for filling the missing values in the attributes of Cholesterol and blood pressure.

Task 2: Elimination of Redundant Values

Redundant values increase the number of records in the dataset used for training the model which in turn affects the time taken to train the model. Secondly, presence of redundant values prohibits the model from producing accurate predictions as the repeated values are provided high importance. Both these factors directly have adverse effects on the performance of the model during the testing phase.

Task 3: Segregation of Data

During the execution of this task, the patients are segregated into four categories depending on the category of chest pain experienced by the patient. The four categories of chest pain are tabulated in Table 1.

Table 1
Categories of Chest pain

Chest pain categories	Chest pain Name
Category 1	Asymptomatic chest pain
Category 2	Non-anginal chest pain
Category 3	Typical angina chest pain
Category 4	Atypical angina chest pain

3.3. Feature Selection Phase

The feature selection of the proposed work is implemented using the Chaotic Harris Hawk Optimization algorithm. The mathematical modeling of the C-HHO algorithm is discussed in detail in this section. The main intuition behind this modeling is determining a suitable strategy to seize the target. The probabilistic strategy used in this technique is the formulation of a plan to identify the food and acquire it without the knowledge of the target. Consider the probability of acquiring the target on each trial as p which is also dependent on the closeness of the other members in the group. Two Equations (1) and (2) are formulated for conditions when p<0.5 and p>=0.5 respectively.

For p>=0.5,

$$A(iteration+1) = A_{random}(iteration) - a_1 \times abs(A_{random}(iteration) - 2 \times a_2 \times A(iteration)) \quad (1)$$

For p<0.5,

$$A(iteration+1) = \left(A_{target}(iteration) - A_{avg}(iteration)\right) a_3 \times \left(l_{bound} + a_4 \times (u_{bound} - l_{bound})\right), \quad (2)$$

Where $A(iteration+1)$ denotes hawk's position in consecutive iteration, $A_{random}(iteration)$ denotes hawk's that are selected in random, a_1, a_2, a_3 and a_4, are values that are chosen in random between 0 and 1. These values under alteration in every iteration which is determined by the bound values u_{bound} and l_{bound}. $A_{target}(iteration)$ denotes the position in which the target is located. $A_{avg}(iteration)$ denotes the average location of the hawk and it is determined using the Equation (3) as,

$$A_{avg}(iteration) = \frac{1}{T}\left(\sum_{k=1}^{T} A_k(iteration)\right) \quad (3)$$

Where $A_k(iteration)$ denotes the hawk's position after consecutive iteration and T denotes the aggregate number of hawks.

Movement of the hawks between the exploration and the exploitation stage is wholly controlled by the energy exhibited by the target to escape and is determined using Equation (4) as,

$$R_{energy} = 2 \times S_{energy} \times \left(1 - \frac{iteration}{iteration_{high}}\right) \quad (4)$$

Where R_{energy} denotes the restraint energy and S_{energy} denotes the energy in the starting stage which ranges between -1 and 1. $iteration_{high}$ denotes the utmost iterations taken.

The updated locations of the hawks is determined using the Equation (5). The success rate of acquiring the target by the hawks is dependent on the strategy used by the hawk to acquire the target and the restraint energy exhibited by the target to escape. The escape transpose represented by E_t is also important for the transition from the exploration and the exploitation stage. For this E_t value in range E_t>=0.5, the hawk will perform a soft attack on the target.

$$A(iteration+1) = \Delta A(iteration) - R_{energy} \times abs(B_{energy} A_{target}(iteration) - A(iteration)) \quad (5)$$

$$\Delta A(iteration) = \left(A_{target}(iteration) - A(iteration)\right), (6) \quad (6)$$

Where $\Delta A(iteration)$ denotes the variation in the present location of the target and hawk.

B_{energy} denotes the bounce energy which undergoes a modification in every iteration and is computed as

$$B_{energy} = (1 - a_5), \quad (7)$$

Where a_5 is a value chosen in random between 0 and 1. When the target becomes fatigued, the hawk will perform a hard attack on the target for $E_t < 0.5$.

$$A(iteration+1) = A_{target}(iteration) - R_{energy} \times abs(\Delta A(iteration))(8) \quad (8)$$

$$B = A_{target}(iteration) - Energy \times abs(B_{energy}\, A_{target}(iteration) - A(iteration)) \quad (9)$$

$$C = B + FF_{path}(P_d), \quad (10)$$

Where FF_{path} *and* P_d denotes the path of the fractal flight and dimensionality of the problem respectively. $FF_{path}(P_d)$ is formulated based on the rules represented in Equations (11)-(12) as,

$$FF_{path}(a) = 0.01\left(\frac{\gamma - \delta}{|\mu|^{\frac{1}{\sigma}}}\right), \quad (11)$$

where

$$\delta = \left(\frac{\lambda(1+\sigma)\times sin(\frac{\omega\sigma}{2})}{\lambda(\frac{1+\sigma}{2})\times\sigma\times 2(\frac{\sigma-1}{2})}\right)^{\frac{1}{\sigma,}} \quad (12)$$

where γ and δ are values that are chosen in random between 0 and 1 whereas σ is a value that is set to hold a constant value of 0.5.

At this point of time, the target gains required energy and the hawk performs an attack on the target based on the Race Levy flight process as shown in Equation (13) which is a soft attack.

$$A(iteration+1) = B;\ if\ func(B) < func(A(iteration))(13) \quad (13)$$

C; *if func*(C) <*func*$(A(iteration))$

$$B' = A_{target}(iteration) - Energy \times abs(B_{energy\, A_{target}(iteration) - A_{avg}(iteration)}) \quad (14)$$

$$C' = B' + FF_{path}(P_d). \quad (15)$$

Now, the hawks are very near to the target and thus executes a hard attack on the target as shown in Equation (16).

$$A(iteration+1) = B';\ if\ func(B') < func(A(iteration))(16) \quad (16)$$

The pseudocode of the C-HHO algorithm is depicted in Algorithm 1as shown below.

Algorithm 1. Chaotic Harris Hawk Optimization(C-HHO) algorithm

Input: population q for iterations m

Output: Target location and its fitness value

Population Initialization $Q_k(k = 1, 2, 3, 4, \dots, q)$

$while(iteration_{high})$

Compute best fitness of hawks

Assign A_{target} as the optimal target location

$for\ each\ Hawk(Q_k)$

Set start energy as S_{energy}

$E_t^{0,1} = random;$

$if\ E_t^{0,1} < 0.5$

$E_t^{0,1}(n+1) = \frac{E_t^{0,1}}{0.5};$

end

$if\ E_t^{0,1} >= 0.5$

$E_t^{0,1}(n+1) = \frac{10}{3} * (1 - E_t^{0,1})$

end

$Set\ p = E_t^{0,1}(n+1)$

$Set\ E_t = E_t^{0,1}(n+1)$

$if\ M >= 1\ then$

$else\ if\ p >= 0.5\ then$

$A(iteration+1) = A_{random}(iteration) - a_1 \times abs(A_{random}(iteration) - 2 \times a_2 \times A(iteration))$

$else\ if\ p < 0.5\ then$

$A(iteration+1) = (A_{target}(iteration) - A_{avg}(iteration)) - a_3 \times (l_{bound} + a_4 \times (u_{bound} - l_{bound}))$

Updated Location

$$R_{energy} = 2 \times S_{energy} \times (1 - \frac{iteration}{iteration_{high}})$$

$$if\ M < 1\ then$$

$$A(\square teration + 1) = \Delta\ A(iteration) - R_{energy} \times abs(B_{energy}\ A_{target}(iteration) - A(iteration))$$

$$if\ E_t >= 0.5\ and\ M >= 0.5\ then$$

Updated Location $\Delta\ A(iteration)\ (A_{target}(iteration) - A(iteration))$

$$else\ if\ E_t >= 0.5\ and\ M < 0.5\ then$$

Updated Location $A(iteration + 1)\ = A_{target}(iteration) - R_{energy} \times abs(\Delta A(iteration))$

$$else\ if\ E_t < 0.5\ and\ M >= 0.5\ then$$

Updated Location $B = A_{target}(iteration) -\ Energ\ abs(B_{energy}\ A_{target}(iteration) - A(iteration))$

$$else\ if\ E_t < 0.5\ and\ M < 0.5\ then$$

Updated Location

$$A(iteration + 1) = \Delta\ A(iteration) - R_{energy} \times abs(B_{energy}\ A_{target}(iteration) - A(iteration))$$

$$end$$

$$end$$

$$end$$

$$end$$

$$return\ A_{target}$$

3.4. Classification Phase

Convolutional Neural Networks (CNN) is a widely adopted technique based on deep architectures that is used for classification purposes. This architecture consists of a convolution layer which is linear in nature and also comprises fully connected layers. In addition to the linear functions it also consists of an activation function in the hidden layers which are nonlinear in nature. These nonlinear activation functions are used to reduce the dimensionality of the final output. Several perceptrons are used to build the CNN architecture which takes inputs and combines it with weights as well as bias. CNN uses a localized domain with spatial features and the parameters are distributed among every node. In the proposed work an improved version of CNN named Enhanced Convolutional Neural Networks (E-CNN) is used. There are five different layers in E-CNN architecture which are discussed in detail in this section along with the E-CNN algorithm.

3.4.1. Convolution Layer

The main operation performed in this layer is the convolution to obtain the feature extracted maps which are passed on to the successive layers. This operation is executed on the input data using the filter matrix by incorporating multiple mathematical computations. Multiplication is performed on all the elements that are available in the input as well as filter matrix. For any input matrix X and filter matrix M, the feature map is computed as shown in Equation (17),

$$F_{map}\ (a, b) = \sum_{y=0}^{a} \sum_{z=0}^{b} X(a, b)M(y - a, z - b). \quad (17)$$

3.4.2. Pooling Layer

The next consecutive layer after the convolution layer is the pooling layer which is used to reduce the dimensionality of the input domain which in turn will reduce the number of computations performed. The size of the kernel in the pooling layer is generally fixed to a size of 2x2 along with the stride value being set to 2.

3.4.3. Fully Connected Layer

This layer is the result of the replication that happens due to the convolution operation. The dimensionality of this layer is in the form T1xT2 where the T1 and T2 are generally used to represent the input as the output units in the network. A dropout may be added after this layer if the overfitting problem occurs. In this way weights will be reassigned to all the nodes in the network to tackle this issue.

3.4.4. Output Layer

This is the final layer in the network which is used to produce the classification output. The activation function most prominently used in this layer is the softmax function. This function assigns a probabilistic value to all the possible classifications in the range 0 to 1. The class value with the highest probability is chosen as the final classification.

3.4.5. Working of E-CNN

Consider the input values $X = X_1, X_2, X_3, \dots, X_n$ and the corresponding output values as $Y = Y_1, Y_2, Y_3, \dots, Y_n$, for these input and output values the task is to map the values appropriately during the training process. This is formulated as a mathematical equation based on probability as in (18),

$$Prob(a(X, l, s_m)|a(Y, l, s_n)). \tag{18}$$

The function to extract the contextual information is represented in Equation (19),

$$func(X) = \delta(x(s)) = prob(\frac{1}{x}) \tag{19}$$

Softmax function is used mainly to perform multi class predictions and is denoted as in (20),

$$func(softmax) = \frac{exp\ (x(s))}{b} = prob(\frac{1}{y_i}) \tag{20}$$

y_i represents the probability for the prediction of output component y.

The pseudo code of the E-CNN algorithm is depicted in Algorithm 2as shown below.

Algorithm 2. Enhanced Convolutional Neural Networks(E-CNN) algorithm

Step 1: Assume feature vectors and corresponding weight vectors

$$FV_k = [FV_1, FV_2, FV_3, \ldots\ldots, FV_n]$$
$$WV_k = [WV_1, WV_2, WV_3, \ldots\ldots, WV_n]$$

Step 2: Multiply feature vectors and weight vectors and find the aggregated sum Sum_{agg}

$$Sum_{agg} = \sum_{k=1}^{n} FV_k WV_k$$

Step 3: Compute the value of the nonlinear activation function using M_k which is the exponential of FV_k

$$Func_{act} = M_k(\sum_{k=1}^{n} FV_k WV_k)$$

$$M_k = e^{-FV_k}$$

Step 4: Compute outcome of hidden layer using bias value BV

$$OV_k = BV + \sum_{k=0}^{n} M_k WV_k$$

Step 5: Compute final output OF_k

$$OF_k = BV + \sum_{i=0}^{n} OV_i WV_i$$

Step 6: Compare obtained output and output present in data and represent as Err

$$Err = AF_k - OF_k$$

Step 7: Determine the function to backpropagate and correct the weights to reduce error by multiplying momentum value γ and error with the feature vector

$$WV_{corr} = \gamma\ Err(FV_k)$$

4. Results and Discussion

This section discusses the results obtained by conducting extensive experiments to measure and compare the performance of the proposed model against the existing machine learning models, deep learning architectures and other existing works.

4.1. Dataset Used

The dataset collected from UCI repository which is the Cleveland dataset is used for the experimental purposes for training the proposed model. This dataset is available in the following url,

https://archive.ics.uci.edu/ml/datasets/heart+Disease

The total number of attributes in this dataset is close to 76 and also consists of samples upto 303.Out of the 76 attributes available in the dataset only the most contributing attributes for the heart disease prediction which is around 14 attributes are also chosen for training the proposed model.The top most attributes chosen from the dataset are described in Table 2.

The experiment executed for the performance measure of the proposed model employed a 10 fold cross validation. Out of the total data available, 80% was used for training purposes, 10% was utilized for testing purposes and the remaining 10% for validation purposes. Once the model is trained it is also tested using the data received from the IoMT framework.

4.2. IoMT Simulation

The simulation of the IoMT framework is implemented using languages such as Java and Python on the Android platform. This framework is simulated by integrating several hardware components including micro controllers and the devices for aiding communication with the cloud network. The age of the patient along with the gender is accumulated in the cloud with a unique number allotted for each individual patient.

Table 2
Important Attributes of Cleveland dataset

Attribute Number	Attribute Name	Attribute Specification
3	age	Specifies the age of the patient in terms of years
4	sex	Specifies the gender of the patient denoted as 1 for male and 0 for female
9	cp	Specifies the category of chest pain(typical angina, atypical angina, non-anginal pain, asymptomatic)
10	trestbps	Specifies the measure of resting chest pain denoted in mmHg
12	chol	Specifies the measure of serum cholesterol denoted in mg/dl
16	fbs	Specifies the measure of fasting blood sugar denoted in boolean(true/false)
19	restecg	Specifies the measure of resting electrocardiographic results denoted as 0,1, 2 based on the severity
32	thalach	Specifies the measure of maximum heart rate
38	exang	Specifies the measure of exercise induced angina denoted as 0 for no or 1 for yes
40	oldpeak	Specifies the measure of ST depression
41	slope	Specifies the measure of peak exercise ST segment denoted as upsloping, flat, downsloping
44	ca	Specifies the measure of major vessels denoted in 0-3
51	thal	Specifies the measure of heart rate denoted as 3 for normal, 6 for fixed defect, 7 for reversible defect
58	num	Specifies the measure of heart disease status denoted as 0 for absence of disease, 1 to 4 for presence of disease

Chest pain parameter is filled with values generated in random between the ranges 1 to 4. FitVII wearable device is used to monitor the blood pressure of the patient in resting position. The values for the other two important parameters such as serum cholesterol and the levels of glucose are also produced through random numbers in a specified range. Certain parameters are also taken from the past medical history of the patient. Oldpeak, slope and heart rate are the features obtained from prior data. The other hardware components used in the simulation setup include transmitter and receiver for LoRaWan, a personal computer with Intel i7 processor, a Raspberry Pi kit with quadcore 64 bit ARM and also the analog devices. T4 graphic card is employed for Keras framework and Scikit-learn toolbox.

4.3. Performance Metrics

The performance evaluation metrics used in this experiment are described as follows. The basic factors for the performance metrics are true positive (x_p), true negative (x_n), false positive (y_p), false negative (y_n).

a Accuracy (Acc):

Accuracy mostly depends on how the data is collected. Evaluation is based on comparing various measures from the same or different sources. It is represented as in (21).

$$Acc = \frac{x_p + x_n}{x_p + x_n + y_p + y_n}. \tag{21}$$

b Disease Likelihood (DL):

This is the likelihood that a person has the condition before a health examination. It is represented as in (22).

$$DL = \frac{x_p + y_n}{x_p + x_n + y_p + y_n}. \tag{22}$$

c Positive Predictability (PP):

This represents the likelihood that a patient who has a positive test result actually has the disease. It is also known as precision. It is represented as in (23).

$$PP = \frac{x_p}{x_p + y_p}. \tag{23}$$

d Negative Predictability (NP):

This represents the likelihood of locating a patient who is not at risk for heart disease. It is represented as in (24).

$$NP = \frac{x_n}{x_n + y_n} \quad (24)$$

e Recall (Rec):

This demonstrates the capability of identifying a patient at risk for heart disease. It is represented as in (25).

$$Rec = \frac{x_p}{x_p + y_n}. \quad (25)$$

f F1 Score(F1):

This measure is basically the value obtained on executing a harmonic mean on the values of precision as well as recall. It is represented as in (26).

$$F1 = 2 \times \frac{PP \times Rec}{PP}. \quad (26)$$

4.4. Performance Evaluation

The metric values exhibited by the proposed E-CNN algorithm with C-HHO optimization is calculated using the confusion matrix shown in Table 3.

Table 3
Confusion Matrix

Outcome	Heart Disease Present	Heart Disease Not Present	Calculation
Positive Outcome	x_p	y_p	$\frac{x_p}{x_p + y_p}$
Negative Outcome	x_n	y_n	$\frac{x_n}{x_n + y_n}$

The performance of the proposed algorithm is evaluated by applying E-CNN algorithm with C-HHO optimization to both the Cleveland Dataset as well as the data that is obtained from the IoMT framework as shown in Figure 5. It is also tabulated in Table 4. It was observed that the model exhibited an accuracy upto 99.2% for the Cleveland Dataset and on the other hand exhibited 98.9% accuracy for the data collected through the sensors. Similarly the other values were also computed and the disease likelihood was found to be closer for the Cleveland data and Sensor data with 93% and 92% respectively. The Positive Predictability and the Negative Predictability for Cleveland dataset

Figure 5
Performance Evaluation for Cleveland data vs IoMT data

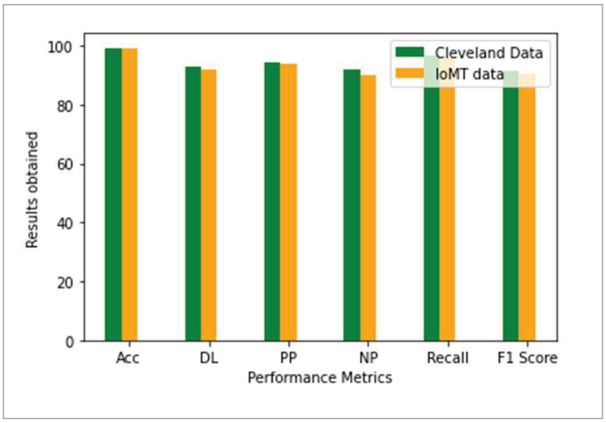


Table 4
Performance Evaluation for Training vs Testing data

S.No	Performance Metric	Values obtained for Cleveland Dataset	Values obtained from IoMT Sensors
1	Accuracy	99.2	98.9
2	Disease Likelihood	93	92
3	Positive Predictability	97.5	93.8
4	Negative Predictability	92.1	90.2
5	Recall	98.9	95.9
6	F1 Score	98.7	90.6

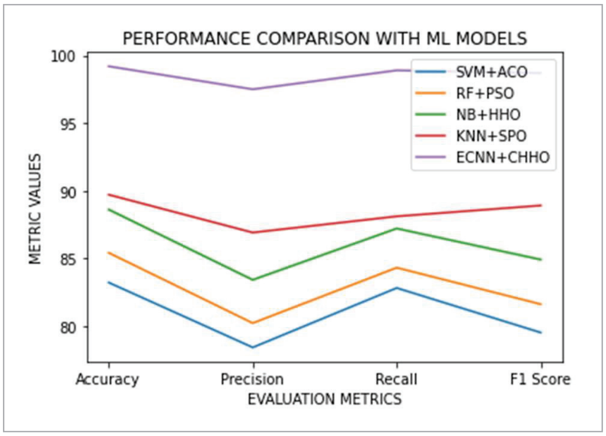
was 97.5 and 92.1 whereas the same values for the data from IoMT sensors were 93.8 and 90.2. The Recall value was estimated to be 98.9 for Cleveland data and 95.9 for the Sensor data. F1-Score which is calculated based on Precision and Recall were 98.7 and 90.6 for the Cleveland and Sensor data respectively.

4.4. Performance Comparison with ML Models

The performance exhibited by the proposed model for the Cleveland data is compared against the Machine learning models in combination with Optimization algorithms as shown in Figure 6. The Machine learning algorithms and Optimization algorithms considered for the analysis include Support Vector

Figure 6

Performance Comparison with ML models



Machine with Ant Colony Optimization (SVM-ACO), Random Forest with Particle Swarm Optimization (RF-PSO), Naive Bayes with Harris Hawk Optimization (NB-HHO), K Nearest Neighbor with Spiral Optimization (KNN-SPO). It was observed that the SVM-ACO model exhibited least accuracy of 83.2% and among the Machine Learning models KNN-SPO exhibited high accuracy of 89.7%. Though KNN-SPO model showed high accuracy among Machine Learning models, this accuracy is lesser than the accuracy 99.2% produced by the proposed ECNN-CHHO algorithm. Similarly, the proposed method outperformed the ML models in terms of other performance evaluation metrics also. The results obtained for the comparison between proposed and ML models is shown in Table 5.

Table 5

Performance Comparison ML Models vs Proposed Model

Algorithm	Optimizer	Accuracy	Precision	Recall	F1 Score
SVM	ACO	83.2	78.4	82.8	79.5
Random Forest	PSO	85.4	80.2	84.3	81.6
Naive bayes	HHO	88.6	83.4	87.2	84.9
K-Nearest Neighbor	SPO	89.7	86.9	88.1	88.9
E-CNN	C-HHO	99.2	97.5	98.9	98.7

4.5. Performance Comparison with DL Models

Deep Learning architectures such as VGG-16, ResNeXt, AlexNet, ZFNet are also considered for performance comparison with the proposed method as shown in Figure 7. The accuracy of the DL architectures was a maximum upto 85.6 which is produced by AlexNet architecture but it is lower than the accuracy showed by E-CNN for heart disease prediction. The values for Precision, Recall and F1 score measures are also considerably lower than that of the proposed algorithm as depicted in Table 6.

Figure 7

Performance Comparison DL Models vs Proposed Model

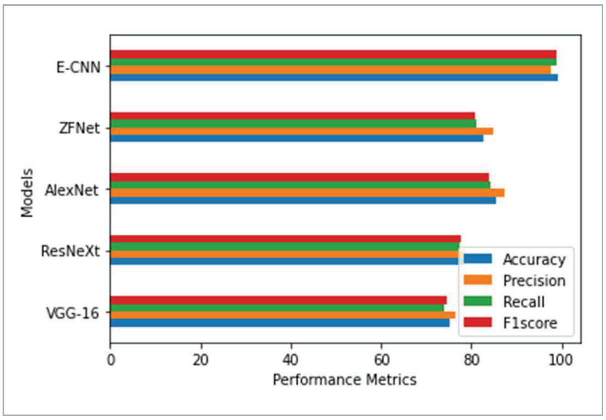


Table 6

Performance Comparison DL Models vs Proposed Model

Algorithm	Accuracy	Precision	Recall	F1 Score
VGG-16	75.2	76.4	73.8	74.5
ResNeXt	78.4	78.2	77.3	77.6
AlexNet	85.6	87.4	84.2	83.9
ZFNet	82.7	84.9	81.1	80.9
E-CNN	99.2	97.5	98.9	98.7

4.6. Performance Comparison with Existing Works

Apart from the comparison of the proposed work with the Machine learning and deep learning mod-

Table 7
Performance Comparison Existing works vs Proposed work

Algorithm	Accuracy	Precision	Recall	F1 Score
Faster R-CNN with SE-ResNeXt-101 [26]	98	96.16	98.47	97.58
MDCNN [13]	98.2	95.1	97.8	95
E-CNN	99.2	97.5	98.9	98.7

els, it is also compared with the models proposed by Mohammad et.al and Manimurugan et.al as in Table 7. The work proposed by Manimurugan et.al includes a Faster R-CNN with SE-ResNeXt-101with ant lion optimization. Mohammad et.al have proposed the MDCNN algorithm with Adaptive Elephant Herd Optimization. Faster R-CNN-ALO has exhibited an accuracy of 98% whereas the accuracy produced by MDCNN-AEHO was 98.2%. However, the proposed model outperformed the considered existing works in the literature with an accuracy of 99.2%. Thus, it is clearly evident from the performance analysis of the proposed method that it exhibits superior performance compared to the other machine learning and deep learning models for heart disease prediction.

6. Conclusion

In this work, a novel deep learning model Enhanced Convolutional Neural Networks is proposed for the effective prediction and diagnosis of heart disease. The proposed method utilizes the dataset taken from UCI repository which is Cleveland dataset to train the model. Further, the real time prediction of heart disease is implemented by receiving data from the sensors connected to the patients through the Internet-of-Medical-Things framework. This data is used for testing the predictions made by the E-CNN model. Further, Chaotic Harris Hawk optimization is applied to extract insightful features from the data before it is forwarded to the heart disease classification using E-CNN model. The performance of the model is evaluated using the Cleveland data as well as the data collected through the sensors and the proposed model 99.2% accuracy for Cleveland data and 98.9% accuracy for sensor data. Moreover, the performance of the model to predict heart disease is compared against Machine Learning and Deep Learning models. In addition to this, two existing works from the literature Faster R-CNN-ALO and MDCNN-AEHO is also considered for the performance evaluation against the proposed method. The proposed model performs better than the models taken for comparison and makes accurate predictions. As a part of future work, intelligent models can be developed for heart disease diagnosis using Artificial Intelligence algorithms to improve the accuracy further.

References

1. Ahmed, F. An Internet of Things (IoT) Application for Predicting the Quantity of Future Heart Attack Patients. International Journal of Control, Automation and Systems, 2017, 164(6), 36-40. https://doi.org/10.5120/ijca2017913773
2. Aieshwarya, B., Chavan Patil, C., Sonawane, S. S. To Predict Heart Disease Risk and Medications Using Data Mining Techniques with an IoT Based Monitoring System for Post-Operative Heart Disease Patients. International Journal on Emerging Trends in Technology (IJETT), 2017, 4, 8274-8281.
3. Al-Makhadmeh, Z., Amr, T. Utilizing IoT Wearable Medical Device for Heart Disease Prediction using Higher Order Boltzmann Model: A Classification Approach. Measurement, 2019, 147, 106815. https://doi.org/10.1016/j.measurement.2019.07.043
4. Awan, M. U., Riaz Khan, A. G. Prediction of Heart Disease using Artificial Neural Networks, VFAST Transaction Software Engineering, 2018, 13(3), 102-112. https://doi.org/10.21015/vtse.v13i3.511
5. Bashir, S., Khan, Z. S., Khan, F. H., Anjum, A., Bashir, K. Improving Heart Disease Prediction using Feature Selection Approaches, In 2019 16th International Bhurban Conference on Applied Sciences and Technology (IBCAST), Islamabad, Pakistan, 619-623. https://doi.org/10.1109/IBCAST.2019.8667106
6. Dutta, A., Batabyal,T., Basu,M., Acton, S. T. An Efficient Convolutional Neural Network for Coronary Heart Disease Prediction. Expert Systems with Applications, 2020, 159, 113408. https://doi.org/10.1016/j.eswa.2020.113408

7. El Zouka, H. A., Hosni, M. M. Secure IoT Communications for Smart Healthcare Monitoring System. Internet of Things, 2019, 13. https://doi.org/10.1016/j.iot.2019.01.003
8. Firdaus, H., Hassan, S. I., Kaur, H. A Comparative Survey of Machine Learning and Meta-Heuristic Optimization Algorithms for Sustainable and Smart Healthcare. African Journal of Computer ICT Ref. Format, 2018, 11(4), 1-17.
9. Gupta, P. K., Maharaj, B. T., Malekian, R. A Novel and Secure IoT Based Cloud Centric Architecture to Perform Predictive Analysis of Users Activities in Sustainable Health Centres. Multimedia Tools Application, 2017, 76(18), 18489-18512. https://doi.org/10.1007/s11042-016-4050-6
10. Habib, S., Moin, M. B., Aziz, S. Heart Failure Risk Prediction and Medicine Recommendation System using Exploratory Analysis and Big Data Analytics. Ph.D. dissertation, Department of Computer Science Engineering, BRAC University, Dhaka, Bangladesh, 2018. https://doi.org/10.1109/ICASERT.2019.8934541
11. Khan, M. A. An IoT Framework for Heart Disease Prediction Based on MDCNN Classifier, IEEE Access, 2020, 8, 34717-34727. https://doi.org/10.1109/ACCESS.2020.2974687
12. Khan, M. A., Algarni, F. A Healthcare Monitoring System for the Diagnosis of Heart Disease in the Iomt Cloud Environment Using MSSO-ANFIS. IEEE Access, 2020, 8, 122259-122269. https://doi.org/10.1109/ACCESS.2020.3006424
13. Kim, J., Kang, U., Lee, Y. Statistics and Deep Belief Network-Based Cardiovascular Risk Prediction. Healthcare Informatics Research, 2017, 23(3), 169-175. https://doi.org/10.4258/hir.2017.23.3.169
14. Li, J. P. , Haq, A. U., Din, S. U., Khan, J., Khan, A., Saboor, A. Heart Disease Identification Method Using Machine Learning Classification in E-Healthcare. IEEE Access, 2020, 8, 107562-107582. https://doi.org/10.1109/ACCESS.2020.3001149
15. Li, J., Liu, L. S., Fong, S. Adaptive Swarm Balancing Algorithms for Rare-Event Prediction in Imbalanced Healthcare Data. PloS one, 2017, 12(7), 0180830. https://doi.org/10.1371/journal.pone.0180830
16. Maheswari, G. U., Sujatha, R., Mareeswari, V., Ephzibah, E. P. The Role of Metaheuristic Algorithms in Healthcare in Machine Learning for Healthcare, Chapman and Hall/CRC, Bocaraton, FL, USA, 2020. https://doi.org/10.1201/9780429330131-3
17. Manimurugan, S., Almutairi, S., Aborokbah, M. M., Narmatha, C., Ganesan, S., Chilamkurti, N., Alzaheb, R. A., Almoamari, H. Two-Stage Classification Model for the Prediction of Heart Disease using IoMT and Artificial Intelligence. Sensors (Basel), 2022, 22(2), 476. https://doi.org/10.3390/s22020476
18. Maragatham, G., Devi, S. LSTM Model for Prediction of Heart Failure in Big Data, Journal of Medical Systems, 2019, 19. https://doi.org/10.1007/s10916-019-1243-3
19. Miao, K. H., Miao, J. H. Coronary Heart Disease Diagnosis using Deep Neural Networks. International Journal of Advanced Computer Science and Applications, 2018, 9(10), 1-8. https://doi.org/10.14569/IJACSA.2018.091001
20. Pan, Y., Fu, M., Cheng, B., Tao, X., Guo, J. Enhanced Deep Learning Assisted Convolutional Neural Network for Heart Disease Prediction on The Internet of Medical Things Platform. IEEE Access, 2020, 8, 189503-189512. https://doi.org/10.1109/ACCESS.2020.3026214
21. Patel, J., Khaked, A. A., Patel, J., Patel, J. Heart Disease Prediction Using Machine Learning. In Proceedings of Second International Conference on Computing, Communications, and Cyber-Security, Springer, Singapore, 2021, 653-665. https://doi.org/10.1007/978-981-16-0733-2_46
22. Phalke, A., Sondur, S. Deep Learning-based Heart Disease Prediction. Asian Journal Converge Technology (AJCT), 2019, 5(1), 1-4.
23. Saha, A., Chowdhury, C., Jana, M., Biswas, S. IoT Sensor Data Analysis and Fusion Applying Machine Learning and Metaheuristic Approaches. Enabling AI Applications in Data Science, 2021, 441-469. https://doi.org/10.1007/978-3-030-52067-0_20
24. Sarmah, S. S. An Efficient IoT-Based Patient Monitoring and Heart Disease Prediction System Using Deep Learning Modified Neural Network. IEEE Access, 2020, 8, 135784-135797. https://doi.org/10.1109/ACCESS.2020.3007561
25. Sharma, H., Rizvi, M. A. Prediction of Heart Disease Using Machine Learning Algorithms: ASurvey. International Journal on Recent and Innovation Trends in Computing and Communication, 2017, 5(8), 99-104.
26. Tuli, S., Basumatary, N., Gill, S. S., Kahani, M., Arya, R. C., Wander, G. S., Buyya, R. Healthm Fog: An Ensemble Deep Learning Based Smart Healthcare System for Automatic Diagnosis of Heart Diseases in Integrated IoT And Fog Computing Environments, Future Generating. Computer System, 2020, 104, 187-200. https://doi.org/10.1016/j.future.2019.10.043

27. Uyar, K., İlhan, A. Diagnosis of Heart Disease Using Genetic Algorithm Based Trained Recurrent Fuzzy Neural Networks. Procedia Computer Science, 2017, 120, 588-593. https://doi.org/10.1016/j.procs.2017.11.283

28. Vijayashree, J., Sultana, H. P. A Machine Learning Framework for Feature Selection in Heart Disease Classification using Improved Particle Swarm Optimization with Support Vector Machine Classifier. Programming and Computer Software, 2018, 44(6), 388-397. https://doi.org/10.1134/S0361768818060129

29. Wang, G. Lauri, F., Hassani, A. H. E. Feature Selection by mRMR Method for Heart Disease Diagnosis. IEEE Access, 2022, 10, 100786-100796. https://doi.org/10.1109/ACCESS.2022.3207492

30. Zhang, Q., Fu, L., Gu, L. A Cascaded Convolutional Neural Network for Assessing Signal Quality of Dynamic ECG. Computational and Mathematical Methods in Medicine, 2019, 2019, 7095137. https://doi.org/10.1155/2019/7095137

31. Zhang, T., Sodhro, A. H., Luo, Z. A Joint Deep Learning and Internet of Medical Things Driven Framework for Elderly Patients. IEEE Access, 2020, 8, 75822-75832. https://doi.org/10.1109/ACCESS.2020.2989143

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