IOT-Based Generic Health Monitoring with Cardiac Classification Using Edge Computing

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Abstract

Background: The current environment of modern computation can offer a smart healthcare monitoring for the early prediction of disease detection. For the domain of healthcare services, the Internet of Things (IoT) has a vital role, and also aids in the enhancement of the data's processing as well as predictions. The transfer of data or reports from one location to another will consume a lot of energy as well as time, and also does result in issues of high energy as well as latency. With edge computing, the disadvantages can be easily resolved. Objectives: This work presents a Convolutional Neural Network (CNN)-based model of prediction which employs edge computing as well as IoT paradigms. The term edge computing will refer to a distributed environment

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framework that facilitates swift resource accessibility and response times by means of the local edge servers for processing at the end of the IoT devices. With this model, there can be an analysis of the health data which has been gathered by the IoT devices. Additionally, the edge devices will employ the edge servers for offering the patients as well as the doctors health-prediction reports in a timely manner. Methods: This work has proposals of an optimized CNN with Tabu Search (TS), Artificial Bee Colony (ABC) as well as the hybrid TS-ABC algorithms. Results: Analysis of these proposed algorithms is done with the parameters of performance such as the rate of error and the accuracy. Also, these algorithms' simulated outcomes have been able to demonstrate their superior performance in comparison to the other technologically advanced approaches.

Keywords: Internet of Things (IoT), Healthcare Monitoring, Cardiac Classification, Edge Computing, Deep Learning, Convolutional Neural Network (CNN), Artificial Bee Colony (ABC), Tabu Search (TS).

1 Introduction

A fascinating topic for the industry, the public sector, as well as the research community, has been the Internet of Things (IoT). Although the standard Internet does facilitate communication between people and a constrained number of devices, the IoT is capable of connecting all kinds of connected “Things” into an extensive interrelated computing intelligence network without any manual intervention. Caregivers can monitor patient conditions in real-time with the IoT adoption as well as the development of technologies of wireless communication. Moreover, most of the available portable devices as well as sensors will use just one touch to assess certain parameters of human physiology like heart rate, blood pressure, respiration rate, and so on. In spite of being in the early stage of development, the IoT's swift adoption by industries as well as businesses into their presently-employed systems has demonstrated enhancements to the user experiences as well as the production (Dang et al., 2019).

The healthcare IoT technology integration does pose various issues pertaining to the storage of data, its management, its interchange between many devices, its associated privacy as well as security, and its ubiquitous as well as unified accessibility. Cloud Computing technology is a potential solution for handling the aforementioned issues. Figure 1 will depict a generic system of healthcare that is able to incorporate the IoT as well as cloud computing for the provision of transparent and ubiquitous access to the shared medical data as well as the common infrastructure, for the provision of on-demand services all across the network, and also for the performance of operations which can fulfill the upcoming requirements.

IoT has numerous use cases as well as applications, particularly in healthcare. One such application is telehealth, in which there is the patients' either real-time or remote ubiquitous monitoring, diagnosis as well as delivery of medicines. Yet another application is fitness tracking's wearable IoT. This will involve sensors capable of reading the users' vitals, and also forwarding this information to the facilities of healthcare (Lomotey et al., 2018).

The paradigm of IoT has enabled the collection and processing of data from various objects, expanding their functionalities for applications such as energy management and accessibility analysis in smart cities. In the healthcare sector, devices are being designed to assist in patient monitoring, chronic condition management, and Ambient Assisted Living (AAL) environments. The concept of m-health utilizes smart mobile devices to provide efficient healthcare services. Biomedical sensors, integrated into wearable devices, have gained popularity due to their lightweight design and non-intrusiveness, allowing them to capture human bio-signals and offer value-added services. Mobile devices have also advanced to handle biomedical data and health-related applications, facilitating the analysis of human behavior and health. Numerous applications and devices now collect personal health data, including wearable devices that monitor heart health metrics for medical care, training, and wellness monitoring (Mora et al., 2017).

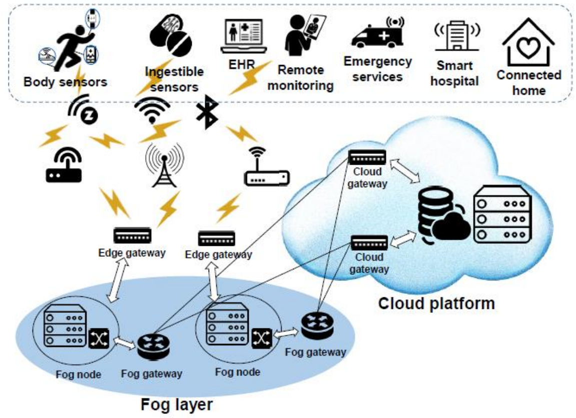

Figure 1: Generic IoT and Cloud Computing-Based Healthcare System (Dang et al., 2019)

Edge computing: While edge computing is capable of processing time-sensitive data, cloud computing is capable of processing data that is not driven by time. In addition to the latency issue, there is a preference for edge computing over cloud computing in remotely-situated sites with either very little or no connectivity to a location that is centralized. Edge computing's technological innovations do make its future outlook quite encouraging. In edge computing, the data as well as the information are moved nearer the user. In the past, the majority of the data was stored in a cloud that was made up of multiple servers with Internet accessibility.

There needs to be the development of an automated health system of monitoring that will either react or produce an alarm during a patient's critical situation. Doctors as well as the concerned parties will get emails and/or tweets of the data which is to be analyzed with the Node MCU microcontroller. Furthermore, this system will record as well as retain the patient's past diagnostic health information. The patient's current condition is transmitted via an online portal to the health experts, and with this information, the patient is given the best-suited treatment. The smart healthcare model of tracking will involve tracking the patient's condition using sensors of humidity, temperature as well as heart rate which are installed all over the hospital room. Upon processing, these values will be forwarded to the doctors for accordingly checking the patient's state. Signals of the sensors of heartbeat, EEG as well as temperature will go through a system of amplification and signal conditioning for raising the signal gains. This data is delivered to a cloud platform for storage as well as for analysis via any microcontroller such as the beagle bone black, the Raspberry pi, or the Arduino (Bhardwaj et al., 2022).

Edge computing will resolve the problem of storage of enormous amounts of physical datasets by means of a hybridized platform of the edge as well as the cloud. Processing of the acquired health data will be done at the edge computing platform. This is inclusive of an IoT sensor physical monitoring device layer, the edge layer as well as the smart log system with the smart patch for processing the IoT data with the human physical system's multimedia technology. The IoT sensor physical monitoring device layer will have multiple biosensors for accelerator gyroscope, respiration, visual, pressure, Electro-Cardio-Gram (ECG), Electro-Encephalo-Gram (EEG), temperature, blood, and sink node in integration with the edge platform for the human body patterns' accurate diagnosis as well as prediction. The technology of edge computing will employ a distributed device to bring the data near the location in which there is a requirement. The wearable smart log patch with an IoT sensor within the edge computing environment will yield accurate data regarding the human physical system's physical activities, and this is more feasible for tracking the health of patients in the multi-access systems of physical monitoring (Manogaran et al., 2019). Even so, it is quite complicated to get early alerts about the organs' improper functioning and its report generation is very time-consuming. This can be resolved with the edge platform due to its operation of distributed networks with a smart router, a storage unit as well as high-power capacities, which are more feasible for multi-access systems of physical monitoring which will physically monitor the human body.

Motivation: Nowadays, Artificial Intelligence (AI) which is inclusive of Data Science as well as Learning (DL) is employed in various techniques for assisting in the mitigation of COVID-19-like pandemics with regards to halting its spread, the disease diagnosis, the patient's care as well as treatment, the discovery of medicine as well as vaccine, etc. However, it is essential to have huge datasets as well as robust resources of computation for this DL's training. Since a significant problem is posed by the data insufficiency as well as its variations over diverse geographic regions, Deep Transfer Learning (DTL) is an efficient solution since it is able to learn from a certain task, and then, after some fine-tuning, be utilized for another task. On the other hand, edge devices have low resources of computation, a representation of edge computing's key challenges. DTL is a potential solution for overcoming this challenge by means of the consolidation of the requisite power of computation as well as the facilitation of more effective edge computing (Sufian et al., 2020).

Objectives: This work presents an IoT-based generic health system of monitoring which is capable of cardiac classification by means of edge computing. The proposed framework will monitor the patient's temperatures for ascertaining any abnormal values through its comparison with the surroundings as well as the ECG for cardiovascular disease detection. The work's remainder has been arranged thus. Related literary works have been presented in Section 2. The employed approaches as well as the simulated outcomes have been discussed in Section 3 and Section 4, respectively. Eventually, the work's conclusion has been given in Section 5.

2 Related Works

Jaber et al., (2022) employed the IoT for monitoring COVID-19 patients. With IoT-based real-time data collection, automatic alerts were delivered to the patient for mitigation of the risk factors. The patient used wearable IoT devices that were interconnected with the edge nodes so as to investigate the data for the determination of decisions associated with one's health conditions. This system was capable of remote exploration of a patient's health condition and was made up of the wearable IoT sensor, the cloud as well as the web layers. Each individual layer had a specific functionality in the procedure of monitoring the COVID-19 symptoms. The initial layer gathered information about the patient's health. Then, this was sent to the second layer for cloud storage of the data. The cloud network's examination of health data as well as its delivery of alerts to the patients is able to assist the users in taking immediate actions. Eventually, the web layer will provide notifications to the family members for taking steps that are appropriate. This model of optimized deep learning does facilitate patient health data management as well as monitoring for further analysis.

Armand et al., (2023) developed an inexpensive cardiovascular patient monitoring system (RPM) with wireless functionalities for application in any part of Cameroon. This low-cost as well as access system was capable of capturing the significant factors that reflected a patient's health condition, and also offered alert mechanisms. With the utilization of the Gothelf and Seiden framework's procedure of lean UX, the proposed IoT-based system had multiple sensors for the measurement of a patient's vitals such as the heart rate, systolic pressure, and diastolic pressure. These sensors recorded these values in a directly automated manner to the system database for analysis purposes. Examination of the heuristic evaluation's validity was done in an ethnographic study of paramedics through the execution of the proposed system's prototype in their work environment.

Nancy et al., (2022) presented a smart healthcare system with Bidirectional Long Short-Term Memory (Bi-LSTM) which monitored as well as accurately predicted the risks for heart disease. The authors had sought to prove that with extensive adoption of the electronic clinical records, the creation of models of prediction with enhanced accuracy was critical for controlling the DL's recurrent neural network variants which were capable of deftly handling the sequential time-series data. In the presented system, the data was acquired from the IoT devices. Also, the cloud-stored electronic clinical data which pertained to the patient's health history were subjected to predictive analytics. In comparison to the currently-employed smart heart disease prediction systems, the presented smart system with Bi-LSTM had achieved the best results with 98.86% accuracy, 98.9% precision, 98.8% sensitivity, 98.89% specificity as well as 98.86% F-measure.

Wang et al., (2023) put forward a feasible approach for the construction of a hybrid as well as a lightweight cluster, which was based on the K3s, for the FogBus2 framework which provided a containerized resource management framework. The work addressed the difficulties associated with the creation of lightweight computing clusters in the environment of hybrid computing. Moreover, it offered the Host Network, the Proxy Server, as well as the Environment Variable as the three distinct patterns of design for the FogBus2 framework's deployment in the hybrid environments. The proposed approach's performance assessment demonstrated its improvement of the real-time IoT applications' time of response by up to 29% with an overhead that was low as well as reasonable.

Nair et al., (2023) proposed a privacy-preserving framework called the Fed_Select which ensured user anonymity in the IoMT-based environments for analyzing the Big data under the scheme of Federated Learning (FL). The proposed Fed_Select employed alternative minimization for constraining the gradients as well as the participants in the system training so as to mitigate the system's vulnerable points. With operation on an edge computing-based architecture, the Fed_Select ensured user anonymity through the utilization of techniques of hybrid encryption together with extra benefits of the central server's reduction of load. Moreover, there was the usage of a Laplacian noise-based differential privacy on the shared attributes to boost security such that the transmitted data had an addition of confidentiality even at the time of adversarial situations. Simulation outcomes on the generic datasets demonstrated that the change in the volume of shared gradients as well as the number of participants was not in proportion to the diverse system performance parameters' variations. In particular, there was a determination of an idealistic range of the client as well as the gradient-sharing fractions together with a feasible value of the noise for the deployment of the differential privacy. The authors analyzed the framework from an outlook of security and also conducted a comparison study with the other schemes.

Hartmann et al., (2022) attempted to examine the presently-employed as well as upcoming edge computing architectures and approaches for applications of healthcare, and also identified the requisites as well as the challenges of the devices for many use cases. Applications of edge computing were mainly focused on the classification of health data which was inclusive of vital sign monitoring as well as fall detection. Other low-latency applications had carried out the monitoring of specific disease symptoms like the abnormalities in gait for patients with Parkinson's disease. Furthermore, the authors presented a comprehensive review of the edge computing data operations which was inclusive of the transmission, encryption, authentication, classification, reduction as well as prediction. In spite of the various benefits, edge computing had suffered from certain challenges such as requisites for sophisticated privacy as well as approaches of data reduction for facilitation of performance that was comparable with that of their cloud-based contemporaries albeit with lesser complexity of computation. There was also the identification of the future directions of research into edge computing for healthcare applications so as to provide users with a higher quality of life.

Dewanto et al., (2020) accomplished enhancements in an IoT monitoring system through the facilitation of real-time heart rate monitoring as well as analysis and also employed PPG sensors in the smart wearables when compared with the other clinical-tested heart rate sensors. The PPG sensor was capable of physically recording an individual's heart rate data. Later, there was the delivery these measurements to the application for pre-processing purposes. Afterward, the application was capable of the pre-processed measurements' transmission to the cloud server for either monitoring or further analysis, that is, for assessment of an individual's health of the heart. This work conducted a comparison study of the application's measurement with that of a Ballistocardiograph (BCG) sensor. Although both of these were not benchmarks for the measurement of heart rates, it was evident from the assessment's findings that the PPG sensor had accomplished near identical input data as well as assessment outcomes during the stages in which an individual was awake. The tested Fitbit sensor was typically prone to underestimations, either due to delays at certain times or was unable to identify a sudden increase in the heart rate when the individual was asleep.

3 Proposed Methodology

In contrast to the generic system of healthcare, there is much efficacy in an IoT-based system of health monitoring (Wang, Y., 2019). Operation with the IoT is in association with the embedded world since electronic data signals are employed by the sensors. At first, synchronization is achieved via the interconnection of multiple devices like the microcontroller, the monitors, the detectors as well as the sensors. The sensors as well as the detectors will identify the analog signals, and then will convert these signals into their digital form. The Spresense microcontroller is a built-in analog-to-digital converter that is employed for getting the data in an appropriate digital format. This section has discussions about the 1DCNN-9 layers, the 1DCNN-Tabu, the 1DCNN-ABC optimized as well as the 1DCNN-ABC-Tabu optimized approaches.

3.1. Details of System Components

The MLX90614 is a non-contact temperature sensor. It is located near the human body for the detection of the values of temperature without any physical contact with the patients. There is the MLX90614's integration with a low-noise amplifier, an a17-bit ADC as well a robust DSP unit so as to accomplish the thermometer's high resolution as well as accuracy.

For the IoT, the Spresense is a low-power board computer that has a GPS receiver, and also will support High-Resolution Audio codecs. It is a combination of the multi-core microcontroller as well as the efficacy of power. Since the board will enable much IoT versatility, it can be devised for a myriad of applications. With Spresense, the IoT will have higher effectiveness as well as more smartness. The Spresense is ideal for edge computing due to its unique combination of solid computational capacity as well as its advanced efficacy of power. The use cases will employ the Spresense board in solutions in which there is a requirement for sensor analysis, image processing as well as data filtering wherein the other microcontroller-based alternate were found to be inadequate.

A wearable ECG device is of diverse forms and also is employed for actively recording heart activity. This device is most apt for users who would like to track their heart health with no disruptions to their everyday activities. This device is portable, highly convenient, and also can detect trends, unlike a one-time test in an ECG machine. Nevertheless, being a portable device, it often had 1 or 2 leads that may be unable to detect heart activity with a hospital-grade ECG machine's accuracy.

The following three distinct steps will constitute the overall workflow: the data capture, the data processing which is followed by the data storage, and the monitor-display of the patients' parameters. A measurement system's accuracy, as well as precision, is solely dependent on the key step of data capture. This step will involve connecting a microcontroller to the sensors which are to be utilized.

3.2. 1DCNN-9 Layers

The deep learning algorithms' popularity surged after ImageNet's competition in 2012. Since then, these algorithms are more prominently employed for academic research. For computer vision applications, an oft-used deep learning network is CNN. The CNN algorithm's development was influenced by the animals' visual center. The CNN structures will use input images for efficient application in computer vision. The CNN will have a single or more convolutional layer as well as single or more fully connected layers, like the typical multi-layer neural network with its Convolution, ReLU, Pooling, Flattening as well as Fully-Connected layers. The CNN's key block is the convolution layer due to its responsibility to perceive the image features. There will be the application of certain filters for the extraction of the image's low-level as well as high-level features. Normally, multi-dimensional matrices as well as pixels are constituents of the filters (Sevi & Aydin 2020).

In accordance with the employed filters, there will be shaping of the feature map, i.e., the final matrix which has been acquired as an outcome of the applied filters. Order-wise, the non-linear layer will follow the convolution layer. This layer is also referred to as the ReLU layer due to the execution of the procedure of activation in this layer. With the ReLU activation function, the feature map's negative values will get set as 0. This layer is responsible for the mitigation of the network's enormous size of the representation, the number of parameters as well as the internal computations. Thus, it is possible to check the network's incompatibility. Here, the key objective is for mitigation of its number of parameters by retaining the most critical parameters while minimizing the subsequent layer's number of entries. In this manner, there will be a minimization of the subsequent layers' cost of computation as well as the avoidance of memorization. The flattening layer's key goal is to prepare the data for the final layer, i.e., the Fully-Connected layer, through the conversion of the matrices from the Convolutional as well as the Pooling layers into an array of one dimension. Eventually, the Fully-Connected Layer will use the Flattening layer's data to execute the procedure of learning through the neural network.

The architecture of a system involves several key aspects, one of which is the definition of the convolution product. This product is obtained by applying operations like padding and stride to the input data. By evaluating the convolution product, a two-dimensional matrix is formed, where each element represents the sum of corresponding elements from a filter cube and a sub-cube of the input image. This relationship is mathematically expressed as equation (1):

$$conv(I,S)_{a,b}=\sum_{i=1}^{n_x}\sum_{j=1}^{n_y}\sum_{k=1}^{n_c} I_{a+i-1,b+j-1,k}.S_{i,j,k} \tag{1}$$

And the dimensions for such representation are given as in (2):

$$\dim\ \left(conv\left(I,S\right)\right)=\begin{cases}\left\lfloor\dfrac{\left(n_x+2p-f\right)}{n_s}+1\right\rfloor,\left\lfloor\dfrac{\left(n_y+2p-f\right)}{n_s}+1\right\rfloor, & n_s>0,\\ n_x+2p-f,n_y+2p-f, & n_s=0,\end{cases} \tag{2}$$

In the given equation, represents the floor function of the value x. The variables and denote the height and width of the image, respectively, while represents the number of channels. The parameter p corresponds to the padding factor, which takes into account the squared filter with an odd dimension denoted as f. This ensures that each pixel is centered within the filter, considering the elements around the input image dataset. Additionally, the filter slides without explicit knowledge of the parameters after a certain step, and a pooling function is applied to the selected elements, as shown in equation (3):

$$\dim\left(pool\left(I,S\right)\right)=\begin{cases}\left\lfloor\frac{\left(n_x+2p-f\right)}{n_s}+1\right\rfloor,\left\lfloor\frac{\left(n_y+2p-f\right)}{n_s}+1\right\rfloor & ,n_c,\ n_s>0,\\ (n_x+2p-f,n_y+2p-f,n_c), & n_s=0,\end{cases} \tag{3}$$

In the final step, multiple repetitions of convolutions, activation functions, and pooling are performed as described in Equation (3). This iterative process allows the extracted features of an input image to be fed into a neural network consisting of fully connected layers and activation functions at regular intervals.

Given in Figure 2 is the nine-layer depth CNN for a window size of 64 × 64 pixels as well as a window size of 80 × 80 pixels. The three original RGB spectral bands will be the inputs of the two distinct aforementioned nine-layer depth CNNs. Afterward, the input dataset will experience the addition of the slope data as an extra layer. The CNN training is done with a composite of four distinct layers. It will employ various feature maps, and there will be the immediate application of a 2 × 2-sized max-pooling layer after any convolution layer with the exclusion of the nine-layer depth CNN's final layer. For the consequent convolution layer, the inputs will be the max-pooling layer's dimensionality-reduced feature maps. The initial convolution will use a kernel size of 5 while the additional convolution layers will use a kernel size of 3. With a 0.5 dropout, the fully-connected layers are able to maximize the approach's generalization ability, and also avoid overfitting, and this, in turn, will lead to the approach's better transferability. There is due consideration of the dropout as an approach of regularization that can be employed during the training. Also, it is able to mitigate overfitting by arbitrarily dropping the connections amongst the network (Ghorbanzadeh et al. 2019).

The input window sizes will form the basis for picking the sizes of the kernels as well as the number of feature maps. Because of the constraint on dimensionality, there is no usage of the six-layer depth CNN's final convolution layer for the 32 × 32-pixel window size, and the nine-layer depth CNN's final max-pooling layer for the 64 × 64-pixel window size. Organization, as well as deployment of the CNN approaches, has been done in Trimble's eCognition software on the basis of the Google TensorFlow software library. There is an evaluation of the resultant gradients for every weighting within every layer. Also, these weightings' optimization is done via a function of statistical gradient descent. Acquisition of the best rate of detection is done using a 50-batch size, a 0.0001 rate of learning as well as 5,000 steps for training.

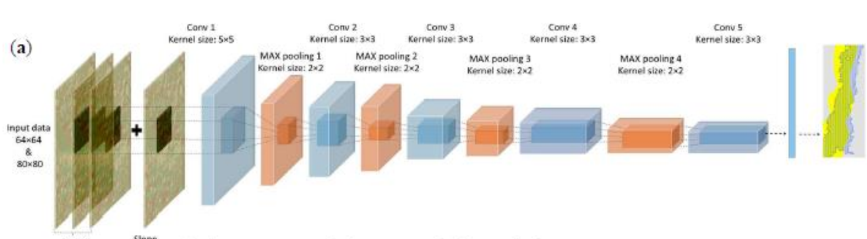

Figure 2: CNN Architectures with a Nine-Layer Depth CNN (Ghorbanzadeh et al. 2019)

3.3. 1DCNN-Tabu

The resolution procedure for problems of combinatorial optimization does suffer from the issue of local optimality. For overcoming this issue, Glover suggested the Tabu Search (TS) algorithm as a technique of intelligent optimization. In this search, there will be the utilization of a neighborhood mechanism. A solution's neighborhood will the set of all the formations which is acquired by a move. The term move will refer to the procedure of changing a search from the present solution to its neighboring solution. The final movement's reversals were prohibited for preventing a move from going back to a lately-visited solution. Such moves are known as 'tabu', and also will be recorded as an entry in the Tabu list. Therefore, the search history is recorded with explicit memory. At first, there will be an empty Tabu list. Later, it will be developed in the consequent iterations of the search, and also will be circularly updated towards the later iterations (Srinivasa et al. 2022).

In the Tabu list, there is the absence of an admissible move. Once a move has been made, if this move's solution is better than the solutions which were acquired by the prior iterations, then, this solution will become the new best solution. Identification of the consequent solution is done on the basis of the Tabu condition as well the principles of valuation. With the usage of the Tabu conditions or the constraints on the potential moves, it is able to avoid the regeneration of previously-acquired solutions. The bases for the Tabu conditions are the frequency as well as the recent memory. In TS, yet another critical factor is the aspiration mechanism. In the event that a move in the Tabu list will end up with a solution that is better than that of the prior solution, then this move will be discarded from the Tabu list. With this attribute, it is possible to prevent good moves from being eliminated for consideration. Further, it serves a vital role in the search procedure.

A hybrid model of TS-CNN Training (Chhabra et al. 2017):

Listed below are the algorithm's five distinct phases.

Phase 1: The CNN's initial training with the backpropagation for establishing the neural network's certain predefined weights.

Phase 2: Upon the CNN's training with the backpropagation, there must be optimization of the weights. This is done by capturing these weights as a tensor, and then, further converting them into a NumPy array for further optimization with the TS algorithm. Due to the TS's ability of Tabu list optimization, there will be the captured taboos' conversion into the consequent phase's Tabu lists.

Phase 3: There is the determination of the values of memory, the cognitive component, the social component, the number of taboos, the condition of termination as well as the max Epochs. Afterward, the TS optimization will search the hyperplane for the optimized solutions with the CNN lost function as the TS training's objective for the assurance of consistency.

Phase 4: For the final computational phase of the outcomes, there is the formation of a new CNN with the weight values that were predefined with the values of weights acquired from phase 4, and the CNN training will not be done on the basis of the output.

Phase 5: The CNN output is obtained, and from this, there is an evaluation of the final outcome, the accuracy as well as the value of cost value.

With the increase in accuracy being the key goal, the algorithm will capture the weights after training the CNN, and then, employ the TS for their optimization. Tensorflow is a freely available open-source library that is custom-built for machine learning. It will facilitate the capture of the CNN model's weight vectors in the form of tensors. Later on, these values will be transferred to the module of TS training for undergoing training as well as updates. Upon the module of TS training's convergence, the CNN weights will get updated via the reversion of the weight values' updated matrix to a tensor.

3.4.1 DCNN-ABC Optimized

In 2005, Dervis Karaboga devised the “Artificial Bee Colony” (ABC) algorithm for optimization purposes. The bees’ search for sources of food is this algorithm’s inspiration. In the ABC, there will be a simulation of the procedure of food search of the following three distinct groups: the onlooker, the scout as well as the employed bees. While the scout bee will perform the procedure of food exploration, the onlooker as well as the employed bees will perform the procedure of food exploitation. A bee colony’s survival is dependent on swiftly as well as efficiently identifying the best sources of food. This is akin to a problem of engineering, where it is essential to swiftly identify a good solution. The ABC algorithm’s pseudo-code has been presented in Algorithm 1 (Gasper et al. 2021).

Algorithm 1: Pseudo-code of the Artificial Bee Colony (ABC)

1) Start the population.
2) The employed bee is placed among the sources of food.
3) The onlooker bees are placed in the source of food on the basis of nectar amounts.
4) The scout bees will get sent to the search area for discovering new sources of food.
5) There will be memorization of best the source of food which has been found so far.
6) Till the fulfillment of all the requisites, there will be the repetition of Step 1 as well as Step 2.

Eq. (4) is a mathematical expression of the ABC algorithm’s arbitrarily-generated solutions which are within a specified range of variables or sources of food, wherein it’s a representation of the population’s size as below:

$$x_i (i = 1, ...S) \tag{4}$$

Here, x_i will indicate the population’s i^{th} solution. Consequently, there will be a new source of food discovery by every employed bee, wherein the quantity will be equivalent to half of the overall number of sources of food. The below Eq. (5) will be employed for yielding the potential source of food’s position:

$$v_{ij} = x_{ij} + \phi_{ij} (x_{ij} - x_{kj}) \tag{5}$$

For the above, $k \not\subset \{1, 2\ldots \text{BN}\}$, in which BN will indicate the number of employed bees, $j \not\subset \{1, 2\ldots \text{D}\}$, in which D will indicate the vector’s dimension while there will be an arbitrary selection of k as well as j so that $k \neq j$, and $\emptyset_{ij}$ will be an arbitrary number from −1 to 1. There will be a comparison of the fitness value of v_{ij}. If this value is better than that of x_{ij}, then there will be the replacement of x_{ij} with v_{ij}. Else, the succeeding iteration will employ the existing value of x_{ij}. The onlooker bee will pick sources of food with a probability as per the following Eq. (6):

$$P_i = \frac{fit_i}{\sum_{j=1}^{SN} fit_j} \tag{6}$$

Wherein, fit_i will indicate the i^{th} solution’s value of fitness or, in other words, the proportionality of the number of employed bees to the nectar amount found in the sources of food which have been identified in the position i. SN will indicate the number of sources of food which will be equivalent to BN, the number of employed bees. If i will end up being a better solution, then, there will be a higher selection probability for the i^{th} source of food. Else, if there is no improvement in the position after a series of iterations, then, there will be an abandonment of the sources of food. Afterward, the scout bee must discover a new source of food so as to replace the discarded sources of food (x_i) according to Eq. (7) as follows:

$$x_i = lb_j + rand(0,1) \times (ub_j - lb_j) \tag{7}$$

For the above equation, *ub* will indicate the upper bound, *lb* will indicate the lower bound while *rand (0,1)* will indicate an arbitrary number that lies between 0 and 1. Till the completion of the maximum cycle of iterations, there will be a continuation of the procedures.

With this approach, the ABC evolutionary algorithms are able to optimize the CNN hyper-parameters like number of convolution layers, kernel size and numbers, activation function, pooling size, number of neurons, batch size, learning rate. However, a point of concern is that the hyper-parameter number under due consideration is enormous to be covered in an effective manner. Therefore, certain simplifications are needed for balancing the algorithm validity as well as the CNN structural variability. Parameterization of the search space is an effective solution for the neuro-evolution procedure's simplification, and the evolutionary algorithm's application can be performed with aid of the hyper-parameter discretization (Zhu et al. 2019). The numerical mapping can discretize the diverse types of values as well as mitigate the number of values.

For the convolutional layers' hyper-parameters, only a single non-linear activation function will have the ReLU as being optional. Since the ReLU's computation will facilitate more rapid learning in comparison with the sigmoid or the leaky ReLU or the hyperbolic tangent. Due to this, ReLU is duly considered the DL's de facto standard. The ReLU type of activation function has the unique ability to mitigate the search space without any significant effect on the algorithm's accuracy. Furthermore, for the purpose of simplification, max-pooling is set as the pooling type while 2 is set as the pooling size. As given in Figure 3, while 4 distinct types of connectivity patterns the feedforward, the recurrent, the LSTM as well as the GRU are taken for the dense layers, 6 distinct types of rules of learning like the SGD, the adagrad, the adadelta, the rmsprop, the adam as well as the adamax are taken for the procedure of learning

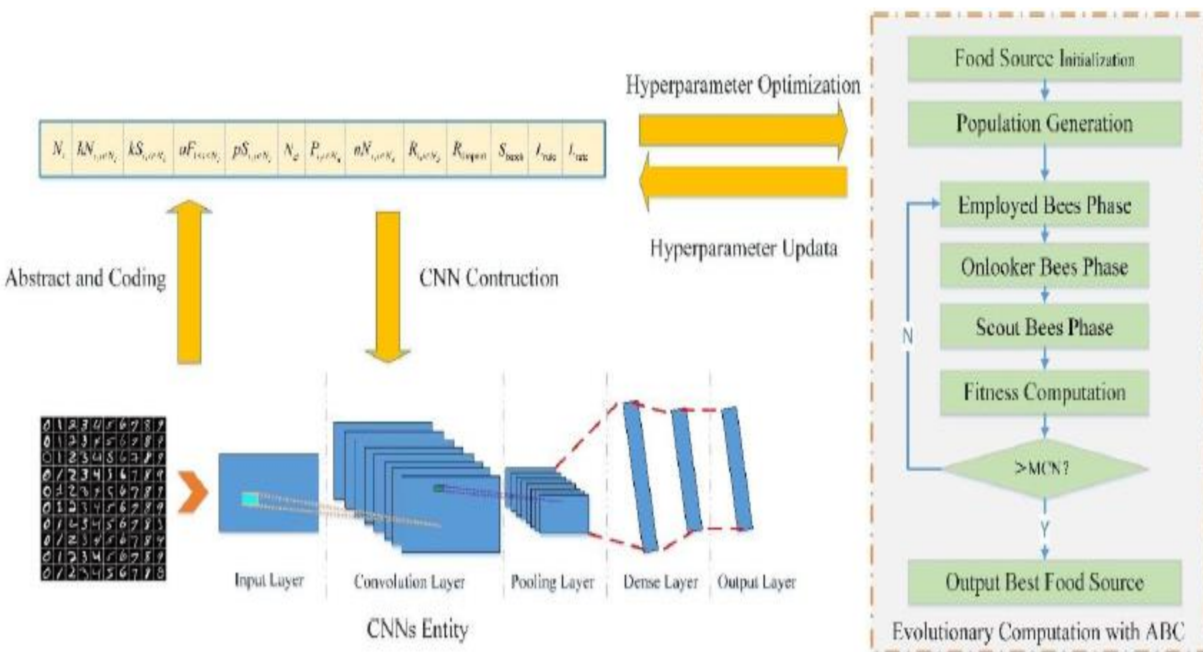

Figure 3: Framework of CNN Optimized ABC (Zhu et al. 2019)

A constrained number of discrete values within the bounds of possibility have been offered for the other hyper-parameters like the kernel size, $kS_{i,\in Nc}$, the number of kernels for every convolutional layer, $kN_{i,\in Nc}$, etc. It has been extremely helpful in mitigating the complexity of computations associated with tuning hyper-parameters.

The work will involve the position of a food source encoding a possible hyper-parameters combination (a point within the multi-dimensional hyper-parametric vector space) that represents the topology of the new CNN design, and the source of food's quality or amount of nectar (i.e., fitness) will correspond to the availability of the new CNN. The bee colony's foraging behavior will assist in searching for a better position of the sources of food (i.e., the hyper-parameter combination) by means of the quality assessment (i.e., the calculation of fitness). The number of either the employed bees or the onlooker bees will be equivalent to the population's number of solutions.

On the basis of the aforementioned assumptions, the ABC-based procedure of neuro-evolution will commence with a step of initialization in which a specific number of sources of food will get initialized with arbitrary positions (i.e., hyper-parameter combinations), wherein SN will indicate the size of the population of the employed bees or the onlooker bees while D will indicate the solution vector dimensions of the positions of the sources of food. A point of note is that there will be certain invalid positions (i.e., hyper-parameter combinations) where it's not possible to perform the combination for designing a feasible CNN topology. As an example, for a 28×28-sized input image, either the number of pooling layers having a 2×2 pool size cannot be set greater than 3, or the number of pooling layers having a 4×4 pool size cannot be set greater than 1. Upon generation of an invalid hyper-parameter combination, the invalid combination has to get abandoned and re-generated.

Upon initialization, the population of positions (i.e., the solutions) will be subject to repeated cycles (i.e., generations) wherein the employed, the onlooker as well as the scout bees will commence their phases of search one at a time. During the employed bee phase, the employed bee will yield a modification for searching for a new position in its memory on the basis of the local information, and it will forget about the earlier position if the new position has a higher amount of nectar (i.e., fitness). For the onlooker bee phase, the onlooker bees will get information (shared by the employed bees) pertaining to all the updated sources of food. Afterward, these bees will be sent to diverse sources of food on the basis of the amount of nectar (i.e., fitness), and they will also update the new sources of food just like the employed bees. At the time of the scout bee phase, upon the bees' abandonment of the nectar of a certain source of food, the scout bee will arbitrarily determine a new source of food, and also will perform its replacement of the abandoned source of food. Till the accomplishment of a predetermined number known as the Maximum Cycle Number (MCN), there will be the repetition of these three distinct phases.

3.5. Proposed 1DCNN-ABC-Tabu Optimized

The standard ABC algorithm has the following drawbacks: weak capability of local search, and a blind as well as arbitrary procedure of search. Hence, its low accuracy will result in its falling into the local optimal solution. For this problem's resolution, there is the enhancement of the procedure of initial and replacement of the bee colony, and also global uniform distribution of the solution's initial value so as to maximize the likelihood of the search's convergence towards the global optimal solution. Suppose β will indicate every iteration's maximum value of the fitness. During the scout bees' procedure of a new solution generation, if the resultant value of fitness of the new solution is lower than β, then there will be direct removal of this value of fitness. Else, if the new solution's value of fitness is larger than β, then there will be a direct replacement of the earlier value β. Every iteration β must be larger than or equivalent to the maximum value of fitness, and the β value must be identical to that of the parameter *Limit* to avoid falling into the local optimal solution (Liu et al. 2021).

The problem of hyper-parameters in neural networks has constantly been quite challenging due to their adverse effect on the performance of the neural networks. For standard research, the empirical parameters only have applicability for a certain study, and substantial resources of material, as well as labor, is required for manually adjusting the parameters. The technique of gradient descent does have certain drawbacks in the neural network since it has a high likelihood of falling into the local minimum point without the global optimum's acquisition. This work has a proposal of the hybrid ABC-Tabu with CNN algorithm (Hao et al. 2018).

Procedure of Initial Solution Generation

The below Eq. (8) will mathematically express how the addition of the *l* parameter can overcome the arbitrary nature of Eq. (7)'s initial solution:

$$x_{ij} = (x_{ij})_{\min} + rand\left(\frac{l-1}{SN}, \frac{l}{SN}\right)\left[\left(x_{ij}\right)_{\max} - \left(x_{ij}\right)_{\min}\right] \qquad (8)$$
$$l = 1, 2, ..., SN$$

This strategy is able to modify the selection range of the arbitrary numbers from the original (0, 1) to the inter-cell which will correspond with every solution, and also will ensure that the same cell is not occupied by two distinct initial solutions. Hence, the overall solution interval will have a uniform distribution of the initial solution.

Enhancement of the Strategy of Search

With the influence of the TS algorithm's Tabu list concept, β ($\beta \geq fit_{i\max}$, $fit_{i\max}$ will indicate every iteration's maximum value of fitness) will be set up and then compared with the new solution which has been acquired by every scout bee. If the new solution has a value of fitness that is larger than β, then this particular value will replace β. Otherwise, if the new solution's value of fitness is lower than or equivalent to β, then it will retain this value of β till the new solution's value of fitness becomes larger than that of β and will get replaced. While a source of nectar that is above β will continuously attract the following bee, a source of nectar source that is below β will get eliminated, and there will be the value's tabulation into the Tabu list.

Steps of the ABC-Tabu with CNN Algorithm

Suppose *MCN* will indicate the maximum number of iterations; *Cycle* will indicate the number of iterations; *SN* will indicate the number of sources of nectar within the bee colony; *Limit* will indicate the maximum number of accesses to the source of nectar, if the value is greater than the *Limit*, there will be an abandonment of the source of nectar; *VN* will indicate the number of visits; and *bf* will indicate the best honey source as well as the CNN hyper-parameters.

The ABC-TS-CNN model is able to realize the synchronous optimization of the hyper-parameters as well as the connection weights, to avoid the infective as well as cumbersome manual adjustment of the parameters, and also to carry out empirical approaches that do not have the standard approach of gradient descent's flaws for the model of prediction's enhancement of the robustness as well as the accuracy.

1. Eq. (5) will produce the initial solution.

2. Comparison of the fitness of *SN* initial feedback information is carried out by the scout bees. Eq. (3) is employed for picking the scout bees' probability. Also, there is an addition of the number of visits, *VN*, so as to be equivalent to the current maximum value of fitness.
3. **Procedure of CNN training:** This will involve the Convolutional Layer, the Pooling Layer, the Full-Connection Layer as well as the Activation Layer.
4. Cycle stage: $\check{n}$ mining bees will guide the visit of the onlooker honey bees. At the same time, there will be an accumulation of *VN*, the number of visits. In parallel, the mining bees will search for the current source of nectar, and also will offer feedback information upon the bee's subsequent modification of the information. If the value of fitness is larger than that of β, the mining bee will continue to remain as a mining bee; Otherwise, the mining bee will continue its search as per formula (10), and also will tabulate the values that are below β into the Tabu list. The current iteration's maximum value of fitness value will get updated β.
5. If *VN* is greater than *Limit*, then there will be Step 1's repetition; Otherwise, there will be the removal of the current source of nectar source as well as an accumulation of the number of iteration cycles.
6. The evaluated outcome will be offered as output upon arrival either at the optimal solution or the maximum number of iterations.

4 Results

The simulations were carried out using Python, open CV, tensorflow, and Keras. The 1DCNN-9 layers, 1DCNN-Tabu, 1DCNN-ABC optimized, and 1DCNN-ABC-Tabu optimized techniques were assessed using MIT-BIH arrhythmia database. The ECG were classified as Normal, Ventricular Ectopic, Supra Ventricular Ectopic, Fusion Beat, and Unknown. The accuracy, sensitivity, specificity, and f measure as shown in figures 4 to 7.

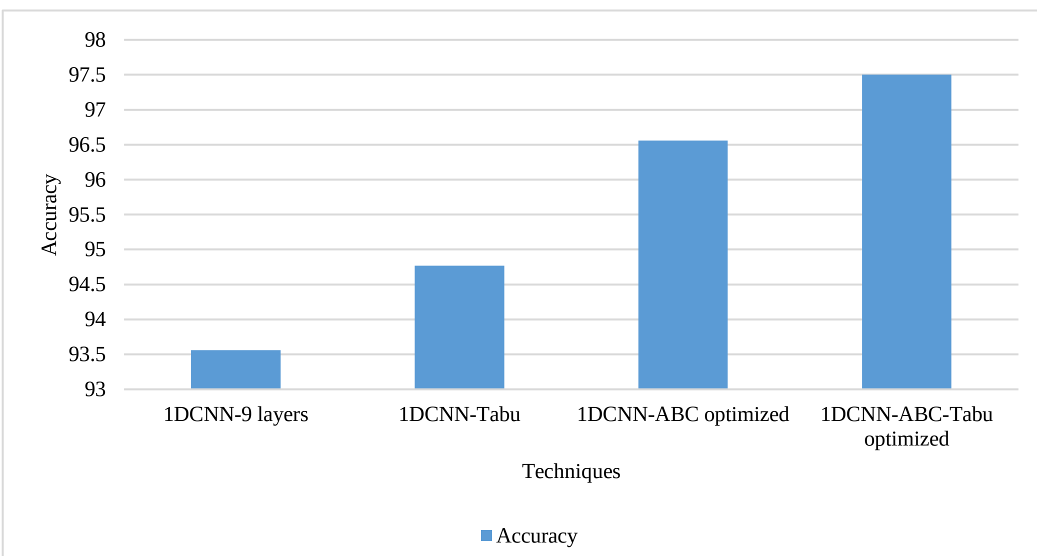

Figure 4: Accuracy for 1DCNN-ABC-Tabu Optimized

From figure 4, it can be observed that the 1DCNN-ABC-Tabu optimized has higher accuracy by 4.12% for 1DCNN-9 layers, by 2.84% for 1DCNN-Tabu and by 0.97% for 1DCNN-ABC optimized respectively.

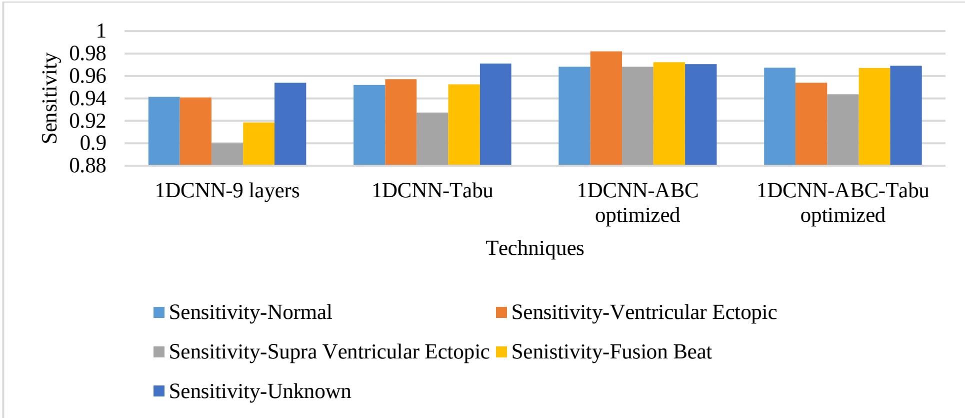

Figure 5: Sensitivity for 1DCNN-ABC-Tabu Optimized

From figure 5, it can be observed that the 1DCNN-ABC-Tabu optimized has higher average sensitivity by 3.11% for 1DCNN-9 layers, by 0.87% for 1DCNN-Tabu and by 1.24% for 1DCNN-ABC optimized respectively.

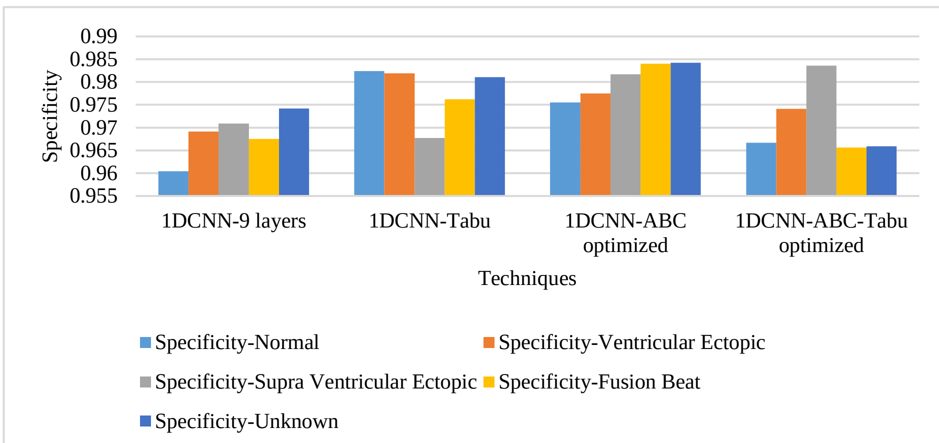

Figure 6: Specificity for 1DCNN-ABC-Tabu Optimized

From figure 6, it can be observed that the 1DCNN-ABC-Tabu optimized has higher average specificity by 0.28% for 1DCNN-9 layers, by 0.68% for 1DCNN-Tabu and by 0.96% for 1DCNN-ABC optimized respectively.

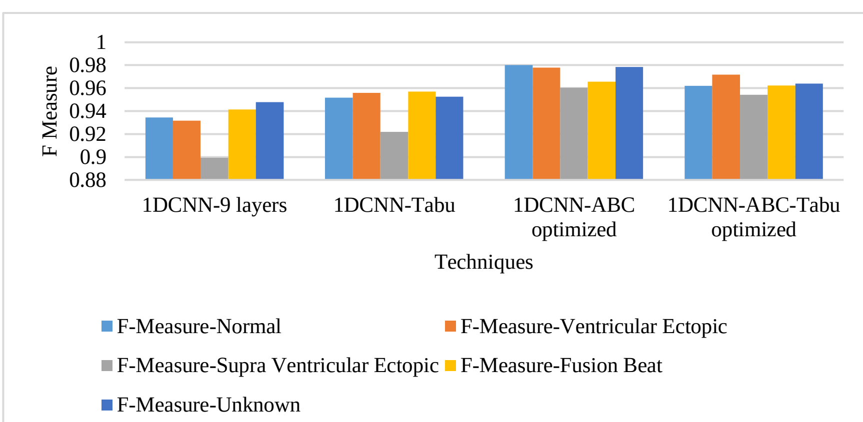

Figure 7: F Measure for 1DCNN-ABC-Tabu Optimized

From figure 7, it can be observed that the 1DCNN-ABC-Tabu optimized has a higher average f measure by 3.37% for 1DCNN-9 layers, by 1.57% for 1DCNN-Tabu and by 1% for 1DCNN-ABC optimized respectively.

5 Conclusion and Future Works

In recent times, IoT-based healthcare systems have gained much prominence over the oft-employed systems of healthcare. With healthcare that employs IoT, doctors are able to remotely monitor the patients and thus, easily communicate with their patients. Furthermore, doctors are able to offer a real-time diagnosis of a patient's health on the basis of the data which has been received from the IoT device. Algorithms of deep learning are capable of disease diagnosis as well as prediction. This work has the presence of a deep CNN which can automatically learn the basic filters, and also hierarchically combine them so as to facilitate the latent concepts' description for recognizing patterns. The Tabu Search (TS) has a semi-deterministic nature since it can serve as a method of local search as well as global search. With the present deployment, from an initial point of commencement, the TS will always get the same solution as its end result. As a technique of optimization, the ABC algorithm is able to replicate the honey bees' behavior of foraging, and also has successful application in diverse practical problems. This work will involve constructing a robust model of optimization using the TS-ABC with CNN, a powerful tool for global optimization tool, and towards its end, there will be computation of a robust optimal solution. This solution will take into account the solution's optimality as well as the CNN weights. It is evident from the simulation outcomes that the 1DCNN-ABC-Tabu optimized has higher accuracy by 4.12% for the 1DCNN-9 layers, by 2.84% for the 1DCNN-Tabu as well as by 0.97% for the 1DCNN-ABC optimized.

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