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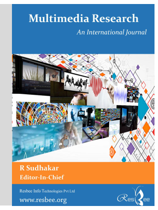

Optimization Driven Distributed Deep Learning for Aqua Status Prediction in IoT

J Rajeshwar
Department of CSE
Guru Nanak Institutions Technical Campus, Hyderabad, Telangana, India.

Abstract: The continuous screening of the quality and characteristics of water in IoT (Internet of Things) is essential due to the increasing requirement on aquaculture in order to maximize the yields. There are various physicochemical parameters used in water quality monitoring, but the analysis of these parameters are needed to obtain the final decision with experts. This paper proposes an aqua status prediction model in IoT using the Fractional Gravitational Search Algorithm based distributed Deep Convolutional Neural network (FGSA-based distributed Deep CNN). Initially, the aqua parameters are analysed using the distributed IoT nodes in the aqua environment. The loss and delay in the transmission of the data related to the aqua status is controlled with the selection of cluster head optimally using the FGSA. The prediction of the aqua status is done with the distributed DeepCNN in the final step. The performance of the proposed method is analyzed with the evaluation metrics, namely accuracy, energy, and throughput. The accuracy, energy, and throughput of the proposed FGSA-based distributed Deep CNN classifier is obtained as 95.4758, 99.4293, and 99.9571, respectively, which is high as compared to the existing methods. This shows the effectiveness of the proposed method in the prediction of the aqua status.

Keywords: Aquaculture, Aqua Parameters, Deep Convolutional Neural Network, Internet of Things, Prediction,

1. Introduction

The socio-economic and the ecosystem management studies at the national, international, and regional scale involve the process to monitor and detect the forest changes [1]. Forests are the livelihood ecosystems that are categorized by the anthropogenic and natural processes, and thus these process are constantly changes. Therefore, it is significant to introduce the methods to monitor the forest areas for revising the inventories of forest to analyze, plan, and to manage the health of forest areas to detect the growth rate. The remote sensing data obtained from the forest areas at various time provides suitable data source to achieve the automatic detection changes in forest [8]. In general, detecting the forest changes is a complex factor to continuously monitoring the environmental changes and to investigate the environmental issues, like biodiversity loss, deforestation, and depletion of natural resources [1]. Deforestation is the process of converting the forest land to the non forest area. However, ranching, road building, fire, logging, and converting the forest to farming area are some of the effective actions that devastate the influence of forests in worldwide. The consequences and the impact of deforestation extend the boundaries of forest land. Some of the deforestation effects are increasing climate change in the rate of soil erosion, global warming, extinction of species, and absorption of greenhouse gases [10]. However, the changes in the forest area affect the agricultural production, water resources, and resource management system [9]. The deforestation not only minimizes the ecological integrity and biomass stock but also aggravates the food damage. The monitoring and the quantification process over time at both inside and surrounding the target areas are crucial for the conservation efforts [2].

The Internet of Things (IoT) has created remarkable contributions to the production of aquaculture, intelligent remote control, early warning, and scientific breeding. With the use of aquaculture IoT the monitoring of dissolved oxygen (DO) content [1], track crab behaviour [2] and the prediction of DO in water are done in various provinces of China. These applications have modified the conventional aquaculture as the intensive aquaculture, but the components of the aquaculture IoT is mostly used in the outdoor ponds that are present in remote areas, and the faults often occur in these environments [3]. In general, the IoT dependent implementation develops new challenges for the supervisors who observe the quality of water with the samples and analyze them in the test center. Because of this intention, the

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IoT has created extra creative in various locations, including systems of environmental pollution monitoring and aqua quality management. It contains various inexpensive sensor divisions in the environment that support the public with the services of modern quality monitoring [4]. The aquaculture IOT system for the aquaculture is a complicated modernized support system of aquaculture that is based on IOT methodologies, like intelligent processing, intelligent sensors, and intelligent control. This function of this system contains image real-time acquisition, data collection, intelligent processing, wireless transmission, auxiliary decision-making and warning information releasing. Depending on accurate detection of parameters of water quality, reliable data transmission, intelligent processing of information, and intelligent equipment control, the system realizes scientific management and breeding of the products of aquaculture [6].

The aquaculture plays a vital role in the field of economics, and the yields of the aquatic organisms, such as fishes, prawns and so on depend on the water quality in the aquaculture pond. To obtain maximum yield, the parameters of water quality, including dissolved oxygen, temperature, turbidity, pH level, diphosphorus, and carbon dioxide must be maintained at an optimum level. The sources of water are easily affected due to formation of bacteria and various other harms that reduces the water quality. For the improvement of quality of water, the water is required to be screened frequently. In addition, the water level must be monitored in a proper manner to protect the aqua growth [9]. The monitoring of water quality acts as a key link for the informationization of aquaculture, and the detection of various equipments of aquaculture water using different sensors helps the a quaculturists to produce accurate scientific data related to the aquatic products living environment and the status of growth. However, the feed residue residues, algae bloom, and aquatic excreta in the aquaculture are mostly attach to sensors that causes variation in the detection of water quality [10]. In recent years, the traditional aquaculture faces various problems because of sudden climatic changes, which produces variations in the parameters of water quality. The aqua farmers depending on manual testing to obtain the parameters of water requires more time and produces inaccurate results due to variation in water quality parameters may with respect to time. Thus, in order to overcome this drawback, the method is needed to be brought to aqua culture that increases the productivity and reduces the losses with constant monitoring of the parameters of water quality [11].

With the continuous aquaculture development, the aquaculture is becoming extremely intensive and large-scaled, and the species of the aquaculture increases that leads to continuous decrease in the quality of aquaculture water and increases the diseases of aquaculture. Thus, the satisfaction of the need for real-time monitoring on the water quality of aquaculture for the detection of quality of water and adjustment of water quality in the deteriorated area has considerable significance on guarantee of the protection of water environment [12]. The prediction of water level acts as one of the significant task in aquaculture that can be performed using different deterministic and theoretical models. Auto-regressive exogenous (ARX) prediction methods are utilized in the collection of accurate data depending on the factors, namely evaporation rate, rainfall depth, features of land used, type of soil, and so on. For the prediction oflevel and quality of water, various methods, like artificial intelligence, data mining, or machine learning methods are utilized. These methods determine the water level with small number of variables [13]. The multi-parameter monitoring system [14] was used to obtain remote real-time monitoring of water quality of aquaculture, for the improvement the aquaculture product quality. When considering the technique of data mining, data classification acts as a major role in the prediction of water quality. In the classification of data, the training data is needed in the classification of hidden examples that contain more observations to the well-known category membership. The data for classification to the prediction of water quality in aquaculture is required to be collected from the physical world [9].

The major intention of this research is to design a model for the prediction of aqua status using the distributed deep learning classifier. The distributed classification is performed with the usage of distributed IoT nodes in aqua environment that are used in the analysis of the aqua parameters including dissolved oxygen, temperature, turbidity, pH level, nitrate, electrical conductivity, total hardness, calcium, ammonia, total alkalinity, hydrogen sulphide, carbon dioxide, biochemical oxygen demand, and diphosp horus. The major need is to handle the loss and delay in transmission of the collected aqua data using the IoT nodes in an effective manner. The cluster head selection is the best way to handle the loss and delay in data transmission and the cluster head selection is performed using the Fractional Gravitational Search Algorithm (FGSA) optimally[17].In the final step, the prediction of aqua status is performed effectively using the distributed Deep Convolutional Neural network (Deep CNN).
The main contribution of the paper is:

- *Aqua status prediction with the use of Fractional Gravitational Search Algorithm based Deep Convolutional Neural Network:* The distributed classification is made possible with the application of distributed IoT nodes in the aqua environment that are used in sensing the aqua parameters. The cluster head selection is the best way to handle the information loss and delay at the time of data transmission. The optimal selection of cluster head with the use of FGSA reduces the energy demand for transmission of data. The collected aqua data are fed to the DCNN for the prediction of aqua status.

The organization of the paper is: Section 1 explains the introduction to aqua status prediction. Section 2 discusses the literature review. Section 3 details the system model of WSN. Section 4 explains the proposed method of aqua status prediction. Results and Discussions are explained in section 5. Finally, section 5 explains the conclusion of the paper.

2. Motivation

In this section, the literature survey of various methods used for the aqua status prediction in IoT is presented, and the challenges of the existing methods are discussed.

2.1 Literature Review

The eight literatures related to the aqua status prediction are discussed as, Chandanapalli, S.B *et al.*[9] developed the Distributed functional tangent decision tree (DFTDT), which was used in the prediction of the parameters of water quality with high accuracy. The main drawback of this method is the lack in usage of advanced optimization algorithms to avoid the issues related to convergence. Parameswari, M. and Moses, M.B [4] designed the Aqua care IoT system that was capable of producing effective performance with very less cost of computation and time of execution, but was very costly due to the presence of costly sensors with reduced life time. Shi, B. *et al.*[7] modelled the WSN system using Tree topology that was used in the achievement of energy-saving and produced very less loss rate of packet. It lacks the solar energy in order to replace the AA batteries, which was considered as the main drawback of this system. Yueting, W *et al.*[10] developed the Self-cleaning aquacultural water quality monitoring system that produced better effects on the sensors of mass spectrometry, but the sensors other than this sensor have the possibility to damage the sensor and reduce the life time of the sensor. Chen, Y*et al.*[8] modelled the Hybrid three-dimensional (3D) dissolved oxygen content prediction model that identified the variation in trends and offers guidance for the aquaculture, but the lack of parameters for the improvement of accuracy is the major drawback of this method. Chandanapalli, S.B *et al.*[15] designed the Functional tangent decision tree algorithm that offered increased accuracy in classification to obtain the quality of water, but failed to use the optimization algorithms for the improvement of accuracy in prediction. Xiang, Y. and Jiang, L., [5] developed the Least squares support vector machine with particle swarm optimization (LS-SVM-PSO) model that provided solutions with enhanced quality within certain reasonable time limit and required very simple mathematical operators. The lack of advanced optimization algorithms for the online update of the parameters of SVM to increase the efficiency in forecasting is the limitation of this method. Han, H.G *et al.*[16] modelled the Radial Basis Function (RBF) neural network (FS-RBFNN) that was Able to predict the output-water quality with high accuracy and acted efficient in case of real-life date classification, but the lack of control efficiency in the system of wastewater treatment was the drawback of this method.

In 2023, Jamroen et al. [21] have implemented narrowband IoT and energy storage through photovoltaic (PV) batteries. Initially, there should be steady electrical energy for monitoring. So, they used BES and PV. Then there were two criteria for techno-economic they were reliability index (RI) for maximum reliability and the Levelized cost of energy at the minimum level. In order to monitor a sensitivity analysis was done to analyze the changes in photovoltaic generators and consumption of the RI systems. Further NB-IoT calculates the water quality through various parameters and finally for visualization Grafana software was used. The output provide an absolute result when there was no lack of electrical energy however they had to pay an amount to the network operator.

In 2023, Kimothi, S., et al.[22] have used a data exchange sensor through IoT, for location identifications GPS was installed, and finally grabbed information through Geo-Information System (GIS). Initially, data was collected and monitored through IoT. Then various parameters were used to track the status of the aquatic life, water quality, and other parameters through geo-mapping and tagging. Finally, ML analyses the gathered data from the sensor and information from GIS and predicts the results. The water quality and other issues were rectified. The result provided real-time information to take critical decisions however the project was fully dependent on IoT and heavy components that will be quite expensive.

In 2023, Ramanathan et al. [23] have applied IoT and the collected data was visualized through a computer or mobile phone. In this research, the data were collected from the local fisherman and a research institute. IoT contains sensors, equipment, and actuators controlled through the internet and data were collected and monitored based on choosing, espousing, and applying technologies. They found that the IoT sensor increases productivity in gathering exert data and helps farmers to provide expert solutions to the problem that leads to better water quality, yield, reduced cost, and time however it was tested only on small scale.

In 2023, Syrmos. E., et al. [24] have experimented with a low-power, long-range wireless protocol called LoRaWAN. And Water quality unit (WQ). Initially, LoRaWAN was used in the transmission of data from the flowmeter and WQ. Then ML algorithm was used for water quality monitoring. Finally, the generated information was displayed on a mobile device for further decision. This method helps to take quality decisions using the monitored details in a limited range. Apart from this, the scalability was complex because of a complex system.

In 2023, Arrighi et al. [25] have tried ML and GIS. Initially, GIS was used to locate the river areas and send information related to the water quality, wildlife, flora, etc. Then with the collected dataset various parameters were allocated and identified the problem and provide suitable solutions to them. Then from the observed results the dataset was separated into two sections namely validation and calibration. Finally, the Canonical collection analyzes the result by comparing the ML classification algorithm.

In 2023, Armitage, D.W., [26] have adopted a generalized additive model (GAM) and ML. Initially, ML predicts the lake surface water temperatures (LSWT) and air in the atmosphere and generates a map globally with ambiguous measures. With the prediction, a deriving bioclimatic layer was created for modeling population dynamics and species distributions. Finally, through ecological niche modeling (ENM) and Population Dynamic Model, the performance of the water and air were compared. This method predicts more accurately in the lab- measurements however the global database was not available in all regions.

In 2023, Zhou, Y., et al. [27] have devised a collection of data through ML, water quality was identified through Water Quality Index (WQI), and to identify the source pollutants through Positive matrix Factorization (PMF). Initially, Water quality was identified using various parameters in different areas and it was overall assessed. Then potential problems such as pollutants and quality were analyzed and provide a suitable solution through the chemical composition through Positive Matrix Factorization Technique. This method was effective and works only in the water monitoring stations however heavy metals and other important parameters were not included.

In 2023, Lv, M., et al., [28] have ensembled different frameworks that combine deep learning (DL) algorithm and some statistical methods. Initially, Mann–Kendall Trend Test and Seasonal-Trend Decomposition using Loess were used to identify the water quality. Then any variation in water quality was identified using Pearson correlation analysis and Analysis of Variance. After that, the reason for the water quality degradation and upgradation was analyzed through grey correlation analysis. Finally, LSTM was used to identify future changes in water quality. It was a real-time water quality prediction and did not experiment with many rivers.

2.2 Challenges

The challenges associated with the existing methods of aqua status prediction are detailed as follows,

- The distributed functional tangent decision tree (DFTDT) classifier [9] is used for the prediction of water quality in wireless sensor networks. In this classifier, if the rate of sensed data is high, the data classification becomes very tedious in the application oriented environments, such as human health care monitoring, environmental and wild life monitoring, military target tracking and surveillance, hazardous environment exploration, precision agriculture, and natural disaster relief.
- The need for the networking process is to sense the quality of water with the sensor nodes lightweight and tiny-powered gathering. However, in the application area, the technology development process is done without any consideration about security that creates the susceptibility in confidentiality of the system [4].
- The components used in the aquaculture IoT is mostly deployed in the outdoor ponds that are located in remote areas. The faults arise frequently in these tough environments, and in addition, the staffs with low professional knowledge and lack of attention in the remote areas make this conventional fault diagnosis technique deteriorate its efficiency in handling losses of resources [3].
- As the demand on aquaculture increases tremendously, the continuous screening of quality and characteristics of water are needed for the maximization of the yields. Large number of physicochemical parameters is available for screening the quality of water, but only the idea of

the domain experts are expected for the analysis of the parameters to provide the final decision related to the water quality[15].

- The prediction of quality of water in the wastewater treatment process has the ability to provide the basis for the decisions of water treatment plant management. However, it is tedious to predict the water quality accurately in the treatment process due to a less knowledge about the parameters that are used in the process, or due to the presence of disturbances present in the system. Hence, the predictor must take the necessary steps to counteract the disturbances present in the system and must be able to adjust itself to the variation in system dynamics [16].

3. System Model

Due to the presence of energy constraint problem in the WSN, the sensors are grouped as clusters with a single node being selected as the cluster head. All the sensor nodes are considered as the IoT nodes in the WSN based IoT that obtains the data and guides them to the base station through its related cluster head. Due to the requirement of considerable amount of energy for the transmission of data, the IoT node with minimum distance on comparison to the other nodes in the particular cluster is selected as the cluster head. Consider S be the simulation are a with the dimension of $A \times B$, where WSN comprises of a base station D and a number of IoT nodes I that are distributed as clusters with the cluster heads C_H. Each of the IoT node $i_k, 1 < k < I$ is placed at (a_k, b_k), while the base station location is indicated as $\left(A^D, B^D\right)$. Fig.1 shows the system model of WSN based IoT, with the node i_k of each cluster transmitting the information to its cluster head $i_g, 1 \le g \le C_H$. For the cluster head node C_H, C_H^e indicates a set of IoT nodes with $e - C_H$ is the normal node count. Fig. 1 shows the system model of WSN based IoT.

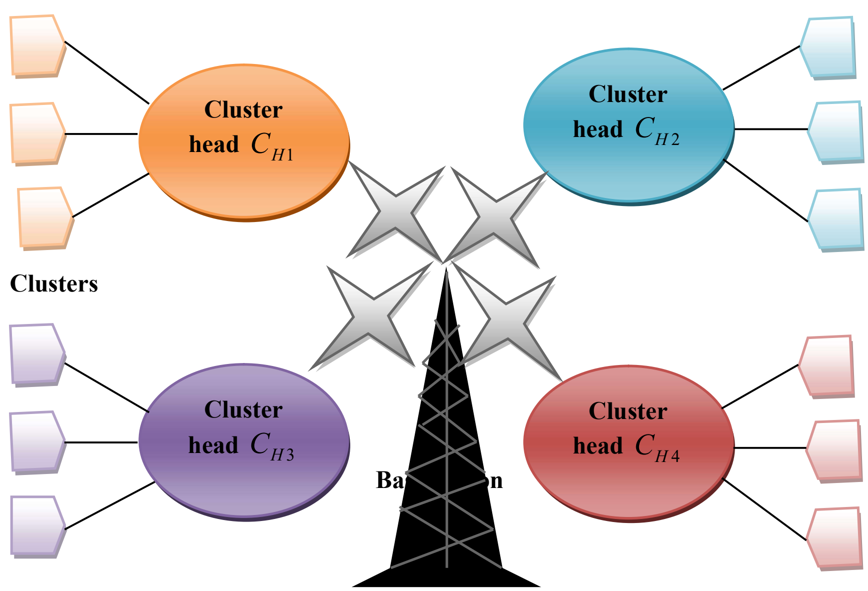


Fig.1. *System Model of WSN based IoT*

The multipath transmission of information in WSN depends on cluster heads created for each cluster. The paths are estimated for clusters rather than sensor nodes, and among the set of generated solutions, better solutions with maximum energy and longer lifetime are selected in transmission from cluster heads to the base station. This type of multipath data transmission has the ability to improve the lifetime of routes butincreases the difficulty in partitioning the network as groups of clusters because of dynamic topology of thee network. Certain nodes consume more power as compared to other nodes of the same cluster that acts as the major problem in clustering based. Thus, an efficient algorithm is needed in the selection of cluster heads to make the multipath data transmission possible.

4. Proposed Method of Aqua status Prediction using Fractional Gravitational Search Algorithm based Deep Convolutional Neural Network

The primary aim of this paper is to develop a model for aqua status prediction through the distributed deep learning classifier. The distributed classification is enabled with the application of the distributed IoT nodes in the aqua environment engaged in sensing the aqua parameters, such as temperature, dissolved oxygen, pH level, turbidity, electrical conductivity, nitrate, calcium, total hardness, total alkalinity, ammonia, hydrogen sulphide, biochemical oxygen demand, carbon dioxide, and diphosp horus. The major objective is to perfectly handle the transmission loss and delay associated with the transmission of the collected aqua data by the IoT nodes. The cluster head selection is a better option to handle the information loss and delay during the data transmission and above all, the cluster head selection is performed optimally, using the Fractional Gravitational Search Algorithm (FGSA) [17].The optimal cluster head selected using the FGSA reduces the energy required for transmitting the data and increase the throughput. Finally, the prediction of the status of aqua environment is done effectively using the Deep Convolutional Neural network (Deep CNN).The block diagram of aqua status prediction with the FGSA based Deep-CNN is shown in fig.2.

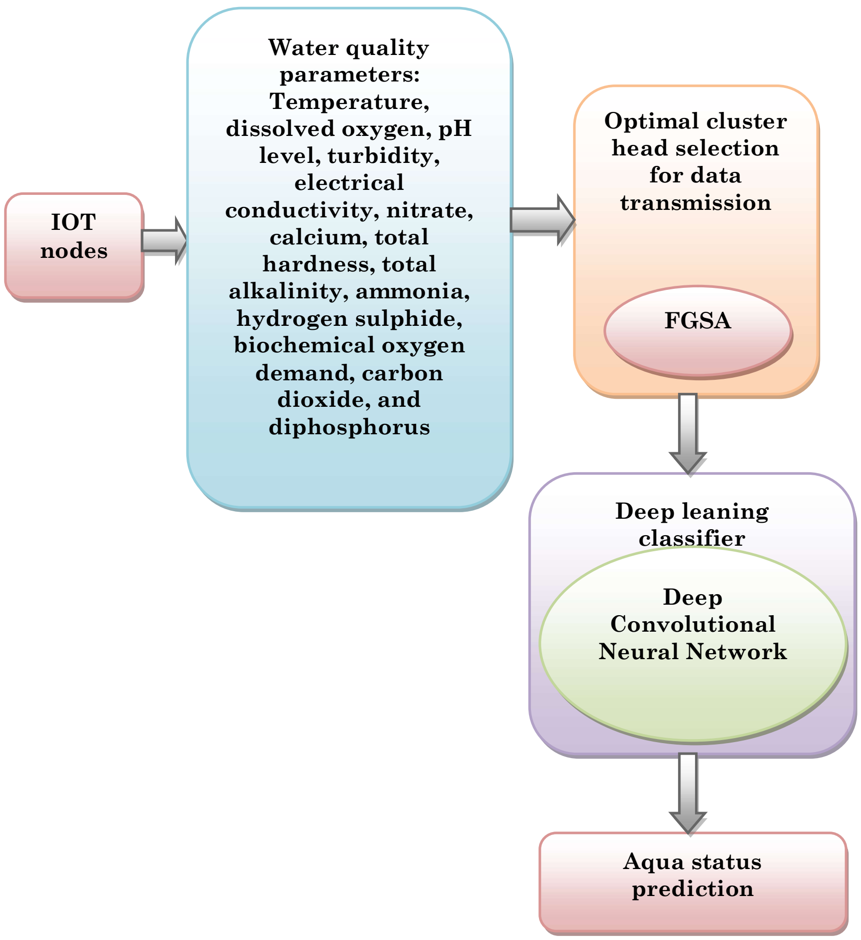


Fig.2.*Block diagram of aqua status prediction using FGSA based Deep-CNN*

4.1 Cluster head Selection with the Concept of FGSA

The selection of cluster head is important in the WSN based IoT for the provision of effective of data transmission without any packet loss. In the wireless environment, the feasible communication can be made with N number of devices termed as nodes, which are grouped as clusters. For all the clusters, it is necessary to know the cluster head C_H that directly performs data transmission. Thus, it is important to obtain the cluster heads with sufficient energy foe the transmission of data to the base station. This can be made possible based on FGSA that selects the cluster heads from a node group with the usage of fractional theory [18] in GSA [19], which estimates the acceleration and force. The implementation of fractional theory into GSA is to update the values estimated in GSA for the reduction of complexity associated with the implementation of GSA. The multiple objectives that were considered in the fitness function are used in the selection of the cluster heads in such a way to obtain the minimum requirement for a node to form a cluster head. Hence, this method develops the cluster head with enhanced convergence rate due to the introduction of functional calculus in the algorithm. The solution encoding of this technique is detailed as below.

4.1.1 Solution encoding

Solution encoding details the way of selection of the cluster head for the transmission in the optimization algorithm. The solution encoding should be indicated in such a way to reduce the time of computation. In addition, this encoding must be capable of identifying the optimal solution with ease. In FGSA, the solution is representedwith an array consisting of a finite number of elements, with each element indicates a node being selected as the cluster head. As in fig. 3, the solution encoding represents the solution array of dimension $1 \times h$, where h indicates the total cluster heads indicating $h == C_H$. Hence, the solution is represented as $\{1,2,...,h\}$, with the elements ranging from 1 to I, where I represents the number of nodes.

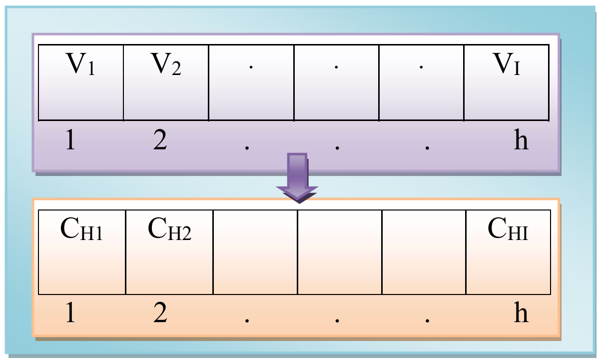


Fig.3. *Solution Encoding*

4.1.2 Fitness Evaluation

Fitness function is the fundamental factor that operates the optimization algorithm. This objective function consists of various parameters to select the cluster head for the provision of effective transmission. The metrics of fitness taken into consideration in this algorithm includes the location of node, delay, energy, and Link life time (LLT). For the provision of transmission without any packet drops, interference and the distance cluster head node from the base station is needed to be very less. Thus, the nodes that are in proximity in a cluster to the base station are usuallychosen as the cluster heads. In addition, the energy and LLT is needed to be high for the nodes to be selected as the cluster heads, and the delay must be less. When the energy of the node is higher, the LLT becomes higher. Thus, the cluster head selected for transmission should be valid in terms of energy, distance, delay and LLT. The fitness function is expressed as,

$$L_l^k = \alpha 1 * \left(1 - L_{l(loc)}^k\right) + \alpha 2 * \left(1 - L_{l(en)}^k\right) + \alpha 3 * \left(1 - L_{l(delay)}^k\right) + \alpha 4 * \left(1 - L_{l(LLT)}^k\right) \tag{1}$$

where, $L_{l(loc)}^k$ indicates the location, $L_{l(en)}^k$ indicates the energy function, $L_{l(delay)}^k$ indicates the delay and $L_{l(LLT)}^k$ represents the LLT, which are explained briefly in [18]. The cluster heads possessing less distance and delay, and high energy and LLT are selected as the optimum cluster head to perform communication.

4.1.3 Fractional Gravitational Search Algorithm

The algorithm for the selection of cluster head on the basis of FGSA optimization is detailed in this section. The cluster head selection from I nodes is carried out with respect to the solution encoding. The criterion for the selection of a node as a cluster head is represented using the fitness function. The FGSA algorithm incorporates fractional theory into GSA in this paper. After the completion of initialization, GSA estimates the fitness function for all the solutions of the population. The gravitational constant is calculated in addition to the best and the worst fitness measures. The calculation of force and acceleration for each agent is the next step in GSA in addition to the update of velocity. The node position is updated with the integrated fractional calculus. The algorithm is continued until the achievement of selection criteria or the better solutions. The steps in cluster head formation depending on FGSA algorithm are detailed as below,

i) Initialization: The first step of the algorithm is the population initialization in random manner. Consider the initialization of population as $P_x, 1 \le x \le E$, where E represents the agents. Each agent is represented as $P_x^k, 1 \le k \le i_d$, with the solutions in p^{th} dimension,

$$P_x^k = \left(P_x^1, P_x^2, \ldots, P_x^{i_d}\right) \tag{2}$$

ii) Evaluation of fitness: The fitness of all the solutions P_x^k of the population is calculated with the fitness function expressed in equation (1). From the overall solutions, the best values and worst values of the fitness are estimated using step (iii).

iii)Calculation of gravitational constant, best and worst values of fitness: The gravitational constant, denoted as J^N is defined as a function of its initial value at the time instant of m and is expressed as,

$$J^N(m) = J^N\left(J_0^N, m\right) \tag{3}$$

where, J_0^N indicates the initial function of J^N.

Because of assumed similarity of inertial mass $K^k(m)$ and gravitational mass, the update is carried out depending on the fitness values and is expressed as,

$$K^k(s) = \frac{L_l^k(m) - u_l(m)}{q_l(m) - u_l(m)} \tag{4}$$

where, $K_l^k(m)$ represents the fitness function, $q_l(m)$ is the best fitness and $u_l(m)$ is the worst fitness values. The minimum fitness value is selected as the best fitness, and the maximum value of fitness is the worst fitness. The relation for best and worst fitness is expressed as,

$$q_l(m) = \min_{n \in (1, \ldots E)} L_l^n(m) \tag{5}$$

$$u_l(m) = \max_{n \in (1, \ldots E)} L_l^n(m) \tag{6}$$

where, $L_l^n(m)$ indicates the fitness of n^{th} agent.

iv)Estimation of force and acceleration: The GSA algorithm estimates the values of force and acceleration for all the agents in this step. The total calculated force depends on the rate of force exerted among two agents and is expressed as,

$$L_x(m) = \sum_{n=1}^{Q} n_i L_{xn}(m) \tag{7}$$

where, n_i indicates a random number and $L_{xn}(m)$ represents the force created among the two agents, such as n and x, and is given as,

$$L_{xn}(m) = d_r(m) \frac{r_v(m) * r_c(m)}{G_{xn}(m) + \gamma} (P_n - P_x) \tag{8}$$

where, $d_r(m)$ is the gravitational constant, $r_v(m)$ represents the active gravitational mass, $r_c(m)$ represents the passive gravitational mass and γ indicates a constant. $g_{xn}(m)$ represents the Euclidean distance among two agents, namely x and n, and are expressed as,

$$G_{xn}(m) = \left\| P_x(m) - P_n(m) \right\|_2 \tag{9}$$

The acceleration developed by the law of motion at the time of m is formulated as,

$$M_j^k(m) = \frac{L_x^k(m)}{K^k(m)} \tag{10}$$

where, $L_X^k(m)$ is the force produced at the i^{th} agent and $K^k(m)$ is the inertial mass produced at the i^{th} agent.

v) Update of position with FGSA model: The agent's position is updated using FGSA with the integration of fractional theory that resolves the problems in search process, which arise in GSA, to provide best position update of agents expressed as,

$$Q_X^k(m+1)=\beta P_X^k(m)+\frac{1}{2}\beta P_X^k(m-1)+j^i(m+1) \tag{11}$$

where, $j^k(m+1)$ represents the velocity at time $m+1$ and β represents a real number between $0\le\beta\le 1$. This is estimated with b respect to the agent position i at current instant of time m, indicated as $P_X^k(m)$, and the position in previous iteration, indicated as $P_X^k(m-1)$, in addition to velocity calculated at the instant of time $m+1$. The update of velocity at the time instant $m+1$ is expressed using the velocity estimated at the time instant m that is multiplied with the random number, and is expressed as,

$$j^k(m+1)=n_O * j^k(m)+M_j^k(m) \tag{12}$$

where, $j^k(m)$ represents the velocity at the time instant m and $M_j^l(m)$ is the acceleration.

vi)Termination: The algorithm is continued till obtaining the optimal cluster heads depending on the updates and the fitness function. Once the termination condition is satisfied, the process of selecting the cluster heads is terminated. In this algorithm, the condition for termination is obtained when the iteration number becomes equal to the user desired threshold.
The selection of the cluster head is done mainly to reduce the delay and the transmission loss that occurs during the transmission of collected aqua data with the IoT nodes. The optimal selection of cluster head using the FGSA reduces the energy needed for the transmission of data. The collected aqua data are transmitted to the DCNN for the prediction of aqua status.

4.2 Aqua status prediction using Deep Convolutional Neural Network

Consider P be the input aqua data needed to be processed to obtain the prediction about the aqua status. The weights of the Deep CNN are obtained to be averaged in the sink node for the prediction of the aqua status.

4.2.1 Structure of Deep CNN: Deep CNN [20] acts an important role in the prediction of aqua status, and it performs better as compared to the other classifiers. In the deep CNN, a neuron patch in a layer is joined to individual neurons present in the successive layer. The Deep CNN architecture comprises of three layers, such as convolutional (conv) layers, pooling (POOL) layers, and a Fully Connected (FC) layer as shown in fig. 4. Each layer carry out a particular action like the formation of feature maps in conv layers, sub-sampling of feature maps in POOL layers, and classification for prediction in the FC layer. When the number of conv layer increases, the accuracy of classification increases.

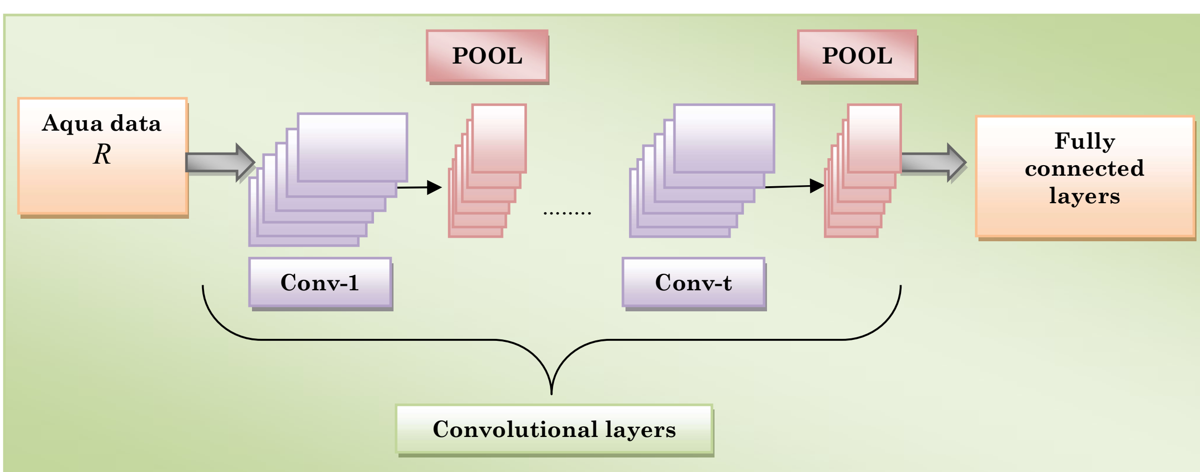


Fig.4. *Structure of Deep CNN*

a) Convolutional layers: The aim of conv layers is the extraction of patches, which are buried in the aqua parameter susing the conv filters connected with the receptive fields that acts as an interconnection between the neurons of previous layer and the successive conv layers using the trainable weights. The feature maps are obtained with the convolution of the input feature vector using the trainable weights that are calculated using the proposed FGSA based distributed DeepCNN. The neuron of the single layer obtains the variable features available in various locations based on variable weights of single layer. Let us consider that the input to Deep CNN is R, and thus the output of conv layer is givenas,

$$\left(R_y^z\right)_{O,R} = \left(X_y^z\right)_{O,R} + \sum_{F=1}^{U_1^{F-1}} \sum_{\delta=-U_1^z}^{U_1^z} \sum_{w=-U_2^z}^{U_2^z} \left(Z_{y,F}^F\right)_{w,\delta} * \left(R_F^{z-1}\right)_{O+\delta,R+w} \tag{13}$$

where, $*$ represents the convolutional operator used in obtaining the local patterns of the alternative conv layers, $\left(R_y^z\right)_{O,R}$ represents the fixed feature map or the output of the z^{th} conv layers, which is centeredat (O,R). The output of the previous $(z-1)^{th}$ layer is responsible for the input of z^{th} conv layer. Consider that the weights of conv layers be $Z_{y,F}^z$, and the bias of z^{th} conv layer be X_y^z. In addition, consider there presents t conv layers, such that $(1 \le z \le t)$ and the notations F, δ, and w represents the feature maps that acts as the output of individual conv filter. The neurons of the conv layers are placed in 3-dimensions along the height, depth, and width for the extraction of the features from all three dimensions. The ReLU layer uses the element-wise activation function to simplifythe computation with the removal of negative values. The output of z^{th} ReLU layer is the activation function of the previous $(z-1)^{th}$ layer, and is given as,

$$R_y^z = Afn\left(R_y^{z-1}\right) \tag{14}$$

The importance of ReLU layer is to offer the ability to deal with increased number of networks.
b) POOL layers: The POOL layer acts as a non-parametric layer with no bias and weights, and thus it performs a fixed operation.
c) Fully connected (FC) layers: The features produced from the POOL layers are fed to the FC layer. At the end of this layer, the output of DeepCNN is produced, and the output of the FC layer is given as,

$$R_2 = \rho\left(R_y^z\right) \text{ with } R_y^z = \sum_{F=1}^{U_1^{F-1}} \sum_{\delta=-U_1^z}^{U_1^z} \sum_{w=-U_2^z}^{U_2^z} \left(Z_{y,F}^z\right)_{w,\delta} \left(R_F^{z-1}\right)_{O+\delta,R+w} \tag{15}$$

The output obtained from the distributed Deep CNN is fed to the sink node that estimates the average mean value based on the trained weights and the data obtained from the pond to classify the aqua status as good or bad.

4.3 Applications of Aqua status prediction models

The applications of models involved in the prediction of aqua status involve the determination of quality of water to be used for the growth of money yielding fishes and aqua products. Domestic applications include normal household purposes, namely drinking, preparation of food, washing clothes and dishes, bathing, and watering gardens.The estimation of the water quality is very effective at removing the potentially harmful contaminants present in water to be used in medical applications.

5. Results and Discussions

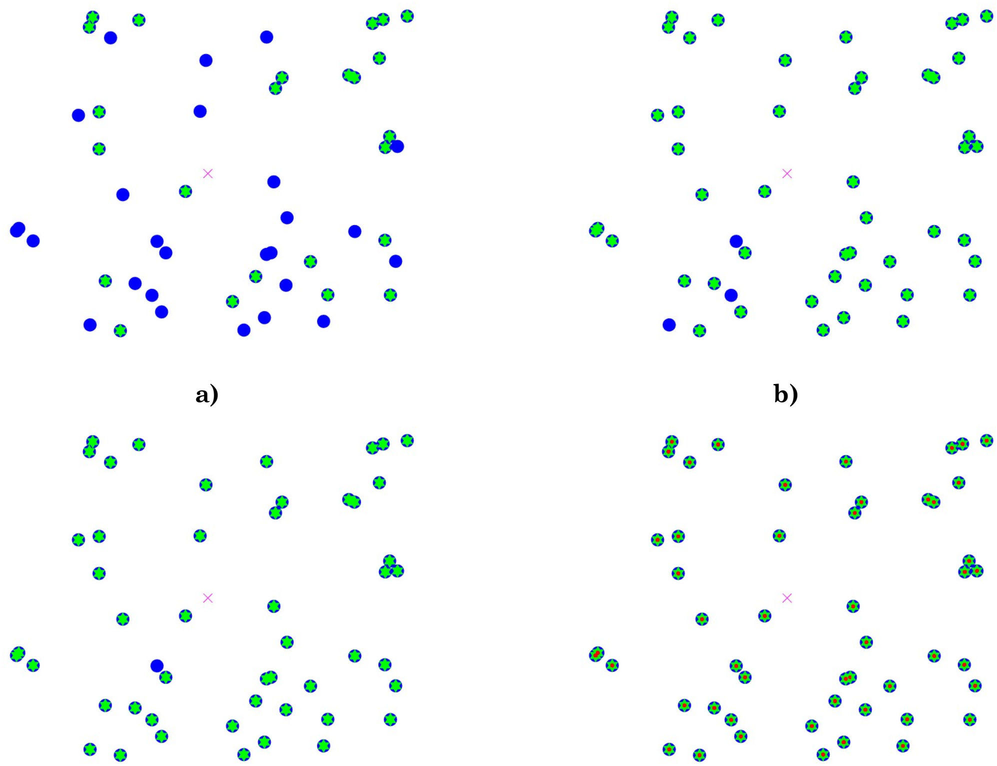
The results and discussion of the FGSA based distributed DeepCNN classifieris discussed in this section. The results of the FGSA based distributed DeepCNN classifierwhen compared with the existing conventional classifiers in terms of accuracy, energy, and throughput is presented.

5.1 Experimental setup

The classifier is implemented in MATLAB with the PC installed with Windows 10 OS and Intel(R) i3 processor using 64-bit operating system and 4GB RAM.

5.2 Experimental Results

This section details the experimental results of FGSA based distributed DeepCNN in aqua state prediction. Four different rounds are consideredfor the location of the nodes with respect to base station. The plot in the presence of 50 nodes is shown in fig. 5. Fig. 5.a shows the plot in 4^{th} round in the presence of 50 nodes, and fig. 5.b depicts the plot in 20^{th} round in the presence of 50 nodes. Similarly, fig. 5.c shows the plot in 32^{nd} round in the presence of 50 nodes, and fig. 5.c shows the plot in 44^{th} round in the presence of 50 nodes. With the increase in number of nodes, the energy of the network decreases.



a) **b)** **c)** **d)**

Fig.5. *Experimental results of the proposed FGSA based distributed Deep CNN classifier in the presence of 50 nodes, a) number of round=4, b) number of round=20, c) number of round=32, and d) number of round=44.*

5.3 Evaluation Metrics

The performance of the proposed FGSA based distributed Deep CNN classifier is evaluated in terms of the evaluation metrics, namely accuracy, energy, and throughput.

5.3.1 Accuracy: The degree of a measurement leading to the correct value is termed as accuracy and is expressed as,

$$\text{Accuracy}= \frac{t_p + t_n}{t_p + t_n + f_p + f_n} \tag{16}$$

where, t_p is the true positive, t_n is the true negative, f_p is the false positive, and f_n is the false negative.

5.3.2 Energy: The capacity of a system to perform any task is termed as energy. The energy of the cluster head is calculated, and the calculated energy must be very high for better performance of the system.

5.3.3 Throughput: The amount of material or items passing through a system or process is termed as throughput. The value of throughput must be high for the algorithm to improve its efficiency.

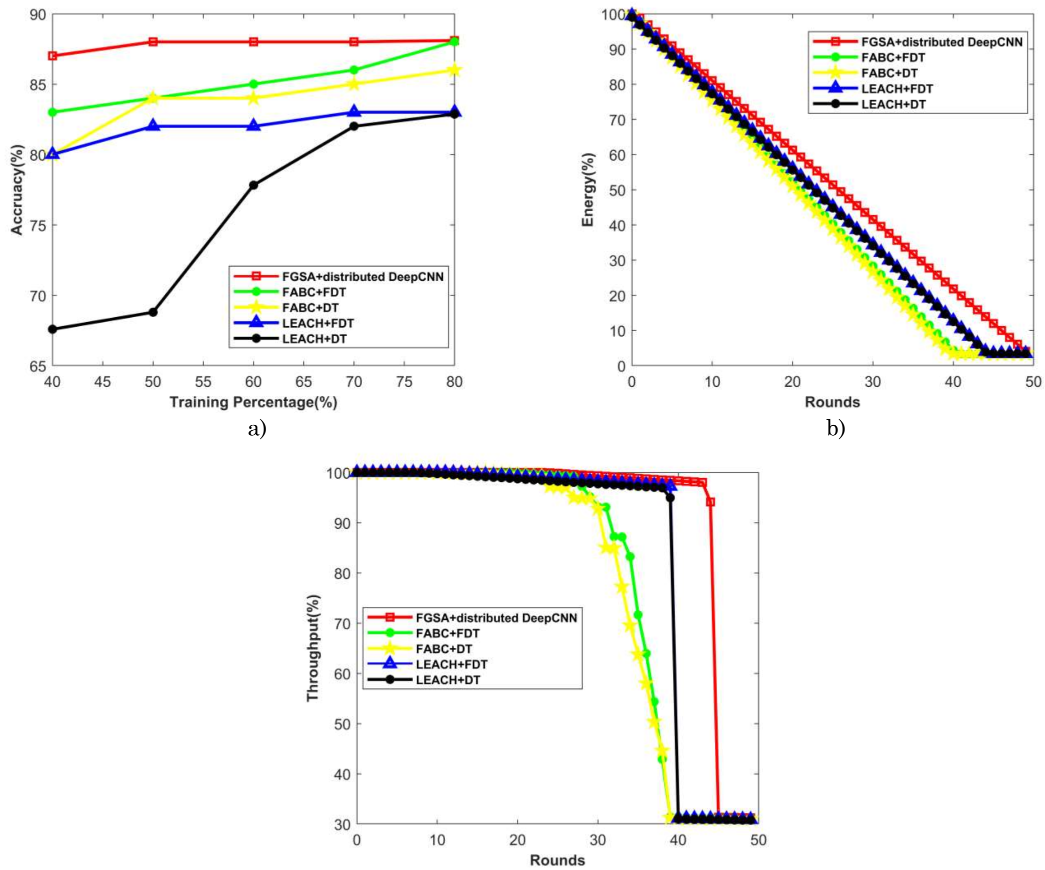
5.4 Comparative Analysis

The comparative analysis of the proposed FGSA based distributed DeepCNN classifier is performed based on accuracy, energy, and throughput for the variation in number of nodes. Various existing conventional methods, such as FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT are compared with the proposed FGSA+disrtibuted DeepCNN in order to convey the effectiveness of the proposed aqua state prediction system. FGSA+disrtibuted DeepCNNis the combination of FGSA and distributed DCNN to perform the aqua state prediction.

5.4.1 Comparative Analysis in the Presence of 50 Nodes

The comparative analysis of the methods involved in aqua state prediction in the presence of 50 nodes in terms of accuracy, energy and throughput is depicted in fig. 6. Fig. 6.a shows the comparative analysis of the methods, such as FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT, and the proposed FGSA+disrtibuted DeepCNN in terms of accuracywith the variation in training percentage. When the training percentage is 50, the accuracy of the methods, such as FGSA+disrtibuted DeepCNN, FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT, in the presence of 50 nodes is88.01, 84.01, 84.01, 82.01, and 68.7953, respectively. Similarly, when the training percentage is 80, the accuracy of the methods, such as FGSA+disrtibuted DeepCNN, FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT, in the presence of 50 nodes is 88.1041, 88.01, 86.01, 83.01, and 82.8814, respectively.
Fig. 6.b shows the comparative analysis of the methods, such as FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT, and the proposed FGSA+disrtibuted DeepCNN in terms of energy with the variation in number of rounds.When the number of round is 10, the energy of the methods, such as FGSA+disrtibuted DeepCNN, FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DTin the presence of 50 nodes is 82.9954, 78.5784, 77.7944, 79.835, and 79.4212, respectively. Similarly, when the number of round is 50, the energy of the methods, such as FGSA+disrtibuted DeepCNN, FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT, in the presence of 50 nodes is 4.096, 3.4325, 3.4321, 3.4317, and 3.4313, respectively. Thus, with the increase in number of rounds, the energy of the nodes decreases.

Fig.6.c shows the comparative analysis of the methods, such as FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT, and the proposed FGSA+disrtibuted DeepCNN in terms of throughput with the variation in number of rounds. When the number of round is 25, the throughput of the methods, such as FGSA+disrtibuted DeepCNN, FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT in the presence of 50 nodes is 99.9571, 99.5571, 97.2311, 98.7571, and 98.3571, respectively. Similarly, when the number of round is 50, the throughput of the methods, such as FGSA+disrtibuted DeepCNN, FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT, in the presence of 50 nodes is 31.2371, 31.1171, 30.9971, 30.8771, and 30.7571, respectively. Thus, with the increase in number of rounds, the throughput of the nodes decreases.



a) b) c)

Fig.6. *Comparative analysis in the presence of 50 nodes, a) Accuracy, b) Energy, c) Throughput.*

5.4.2 Comparative Analysis in the Presence of 100 nodes

The comparative analysis of the methods involved in aqua state prediction in the presence of 100 nodes in terms of accuracy, energy and throughput is depicted in fig. 7. Fig. 7.a shows the comparative analysis of the methods, such as FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT, and the proposed FGSA+disrtibuted DeepCNN in terms of accuracy with the variation in training percentage. When the training percentage is 50, the accuracy of the methods, such as FGSA+disrtibuted DeepCNN, FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT, in the presence of 100 nodes is 87.3235, 85.01, 84.01, 82.01, and 80.01, respectively. Similarly, when the training percentage is 80, the accuracy of the methods, such as FGSA+disrtibuted DeepCNN, FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT, in the presence of 100 nodes is 93.5466, 88.01, 87.01, 84.01, and 82.01, respectively.

Fig. 7.b shows the comparative analysis of the methods, such as FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT, and the proposed FGSA+disrtibuted DeepCNN in terms of energy with the variation in number of rounds. When the number of round is 10, the energy of the methods, such as FGSA+disrtibuted DeepCNN, FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT in the presence of 100 nodes is 88.1654, 84.518, 83.8914, 85.2821, and 84.7596, respectively. Similarly, when the number of round is 50, the energy of the methods, such as FGSA+disrtibuted DeepCNN, FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT, in the presence of 100 nodes is 7.2504, 6.7658, 6.7654, 6.765, and 6.7646, respectively. Thus, with the increase in number of rounds, the energy of the nodes decreases.

Fig. 7.c shows the comparative analysis of the methods, such as FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT, and the proposed FGSA+disrtibuted DeepCNN in terms of throughput with the variation in number of rounds. When the number of round is 45, the throughput of the methods, such as FGSA+disrtibuted DeepCNN, FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT in the presence of 100 nodes is 91.3043, 34.1243, 33.9743, 33.8843, and 33.7643, respectively. Similarly, when the number of round is 50, the throughput of the methods, such as FGSA+disrtibuted DeepCNN, FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT, in the presence of 100 nodes is 34.0943, 33.9743, 31.3103, 33.7343, and 33.6143, respectively. Thus, with the increase in number of rounds, the throughput of the nodes decreases.

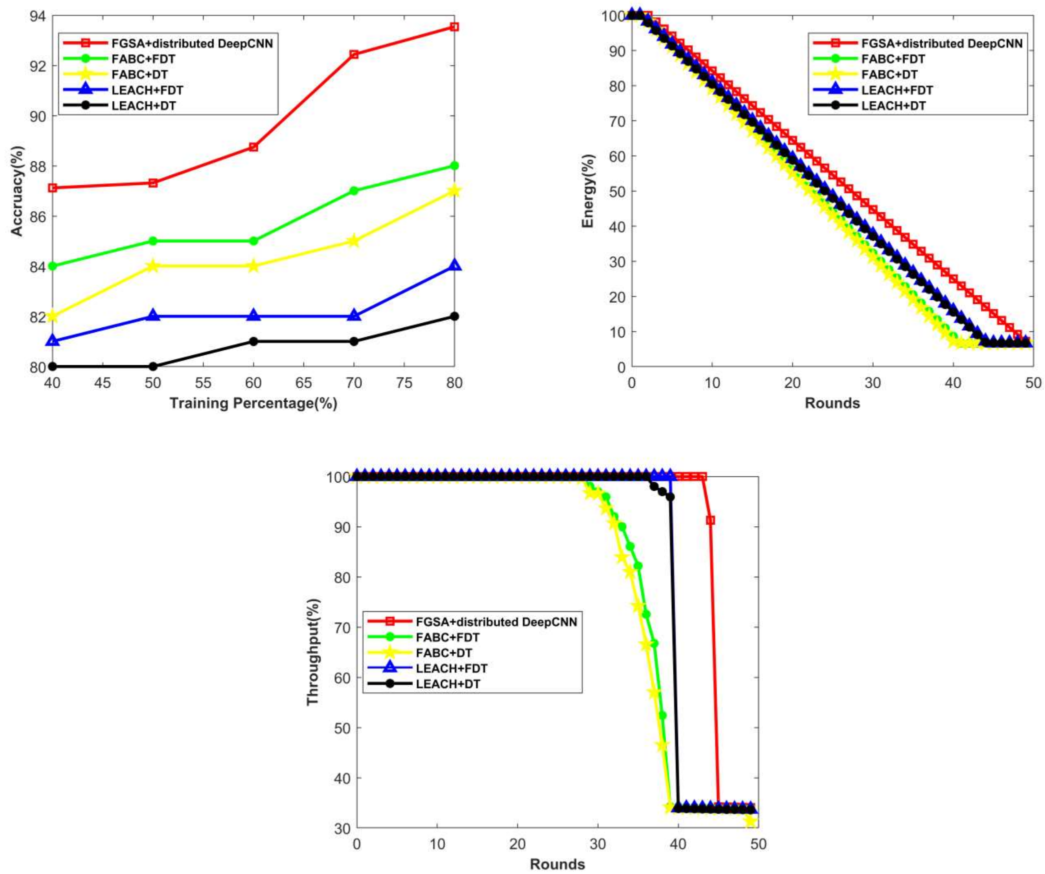


Fig.7. *Comparative analysis in the presence of 100 nodes, a) Accuracy, b) Energy, c) Throughput.*

5.4.3 Comparative analysis in the presence of 150 nodes

The comparative analysis of the methods involved in aqua state prediction in the presence of 150 nodes in terms of accuracy, energy and throughput is depicted in fig. 8. Fig. 8.a shows the comparative analysis of the methods, such as FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT, and the proposed FGSA+disrtibuted DeepCNN in terms of accuracy with the variation in training percentage.When the training percentage is 50, the accuracy of the methods, such as FGSA+disrtibuted DeepCNN, FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT, in the presence of 150 nodes is 92.2398, 85.01, 83.01, 81.01, and 80.01, respectively. Similarly, when the training percentage is 80, the accuracy of the methods, such as FGSA+disrtibuted DeepCNN, FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT, in the presence of 150 nodes is 95.4758, 87.01, 86.01, 84.01, and 82.01, respectively.

Fig. 8.b shows the comparative analysis of the methods, such as FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT, and the proposed FGSA+disrtibuted DeepCNN in terms of energy with the variation in number of rounds.When the number of round is 5, the energy of the methods, such as FGSA+disrtibuted DeepCNN, FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT in the presence of 150 nodes is 99.4293, 97.3766, 96.9256, 97.1514, and 96.8868, respectively. Similarly, when the number of round is 50, the energy of the methods, such as FGSA+disrtibuted DeepCNN, FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT, in the presence of 150 nodes 10.5447, 10.0992, 10.0988, 10.0984, and 10.098, respectively. Thus, with the increase in number of rounds, the energy of the nodes decreases.

Fig. 8.c shows the comparative analysis of the methods, such as FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT, and the proposed FGSA+disrtibuted DeepCNN in terms of throughput with the variation in number of rounds.When the number of round is 45, the throughput of the methods, such as FGSA+disrtibuted DeepCNN, FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT in the presence of 150 nodes is 93.5274, 36.9514, 36.8314, 36.7414, and 36.6214, respectively. Similarly, when the number of round is 50, the throughput of the methods, such as FGSA+disrtibuted DeepCNN, FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT, in the presence of 150 nodes is 36.9514, 29.5154, 33.2194,

36.5914, and 36.4714, respectively. Thus, with the increase in number of rounds, the throughput of the nodes decreases.

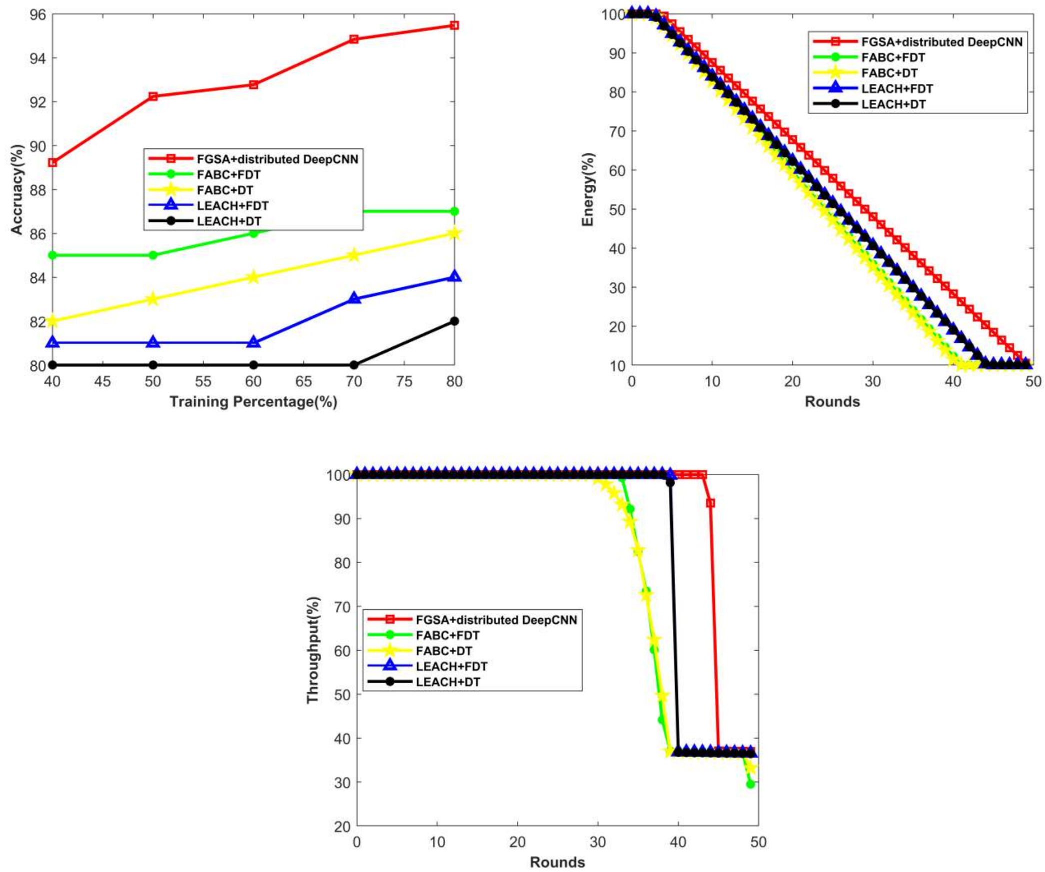


Fig.8. *Comparative analysis in the presence of 100 nodes, a) Accuracy, b) Energy, c) Throughput.*

5.5 Comparative Discussion

Table 1depicts the comparative analysis of the existing methods of aqua status prediction and the proposed FGSA+disrtibuted DeepCNN in aqua status prediction. The accuracy of the methods, such as FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT, and the proposed FGSA+disrtibuted DeepCNN is 87.01, 86.01, 84.01, 82.01, and 95.4758, respectively. Similarly, the energy of the methods, such as FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT, and the proposed FGSA+disrtibuted DeepCNN is97.3766, 96.9256, 97.1514, 96.8868, and 99.4293, respectively. The throughput of the methods, such as FABC+FDT, FABC+DT, LEACH+FDT, and LEACH+DT, and the proposed FGSA+disrtibuted DeepCNN is 99.5571, 97.2311, 98.7571, 98.3571, and 99.9571, respectively. thus, from the analysis, it is clear that the accuracy of the proposed FGSA+disrtibuted DeepCNN is high as compared to the conventional methods. In addition, the energy and the throughput of the methods decreases with the increase in number of rounds, and the values of energy and throughput are high for the proposed FGSA+disrtibuted DeepCNNon comparison with the conventional methods. Hence, it is clear that the proposed method of aqua status prediction performs in an enhanced manner.

Table 1: Comparative analysis of the methods involved in aqua status prediction

Methods	Metrics		
	Accuracy	**Energy**	**Throughput**
FABC+FDT	87.01	97.3766	99.5571
FABC+DT	86.01	96.9256	97.2311
LEACH+FDT	84.01	97.1514	98.7571
LEACH+DT	82.01	96.8868	98.3571
Proposed FGSA+disrtibuted DeepCNN	**95.4758**	**99.4293**	**99.9571**

6. Conclusion

In recent years, various researches were conducted related to the forecast model of water quality. Due to the fact that the quality of water being affected by various factors, the conventional methods of aqua status prediction are not better enough to solve the problem. In order to overcome this drawback, an aqua status prediction model in IoT is proposed using the Fractional Gravitational Search Algorithm based distributed Deep Convolutional Neural network (FGSA-based distributed Deep CNN). In the first step, the analysis of the aqua parameters is done with the distributed IoT nodes present in the aqua environment. Then, the cluster heads are selected optimally using the FGSA in order to control the loss and delay in the aqua status data transmission. Finally, the aqua status is predicted using the distributed DeepCNN. The effectiveness of the proposed FGSA-based distributed Deep CNN classifier is analyzed using the metrics, such as accuracy, energy, and throughput. The accuracy, energy, and throughput of 95.4758, 99.4293, and 99.9571, respectively are obtained by the proposed method, which is high on comparison with the existing methods. In future, some other advanced algorithms will be used for enhancing the forecasting efficiency of the model.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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