Local Maxima Niching Genetic Algorithm Based Automated Water Quality Management System for Betta *splendens*

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Abstract

Rearing Betta *splendens* is one of the most popular aquarium hobbies around the world. There are many IoT solutions done so far to monitor the water quality of the aquarium. Some machine learning and IoT based solutions are also available to do regression on the sensor data. In this paper, we propose a new framework and algorithm to predict the abnormalities in water quality which may affect the health of the fish. The algorithm proposed in this paper uses a local maxima niching genetic algorithm for optimization which effectively finds the local maxima on the new data streaming in and provides the approximate timestamp on the next possible water change or treatment to avoid the fish from getting infected. Many existing timestamp methods are seasonal but in terms of optimization in terms of unpredictable environment such as water, there needs a better technique for optimization. The qualitative and quantitative results proved that the health of fish using the proposed framework had better living conditions and avoided the attack of parasitic infections than those in existing and normal captivity methods. The accuracy of the proposed methodology increased by 5% within the variations made.

Keywords: Smart Aquarium, Genetic Algorithm, Water Quality, Betta splendens

I. INTRODUCTION

Aquarium keeping is one of the most affordable and therapeutic hobbies around the world. Hobbyists normally make various types of aquariums like freshwater, marine, aqua-scape and crustaceans. Most of the freshwater aquariums use tropical fish species originated from the south east Asia. There are many instances of creating unsuccessful aquarium where the mortality rate of fish purchased is more. This is mainly due to poor water quality and mismanagement of the aquarium system [1]. The biochemical and ecological factors play a vital role in maintaining the fish stress-free and free from parasitic attacks. There are many tropical fish available in the market but Betta *splendens* is chosen for the experiments in this paper. The technology proposed in this paper will be useful for hobbyists, aquarium retailers and Betta breeders to maintain better living condition for the B. *splendens* in captivity.

Table 1 List of Abbreviations

Acronym	Expansion
IoT	Internet of Things
B.splendens	Betta splendens
GA	Genetic Algorithm
SVM	Support Vector Machine
NB IoT	Narrow Band IoT
CO2	Carbon dioxide
pH	Hydrogen Ion concentration
H2CO3	Carbonic acid
SVR	Support Vector Regression
ESM	Electric Smart Meter
CO	Carbon Monoxide
Cc	Centimeter cube
CSV	Comma Separated Values
Ich	Ichthyophthirius multifiliis

A. Betta splendens

Betta *splendens* is the scientific nomenclature for the Siamese fighting fish. It is predominantly bred for pet aquariums of hobbyists and for fish fighting as a hobby. It is originated from Thailand. This species is known for its aggression due to low levels of Serotonin [2]. B.*splendens* is an affordable ornamental tropical fresh water fish available in market with various types of fins and vibrant colors. The frequency and intensity of the pelvic fin flickering and tail beating is used for male-male and male-female interactions [3]. Therefore, the health of the fins is more responsible to communication than appearance. This species of aquarium fish is more sensitive towards diseases due to poor water quality [4] like bacteria infected fin rot [5], Ichthyophthirius *multifiliis* and other parasitic infections [1]. Factors like pH, Ammonia, dissolved CO2 needs to be in the teleost recommended ratio as the excess presence of any of these may turn poisonous for the fish [6].

B. Internet of Things

Internet of Things (IoT) is spanning its wings in all domains and transforming the usage of industries and lifestyle. It reduces power consumption and increases the robustness and connectivity to the accessible data across the globe [7]. IoT is used as a bridging tool with Machine learning techniques to manage and predict data in many cases. A new evolutionary algorithm based supervised learning framework is proposed in this paper to maintain water quality and predict the condition of aquarium to prevent parasitic attacks and increase the lifespan of B.*splendens* in captivity. Some external and submersible sensors coupled with ATMEGA microcontrollers are used in this methodology. Normally there is a recommended weekly replacement of water with 20% of the total capacity of the captive aquarium tank [4].

i) *External Sensors*; DHT 11 sensor is used to measure the atmospheric temperature and relative humidity. MQ9 sensor is used to measure the concentration of carbon monoxide in parts per million from the surface of the aquarium.

ii) *Submersible Sensors*; Water temperature and pH are measured using submersible sensors. PHC4502C is used to measure from the pH voltage measured by the potentiometer in the sensor and DS18B20 is used to measure water temperature. Source code is given in https://github.com/ferdinjoe/ Water-Quality-Management.

C. Multi-Objective Genetic Algorithm

Genetic Algorithm is a widely used evolutionary algorithm which mimics the human evolution theory of Charles Darwin [8]. This algorithm is used to evolve data and speculate the possibilities of future outcomes. Multi objective genetic algorithm is available to evolve based on multi dimensions and multiple fitness functions [9], [10]. Multi objective genetic algorithm has scope in all types of data including images and videos for graph based searching of pattern recognition [11]. There is a need for a local maxima based optimization for time series data obtained for IoT systems in aquarium.

D. Support Vector Machine

Support Vector Machine (SVM) or Support Vector Networks was invented by Vladimir N. Vapnik and Alexey Ya. Chervonenkis in 1963 for linear classifiers. Later Vapnik developed the algorithm to be used by nonlinear classifiers. For this purpose, he developed Support Vector Networks with Corinna Cortes [12]. This formed the base for the modern day Support Vector Machine classifier used for many supervised learning based machine learning applications. LIBSVM toolbox [13] is used for the experiments in this paper.

Let the data fed into SVM is represented as follows.

$$\{x_1, y_1\}, \{x_2, y_2\}_{\dots,}\{x_n, y_n\} \tag{1}$$

A hyperplane can be drawn over these points in (1) with a normalized vector as in (2).

$$\omega \, . \, x - b = 0 \tag{2}$$

The soft margin of this hyperplane is given as

$$max\big(0,1 - y_i(\omega . x_i - b)\big) \tag{3}$$

Therefore the hard margin is given as

$$(\omega . x_i - b) \ \geq 1 \tag{4}$$

This applies for the limit of $1 \leq i \ \leq n$.

The time series data in the IoT sensors are made as vectors in this form. These vectors are converted to the type of chromosomes explained in section III. This is because we propose a new way of creating chromosomes based on the vectors and hyperplanes.

In this paper a new local maxima based niching genetic algorithm is used to manage water quality and predict the quickest possible time to change water in the captive tank is proposed in a framework which has given promising results to increase the lifespan of B. *splendens* in small captive nano tanks. The remaining part of the paper is organized as the existing methods and other related literatures reviewed in related work, proposed methodology and results in qualitative and quantitative aspects. Prior to results, the experimental setup and various algorithm tried for optimization and their performance are listed in Experiments section.

II. LITERATURE REVIEW

IoT based aquaria has been developed and proposed with various technologies and environmental control. Most of the literatures given below are used for monitoring and storing the data collected from the sensors and thereby operating actuators.

A study on B. *splendons* was done by [6] and it used many sensors and actuators to observe the behavior of the fish in a small unheated aquarium tank. This is a controlled environment as it was taken to the region where it is not conducive enough to raise tropical fish. The report on this study says that there is an aggressive behavior in the species where the movement was less and tank size is smaller. This indicated in a dominant – submissive relationship. The same behavior was observed in aggressive Midas cichlids [14] and semi aggressive zebra danios [15]. The most lethal abnormalities include pH going beyond 8, increase in ammonia due to accumulation of fish waste and increase in acidity of water by H2CO3 due to dissolved CO2.

IoT based aquarium system named FishTalk was proposed in [16]. This is an NB IoT based system developed with various sensors and actuators. This includes water level, temperature and actuators like filters and fish feeders. This is a mobile based monitor for water quality sensors in the aquarium and it is proven cost effective than many other systems developed earlier. This monitoring gave a way of calibrating sensors to work specific to the IoT based aquarium systems, intelligent feeding system and the analytics to understand the effects of IoT message loss and delays in domestic aquarium systems rearing tropical species. Python is used to develop the analytic system of FishTalk. Smart cloud based IoT system for domestic aquarium systems was developed using Arduino Nano [17]. This has limited functionalities but has fully automated system to feed and to change water periodically. A cloud based system was developed to control the actuators of feeder and water changing model from being in any remote location. This is developed as an application using mobile app with firebase cloud as backend. A smart live aquarium monitoring using Raspberry Pi was developed in [18]. This uses a webcam server of raspberry pi and connects to the heater, feeder and temperature sensor. It is developed as an IoT application to watch the condition of the tank live using the webserver with an android app as front end and thereby doing the necessary actions. Similar IoT based smart fish aquarium is developed in extensively in various literatures like [19].

Application of machine learning techniques in IoT are discussed extensively in [20]. It is a survey which spans over the machine learning in IoT applications using the domain of Edge, Fog, cloud and distributed computing. SVM, Naïve Bayes and K Nearest neighbor algorithms are used in smart agriculture or smart farming. The feature selection or reduction methods like Principal Component Analysis and Canonical Correlation Analysis on time series and sequential data obtained from IoT data. SVR is used to find the future progression of sequential data and single class SVM is used for classification of various conditions in the IoT applications. In a nutshell, analytic algorithms are used to retrieve knowledge from the collected data, feature selection from the given data and the choice of algorithm depends on the data collected. A decision support system for machine learning to improve IoT based smart meter is proposed in [21]. The method proposed to improve decision support was compared using methods like Naïve Bayes, Random Forest and Decision Trees. The data driven decision support system for ESM to work more efficiently using an IoT ecosystem. Most of the existing methodologies in IoT are spanning towards agriculture and even to crop centric domains [22].

IoT system for rearing B. *splendens* is proposed in [16] and [23]. The latter developed as an IoT based application and shows insights on data collected. It also describes about the literatures on how Acquasmart system is developed. The performance metrics used in the literatures discussed in this section includes accuracy, F-score, correlation factor etc. The architecture proposed in this paper is promising enough with the data analytics obtained qualitative and quantitative for data scientists working on smart aquarium and develop monitoring system to have a fully automated system to control the environment of B. *splendens* in small Nano tanks. The performance of this proposed architecture is validated quantitatively against various experimental setup and parameters involved in all phases of the system development. A research on water contamination detection using genetic algorithm is proposed in [24]. This gives an insight on the optimization approach mentioned in the proposed methodology listed below.

III. RESEARCH METHODOLOGY

The proposed methodology includes an IoT based architecture and a machine learning based evolutionary algorithm to predict the possible abnormalities in the water quality and conduciveness of B. *splendens* to suit the environment.

A. *IoT Based Architecture*

The IoT based architecture is given in Figure 1. This presents the sensors and actuators attached to the microcontrollers and the means of collecting data from the tank taken for experimentation. The choice of sensors and actuators used in this proposed framework was based on the features to be extracted and the minimum common data collected by most of the frameworks in the existing methodologies.

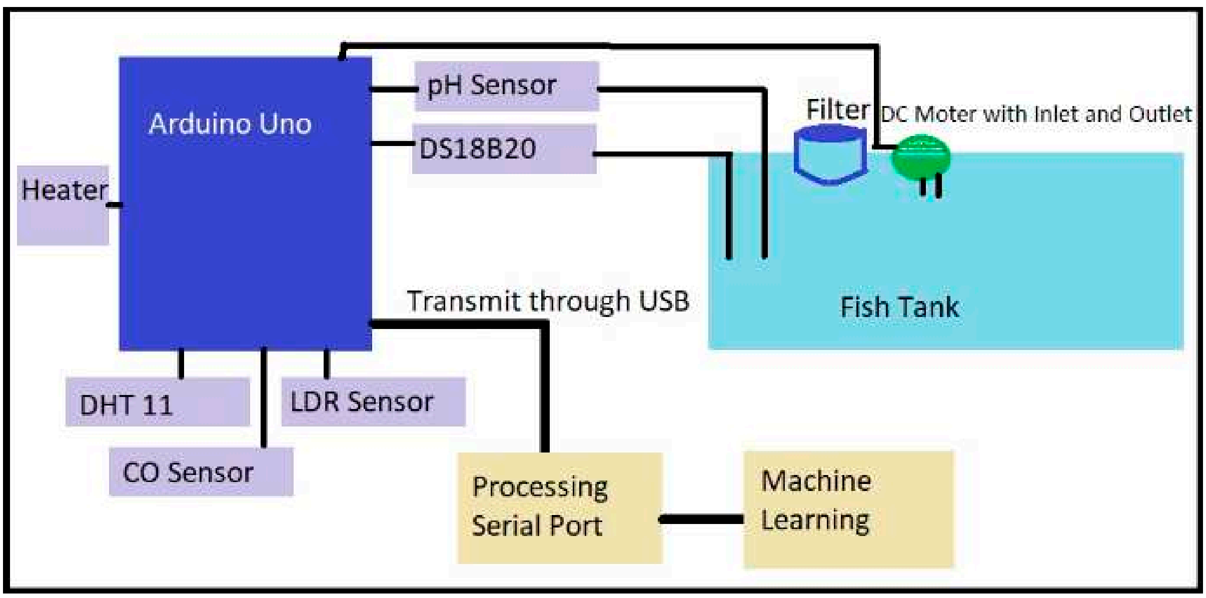

Figure 1 IoT architecture of the proposed methodology

The proposed IoT architecture uses Arduino Uno connected to a PC via USB interface. An external hanging filter is added with a capacity of 260 liters per hour. This filter is attached to the experimental aquarium of size 1500 cc. The aquarium has water added to 1000 cc. PHC4502C is used as a probe from the Arduino as a pH sensor. The pH volt from the sensor is calibrated to provide pH values with the range 1-14. This calibration is done with NaOH, distilled RO water and battery acid whose pH values are known. pH, LDR and CO sensors are connected to the analog pins in the microcontroller and other sensors are connected to the digital pins. Adafruit, One Wire and Dallas Temperature libraries are used to get data from DHT 11 PHC4502C and DS18B20 sensors respectively. DHT 11 sensor is used to record the external temperature and relative humidity and DS18B20 is used to record water temperature. MQ-9 sensor is used to record the CO concentration in ppm. LDR sensor is used to record the light intensity on the transparent face of the aquarium. These data are transmitted to a PC via USB interface and connected to Processing software.

B. Machine Learning

The data collected from the sensors are transmitted through USB interfacing in Arduino and read through Processing software which parses the string transmitted.

i) *Data Collection*; The string data obtained from the microcontroller is concatenated with the timestamp and stored in a CSV file. The data stored in the CSV file as database are processed using Python in Jupyter Notebook. Pandas library is used to parse the data stored in the database. This is done simultaneously from all the experimental tanks. Separate CSV files are used for each tank. When it is populated using pandas in python, all the files are taken together with tank ID as identifier. The proposed genetic algorithm is used after taking a minimum of 500 readings. While taking the 501st reading, the previous data form chromosomes in the population set generated for the genetic algorithm proposed. The training and testing data is collected over a span of six onths and each month had an average of one million entries. When the entries are flooding the csv files, they were stored in mongo DB database in json format. Approximately 24 million data entries were stored for producing classifier models and perform optimization. The first four-month data with uncontrolled environment setup is used to label manually and used for training. This accounts to 16 million entries. Labels were required only when abnormality is observed and water change was done due to poor water quality or medication added due to parasitic attacks.

a) *Data Cleaning*; The data collected in the mongo DB database was found to be inconsistent with missing values. These missing values are filled with a median values and those with incomplete or too less data recorded are ignored and removed from the database. Data cleaning is done in this way and made sure that all data entries have all data fields filled.

ii) *Feature Extraction;* Most of the training are done using the evolutionary algorithms like ant colony optimization, particle swarm algorithm and genetic algorithm. The combination of timestamp and data acquired by the sensors are collected. The sensors provided both the internal and external environment of the system. In the preliminary experimentation, the performance of genetic algorithm was found to be better than other algorithms tried. Normal genetic algorithm with every timestamp as chromosome in a population is better in predicting water change but failed to predict the insufficient water quality with respect to the parasites. So we used a niching based genetic algorithm similar to [25] for calculating the environment of the aquarium based on the classes a) normal, b) abnormal water quality and c) parasitic attack based abnormality. The fitness score is done by a hybrid SVM based regression. The machine learning framework is given in the Figure 2 below.

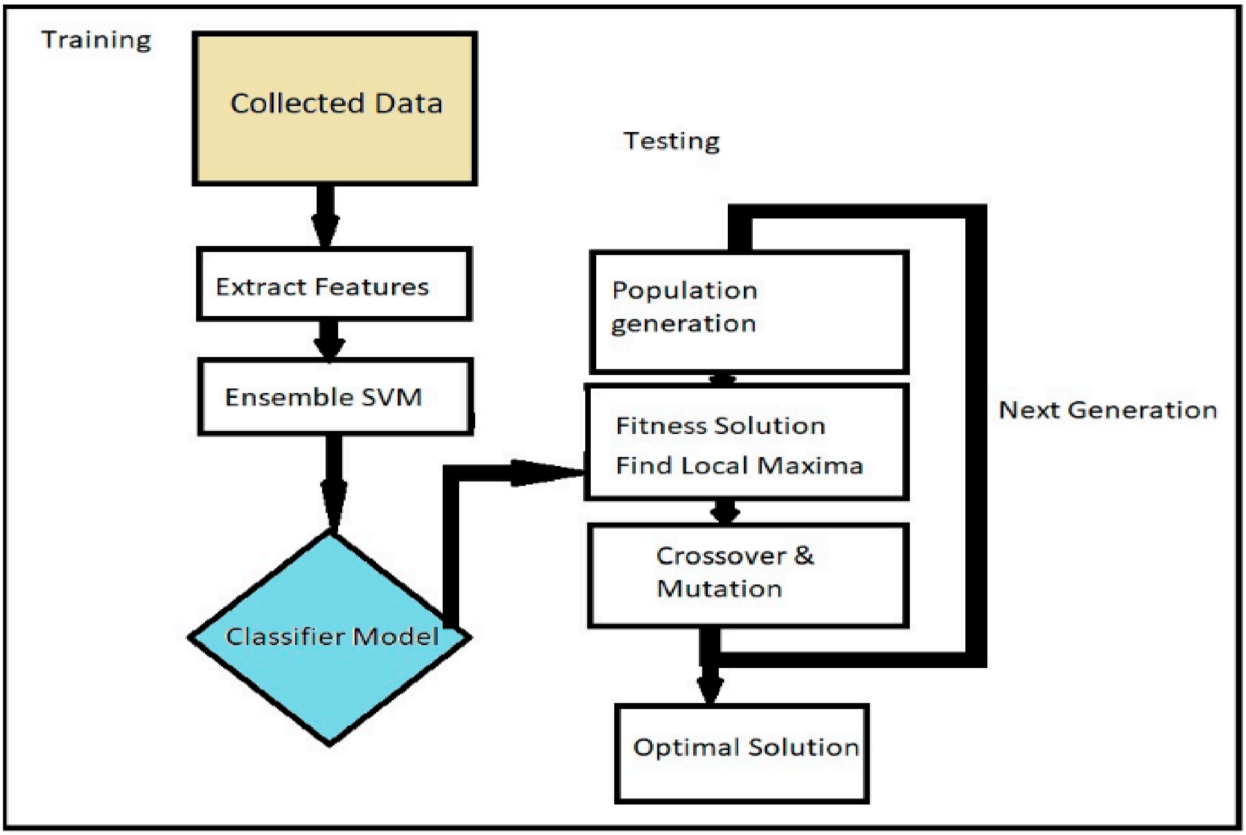

Figure 2 Machine Learning Framework

This framework has the optimization and fitness function applied. The optimization is done using a local maxima niching genetic algorithm where the SVM used finds the fitness score.

iii) *Training Data;* Samples of B. *splendens* in nano size tanks were taken with different sub species and different water conditions by varying the pH values. Some were observed to get affected by fin rot, swim bladder and ich diseases predominantly due to poor water quality and parasitic attacks. These samples were rescued and treated as per expert advice using medications like bath in Potassium permanganate solution, Methylene Blue solution and feeding with spirulina based algae mixture. The water condition and the sensor data obtained are recorded for each disease and subjected to training using an Ensemble SVM. This Ensemble SVM will create a classifier model based on the labels given to training data. This model is used as a map for calculating the fitness score for each chromosome in the testing data. The genetic algorithm parameters are chosen based on hybrid algorithms reported in [26], [24] and [27].

iv) Proposed *Local Maxima Niching Genetic Algorithm*

Initially the first 500 readings of sensors and timestamp data are taken. Each part of the timestamp like day, hour, minute and sensor data are taken column wise and concatenated for every 50 readings. A sample chromosome in the population is represented below.

<pH1, pH2, pH3...pH50> <iTemp1, iTemp2, iTemp3 ... iTemp50> .. <dayval1, dayval2, ...dayval50 >

There are 10 parameters with 50 readings each. So there are 500 genes taken in the population. In the above chromosome, the data enclosed in <> corresponds to a particular data. The crossover and mutation are done within the subset of genes alone. Crossover and mutation does not apply to the genes' subset of timestamp data.

For each generation, the population is taken to Ensemble SVM and fitness score is calculated. Among the scores in the fitness solution, the local maxima are chosen. The chromosomes above the average fitness score are retained for the next generation and the below average chromosomes are subjected to crossover and mutation.

a) *Crossover;* Crossover of the above average chromosomes are done based on a tournament selection process. Initial experimentation showed that tournament selection method is quick enough to converge the population with optimal local maxima than random selection. The subset of gene is selected based on a threshold ratio set for each subset. Timestamp subsets are given negative threshold to avoid those genes' set to perform crossover. A two-point crossover is done and that gives rise to 4 new chromosomes with respect to that gene. This count is a part of the permutation taken for the combination of genes subset performing crossover. As a result of crossover there will be above average chromosomes from previous generation, crossed over chromosomes and below average genes waiting to get mutation.

b) *Mutation;* Mutation is performed on a single gene. The single gene in a gene subset is chosen and it is converted from decimal to binary. Using a random probability, the bit which needs to mutate is identified and flipped. Then the mutated gene's chromosome will replace the below average chromosome which it actually mutated from. As a result of this mutation there will be same amount of chromosomes in the previous population and the chromosomes obtained using crossover. Therefore, the number of chromosomes increases with each generation forward.

IV. RESULTS AND DISCUSSION

The experiments carried out for the proposed framework consists of internal and external aquarium setup. This setup is done in four tanks for four different samples of fish. The external sensors are used to measure environmental conditions outside the aquarium and internal setup is to measure the water quality and the livable conditions of the fish.

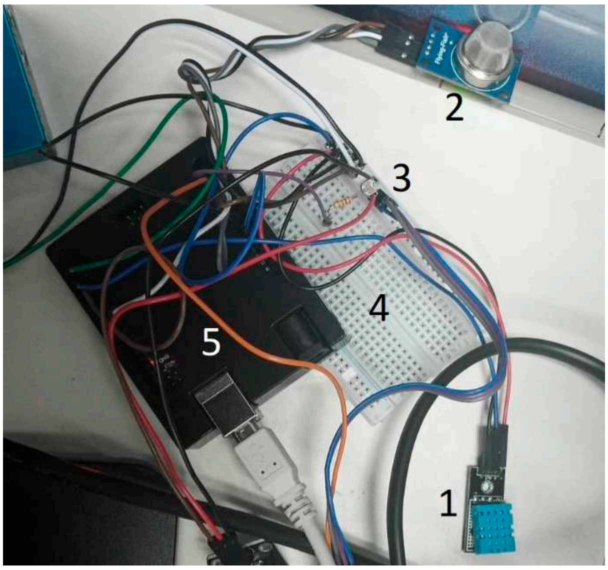

Figure 3 External Aquarium setup. 1. DHT 11 sensor, 2. CO sensor, 3. Light intensity sensor, 4. Breadboard to bridge Arduino with sensors and 5. Arduino Microcontroller

The Figure 3 above shows the external aquarium setup. This includes the sensors and microcontroller used to measure the atmospheric conditions surrounding the aquarium.

Figure 4 Internal Aquarium Setup. 1. pH sensor, 2. Water temperature sensor, 3. Indian Almond leaf, 4. Betta Fish, 5. Coarse gravel and marble base and 6. External hanging filter coupled with surface skimmer.

The internal setup of the experimental aquarium is given in Fig. IV above. It consists of external hanging filter with surface skimmer. Surface skimmer is used to extract the oily substances on the surface of water. The oily substances come from the pheromones secreted by the fish and breaking up of food and fecal wastes of the fish. Oily surface is responsible for the blockade for atmospheric oxygen from mixing with water. This condition is peculiar for Nano sized captive aquaria. The rear and side walls of the aquaria are wrapped with polymer sheets with 100% opacity. This is done to decrease the aggressiveness of betta. B. *splendens* are prone to aggressiveness when they get exposed to mirrors, glasses, other fishes outside and some bright objects [28]. This aggressiveness is increased due to the drop in serotonin hormone in the fish. When the captive aquaria are covered with opaque polymer sheets, aggression of B. *splendens* males are proved to be controlled [29]. This reduces the stress buildup in the fish taken for experimentation. The total setup of the aquarium is given a polymer shield to limit the light exposure inside the tank. This is a manually controlled environment to aid an environment for the fish to be with less stress and conduciveness to survive. Indian almond leaf is added to provide necessary minerals soluble in water. Moon tail B. *splendens* are used in the experiments. Indian Almond leaf is responsible in maintaining the quality of water conducive for B. *splendens* to survive [30]. Increase in serotonin will effect in lifespan of B. *splendens* within itself. As a result of this controlled environment setup, the water quality and the effect of parasites due to external factors are taken into account for the prediction of water change time using machine learning algorithms. A DC motor is connected with a base sump and water supply. It is automated to change 25% of water weekly by default. It will initiate water change of 30 % when the machine learning module predicts any abnormality and maintains the water quality. The proposed methodology is applied on 3 out of 4 tanks with less control over the environment. The proposed method is validated against the existing methodologies with the following configurations.

Table 2 Experiment configurations

S.No	Evolutionary Technique	Classifier	Classifier Parameter
1	Ant Colony Optimization	SVM in LIBSVM	Radial basis function
2	Ant Colony Optimization	SVM in LIBSVM	Polynomial kernel
3	Ant Colony Optimization	Ensemble SVM	Naïve Bayes for timeseries subset and polynomial kernel for sensor data
4	Ant Colony Optimization	Ensemble SVM	Naïve bayes for timeseries and rbf kernel for sensor data
5	Particle Swarm Optimization	SVM in LIBSVM	Radial basis function
6	Particle Swarm Optimization	SVM in LIBSVM	Polynomial kernel
7	Particle Swarm Optimization	Ensemble SVM	Naïve Bayes for timeseries subset and polynomial kernel for sensor data
8	Particle Swarm Optimization	Ensemble SVM	Naïve bayes for timeseries and rbf kernel for sensor data
9	Proposed Local Maxima Niching GA	SVM in LIBSVM	Radial basis function
10	Proposed Local Maxima Niching GA	SVM in LIBSVM	Polynomial kernel
11	Proposed Local Maxima Niching GA	Ensemble SVM	Naïve Bayes for timeseries subset and polynomial kernel for sensor data
12	Proposed Local Maxima Niching GA	Ensemble SVM	Naïve bayes for timeseries and rbf kernel for sensor data

Identical tanks with same species of fish belonging to the same age group were used to check the performance of the algorithm. Pandas library was used for data collection and cleaning. Numpy was used as a support for ga library used for genetic algorithm. The usage of this library was customized based on the proposed genetic algorithm. Scikit learn was used to create the ensemble classifiers in the fitness solution.

After providing a manually controlled environment to one of the sample aquaria, the vital parameters of the water quality remained constant. Internal and External temperatures had its ideal variance and pH remained between the range of 6.5 – 7. The water when maintained with lesser transparency and more soluble solids and minerals, the water in the aquarium appeared as in the Figure 5 below. The color of water is not transparent due to the mixing of soluble iron, calcium and other vital minerals from the almond leaf. This is obtained 8 hours after the setup of the aquarium. Remaining three aquaria are not controlled with any of the above factors.

Figure 5 Ideal condition maintained

The tanks with no manual control over environment are taken to collect data and processed to predict the possible water change. This has been compared with some normal evolutionary methods like Ant colony optimization, particle swarm optimization, normal genetic algorithm and crowding multi objective genetic algorithm coupled with various classifiers and their parameters as shown in the configurations mentioned in the experiments section above. The accuracy obtained for primary experimentations and the proposed methodology is given in Table 3.

Table 3 Accuracy obtained for each experimental configuration

S.No	Evolutionary Technique	Accuracy
1	Ant Colony Optimization with SVM – rbf kernel	66.0%
2	Ant Colony Optimization with SVM – polynomial kernel	63.55%
3	Ant Colony Optimization with Ensemble SVM combination 1	62.67%
4	Ant Colony Optimization with Ensemble SVM combination 2	61.11%
5	Particle Swarm Optimization with SVM – rbf kernel	54.55%
6	Particle Swarm Optimization with SVM – polynomial kernel	58.22%
7	Particle Swarm Optimization with Ensemble SVM combination 1	75.58%
8	Particle Swarm Optimization with Ensemble SVM combination 2	70.22%
9	Proposed Local Maxima Niching GA with SVM – rbf kernel	76.12%
10	Proposed Local Maxima Niching GA with SVM – polynomial kernel	73.77%
11	Proposed Local Maxima Niching GA with Ensemble SVM combination 11	74.55%
12	Proposed Local Maxima Niching GA with Ensemble SVM combination 12	79.70%

The proposed methodologies gave better accuracy with the second combinations of Ensemble SVM. The confusion matrix of the best performing methodology listed in Table 3 is given in Table 4 with the split of class-wise accuracies. Combination 11 and 12 corresponds to the respective ensemble SVM configuration mentioned in Table 2. There are few challenges in the approximation of timestamp data. Clouding of water due to over feeding, external dust mixing with water changes the condition of water and prepares a non seasonal trend. The proposed methodology is considerably successful in managing this issue by dynamically creating niches by the local maxima. So it will be automated to change niches over the course of time also.

Table 4 Confusion Matrix for Local Maxima Niching GA with Ensemble SVM combination 12. Accuracy listed in percentage of instances tested

	Normal	Water change due to poor water quality	Water change due to parasitic attacks
Normal	88.55	11.45	0
Water change due to poor water quality	11.53	78.69	9.78
Water change due to parasitic attacks	16.68	11.45	71.87

The data collected was huge in number and storage space and the evolutionary algorithms took many generations over time for each decision to make. Despite the fact of time consumption, this methodology used less water consumption than manual water change scheduled once in a week.

Figure 6 Fin rot observed due to fungal attack and parasite ich

Table 5 Vulnerabilities observed with various pH level

S.No	pH value range	Vulnerabilities
1	6.5 – 7.5	Nil
2	7.6 – 11	Irreversible Fin rot, mortality, Parasites
3	<6.5	Poor water quality, ich, fungus, parasites, mortality, inadequate oxygen, increased carbonic acid, increase in CO and methane emission

Various vulnerabilities are listed in table 5. Thought parasites flourished below and above the normal pH range, other sensor data as features helped to increase the inter class distance between the classes by the classifier used in the proposed methodology.

Table 6 Conditions of fish observed with various methodologies

S.No	Evolutionary Technique	Final status	Diseases observed and treated
1	Ant Colony Optimization with SVM – rbf kernel	Alive	Ich, fin rot
2	Ant Colony Optimization with SVM – polynomial kernel	Died – 1 month	Ich, Nitrate poisoning
3	Ant Colony Optimization with Ensemble SVM combination 1	Alive	Fin rot
4	Ant Colony Optimization with Ensemble SVM combination 2	Died – 2 months	Ich, swim bladder
5	Particle Swarm Optimization with SVM – rbf kernel	Died – 1 month	Ich, Nitrate poisoning
6	Particle Swarm Optimization with SVM – polynomial kernel	Died – 3 months	Fin rot
7	Particle Swarm Optimization with Ensemble SVM combination 1	Alive	Fin rot
8	Particle Swarm Optimization with Ensemble SVM combination 2	Alive	Gasping due to CO2 concentration
9	Proposed Local Maxima Niching GA with SVM – rbf kernel	Alive	NIL
10	Proposed Local Maxima Niching GA with SVM – polynomial kernel	Alive	Gasping due to CO2 concentration
11	Proposed Local Maxima Niching GA with Ensemble SVM combination 11	Alive	NIL
12	Proposed Local Maxima Niching GA with Ensemble SVM combination 12	Alive	NIL
13	Ideal conditions with controlled environment	Alive	NIL
14	Normal instructions followed by beginner in hobby	Died – 1 month	Ich, fin rot, swim bladder

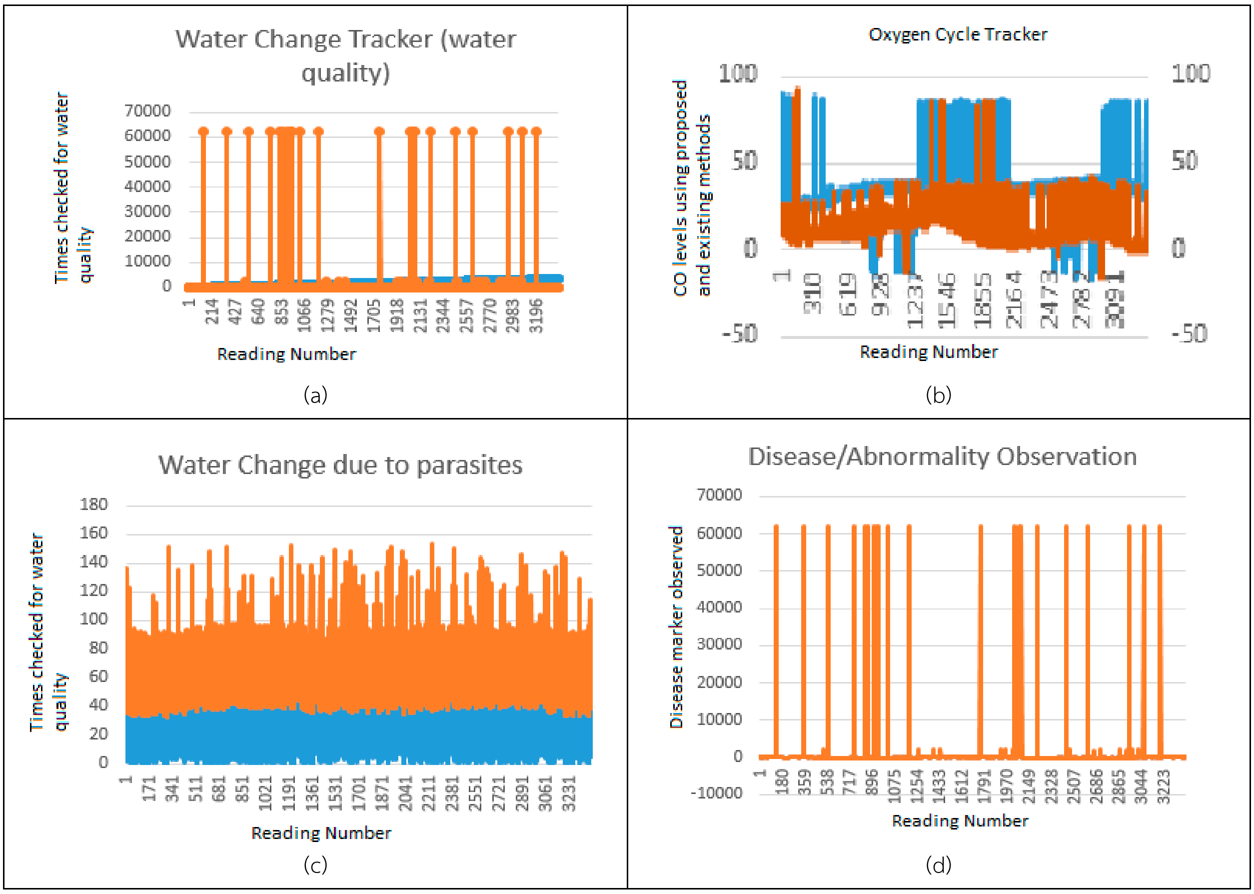

Figure 7 Performance of various water quality parameters of proposed methodology with respect to cumulative mean of all other methodologies. Orange series belongs to proposed and blue belongs to existing methodologies. (a) Total water changes done over every week due to poor water quality, (b) Total water changes done due to parasitic attacks, (c) Oxygen – CO2 cycle maintained and (d) Diseases observed and treated.

The qualitative results from Figure 7 clearly shows that the proposed methodology hold better in maintaining water quality of the captive aquaria of B. *splendens* when compared to many other methodologies tried. The mean of all the existing methodologies are compared against the performance obtained in proposed methodology. There was less water changes for the tank using proposed methodology which resulted in 80% savings in terms of water usage. The O2 – CO2 cycle also maintained optimum using the proposed methodology. This system holds good even to leave the aquaria unattended during vacations provided an automatic digital feeder is attached to the tank. However, the amount of food consumed and wasted also contributes to decrease in water quality. Water quality due to food wastage is not considered in the experiments reported in this paper.

V. CONCLUSION

The proposed IoT framework and its machine learning approach of genetic algorithm as a product proved to predict abnormalities in water condition and poor water quality. This triggered in necessary water change automatically using a small DC sump motor. The accuracy reported in the results looks promising and increases the healthy lifespan of B. *splendens*. There are still some issues in finding the local maxima niche when it comes to the timestamp data. The local maxima found in one generation has to be constant or close to the concordant values. Else the accuracy in predicting water change for poor water quality and water change for parasitic attack will have an under-fitting of classification and thereby the accuracy of the proposed methodology dropped considerably. However, with the accuracy factor obtained, the healthy lifespan of B. *splendens* increased when compared to water change and monitoring done by human intelligence as per recommended settings. The proposed method holds good for tanks with single male B. *splendens*. The calibration of the classifier will change for huge water sources housing the fish in large quantities like breeder facilities and retailer's tanks. This research area has scopes to expand to various other species, tanks with mixed species, schooling fish species in fresh, marine and brackish water ecosystems.

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