# Fish Growth Performance Classification Based on Ammonia Concentrations

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**Abstract.** Ammonia is defined as the hidden assassin of a variety of aquatic organisms including fish. Moreover, The ammonia concentrations affect fish hatcheries and growth rates. Relatively, this affects a main source of protein for human consumption, plus the toxicity that may be a cause of convulsions, coma, and human death. Therefore, monitoring ammonia levels and their effects are important for human safety. This paper introduces a classification of growth performance levels those produced by Nile Tilapia fish, which are related to the concentration of ammonia in water. The proposed approach is a hybrid approach that uses Water Wave optimization (WWO) technique and Support Vector Machine (SVM) classifier for optimally classify fish growth level. Through breeding 160 Tilapia fish, a number of physical measurements, such as length, weight and protein level of a fish, were gathered through time duration of 60 days. The experimental results show an improved classification accuracy of the proposed hybrid approach over the traditional SVM that reached to 90.48% detection accuracy.

**Keywords:** Tilapia Fish, Support Vector Machine SVM, Ammonia Concentration, Water Wave Optimization (WWO), Fish Protein.

## 1 Introduction

Nile Tilapia (O. Niloticus) is the most farmed Tilapia species in the world as an important source of humans' protein. There are numerous factors that badly affects the Tilapia protein production such as Water pollution. uncontrolled concentrations of Ammonia is a type of pollution that affects on fish farming and the net production. Ammonia is the principal nitrogenous waste product of fish that represents 60% to 80% of nitrogenous excretion of the fish [1]. Although it is the end product of protein catabolism [2], it is a main nitrogenous waste material excreted by gills along with both urea and amines. Under intensive rearing conditions, especially, when affluent is reused, ammonia concentrations may reach levels that limit fish survival and growth [3] [4].

The new advances in Machine Learning (ML) facilitated the automation of fish detection and classification [5], [6]. Also, a number of researches had introduced the use of ML techniques for fish diseases detection such as [7], [8]. The current research proposes the use of a machine learning technique that is based on the SVM classifier for evaluating parameters of a meta-heuristic optimization algorithm.

The remainder of the paper is presented through the following sections; Section 2 focuses on other former researches. Section 3 defines fundamentals about the meta-heuristic approach applied within the paper. The proposed fish growth classification approach is introduced in Section 4. Section 5 evaluates the experimental results. Finally, Section 6 concludes the paper contributions and provides future research directions.

## 2 Related Work

Classification optimization using optimizer algorithms have been applied in a number of former researches. [9] introduces the idea of convex hull classifier optimization and binary classification in general. Genetic Algorithm (GA) applied for optimizing k-nearest neighbors classifier given the weight and offset parameters as search dimensions [10]. Also, the GA has been combined with SVM to accurately classify colon, leukemia, and lung cancer datasets [11]. In [12], gradient descent optimizer is employed to fine-tune the Area Under the Curve (AUC metric) using multiple classifiers. Particle Swarm Optimization (PSO) algorithm has been used by several researchers to optimize the output of classification. [13] had applied PSO to get maximum generalization of SVM classification accuracy for Electromyography (EMG) signals. Classification procedure had been run on all PSO particles at each generation and fine tuned the kernel parameters. [14] also gives an approach for SVM parameters tuning using Simulated Annealing Optimizer where search dimensions are set to be classifier parameters such as the kernel selection (Radial Basis, Polynomial and other functions) and the kernel parameters (penalty and gamma). This as well as feature selection and hence, optimizer heuristically searches for the best setting of all classification variables. [15] Also showed a prediction approach for the growth cycle of the Spirulina platensis from raceway experiments data.

SVM is a reliable classification mechanism, originated at 1990s and has been applied for pattern recognition problems, showed success in various machine learning problems and has proved to achieve highly generalized classification results. SVM tends to find greatest separating margin (Vectors) among classes of data using a kernel function [16]. A great number of applications based on SVM has been proposed in former research over the last twenty years. In addition, Fouad et al. [5] introduced research effort where SVM algorithm was used to detect Nile Tilapia fish. Their work gave a performance analysis of integrating the SVM with feature extraction algorithms such as Scale Invariant Feature Transform (SIFT) [17] and Speeded Up Robust Features (SURF) algorithms [18]. The accuracy of the work reached near to 94% with the SURF feature extraction algorithm. Moreover, the work of [19] where the performances of a number of classifiers (SVM, Neural Network, K-Nearest Neighbor) were compared after the application of feature reduction phase by the bat optimizer over a Nile Tilapia images data set. The results showed degrading of the detection accuracy of SVM algorithm after feature reduction phase compared to the K-Nearest Neighbor algorithm.

This research paper proposes a machine learning approach for classifying fish growth indicators (weight, and height) levels based on different ammonia concentrations dissolved in water. Data collection was accomplished through the farming of more than one hundreds of Tilapia fish that were separated in equal groups, with exposure to different ammonia concentrations.

## 3 Water Wave Optimization Algorithm (WWO)

WWO is a new meta-heuristic optimization algorithm [20]. It had been extended with advanced learning technique [21]. Search agent here is a water wave performing exploration and exploitation mechanisms updating wave location for candidate better solutions. The basic WWO algorithm initiated search space of waves ($w$) of length 0.5 and fixed hight value ($h_max$). Through searching for the optimal solution the algorithm mimics the water wave motion in terms of wave propagation, refraction and wave breaking. Figure 1 illustrates the increase of energy of the water wave along with significant decrease in their length when reaching the best solution.

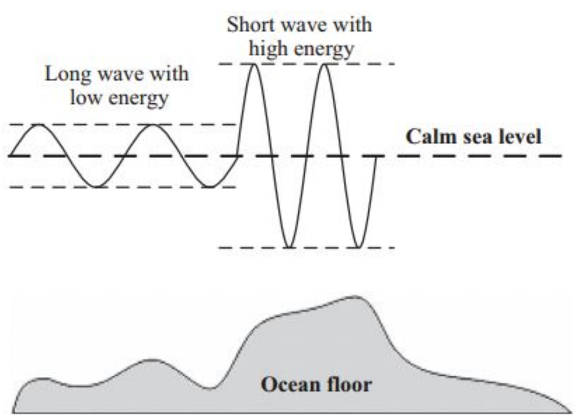


**Figure 1:** The Water Waves through their search for the Best Solution. [20]

As all optimization algorithms, WWO applies a set of exploration and exploitation equations to move waves (search agents). first one propagates a wave to new position through appending a new random value per each dimension of the current wave [21]. A Breaking equation performs exploitation, works with the new waves, those of higher values over the best wave in search space. Finally a refraction equation performs position updates on the waves which preserved their original position for each generation.

After a number of iterations Algorithm provides optimal solution found so far. The main feature of WWO is its quick convergence to an optimal solution. Its simple characteristic is inherited from the simplicity of the algorithm parameters and settings those required in the run time.

## 4 The Proposed Classification Approach

### 4.1 Ammonia-Protein Data Set

Data was collected from real in-vitro experiments (fish tanks), that started with five equal-sized groups of Tilapia fish (40 fish per group) as in [22]. All groups have shared the same physical geometries of their members (length, and weight). Each group had been subjected to a specific unionized ammonia nitrogen (UIA-N) concentration (0.1, 0.2, 0.4 and 0.6 mg/L). In order to control ammonia levels, the ammonium chloride powder (NH4CL) was dissolved in the tanks with controlled amounts. The Spectrophotometry was used to monitor the ammonia concentrations.

Experiment was established by maintaining fixed levels of water temperature and $pH$ for a duration of 60 days, fish growth physical symptoms were measured biweekly. The weight of each fish was collected through a digital scale and length was measured with flat board.

Table 1 illustrates the five groups of fish; The first group is the control group of experiment and the rest represent higher concentrations of ammonia ($AmmConc$). $L$ in the table represents fish length, $W$ is the weight, $OGV$ is the oxygen gill ventilation, and finally the $DWO$ indicates the dissolved water oxygen.

Figure 2 shows the layout of classification optimization process. Ammonia Dataset is fed to the system in three pairs of equal partitions (three training and three validation), each representing a one third of the dataset. Secondly, WWO started by initiation for all waves locations. Each wave location is to represent a combination of Penalty, Gamma parameters and features set (G, P, F). Once wave location is updated the fitness is calculated by performing three training-validation tests on the three pairs of data partitions, then the results were averaged. As from the WWO optimization, the WWO algorithm runs its previously mentioned exploration and exploitation strategies (refraction, propagation and breaking) to update waves' location based on the fitness function.

WWO fitness function is evaluated by calculating SVM classification accuracy measure averaged over three folds of data. At fitness calculation, the SVM is trained by three training sets and validated against three validation sets.

**Table 1**
The Ammonia Concentrations Over 60 Days for 5 Groups of Nile Tilapia

| | | Days | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | AmmConc mg/l | 0 L | 0 W | 15 W | 30 W | 45 W | 60 L | 60 W | OGV | DWO | pH |
| control | Sample1 | 0.013 | 14 | 42.6 | 54.2 | 73.3 | 88.6 | 17.3 | 101.3 | 6.4 | 7.1 (+/-) 2 | 7.4 (+/-) 1.1 |
| | sample2 | | 14.2 | 43.1 | 56.3 | 73.4 | 89.8 | 18.2 | 102 | 6.3 | | |
| Group1 | S1 | 0.1 | 14 | 42.7 | 49.3 | 57.2 | 74.5 | 16.3 | 81.6 | 5.9 | 6.6 (+/-) 1.8 | 7.2 (+/-) 0.85 |
| | s2 | | 13.9 | 42.4 | 48 | 56.1 | 70.5 | 15.5 | 79 | 5.2 | | |
| G2 | s1 | 0.2 | 14 | 42.5 | 46.7 | 53 | 61.8 | 15.3 | 61 | 4.6 | 6.5 (+/-) 1.23 | 7.6 (+/-) 1 |
| | s2 | | 14.4 | 43 | 48.2 | 54.6 | 62 | 15.6 | 61.8 | 4.5 | | |
| G3 | s1 | 0.4 | 14.3 | 43 | 46.2 | 50.2 | 51.7 | 14.8 | 51.1 | 3.6 | 6.8(+/-) 1.5 | 7.4 (+/-) 0.7 |
| | s2 | | 14.2 | 42.7 | 45.9 | 49.8 | 51 | 14.5 | 49 | 4.7 | | |
| G4 | s1 | 0.6 | 14,2 | 42.5 | 42.6 | 42.3 | 42.2 | 14.5 | 41.7 | 4.1 | 6.3(+/-) 1.5 | 7.3 (+/-) 1.8 |
| | s2 | | 14 | 42.6 | 42.5 | 42.1 | 42.1 | 14.5 | 41.1 | 4.6 | | |

### 4.2 The WWO-SVM based Fish Growth Algorithm

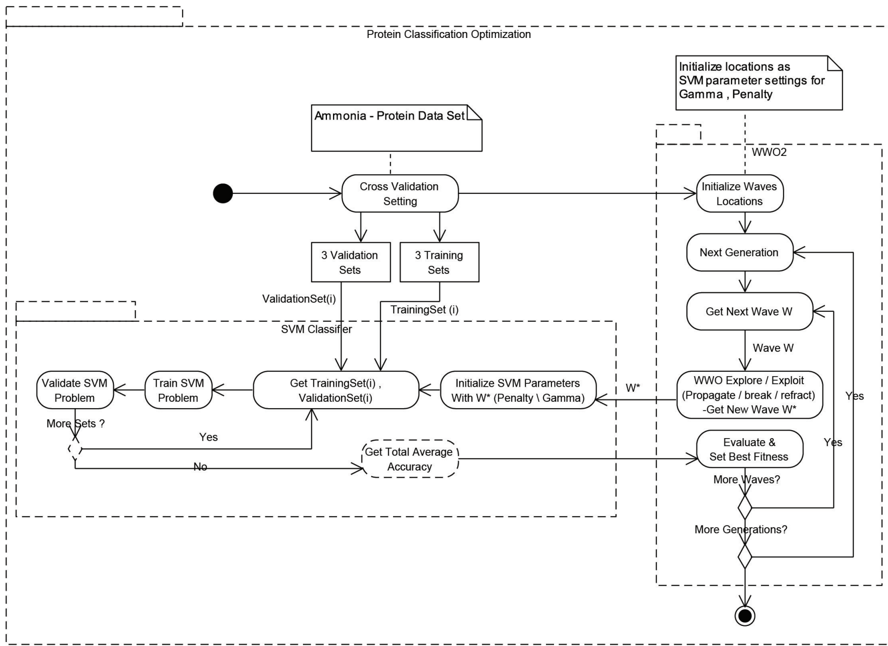


**Figure 2:** Protein Classification - WWO Optimization

Validation is obtained by a construction of confusion matrix. But for $n$ classes. Total accuracy is calculated as the average of true positive (TP) predictions, this is the sum of diagonal of confusion matrix [23] divided by class count (1). Step 8 in algorithm 1 shows the role of the SVM (algorithm 2) for calculating the objective function of the WWO through the training of its parameters; Where P, G and F represent the penalty, gamma and feature set parameters respectively.

$$Accuracy = \frac{\sum_{i=0}^{n} M_{ii}}{n} \tag{1}$$

## 5 Experiments and Performance Evaluation

While SVM classifier was acquired from an open source library *libsvm* [24], implementation of WWO was implemented over C#.NET language. As discussed before, SVM classifier was employed to calculate objective function of WWO

**Algorithm 1** Ammonia-Protein Effect Classification

```
Input: 3 Ammonia Training Sets (Folds) (T1, T2, T3)
Input: 3 Ammonia Validation Sets (Folds) (V1, V2, V3)
Output: Total Accuracy, Precision, Recall and Fmeasure
Initialize WWO Waves
for G ← 1 to GenerationsCount do
    for W ← 1 to WavesCount do
        WWO move W to new location W* = (P,G,F).
        WWO Evaluate_Fitness at (P,G,F) (Algorithm 2).
    end for
    BestWave ← Find Best Wave with highest Fitness
end for
Retrieve Best Wave with Best Fitness
EXIT
```

**Algorithm 2** Evaluate Wave Fitness

```
Input: 3 Ammonia Training Sets (Folds) (T1, T2, T3)
Input: 3 Ammonia Validation Sets (Folds) (V1, V2, V3)
Input: Classification Parameters (P, G, F)
Output: Total Accuracy, Precision, Recall and Fmeasure
for Each Training Set T_i ∈ T1, T2, T3 do
    Train SVM on T_i with parameters (P, G, F)
    Validate Training on V_i Set
    Acc ← Acc + ValidationAccuracy
end for
TotalAccuracy ← Acc/3
Fitness ← TotalAccuracy
EXIT
```

**Table 2**
Protein-Ammonia Classification Resutls

| Run | Acc | Prec | Rec | FM | Spec | P | G |
|---|---|---|---|---|---|---|---|
| 1 | 76.98% | 64.59% | 63.99% | 61.03% | 97.24% | 690 | 0.299 |
| 2 | 90.21% | 68.68% | 72.49% | 69.96% | 98.78% | 690 | 0.299 |
| 3 | 89.95% | 68.50% | 72.25% | 69.69% | 98.75% | 630 | 1.255 |
| **4** | **90.48%** | **69.00%** | **73.30%** | **70.69%** | **98.82%** | **630** | **1.255** |
| AVG | 86.90% | 67.69% | 70.51% | 67.84% | 98.40% | | |

***FS : Features Selection / P,G : Penalty and Gamma optimization**

optimizer. Moreover, the dataset was normalized to the nearest integer number over growth indicator columns, and it was classified to five classes based on these indicators.

Performance evaluation of the proposed algorithm considers the accuracy of classification of growth indicators for each ammonia concentration, as the main performance indicator. Also, evaluation uses other measurements such as the *recall* and *precision* by statistical equations shown in equation (2) and equation (3) , respectively [25].

$$Recall = \frac{TP}{totalinstances} \quad (2) \qquad Precision = \frac{TP}{TP\ +\ FP} \quad (3)$$

Where $TP$ is the total number of correct (positive) predictions and $FP$ is the total number of false (negative) predictions [23], total instances is the total number of predictions. $TP$ is calculated over the diagonal of confusion matrix, while $FP$ is the average of columns of confusion matrix.

Table 2 shows classification results in terms of Accuracy (Acc), Precision (Prec), Recall (Rec), F-Measure (FM), Specificity(Spec), Penalty(P) and Gamma(G). It states a maximum accuracy for all runs of 90.48%. Such measures are calculated separately for each class of data (growth indicator level) and then averaged over all classes obtained on the dataset. Max precision and recall are 69% and 73.30%, respectively.

Important to note that optimization has been accomplished through 4 stages (4 runs), each stage switches between SVM parameter optimization and feature optimization. Each stage maintains either parameters set or features set constant, while optimizing the other classification variables. Figure 3 also shows penalty and gamma values among the four stages. Results also show how useful is the staged optimization, we can see that stage 4 reached the highest accuracy and performance.

A test was repeated five times on the same dataset for the five consecutive runs with same chunks of training and validation. The outcomes of five tests are in terms of the overall classification accuracy. Table 2 shows the classification results in terms of the previously mentioned measures. The table also shows the best penalty and best gamma parameters set for SVM classifier.

## 6 Conclusion and Future Work

This research proved the effect of Ammonia Concentration in fish environment on the amount of fish growth indicators which reflects production quality. Experiment is accomplished in two stages; the first is in lab experiments for data collection. Where, five groups of Tilapia fish were bred in water tanks for 60 days with different level of ammonia concentrations (ammonium chloride powder). The 40 fish in each tank shared same geometrical properties and environmental parameters. Then applied an optimized version of a machine learning technique (SVM with WWO optimization) to classify growth indicators (weight, and length) levels based on ammonia concentrations. Classification results of the hybrid approach showed acceptable classification accuracy that reached to 90.48%. Although the result suggests the use of the proposed approach for monitoring fish production, it still needs more modification to increase the detection accu-

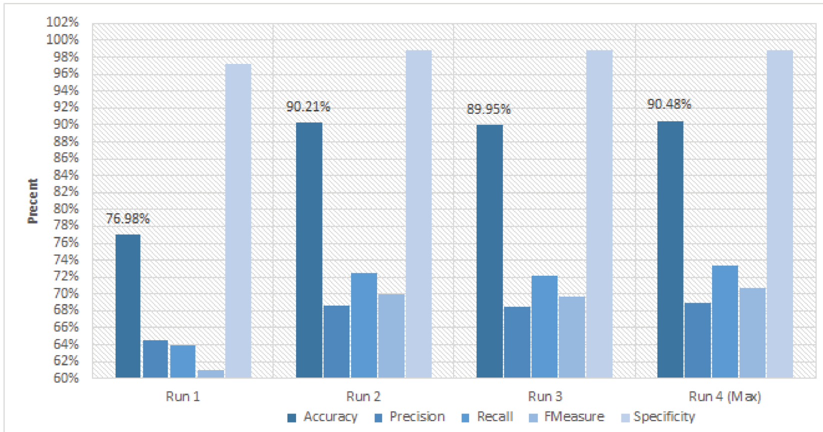


**Figure 3:** The perofmance evaluation of the proposed appraoch

racy. Moreover, the use of another optimization approach is to be considered in future studies.

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