Toward Sustainable High-Yield Agriculture via Intelligent Control Systems

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Abstract -- **Hunger ranks as the number one health risk facing the world today, with scarcity of natural resources playing a key part in the problem. Aquaponics has the potential for high-yield plant and animal production but has parameters that are substantially more difficult to maintain. To prevent failure and ensure maximum yields for minimal outside input, this paper proposes AI-based data mining to learn and maintain proper environmental conditions. Experiments are conducted that determine the appropriateness of various AI techniques for this project. These AI techniques are being applied in a real-world aquaponics farm.**

Keywords: artificial intelligence, agriculture, aquaponics

I. INTRODUCTION

With approximately 870 million malnourished people in the world today, hunger tops the list of the worst health risks facing mankind (FAO, 2011). This problem is being addressed from multiple directions, including technological developments, policy implementation, education improvements, and financial assistance (Sanchez, 2009; Bratspies, 2012).

One cause of hunger is scarcity of natural resources, particularly water and fertile ground. Aquaponics has shown potential as a method of overcoming this problem by completely eschewing the use of soil and needing only 2 to 10% of the water required by traditional farming methods.

The term *aquaponics* is a portmanteau of the terms *aquaculture* (raising aquatic animals such as fish) and *hydroponics* (cultivating plants in water). In such a system, plants and animals exist in a symbiotic relationship, nourishing each other and removing toxins harmful to the other. In its most basic form shown in Figure 1, bacteria break down the toxins created by fish and provide nourishment to the plants in the form of nitrogen compounds. The plants then filter out the nitrogen and provide a beneficial habitat for the fish.

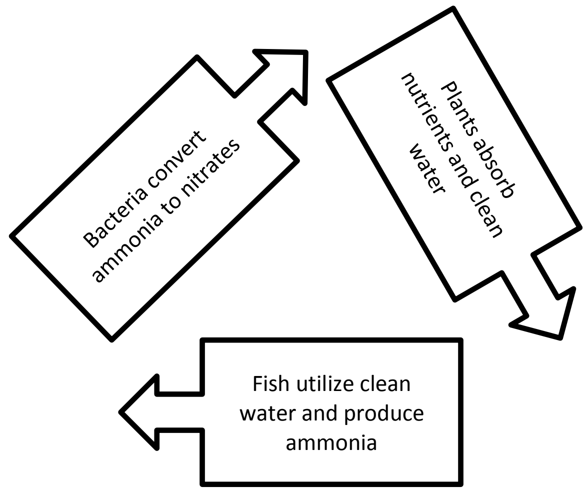

Figure 1: Aquaculture Cycle

One complication with the use of aquaponics is the margin of error restrictions when compared to traditional farming techniques. While traditional farming can be successful under a variety of conditions, aquaponics is far less forgiving. If the margin of error in traditional farming could be compared to the width of a two-lane highway, the margin of error in hydroponics is a six-foot sidewalk, and aquaponics' is a narrow footpath. Thus, constant monitoring must be provided to maintain ideal conditions lest the system break down with disastrous results.

In its most basic form, this monitoring could be performed manually by humans. However, as the size and complexity of the aquaculture system increases, the chance of human error increases. In fact, the complexity of the system could prevent humans from even noticing correlations between events occurring in seemingly unrelated portions of the structure. This problem increases as modern sensor technology is added; although sensors provide round-the-clock monitoring, the significance of particular details in massive amounts of data can easily be obscured.

This paper proposes the use of artificial intelligence to provide data mining of relevant sensor data in an aquaponics system. The AI could discover growing parameters that are most successful in the farm's particular climate and maintain those parameters once reached. The experiments in this paper aim to isolate AI techniques that pertain to this goal.

The remaining portions of this paper are as follows. Section 2 explores the history of aquaponics and current research on the topic. Section 3 examines potential methods for modeling the farm and AI. Section 4 details our experimentation and results. Section 5 describes our on-going real-world work on this topic.

II. Aquaponics Background

Aquaponics has been in use for many centuries, notably in ancient Central American and Southeast Asian cultures. However, recent developments in large-scale deployment have been pioneered by researchers at the University of the Virgin Islands (Rakocy, 2013). Many other tropical countries and islands have followed suit, attracted to the prospect of food production in resource-poor regions. Unfortunately, these efforts have focused on tropical climates where plant growth is at its most ideal.

Modern aquaponics consists of two separate components, one for fish and one for plants. The separation prevents the fish from eating plants destined for human consumption. Fish are further separated between young fish fry and older fish that may eat the fry.

The system in which the plants and fish are raised is a closed loop. This would generally limit the inclusion of no more than a few plants or fish before the system became toxic. However, the synergistic properties of plants and fish, combined with aggressive oxygen dissolution, allow a much higher concentration of agriculture yield than would normally be found in nature.

While many different species of plants and fish are possible, certain types are more commonly used. Tilapia are commonly grown fish, while leafy vegetables such as lettuce appear to perform well in an aquaponics system (Pantanella, et al, 2010).

There are several high-tech hobbyists who have begun to integrate sensors into aquaponics (ManyLabs, 2013; Robb, 2012). However, these systems are exclusively for monitoring conditions and alerting the operator to out-of-bounds conditions. They provide no control systems, nor do they quantify the effect of their sensors on the food yield (e.g., fewer dead fish leading to increased number that reach maturity).

Variations on the system are possible. Some could include additional small animals such as rabbits and chickens. The waste products of these animals can be used for fertilizer while the unused portions of their carcasses can be ground into meal for cross-feeding to the other species of animals in the system. In nutrient-poor conditions, additional fertilizer could be safely composted from many different types of waste materials, including sewage if necessary.

III. Methodology

Our real-world aquaculture farm utilizes many measurements taken from a number of locations. However, our data gathering experiments only those measurements that are provided by automated sensors. These sensors include sensors in both water and air. Air sensors are limited to brightness and temperature. Water sensors include clarity (brightness), temperature, dissolved oxygen, pH, nitrogen, and water current. These sensors are located at the entrance and exit of each tank in the aquaponics system.

Additional inputs come from human operators that designate when certain maintenance functions are performed. These include adding new fish, extracting healthy fish for food production, presence of dead or sick fish, addition of fish food, addition of water, addition of nutrients, and addition or removal of plant material. The location of each of these events is also recorded. Finally, the user records a range of times and dates where the system appears to be working well or poorly and assigns a confidence in the score.

We examined several potential methods for extracting relevant information from the data. Of particular interest for this paper were two AI techniques: artificial neural networks and nearest neighbor models. Each of these techniques should be able to utilize the user’s assessments of times and dates as training data for future decisions.

IV. Experimentation and Results

Utilizing simulation recommendations from other researchers in environmental information systems (Boote, et al, 2010) and data generated from existing sensors, we built a simple agriculture simulator to determine which, if either, of our methodologies would show potential capability for predicting events and determining appropriate behaviors in our aquaponics system.

We implemented the nearest neighbor model (Stanfill and Waltz, 1986) using a k-d tree, allowing it to search in $O(\log N)$ time and allowing real-world data to logged and used as training data at the same time. Accuracy was boosted by utilizing a support vector machine (Boser, et al, 1992) to kernalize the algorithm. This model did a good job of recognizing situations that were similar to known events, labeling them properly, and determining appropriate actions. However, solution time was over 100 times slower than a simulated neural network as shown in Figure 2. A neural network implemented in hardware would show significant improvements.

The neural network was implemented as a basic multilayer feed-forward network utilizing back-propagation for inputting the training set. This method had success rates lower than the nearest neighbor model, but the results were returned significantly faster.

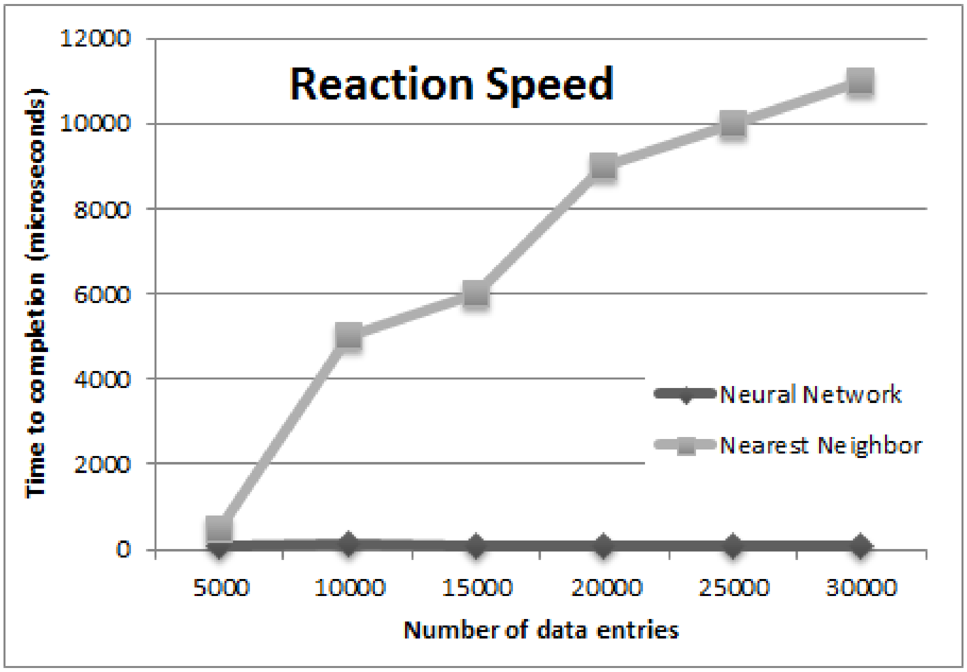

Figure 2: Reaction speed of Algorithms

Errors in the returned data were most likely caused by errors in the recorded times for events. If operators over- or under-estimate the time in which an event occurred (such as dying fish), unrelated data would be erroneously accused of being involved in the event.

Examination via qualitative analysis of these two algorithms provides similarly murky conclusions.

The slower speed of nearest neighbor doesn't appear to be a significant problem in an aquaponics system. While poor conditions can quickly kill fish stock, these times are measured in hours, not minutes or seconds. Thus, the slower speed should not impact our decision.

The nearest neighbor algorithm is also able to continuously learn from new data. This allows it to incorporate unforeseen events into its knowledge base. The neural network would require its operator to manually feed the new event data back into the AI as additional training information. On the other hand, the neural network's lack of a growing database allows for much cheaper memory requirements.

Additionally, the neural network can be implemented in much simpler hardware than the nearest neighbor algorithm. While the nearest neighbor algorithm may seem to be the clear winner, the reality is that the aquaponics system will likely be deployed in "rugged" conditions where maintenance of a complex computer system is not feasible. The neural network would be implemented as a simple "black box" control circuit.

It appears the best solution would be a neural network with a limited data memory. If a new training case was encountered, the data memory would allow the information to be fed back into the network for additional training. This capability should be provided in a very simple user interface, ideally with two dials to set the time range to include and a button to execute the retraining. Thus, the basic neural network could be trained for a general climate, with future modifications adjusting it to the local microclimate.

V. On-going and Future Work

This sensor network is currently being implemented on a farm in western Arkansas. One initial goal is to determine if such a system can boost the yield of an actual aquaculture system in a temperate zone. The farm has been in place for a year and has produced an average of over 3.5 pounds of food per square foot, a significant improvement over traditional farming at almost 0.25 pounds per square foot. Experiments will show if the AI can actually improve those numbers further. Experiments are currently being performed on tilapia and lettuce, but future trials will be performed on beans and roses.

Future experimentation will focus on association rule learning to allow an AI to determine appropriate actions for complex systems without requiring human input. For example, feeding fish may trigger a chain reaction that alters the pH of the hydroponic plant tanks. If the relationship is discovered, the AI could take pre-emptive measures to level the pH and prevent a spike whenever the fish are fed.

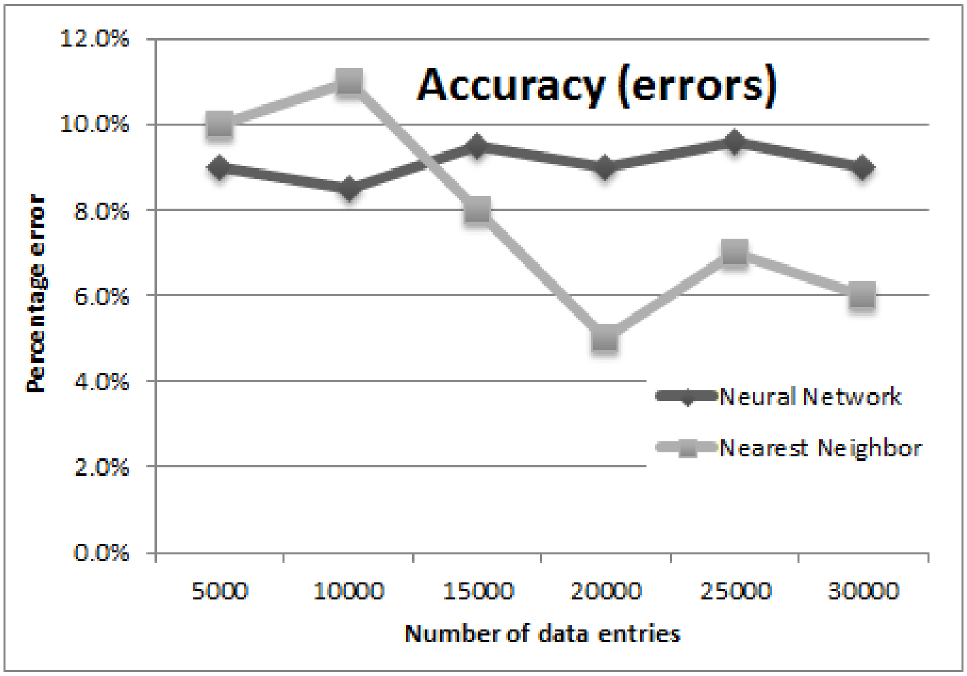

Figure 3: Error rate of algorithms

On the engineering side, steps will be taken to ruggedize the components for use by non-technical personnel.

Regarding quality assurance, steps can be taken to allow this system to degrade gracefully. Experiments will be run which will intentionally limit the capabilities of components to see if the system can be made to successfully adapt.

VI. References

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