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Evaluation of Mangrove Crab Classification System

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***Abstract* --- Mangrove crab has a growing demand in the Philippines and international market. However, the use of information technology to improve mangrove crab farming practices has been very limited. This study aims to develop mangrove crab classification using machine learning as well as use environmental sensors to monitoring temperature, water quality in real time basis. Images were analyzed using KNN. Results of this project show high recognition rates of the larval images in different stages with an average of 85% accuracy. Also, this project evaluates the software developed that monitors larval growth stages and classification having 4.68 overall weighted mean. Hence, the system is accurate and efficient in classification and growth stages monitoring activities.**

***Keywords:* object analysis, image processing, KNN, raspberry pi.**

I. INTRODUCTION

Mangrove crab also is known as king mud crab (Scylla Serrata) is one of the most expensive seafoods in both domestic and local markets. The most common variety of mud crabs found in the Philippines are: Scylla Serrata, Scylla Olivacea and Scylla Tranquebarica. Scylla Serrata is considered to be larger and less aggressive than other mud crab species [1]. SEAFDEC/AQD Department, Southeast Asian Fisheries Development Center (2004) found that the Philippines is the 3rd country with the highest mangrove crab production having 6,245 tons. However, culturing mangrove crab especially the embryo and larval are very difficult, embryos and larval fail to reach maturity due to food, water quality, and environment conditions.

However, there are severe disease causes of mangrove larvae which affect growth and production. On the other hand, water quality determines the ultimate success or failure of aquaculture that's why farmers regularly measure, record and manage water quality all through the growing season. Thus, image processing can be used to monitor the growth stages of larval. Moreover, it is not sufficient to provide support and feedback system. Also, machine learning is recognized in analyzing mangrove crab growth stages for a deeper understanding of the characteristics of mangrove crab larvae. Hence, there is the growing appreciation of the use of machine learning with image processing approaches to respond to this emerging need.

The prior study aims to classify the mangrove crab larval images using image processing and machine learning techniques. This study briefly presents the classification and evaluation results system using a widely accepted evaluation tool.

II. RELATED WORK

A. The environment of Mangrove crabs.

Scylla crabs dig and inhabit in mangroves and soft-bottom shallow intertidal water that's why mud crab is sometimes called mangrove crab. Culturing Mangrove crabs especially the embryo and larval are very fragile regarding their food and environment. Many embryos and larval failed their maturity simply because of the water quality especially when it is cultured. (Table 1) The parameters of water quality for larval are temperature, salinity, dissolved oxygen, pH, unionized ammonia, and nitrite. In monitoring the salinity of water of mangrove crab, the parameter should be 22 – 32 ppt [2]. This following parameter is the one to be monitored in this study.

Table 1. Suitable ranges of water quality for Mangrove crab larvae

Parameters	Range
1. Temperature	27-31 °c
2. Salinity	22-32 ppt
3. Dissolved oxygen	>4 ppm
4. pH	7.5-8.5

Another country like China is having a problem with the water quality particularly with the water temperature; one of the factors that affects the growth of mangrove crab is the water temperature, as well as the development and reproduction and even the survival of Mangrove crabs [3]. Since China is a country also falls into freezing winter maintenance of water for crab tanks are handled carefully, Unlike the Philippines, the weather is only dry and wet, no winter or cold season will affect the water temperature of mangrove crab environment. Hence, the Philippines is one of the Asian countries that produces a large number of mangrove crab. One of the studies conducted by the group in Northern Samar, the Philippines about the technology transfer of mud crab pond to rural aquaculture [4]. This study concluded that technology is a viable enterprise for aquaculture and farming, other factors such owner area, another is the farm distance from household and market is considered to be a challenge up to this time. However, water temperature was never an issue. Mangrove crab is generally found in mangrove water environment. Mangrove water is characterized by halophytic (salt-loving) trees,

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shrubs and other plants growing in brackish to saline tidal waters [5]. This study of problems in the environment of mangrove crab temperature especially in the country with a cold climate particularly in China remains a challenge in the industry. Another study about the problem in Mangrove crab environment is the changes of pH and sea level due to anthropogenic emission of CO2, another is the heat and oxygen content, vertical stratification, and other greenhouse gasses [6]. This greenhouse gasses are unlikely to decrease by decades. Thus, the prediction of these changes provides a significant problem in the marine life. Providing an innovative mangrove crab environment using tanks will help and can provide a great solution with the changing saltwater quality and environment.

B. Water monitoring of mangrove crab.

There are different effects of cultured water management on the survival of mangrove crab. Many fail in mass cultures of mud crab larvae were attributed to bacterial infections. An attempt was made to deliver the highest quality water and temperature monitoring. Water with more free hydrogen ions is acidic pH is the best indicator if the water is changing chemically [7].

Raw seawater was filtered through rapid flow sand filters to approximately 5µm. It was then slowly pumped through a secondary bank of sand filters before being passed through a 1µm filter bag. From here the water was passed through a UV light unit and was then foam fractionated and settled for approximately 4–10 days before use. Also, water passed through activated carbon as part of the re-circulating system. The high filtration aimed to establish a stable non-pathogenic bacterial flora so that opportunistic, pathogenic bacteria are unable to establish.

Furthermore, a seeding program was put forward as a means of further preventing the establishment of pathogenic bacteria. It is also the best platform that can be used in building automation system that can be attached to different hardware like sensors [8]. Benign bacteria could be introduced to the system to occupy the niche of potential pathogens. The distribution of the water substance is calculated by water quality model [9]. Thus, far no specific probiotics have been developed for mud crab larval rearing in Australia, a broad spectrum of bacteria was suggested as a source [10]. Biofilters are a known bacteria-rich environment, and although pathogenic bacteria may also reside amongst the microbial flora, the risk of introducing these pathogens may be minimized by using biofilter material from a re-circulating system where the host has not been present [11]. In our situation, live bacteria from a finfish system was suggested as a source of nonpathogenic bacteria for our mud crab larval rearing system. The following larval rearing run was conducted to assess the influence of incorporating established bacterial flora in the larval rearing system.

A. Larval Image classification

KNN or k-nearest neighbor classification algorithm process is, from the feature of the given vector, it finds the nearest neighbors among the training vectors then categorize it to determine the test vector [12] [13]. Furthermore, for the binary case used for each test frame, ratio is calculated then all the positive examples within it KNN will be declared as the positive likelihood. It also classifying objects based on the closest or most similar training samples. The nearest neighbor is determined using distance function which is given by

$$d(x, y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \tag{1}$$

An object is classified by a majority vote of its neighbors [14]. The difference of KNN to other supervised classification techniques, to increase its processing time, its algorithm does not derive any signatures or generalization from the training data, and thus it requires the training data in the testing phase. Thus, it is an extension of the nearest neighbor algorithm as it considers nearest k neighbors instead of a single nearest neighbor to vote for most classification for a pixel.

A. Raspberry Pi 3 Model B

Raspberry Pi, it is a platform in building automation system also, it can be used as “hub” in connecting other open-source hardware parts like sensors [15]. Raspberry pi is also compatible with IOT technology, with this technology, raspberry pi reaches the ground level with its application in agriculture and aquaculture. Using sensors to determine the water quality is a critical factor in culturing aquatic organisms. As a result, preventive measures can be taken in time to minimize the losses and increase the productivity [16].

A. Image Processing

Image processing methods performs operations to a certain image that can be extracted to get some useful information or to enhance the image. Processes in imaging includes the following: (1) Image acquisition; (2) analyzing and manipulating the images; (3) output in which can be an image enhancement or report on the image analysis [17]. There are lots of algorithm for image processing depending on the classification of the need result, one of this is the image segmentation, it is the operation at the threshold between low-level image process and image analysis [18]. Moreover, image segmentation also refers to the process of partitioning a digital image into N number of parts. The images are segmented based on a set of pixels or pixels in a region that are similar based on some homogeneity criteria such as color, intensity, or texture, which helps to locate and identify objects or boundaries in an image [19].

Using frame-by-frame can be used to compare images, this method was optimized and implemented using OpenCV with CUDA for GPGPU, which proved to significantly accelerate some of the image processing operations [20].

III. METHODOLOGY

A. Software Design

The classification task is to assign each image to one of the zoea stages. The performance is measured using a confusion table, and the overall performance rates are

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measured by the average value of the entries of the diagonal entries of the confusion table.

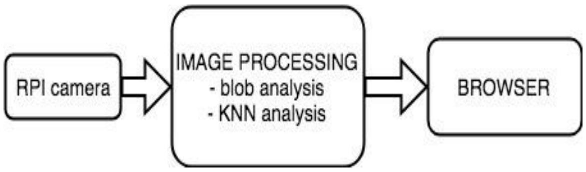

Figure 1. Block Diagram of Image Processing

Basic4 Android was used in creating the application. Particularly, Python 3.1 is the ideal language to test-skipping and new assert methods, much faster IO module. The data gathered from the Raspberry Pi will be passed to MySQL database e.

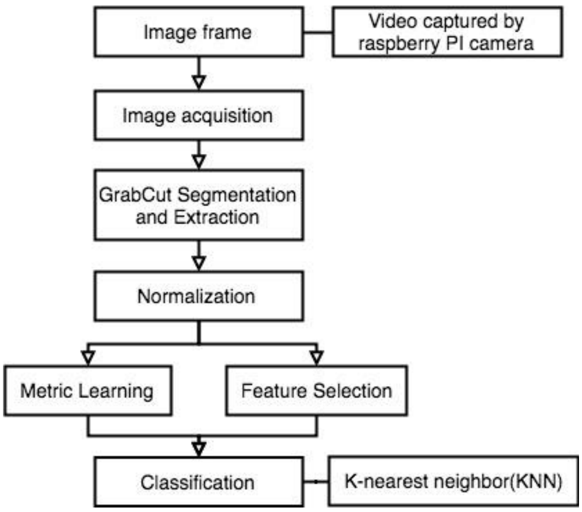

Figure 2. Image classification process using KNN algorithm

1) Image Acquisition:

In this steps, after the image is captured using camera(raspberry pi camera), it will then be converted to raw video frame with RGB color space.

2) Grabcut:

GrabCut is an iterative algorithm for clearing the process of the first segmentation between the foreground and background of the object, also, is used to split the pixels of multiple foreground objects [21]. In Figure 3, the system captures images of larval in the nursing tank and selection of images used to perform the segmentation and draws a rectangle around the object of interest that should be segmented. The GrabCut algorithm performs the segmentation [22].

The graph has two parts, first part describes how much each pixel, m and n, is connected to its neighborhood, the N-links. To compute for the connected pixel to its neighborhood using (1).

$$N(m,n) = \frac{\gamma}{dist(m,n)} e^{-\beta||z_m - z_n||^2} \qquad (2)$$

The second part of the graph are the connections or links to the background and foreground, the source and the sink of cut.

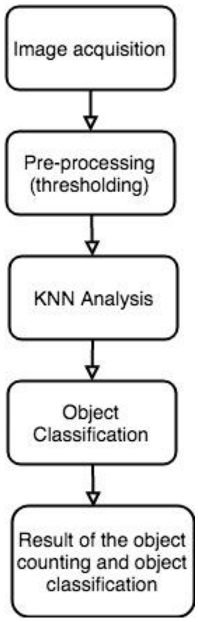

Figure 3. Image Processing Steps

3) Pre-processing:

It is required to pre-process the captured video frame to extract the features. The following steps are: first, pre-processing is automatic thresholding, where the captured color video frame is converted to grayscale and then to binary. In binary representation of the image, the pixels are valued as “0” and “1” which help in feature extraction. The next is Edge Detection using which the edges in the captured frame will be extracted to get the object contours.

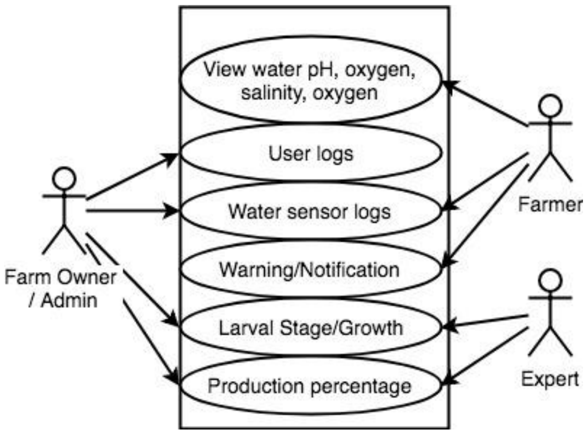

Figure 4. Use case diagram

The users of the system are: (a)Farm owners/Admin can view user logs, water sensor logs, larval growth, and production percentage (b) farmer can view and receive notification of the real-time status of the water (c) expert can monitor the growth and production percentage of the larval.

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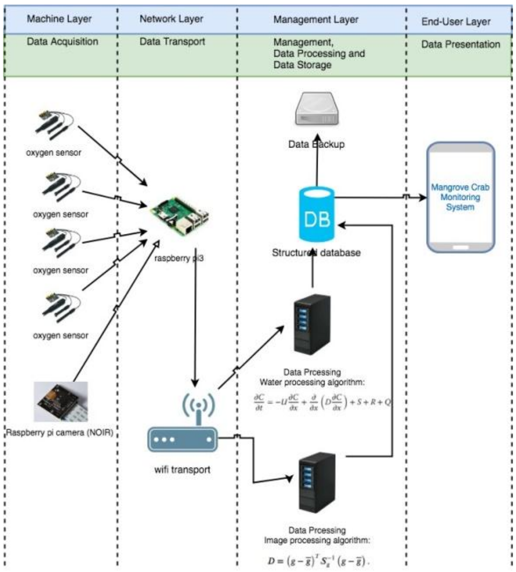

Figure 5. System Architecture

Figure 5 presents the system architecture of the study. It is composed of 4 layers (a) machine layer (b) network layer (c) management layer and (d) end-user layer. For the machine layer, it includes data acquisition. The data are collected using different sensors such as (a) salinity sensor, (b) temperature sensor (c) pH sensor (d) oxygen sensor this sensor is used to get the water characteristic inside the nursing tank and (e) camera for collecting the images of larval inside the nursing tank. Next layer is network layer this layer is for data transport. Raspberry Pi3 collects the data from the sensor and will be transferred wirelessly in the cloud. Another layer is the management layer which includes: (a) management for the structured database, (b) data processing for the algorithm of water which is an image processing lastly (c) data storage for database and backup. Furthermore, the last layer is the end-user layer for data presentation. In this study, data are presented using mobile technology, the feedback and notification about the status of water quality condition and the larval growth status will be received by the end-user or the farmer worker and farm owner.

$$\frac{\partial C}{\partial t} = -U\frac{\partial C}{\partial x} + \frac{\partial}{\partial x}\left(D\frac{\partial C}{\partial x}\right) + S + R + Q \qquad (3)$$

$$D = \left(g - \overline{g}\right)^{T} S_g^{-1} \left(g - \overline{g}\right) \qquad (4)$$

IV. RESULTS AND DISCUSSION

Experiment Setup

The initial experiment (dataset) was conducted in a nursing tank with 100 larvae. Using a high definition camera each stage of larval was captured. During the experiment capturing of images is done five times. The first captured image is for the first stage zoea one larval at two days old. Second is the zoea two at five days old, third is zoea three at an 8th day old, fourth is zoea four at the 12th day old and lastly zoea five at 16th day old. Therefore, test the algorithm for identifying if the images meet the characteristics of growth stages and characteristic of larval.

TABLE 2 LARVAL GROWTH AND CHARACTERISTICS EXPERIMENT

Larval Stage	Test Bed 1	Test Bed 2
Zoea I	58/70	55/70
Zoea II	62/70	61/70
Zoea III	59/70	60/70
Zoea IV	58/70	59/70
Zoea V	59/70	62/70

Table 2 presents the recognition rates of the larval images in different stages. Regarding zoea I, there was an average of 81% accuracy. For zoea II, an average of 89% accuracy in recognition of larval images was achieved. In zoea III larval images, 85% accuracy in recognition of attributes were attained. For zoea IV, the algorithm achieved an average of 84% accuracy in most of the larval images. In zoea V, 86% recognition accuracy was achieved.

The final experiment, capturing of zoea in real-time on a nursing tank. Capturing of image is doneevery 9am, from zoea 1 to zoea5 or total of 18 days.

TABLE 3.0 SUMMARY OF THE SOFTWARE EVALUATION

Criteria	Mean	Interpretation
FUNCTIONALITY	4.68	Strongly Agree
RELIABILITY	4.48	Agree
USABILITY	4.60	Strongly Agree
EFFICIENCY	4.65	Strongly Agree
MAINTAINABILITY	4.48	Agree
PORTABILITY	4.53	Strongly Agree

Table 3.0 shows the summary of the system evaluation and the system functionality rated the highest which is 4.68, which means that larval classification and water quality monitoring functions of the system was also achieved.

V. CONCLUSION

The classifier achieved 85% recognition on the initial experimental setup activity. Second, this study provides empirical evidence of mangrove crab characteristics and growth account in the Philippines, which has seldom been explored based on the available academic and expert publications. Third, the result also includes a training data gathered from the actual nursing tank of mangrove crab in the study, which is used for real-time classification of the stages, provide an accurate classification, however, the accuracy for zoea1 and zoea two had the lowest accuracy because of is less detailed features. Forth, the system evaluation the functionality got the highest mean score which is 4.68. This attests that the system is functionally based on its intended usage and meets the specification and requirements given by the end – users.

The future works include: First, additional codebook training methods, such as supervised training, will be investigated; Second, convolutional algorithms will be evaluated to improve the computational efficiency further; Third, integration of the BLOB technique for zoea five counting.

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