Increase the Quality of Seaweed Exportation by Enhancing the Seaweed Culture of Sri Lanka

***Abstract*— Sri Lanka's Northern Coastal Seaweed Industry shines as a beacon of quality and sustainability in global markets, enticing industries worldwide with its unique offerings. Introducing Seaweed, a ground-breaking mobile application designed to help Sri Lankan seaweed producers overcome their obstacles. This mobile application provides a comprehensive solution for predicting growth rates, identifying illnesses, monitoring moisture levels, and measuring the weight of dried seaweed bunches by combining powerful image processing techniques and IoT devices. This cutting-edge technology allows growers to optimize harvest dates, perform timely treatments, improve export-quality drying procedures, and properly anticipate sales revenue based on environmental factors and currency variations. The mobile applications' user-friendly interface enables seaweed farmers to transform their cultivation processes, increase productivity, and assure long-term success in the ever-changing seaweed business and will put an end to uncertainty and usher in the future of seaweed cultivation.**

Keywords—Seaweed, Mobile application, Image processing, IoT

I. Introduction

The age-old practice of seaweed farming which mostly uses the prized species "Kappaphycus alvarezii" [1] remains strong in Sri Lanka's unspoiled northern coastal region. Seaweed goods from Sri Lanka are highly sought-after worldwide due to their unique qualities and extraordinary demand over time. The unwavering dedication to quality in farming methods and the unmatched qualities inherent in Sri Lankan seaweed are the reasons for this spike in demand. These highly valued items are used in a variety of industries, from fine dining to high-end cosmetics and life-saving medications [2]. The unmatched offerings of Sri Lanka continue to enhance worldwide markets, cementing the country's status as a top hub for premium seaweed goods, as buyers from around the world demand these gems from the deep.

Cultivators couldn't recognize at which level cultivation was going on and couldn't predict seaweed's appearance and which stage of cultivation going on are the major drawbacks of the correct harvest. It leads to not having considerable output. Changes in the water temperature, solar irradiance, nutrient levels, pH, and oxygen levels of water affect seaweed diseases [3] . Identifying seaweed diseases can be a difficult task, as many of the symptoms are not immediately visible. The diseases reduce the quality and the harvest of seaweed. Therefore, identification of the right seaweed disease at the right time helps to prevent the wastage of seaweed culture. Also, doing treatment that is suitable for the disease is an essential thing. Also, cultivators and exporters don't have any clear idea about how sales are going and do future predictions and couldn't get a clear idea about their seaweed revenue. Therefore, they don't have any idea how to market their seaweed for international trade and it is a huge loss for the country. The major challenge that faces the Sri Lankan seaweed industry is global competition. The high quality of dried seaweed gets a high place of demand in the global market. The moisture level should be more than 15% and lower than 40% and the weight should be five Kilograms for a seaweed bunch. For exportation. The seaweed cultivators check the moisture of dried seaweeds according to hand practice without using any tool. Due to lack of proper weight and moisture, the profits go down and international buyers cannot deploy those for their manufacturing process such as making pharmaceutical products, foods, and so on.

This mobile application leads farmers to overcome the drawbacks of the Sri Lankan Seaweed culture and easily enter the global competitive market by enhancing the quality of the dried seaweed exportation.

II. Literature Review

Sri Lanka's rich coastal ecosystem, particularly in the Northern Coastal Area, provides an ideal environment for cultivating the prized "Kappaphycus alvarezii" species, renowned for its superior quality and versatility. However, to capitalize on this natural advantage, it is essential to optimize cultivation methods, streamline processes, and implement stringent quality control measures. The study mainly focuses on how to optimize those things through this solution.

Gerlo, J., Kooijman, D. G., Wieling, I. W., Heirmans, R., & Vanlanduit, S. (2023, November 15). Seaweed Growth Monitoring with a Low-Cost Vision-Based System. Sensors. [4] This research provides an automated RGB and stereo vision camera-based seaweed growth monitoring system. The method extracts the size of seaweed from RGB photos using image segmentation based on deep learning. In a seaweed farm in the Netherlands, the system measures seaweed size with a 0.9 intersection of the union, 6% repeatability, and 18% precision despite low visibility.

Paul, & Sharma. (2016, September). Plant Disease Detection Using Image Processing Technique. International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering. [5] An effective method for identifying plant diseases through image processing is presented in this research. The method entails utilizing a webcam to take pictures of diseased leaves through a MATLAB graphical user interface. Pre-processing is done on the photos to improve their quality and get rid of noise. The afflicted area is divided into sections to identify features and limits. To identify the condition, the pertinent features are taken out and contrasted with the features of previously taught photos. The outcomes demonstrate how effectively and accurately this method can identify leaf disease with little computational work.

Erawan, I. M. S., Handoyo, W. T., & Sarwono, W. (2021, April 1). Data integration of humidity sensor and image texture for water content prediction of Gracilaria sp. during sun drying. IOP Conference Series: Earth and Environmental Science. [6] The study assessed how well image texture, resistance, and capacitance data from a humidity sensor could be used to forecast the water content of Gracilaria sp. seaweed as it dried in the sun. Gracilaria sp. rehydrated data was obtained, and multiple linear regression and multiple-layer perceptron-based neural networks were used to analyze the data. According to the findings, there was a great deal of promise for forecasting water content during sun drying when combining the humidity sensor with the image texture.

Elbaşi, E., Zaki, C., Topcu, A. E., Abdelbaki, W., Zreikat, A. I., Cina, E., Shdefat, A. Y., & Saker, L. (2023, August 16). Crop Prediction Model Using Machine Learning Algorithms. Applied Sciences. [7] This study investigates the possible advantages of incorporating machine learning algorithms into contemporary agriculture to maximize crop yield and minimize waste. The article includes experimental results showing the effect of modifying labels on data analysis algorithms, discusses the current status of machine learning in agriculture, and emphasizes potential and obstacles.

The previous method of monitoring seaweed growth using a low-cost vision-based system faced several challenges, such as issues with lighting, algae, undesired plant material, and shapeless seaweed, which could all hinder image recognition. To overcome these obstacles, the segmentation method should ignore these components. Additionally, the presence of a second row of seaweed behind the foreground plants can reduce sharpness due to distance differences. This new solution effectively minimizes these challenges and utilizes image processing techniques to identify the growth stage of the seaweed accurately. The previous research also utilized image processing techniques to identify different plant diseases, this solution mainly focuses on the Ice-Ice disease identification of Kappaphycus alvarezii seaweed species using the image processing technique. Previous research included forecasting the water content of Gracilaria spices, while this new solution focuses on the moisture level and weight of dried seaweed bunch using soil moisture and load cell sensors for Kappaphycus alvarezii species. Furthermore, the solution employs machine learning algorithms to predict sales revenue, similar to the previous crop prediction model.

III. Methodology

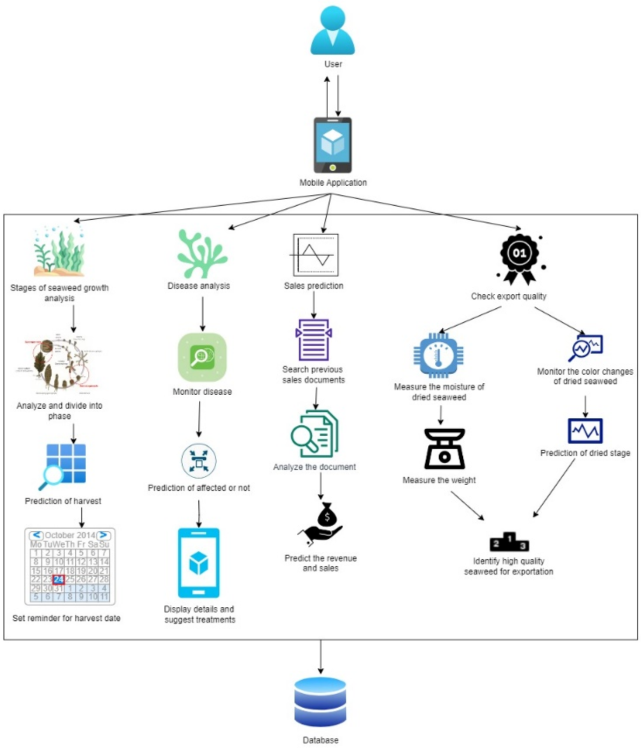

Fig. 1. System diagram

According to the system diagram shown in Fig. 1, user can determine the harvest date with reminders, identify the seaweed disease with suitable treatments that help to prevent the spread or eliminate the disease, and view the revenue that farmers can earn by entering the seedling weight and the climate changes that happened during the 8 weeks, and users can check the quality of the dried seaweed by uploading the dry seaweed images or by using the IoT device that measures the moisture level and the weight of the dried seaweed bunch.

The images of different levels of growth, the seaweed affected by Ice-Ice disease, and the different levels of the dried process were collected from NAQDA(National Aquaculture Development Authority of Sri Lanka) of Jaffna. To capture the images of Ice-Ice disease growth levels were collected from different fields of Jaffna. Captured the dried seaweed levels and tested the moisture levels and weight using the IoT device from the seaweed store located in Jaffna. The needed annual sales reports were collected from the NARA(National Aquatic Resources Research and Development Agency) public library of Colombo. The related images were not found in the e-resources, the available images do not consist of high quality for applying the image processing techniques.

The pictures were taken with smartphones and a professional DSLR camera to have high pixel values for the color changes. Different angles were captured to increase the volume of the dataset and get high accuracy. The gathered data from the NAARA library were entered into the Excel sheet to apply the machine learning algorithms.

Because CNNs can handle massive amounts of data and generate extremely accurate predictions, they are particularly helpful for computer vision applications such as picture recognition and categorization. Multiple iterations are all that CNNs require to learn an object's features, which eliminates the need for manual feature engineering chores like feature extraction. A CNN can be retrained for a different recognition task, or a new model can be constructed from an existing network that has been trained with weights. We call this transfer learning. Because of this, developers of ML models can apply CNNs to many use cases without having to start from scratch [8].

Using pre-trained CNN architecture modules like VGG16 [9] and VGG19 [10] typically for image classification and feature extraction applications. GradientBoostingRegressor [11] is also used to predict sales using attributes that are taken from the dataset. These photos are processed by the CNN models constructed for growth level identification, disease identification, and dry level identification on the flask server placed on the backend. To create the dataset, which is then utilized to create the CSV file, the images are taken according to their sizes and grades. The main functions of this model are feature extraction, object recognition, and image segmentation. The MATLAB [12] software suite is the most effective tool for evaluating and utilizing unique CV methods to extract morpho-colorimetric data from images.

A. Identify the correct growth stage

Predicting the next harvest date is crucial because cultivators do the seedlings at different periods in the same field.

Fig. 2. Growth level

The method builds a CNN with the VGG19 architecture for picture categorization. It first preprocesses input photos with dimensions of (224,224,3), then applies two MaxPooling2D layers for downsampling after going through VGG19 layers. Two Dense layers with ReLU activation and dropout are added for classification after the features have been flattened. Three classes are created for each image by the output layer using softmax activation. To avoid overfitting, this design makes use of additional layers in addition to the feature extraction capabilities of VGG19.

B. Identify disease-affected seaweed

Seaweed disease detection is very hard for inexperienced cultivators. The Sri Lankan seaweed cultivators identify the seaweed disease by the key physical appearance changes with their experiences. There is only one disease found in Sri Lanka named Ice-Ice.

The VGG16 model will be utilized to apply transfer learning to convolutional neural networks (CNNs) for disease identification. The Sequential API is used to add more layers to the model, such as Dense layers with ReLU activation for classification, Flatten layers to turn the 2D feature maps into a vector, and MaxPooling2D layers for downsampling. Additionally, dropout layers are used to lessen overfitting. To facilitate classification into two classes, the model is ultimately constructed using a SoftMax activation function for the output layer. This setup exemplifies a transfer learning strategy in which the trained VGG16 model is leveraged to adjust its learned features for a particular classification job.

Fig.3. Ice-Ice disease affected seaweed.

Preprocessing guarantees 128 × 128-pixel image homogeneity. The image upload and preprocessing interfaces are designed to be user-friendly and intuitive. Backend features optimize images seamlessly in the background.

C. Test the quality of the dried seaweed for exportation

Fig. 4. Dry phases

Before the exportation, Sri Lanka seaweed cultural farmers sun dry their harvest and ensure the quality with their practices without using any devices.

The provided solution snippet shows how to use the VGG19 architecture to create a convolutional neural network (CNN) for image categorization. TensorFlow's distribution technique for multi-device training is used in the model's construction. TensorFlow is included after the first 19 frozen layers for training. Dropout for regularization and regularizers are examples of keras components. A Sequential framework is used to unfold the model architecture, which includes pre-trained VGG19, MaxPooling2D layers for downsampling, and a Flatten layer for reshaping. ReLU activation powers the stacking of dense layers for classification, with dropout layers inserted for regularization. The last layer probabilistically divides input images into one of four classes using softmax activation.

The cultivators export quality dried seaweed by checking the moisture level using hand practices and measuring the weight using the scale. For the quality dry seaweed bunch should have more than 15% and less than 45% moisture level and 5 Kilogram of weight. Figure 5 shows the IoT device that was implemented to get the previously mentioned measurements. It consists of the soil moisture sensor and the 5-kilogram load cell sensor to get the measurements and the ESP32 microcontroller. to function properly. Also, the real-time data stores the Firebase to connect to the mobile application.

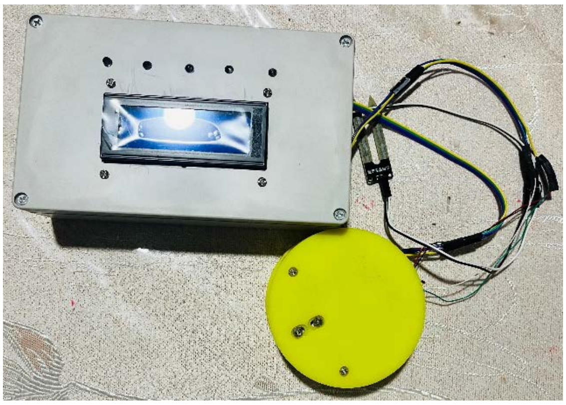

Fig. 5. Implemented IoT device.

D. Predict the sales

The harvest of seaweed differs because of the weather conditions. The sales revenue also differs because of the fluctuation rate. By entering the current dollar rate, the number of seedlings that are used to farm, and weather conditions each day for 7 weeks using this mobile application, seaweed cultivators can get predictions about sales.

A Gradient Boosting Regressor (GBR) model with 100 decision trees, a 0.1 learning rate, a maximum tree depth of 3, and a random state for repeatability are initialized by the code. The fit() function is then used to train it using the supplied training data (X_train, y_train). This method fits decision trees to the residuals of previous trees in an iterative manner to improve predictions. The GBR model can forecast target values for fresh data once it has been trained.

IV. Results and Discussion

A. *Predicting the harvest date according to growth level*

The pre-trained VGG19 model accuracy consists of 93.10%. After recognition of the stage level of growth, it represents the child, middle, and harvest stages respectively. Also, cultivators can set the harvest date reminder according to the identified stage using the calendar.

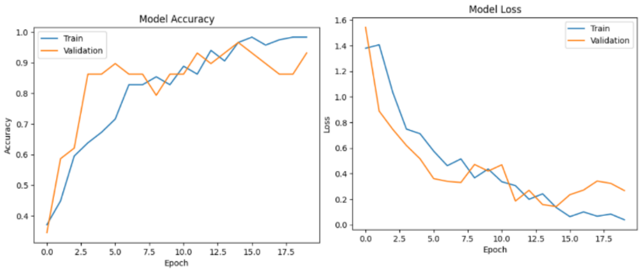

Fig. 6. Growth test accuracy and loss.

The Fig. 6 represents the test accuracy and loss respectively. The y-axis represents the accuracy of the model, while the x-axis represents the number of epochs. The graph illustrates the accuracy of the model over time on training and test datasets. The percentage of accurate forecasts made relative to all guesses is how accuracy is determined. With the number of epochs represented by the x-axis and the model's loss represented by the y-axis, the graph also displays the model's loss with time. Lower numbers indicate greater performance. The loss quantifies how well the model's predictions match the actual dataset values.

TABLE I shows pre-trained VGG19 model accuracy using the 20 epoch. A learning rate reduction callback is included in the training setup, which uses a 128-bit batch size and 20 epochs. The model's accuracy and generalization are increased through iterative refinement over 20 epochs, improving predictions in practical situations. The batch size influences convergence and performance by dictating sample processing and learning rate.

TABLE I. Growth model accuracy

Epoch	Accuracy	Loss	Val Accuracy	Val Loss
6/20	0.7155	0.5753	0.8966	0.3602
12/20	0.8621	0.3054	0.9310	0.1850
20/20	0.9828	0.0384	0.9310	0.2667

B. *Detection of the correct seaweed diseases*

The pre-trained VGG16 model accuracy consists of 87%. After the detection of the seaweed disease, the system navigates to the treatment interface that is relevant to the identified disease. The suggestions for the treatment were collected from the previous research.

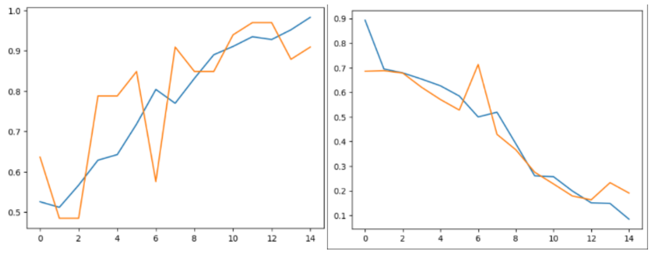
Fig. 7. Disease test accuracy and loss.

Fig. 7 represents the test accuracy and loss.

Epochs, which indicate how many times the training dataset is run through the neural network during training, are essential for fine-tuning model accuracy. By modifying its parameters every epoch according to calculated gradients, the model enhances its accuracy on the training set of data. Iterative learning made possible by running many epochs improves the model's fit to the data. Excessive epochs, however, may result in overfitting. Finding the ideal balance between underfitting and overfitting is essential to guaranteeing the model achieves high accuracy on the training dataset and well-generalizes new data [13].

Every one of the 15 epochs in the pre-trained VGG16 model entails adjusting the model's parameters using the complete dataset. These epochs increase the model's performance in classification on both training and validation data by strengthening its recognition of complex patterns in the images.

TABLE II. Disease model accuracy

Epoch	Accuracy	Loss	Val Accuracy	Val Loss
7/15	0.7182	0.5849	0.8485	0.5278
10/15	0.8316	0.3909	0.8485	0.3666
14/15	0.9519	0.1484	0.8788	0.2330

C. *Dry level identification*

The pre-trained VGG19 model accuracy consists of 84%. The system displays the phase of the dry like low, average, and high by capturing the images. Also, it connects to the IoT device and cultivators can get measurements from it. This model runs 20 epochs to obtain the accuracy.

TABLE III. Dry-level model accuracy

Epoch	Accuracy	Loss	Val Accuracy	Val Loss
8/20	0.8276	0.5144	0.8621	0.3299
10/20	0.8276	0.4356	0.8621	0.4191

19/20	0.9828	0.0828	0.8621	0.3231

After a thorough assessment, the load cell sensor proved to be an incredibly accurate and reliable instrument. It was verified that the sensor weight precisely matched the physical scale measurements when its accuracy was compared to those measurements. Achieving precise measurements of the moisture content requires this degree of accuracy. To guarantee the highest level of accuracy in the measurements, advice from specialists in the seaweed culture sector was sought. Their insightful advice and insightful comments have greatly improved the moisture level measurement technology and produced incredibly accurate findings.

D. Prediction of approximate sales

The evaluation metrics that are supplied offer valuable information about how well a prediction model likely a regression model performs on a particular dataset. With a value of 1272.92, the Mean Absolute Error (MAE) [14] represents the average absolute difference between the expected and actual values. The average squared difference between the expected and actual numbers is measured by the Mean Squared Error (MSE) [15], which comes out to be 2216768.22. The square root of the average squared discrepancies is measured by the Root Mean Squared Error (RMSE) [16] , which is calculated from the MSE and has a value of 1488.88. The R-squared (R2) number, which often falls between 0 and 1, is the last metric used to evaluate how well the model fits the data. Nonetheless, the model appears to perform worse than a model that merely predicts the target values' mean, as indicated by the negative R2 value of about -0.11. When taken as a whole, these metrics offer a thorough assessment of the model's correctness and data fit, directing future improvements or alterations to improve its functionality.

V. Conclusion and Future Work

For seaweed farmers, this mobile app offers an extensive range of helpful functions. First, it can forecast the harvest date, which can assist farmers in more efficiently allocating their labor and resources. Secondly, farmers can optimize their pricing and marketing tactics because the software can predict sales. Thirdly, the app's ability to identify illnesses is essential for safeguarding the seaweed's health and avoiding crop losses. Finally, the app's ability to determine dried seaweed's quality is crucial for upholding strict guidelines and satisfying clients.

All things considered, seaweed farmers aiming to enhance their farming methods will find this smartphone application to be a very useful resource. They can obtain important insights and make better judgments by utilizing these different functions, which will ultimately result in higher yields and better profitability.

The "Kappaphycus alvarezii" species is the main subject of this study, focusing on the "Ice-Ice" diseases that impact the species' growth and general health. This study explores some topics related to this migratory species, such as growth rates, disease susceptibility, dryness levels, and sales information. Additionally, the smartphone application may investigate several diseases that affect seaweed culture and broaden its use to other species. The study aims to shed light on the most effective methods for growing seaweed and reducing disease risks by thoroughly analyzing these variables.

A soil moisture sensor built into the IoT (Internet of Things) device allows it to gauge the soil's moisture content. This sensor can be used to track the amount of water that crops and plants contain, giving important information about how they are growing. Furthermore, the apparatus has a leaf sensor that can be attached to it, enabling more exact and accurate readings of the moisture content of dried seaweed.

The system can also add further factors that affect the seaweed harvest to predict the sales such as the measurement captured from devices in real time.

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