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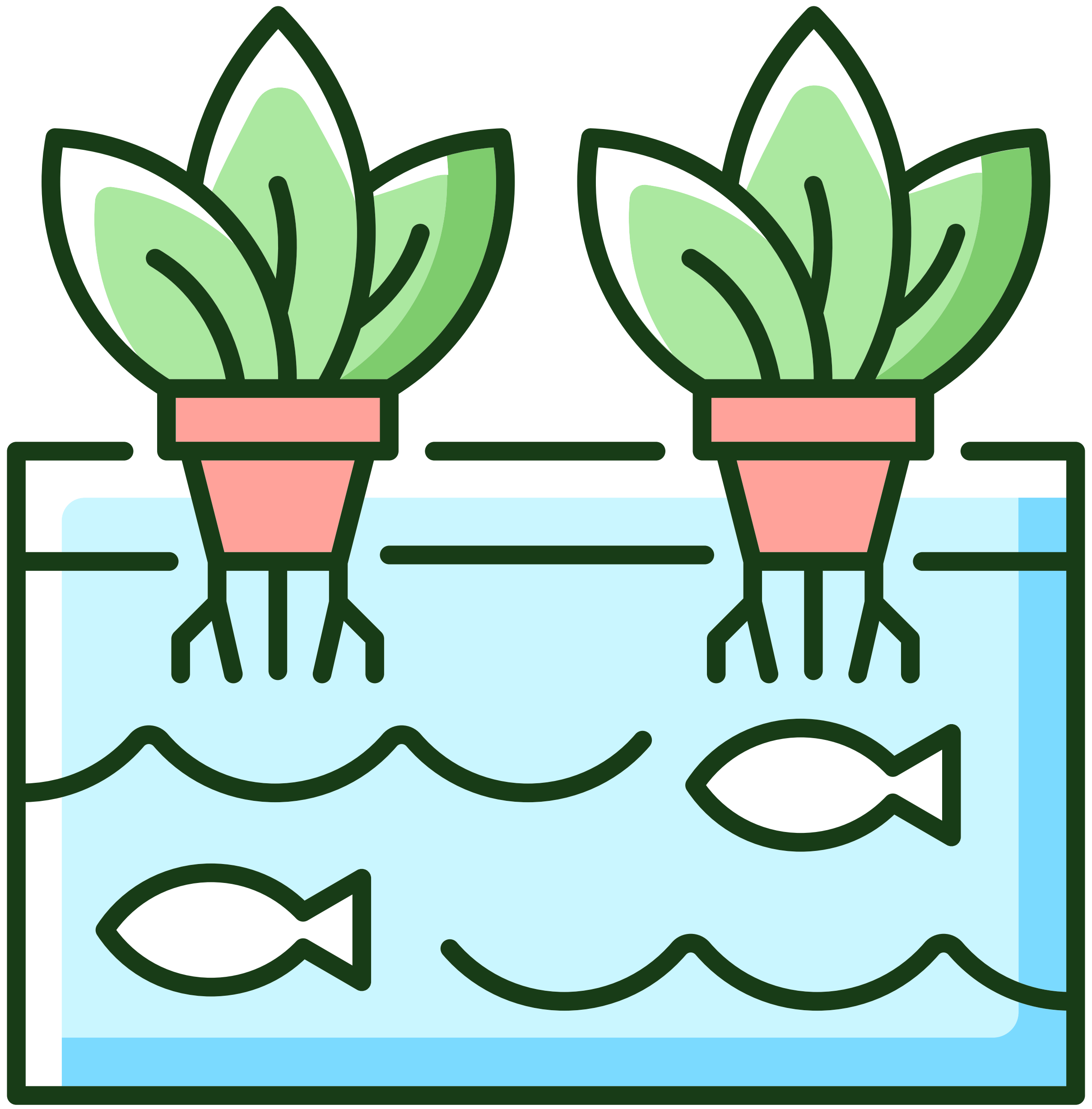
Lyceum of the Philippines University - Manila

Aquaponics Handbook: A Deep Convolutional Neural Network helper tool for Aquaponics



STUDENT

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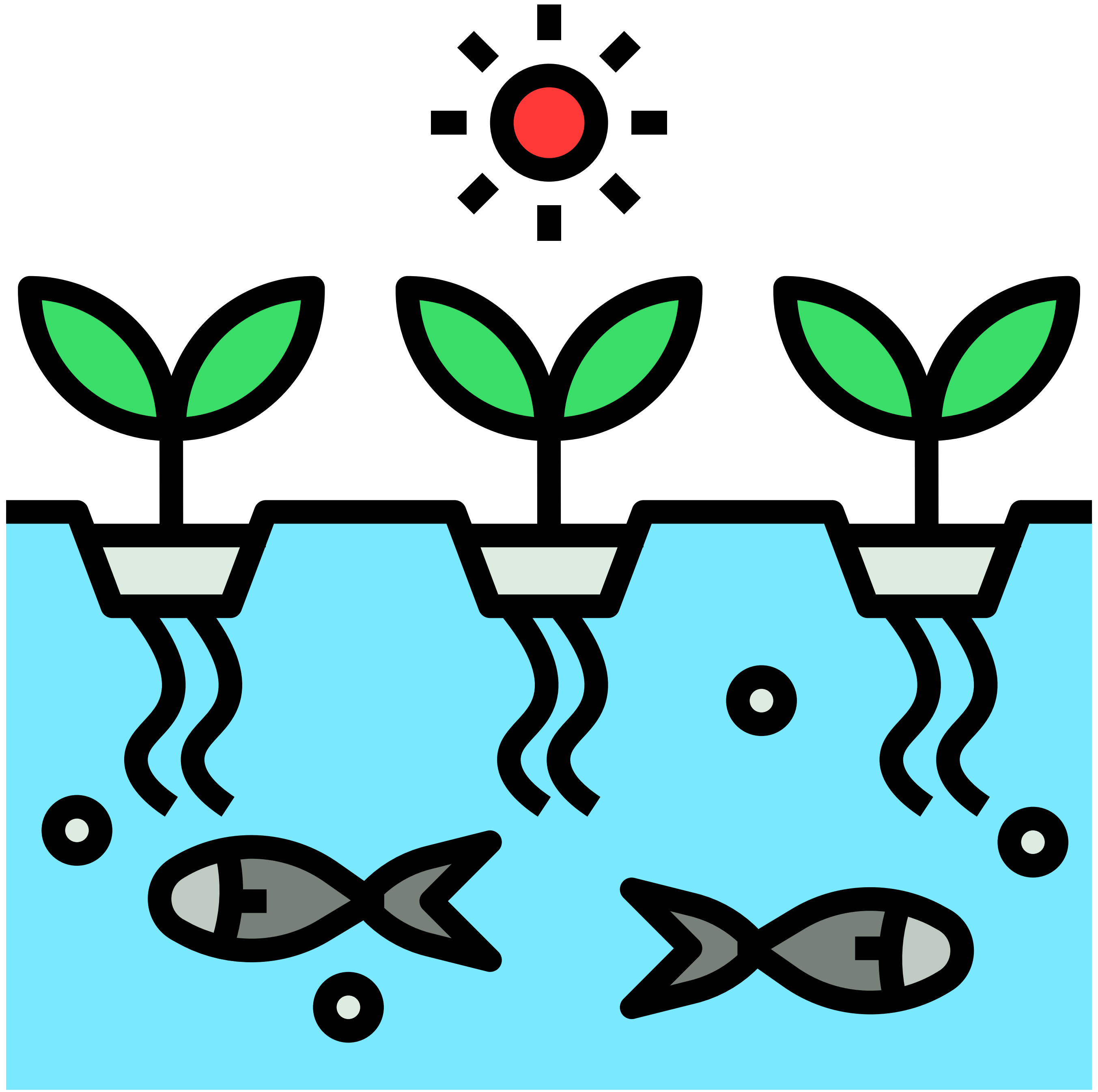
2019-1-01860

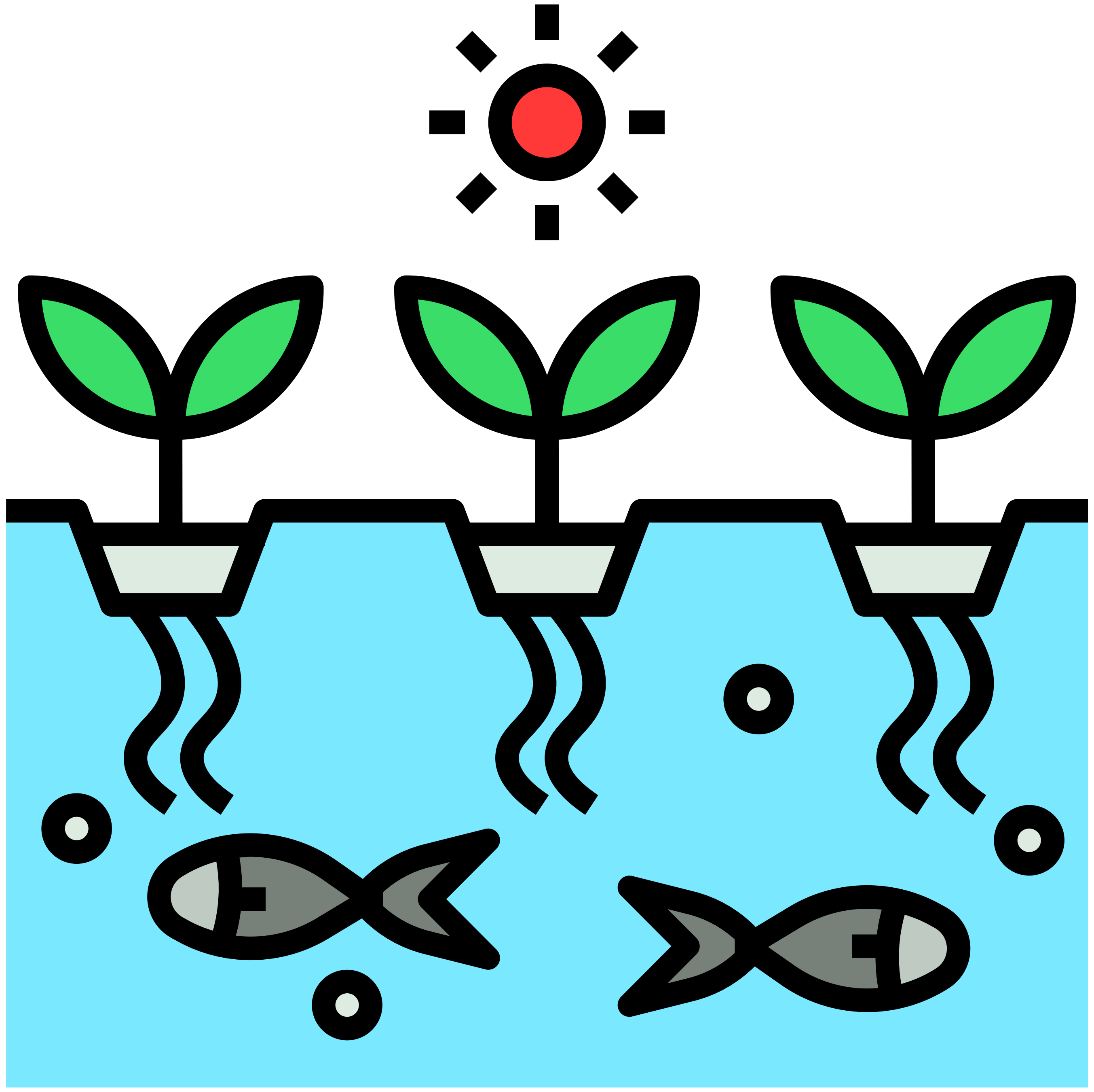
SUBJECT

Software Engineering 2

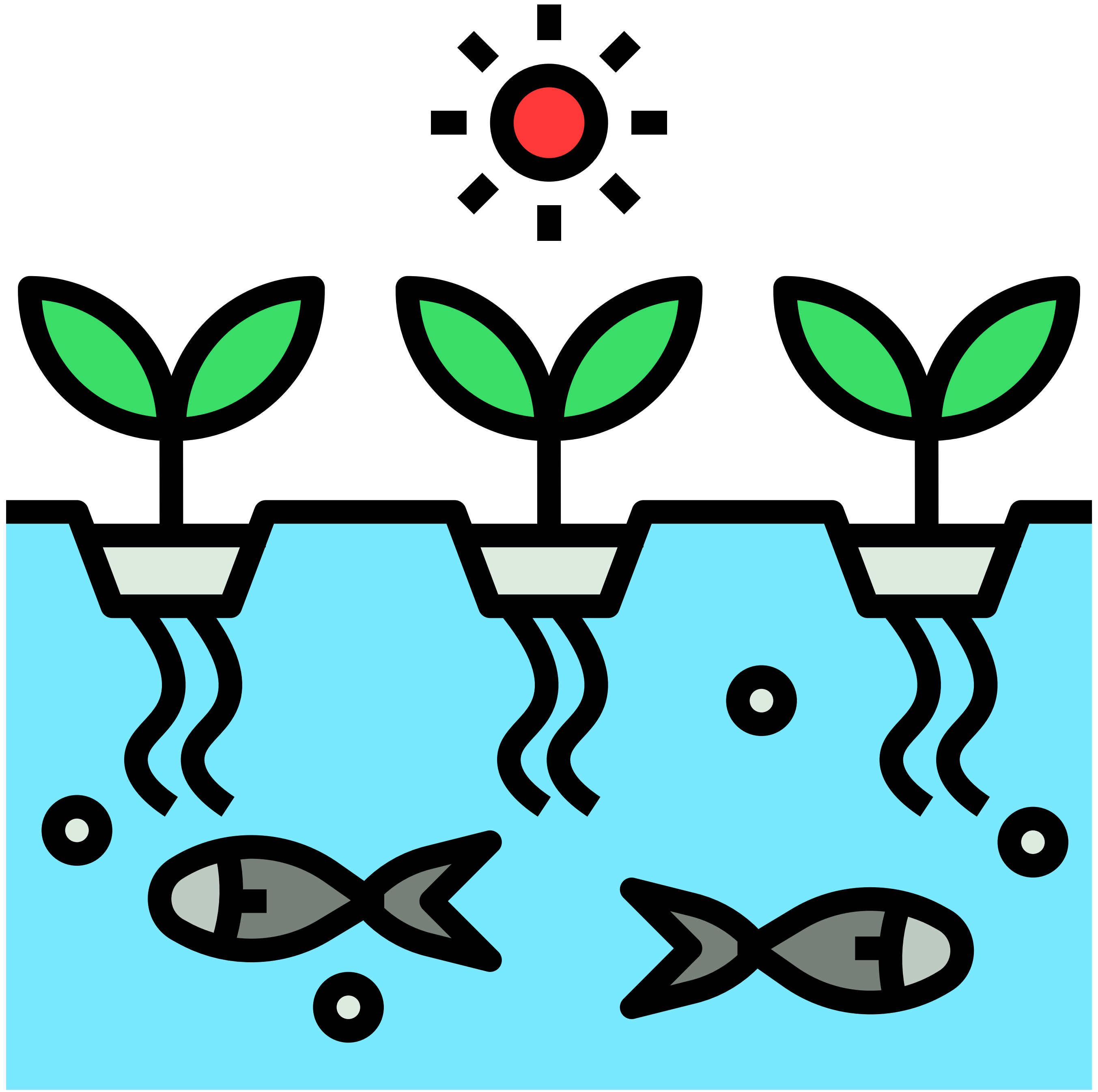
Table of Contents



- Aquaponics is a typical bio-integrated method of production that links the cyclic nature of aquaculture with hydroponics, which shares a sustainable agricultural system.
- The mechanism works by combining these two agricultural sciences to sustain the recirculating system by natural biological cycles (nitrification) to supply nitrogen and reduce water inputs together with the non-renewable fertilizers.



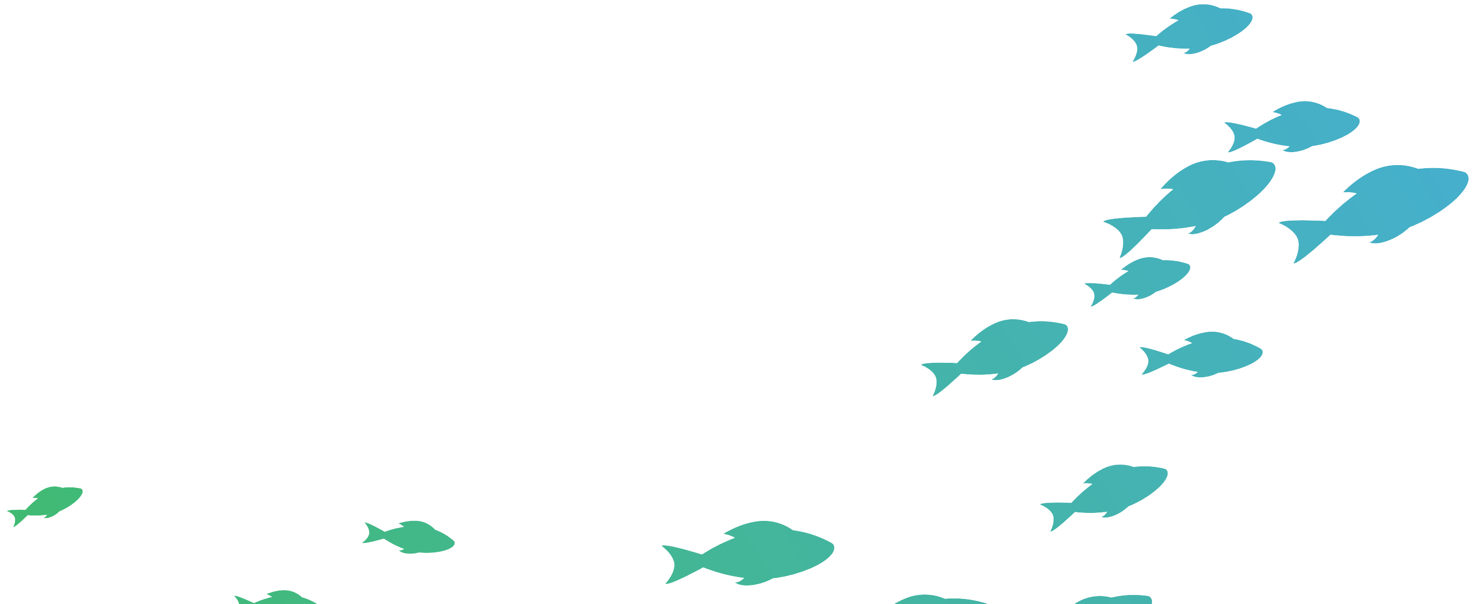
- Producing plants hydroponically and farming fish using aquaculture requires special methodologies to make sure that the respective systems are implemented and managed properly
- Within the emergence of IoT based smart systems and the advancements in Artificial Intelligence, more innovative approaches would be developed to further advance the field of aquaponics and minimize the trade-offs enabling it to become a household or commercial venture.



- Proper recommendations and guidelines for aquaponic farming are still lacking and requires more research investments focusing on possible production systems and different varieties of crops.
- As of the writing of this paper, there are only handful of AI-based papers that focuses solely on aquaponics and to the best of my knowledge, this is the first paper to provide a handbook for aquaponics covering several preliminaries using both Machine Learning and Deep Learning from the gathered datasets.

Fish Dataset

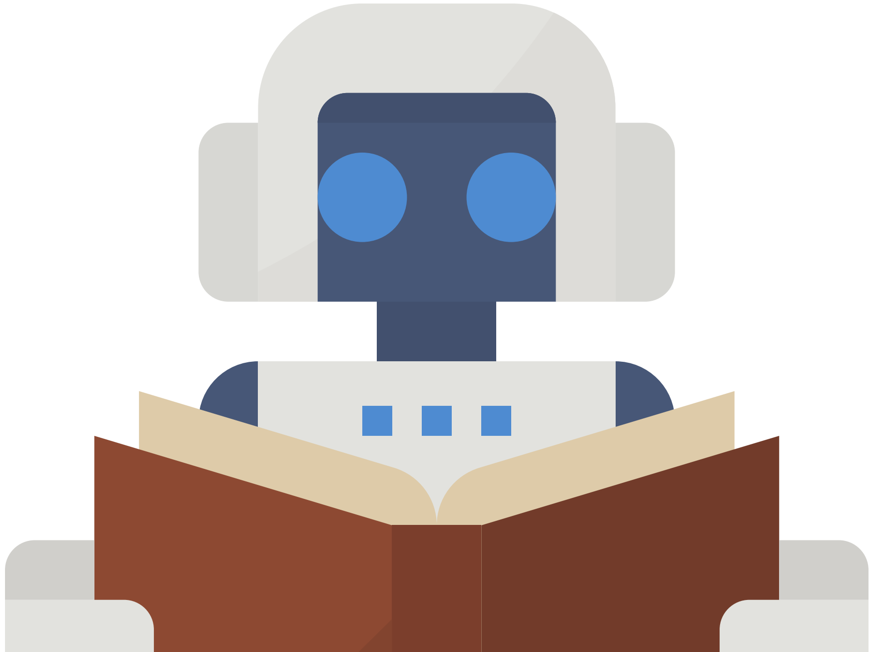
The largescale fish dataset was adapted from the fish segmentation and classification study by Ulucan, et al. The dataset is composed of raw fish images separated through nine different classes namely: Black Sea Sprat, Gilt Head Beam, Horse Mackerel, Red Mullet, Red Sea Bream, Sea Bass, Shrimp, Striped Red Mullet, and Trout.



Plant Disease Dataset

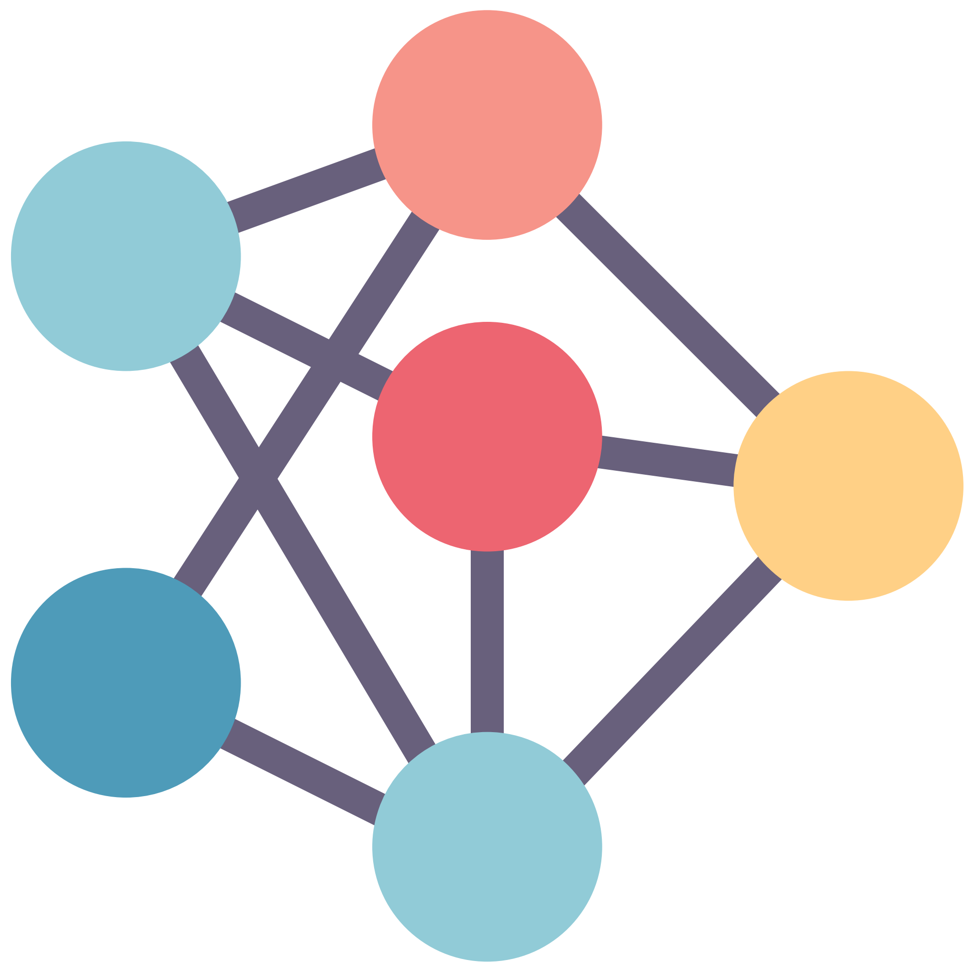
The image dataset for plant disease classification was taken from a publicly known dataset called Plant Village from Pennsylvania State University that is available in many machine learning repositories. In this data-set, 38 different classes of plant leaf and background images are available.

The Image classification features of the aquaponic handbook website utilized the pre-trained Deep Convolutional Neural Network(CNN) model called MobileNetV2 as base model for transfer-learning. This was implemented through the TensorFlow, Keras, and pandas libraries which use the Python programming language. The source code was written on Google Colaboratory which offers a free Graphics Processing Unit(GPU) that makes training and testing the models faster. The trained weights were then downloaded locally and integrated to a Streamlit backend which was used to create the website. The overall web application was then uploaded at GitHub and hosted at Streamlit sharing.



The Deep Learning model's optimization and training is a computationally intensive and time-consuming operation. As mentioned earlier, a powerful graphics processing unit(GPU) is required for training the model, as well as large amounts of data. However, transfer learning, which is deployed in deep learning, solves these problems. The pre-trained Convolutional Neural Network (CNN) used in transfer learning is optimized for one task and transfers knowledge to different modes. The images from the gathered datasets were compromised of different file sizes. Due to this, it was resized to a size of 224 x 224 with three channels to cater its 'rgb' type. The pre-trained CNN used is MobileNetV2 was used to find patterns within the input images and it's corresponding final layers have to be connected to a dense layer. The final layers before the softmax is a 11 x 11 Dense layer for the Fish classification, and a 38 x 38 Dense for the plant disease classification. The basic picture preparation is necessary for the transfer learning considerations with the data augmented images.

Fully connected layers are needed for extracted images classification features because of their special purpose. The softmax function predicts earlier extracted image attributes from preceding layers. Softmax is a multiclass classification activation function in the output layers. The neural network layer uses a multilayer perceptron model (MLP) as a classifier for two-class classification. The model with nonlinearity, which is introduced in the full vectors using rectified linear unit (RELU) activation.

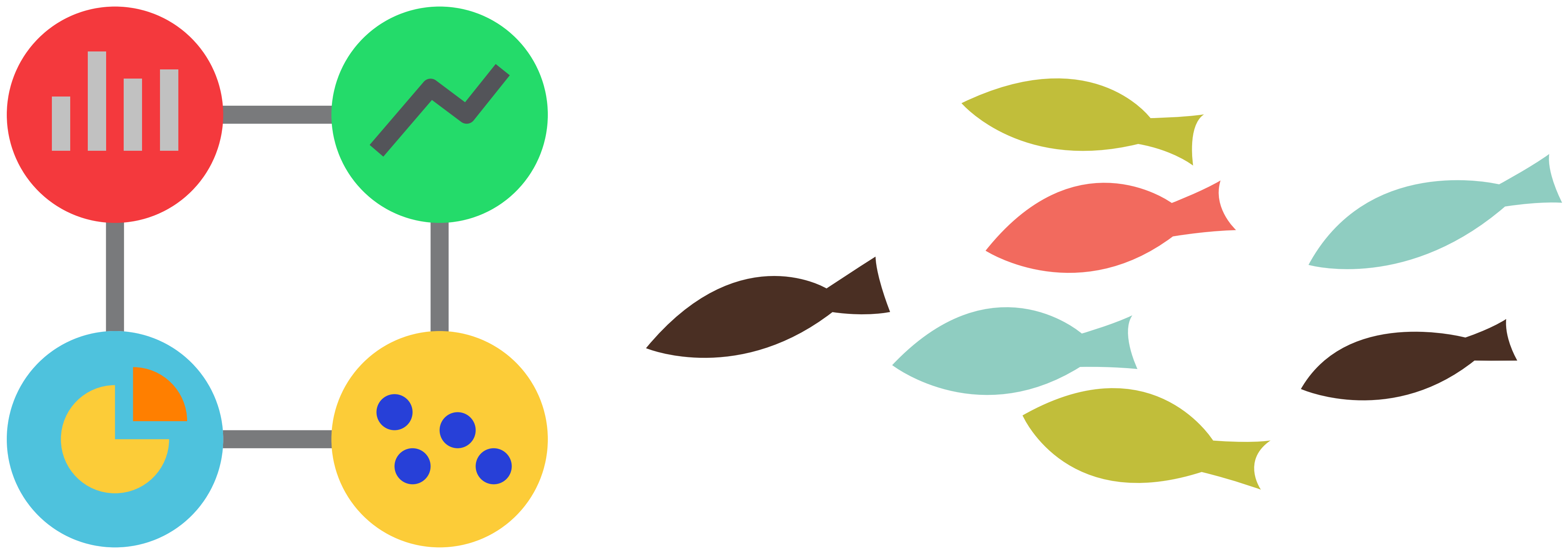


The test dataset gathered from the splitting of the dataset during the data preparation stage was used to evaluate the trained model. Classification metrics from scikit-learn library were also used. This includes the classification reports and confusion matrix. Throughout the training of the model, the training accuracy, training loss, validation accuracy, and validation loss were also tracked to determine if the model is overfitting or underfitting.

The saved weights from the trained models were downloaded locally. The image classification features were made through the Streamlit library that use the Python programming language. The finished website was then uploaded to GitHub pages together with the images, weights, and helper python files.

The metrics used to evaluate how well the model performs are precision, recall, F1 score and the confusion matrix. Higher precision leads to less false positives, higher recall leads to less false negatives, f1-score is the combination of precision and recall, usually a good overall metric for classification model. When comparing predictions to truth labels, a confusion matrix can be used to see where the model gets confused.

The images from the fish classification was trained using the proposed Deep Convolutional Neural Network. The model scored a test accuracy of 99.78% and a test loss of 0.00722. The timeline for the accuracy and loss of the training and validation datasets are presented on Figure V and Figure VI respectively. The corresponding classification reports are presented on Table I and the confusion matrix on Appendix A. Sample predictions on the test data are presented on Figure VII.



The images from the plant disease classification was trained using the proposed Deep Convolutional Neural Network. The model scored a test accuracy of 96.35% and a test loss of 0.11303. The timeline for the accuracy and loss of the training and validation datasets are presented on Figure VIII and Figure IX respectively. The corresponding classification reports are presented on Table II and the confusion matrix on Appendix B. Sample predictions on the test data are presented on Figure X.

In this paper, two datasets were collected, prepared, analyzed, and implemented as a feature for an Aquaponics helper website. These datasets are fish images and plant disease images taken from previous similar studies available in public repositories. The techniques of data augmentation, dataset pre-processing, training, and testing are applied to the convolutional neural network-based MobileNetV2 model. The proposed model is built and tested to improve the performance measured and compared it throughout different parameters. The evaluation metrics like precision, recall, and f1-score were utilized to evaluate the model as the hyperparameters are adjusted to determine the best model for the image classification. After the training and evaluation, two classifier weights were eventually achieved. The first model which was trained with the fish images achieved a test accuracy of 99.78% and loss of 0.00722. On the other hand, the second model which was trained with the plant disease images achieved a test accuracy of 96.35% and a loss of 0.11303. Always improving the performance of our models for fish and plant disease classification and analysis is a critical step, but our model achieved a satisfactory performance, which hopefully will support aquaponics practitioners.

The major focus of this research is to provide a helper tool that would help non-experts in the field aquaponics to have a guide for data driven decisions about creating and maintaining an aquaponic system. The collection and preparation of genuine datasets and it applications to aquaponics to add more features to the website is a future target. Using more sophisticated deep learning models and gathering more datasets for better classification and analysis are anticipated. My work encourages and stimulates aquaponics practitioners and hobbyist alike, which ultimately helps raise their respective incomes and promotes a bio-friendly way of agriculture that could be implemented by anyone.

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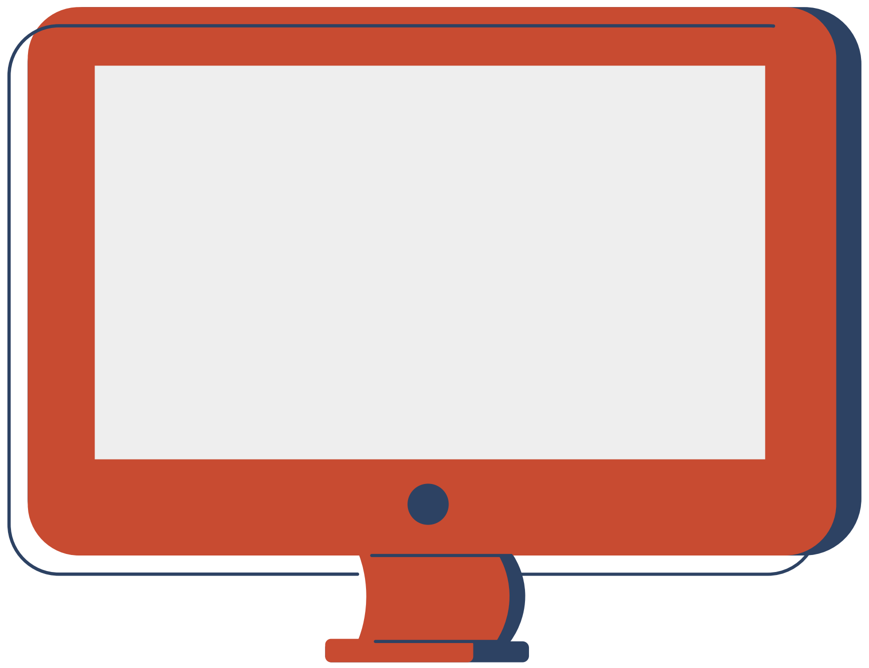
VI Thank You!



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Title

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Subject

Software Engineering 2

The End

Thank you for listening