INTRODUCTION

Lettuce (*Lactuca sativa*) is a leaf vegetable with loose and compact leaf attachment architecture that is normally cultivated up to 30 cm height. It increases the number of its leaves as it proceeds to plant maturity stage. Most of its variants are compatible with cold-weather cultivation. Hot temperature makes the taste bitter, the leaves elongated and leaf tip burning, thus, recommendable to plant at end of the summer season. It is considered as a high-value commercial crop in the Philippines based on the Bureau of Plant Industry-National Crop Research and Development Center (BPI-NCRDC) of the Department of Agriculture (DOA) due to its significant impact on medicinal, culinary, and health perspectives. Loose-leaf lettuce makes up its harvest growth stage after 45 to 90 days after transplanting that normally takes 12 to 14 days from germination. The sensitive way of growing lettuce is inclusive to the beneficial application of smart farming (Ge, Zhou, Kellomäki, Peltola, & Wang, 2011; Jindarat & Wuttidittachotti, 2015). It also demands a heuristic approach of monitoring to enhance its agricultural process.

The lettuce growth, similar to the other higher value leafy crops, is primarily affected by light-dependent and gas-dependent reactions. The growth and development changes are verified to the changes occurred on its fresh weight, dry weight, volume, height, surface area, root zone depth
and other irreversible increase on its allometric properties in which surface area that is more technically known as leaf canopy area is considered a fundamental visible growth indicator (Fan et al., 2018). Broader leaf corresponds to maturity as part of its phenological development. Several studies have already developed a non-destructive approach on estimating individual leaf area of carrot (Haug & Ostermann, 2015), cauliflower (Hamuda, Mc Ginley, Glavin, & Jones, 2017), cucumber (Xie et al., 2014), lettuce (Hernández-Hernández et al., 2016; Tian & Wang, 2009; Zou et al., 2019), maize (Burgos-Artizzu, Ribeiro, Guijarro, & Pajares, 2011), potato (Boyd, Gordon, & Martin, 2002), radish (Dang et al., 2018), sugar beet (Chebrolu et al., 2017) and tomato (Boulard, Roy, Pouillard, Fatnassi, & Grisey, 2017; de Luna, Dadios, Bandala, & Vicerra, 2019) considering the length and width of the leaf shape (Saleem, Akhtar, Ahmed, & Qureshi, 2019; Wang, Jin, Shi, & Liu, 2019).

The Otsu algorithm, otherwise known as the maximum class variance, threshold selection method, was implemented in lettuce leaf blade segmentation from its background. The threshold was automatically determined with the very significant difference of the occluding background from the region of interest. The saturation and intensity components of the HSI color space was (Meng, Cui, Zhang, Wu, & He, 2018). This system further added a new step in the conventional Otsu algorithm by determining the B threshold of the RGB image and morphological operations and multiplications as post image processing steps which results in a more significant increase in the clarity of segmentation. Individual leaf segmentation and identification were implemented based on leaf skeleton transformed imaging (Zhang, Weckler, Wang, Xiao, & Chai, 2016). The algorithm involves tangential direction (TD), multi-thresholding, and successive denoising procedures. Character points on leaf shape were recorded and used as basis for leaf area measurement in developing a leaf growth framework (Kierzkowski et al., 2019). On the other hand, a convolutional neural network (CNN) with modeled encoder-decoder architecture was developed to segment fig crop from its complicated background (Fuentes-Pacheco et al., 2019). Ten color vegetation indices were derived from RGB components of the image and assessed using SegNet-Basic deep learning model and the developed architecture. CIVE, COM2, ExG, and MExG indices yielded satisfactory performances for segmentation.

The foliar surface area of lettuce is considered as a physiological indicator of its growth. For non-vision systems, chlorophyll pigments of lettuce leaf were correlated with the surface area using plasma technologies (Stoleru et al., 2018). The light detection and ranging (LIDAR) data points of plant volume were utilized for the development of a regression model correlating it to leaf area with a maximum correlation coefficient of 0.87 (Berk, Stajinko, Belsak, & Hocevar, 2020; Sinha, Padalia, Dasgupta, Verrelst, & Rivera, 2020). Leaf area and its consumption of carbon dioxide (CO$_2$) were modeled to estimate the demanding vegetation area (Jin et al., 2013; Rahman, Duursma, Muktadir, Roberts, & Atwell, 2018). A leaf area model based on a series of light test cases was developed using a vision system (Hang, Lu, Takagaki, & Mao, 2019). Three photoperiods were implemented for light and dark treatment namely, 12h-12h, 6h-6h, and 3h-3h. Lettuce leaf responded greatly with 6h-6h photoperiod treatment with an increase in the stomatal conductance of the leaf. This increase corresponds broadening of the leaf.

A scale-invariant calculation of leaf area of lettuce was developed using the Viola-Jones cascade marker detection method based on Haar features (Loresco, Valenzuela, Culaba, & Dadios, 2019). The Haar object marker is made of printed square-shaped paper with printed four different black-shaded boxes of different dimensions. During image acquisition, it was placed alongside the lettuce crop and being detected by the vision system. The detection of the Haar marker resulted to 97.5% and proves that the developed approach on leaf area calculation is valid to solve scale-invariance problems. Predictive models for lettuce quality monitoring were developed using support vector regression (SVR), multiple linear regression (MLR), and artificial neural network (ANN) (Gerthphol, Chulaka, & Changmai, 2018). The learning models were fed up with vector’s environmental data such as light intensity, humidity, air and water temperatures, and water nutrients composed of pH and electrical conductivity, that are collected every 5 minutes throughout the five-week cultivation period. The use of models varies every week. For leaf area prediction, the ARD Regression model bested out other regression classifiers but is only accurate for estimating leaf area for three-week-old lettuces.
A vision-based system for measuring lettuce canopy area was developed based on pixel counts for each inputted image (Calangian et al., 2018; Lauguico et al., 2020; Concepcion et al., 2020). The algorithm includes color space conversion for CIELab2, thresholding, binarization, and pixel counting. C922 Logitech digital camera was used for image acquisition for every 12 hours. Using the region properties of morphological operations, the surface area value was extracted and fitted with the number of pixels of the same object that resulted in a first-order regression equation of \( y = 0.1797x + 75.595 \) where \( y \) is the canopy area and \( x \) is the number of pixels of the lettuce crop. This approach is effective in estimating the canopy area in terms of the regression coefficient. Leaf cover area was also computed using a novel approach of 3D point cloud segmentation (Mortensen et al., 2018). An agricultural robot named Ladybird scans the lettuce cultivation bed for eight weeks using stereo cameras. The Agisoft PhotoScan Standard software generated the point cloud for color analysis which resulted in a coefficient of determination of 0.94. Despite the above mentioned advances in developing an effective leaf area growth model, numerical image textural features are narrowly used as it normally yields unacceptable accuracy. In this study, a new approach to measuring the leaf canopy area using a vision-based system and machine learning models was presented. Specifically, the study developed a machine-vision system composed of a digital RGB camera that collects lettuce images on weekly basis with the presence of white artificial illumination inside an enclosed lettuce growth chamber. The determination of the most effective color space for this segmentation case was done based on performance metrics such as sensitivity, specificity, accuracy, precision, and f-measure. Numerical image textural feature extraction was also implemented to experiment and determine the suitability of chosen four static supervised machine learning models in measuring leaf canopy area based only on eight texture features which are contrast, correlation, energy, homogeneity, entropy, variance, and information measure of correlations 1 and 2.

**MATERIALS AND METHODS**

**Plant Material and Cultivation Method**

Green loose-leaf lettuce (*Lactuca sativa*) is cultivated on an aquaponic system. All its bunching leaves branch out from a single stalk that is embedded on the substrate. It is the chosen lettuce type due to its rapid morphological growth depending on how it responds to photosynthetic stimuli. The arrangement of leaves of loose-leaf lettuce is mixed of alternate and opposite. The general structure of the leaf during the early stage of the vegetative life cycle is considered a compound and gradually changes to simple and lobed as it mature. It is morphologically convex without partitions. The leaf margin is undulate, leaf attachment is perfoliate and leaf shape is obovate.

A smart soilless controlled-environment agriculture (CEA) was configured through an aquaponic system that grows tilapia and carps and lettuces. The lettuce crops are planted on a three-layer nutrient film technique (NFT) growth bed constructed using food-grade polyvinyl chloride (PVC) pipes with a diameter of 4 inches shown in Fig. 1. Each hole is with a size of 2 inches in diameter and separated in a row by 4 inches distance. There is a total of 141 lettuces planted on it using 1 by 1-inch rockwool and transparent plastic cups. Artificial white T8 LED lighting was used to provide a photoperiod of 24, 21, and 12 hours during vegetative, head development, and harvest growth stages. Temperature is maintained using two exhaust fans in a 25.5 m\(^3\) room. The pH and electrical conductivity (EC) levels are maintained using the combination of fish effluent-concentrated pond water and freshwater sources.

**Dataset Description**

The image set was gathered in a lettuce smart farm in Morong, Rizal, Philippines. The collection ranges ten weeks from August to October 2019 using a digital camera with a 1:1 ratio for a complete lettuce growth life cycle. There are 30 lettuce images collected for each week making a total of 300 lettuce-captured images differing in morphological and texture indices. The first 2 weeks of the lettuce cycle are considered vegetative and the next 5 and 3 weeks are considered head development and harvest growth stages respectively as shown in Fig. 2. As lettuce matures, its leaf canopy area ideally increases with changing textures. The numeric Haralick features used are entropy, variance, information measure of correlation 1, and information measure of correlation 2. The gray level co-occurrence matrix texture features used are contrast, correlation, energy, and homogeneity.
Table 1 shows the descriptive statistics of these texture features and the leaf canopy area of the collected image set. Each model has an input vector of 240 samples for training and 60 samples for testing.

**System Architecture**

The system architecture is shown in Fig. 3 which is divided into four main parts namely: image acquisition, segmentation through multiband color space thresholding, numerical image textural analysis, and machine learning models development for lettuce canopy area measurement. The distance of the camera to the planted lettuce is 12 inches from the top surface of the PVC pipe. The input image is a colored digital image and pre-processed using chromatic adaptation enhancement. Eight textural features are extracted from the image producing a dataset of 300 rows by 8 columns as input to each machine learning model. The performance of each machine learning model is determined using root mean square error by mathematically comparing the theoretical leaf canopy area computed using morphological operations with the model results based on numerical image textural features.
Table 1. Descriptive statistics of numerical image textural and phytomorphological features

| Feature                  | Mean   | SE Mean | Std. Dev | Min.   | Q1    | Median | Q3    | Max.   |
|--------------------------|--------|---------|----------|--------|-------|--------|-------|--------|
| Contrast                 | 0.1121 | 0.00516 | 0.0894   | 0.0007 | 0.0418 | 0.1095 | 0.1558 | 0.5603 |
| Correlation              | 0.9576 | 0.00289 | 0.0499   | 0.4887 | 0.9518 | 0.9743 | 0.9811 | 0.9914 |
| Energy                   | 0.5893 | 0.02250 | 0.3898   | 0.1032 | 0.1210 | 0.7921 | 0.9542 | 0.9984 |
| Homogeneity              | 0.9693 | 0.00174 | 0.0301   | 0.9132 | 0.9374 | 0.9856 | 0.9954 | 0.9999 |
| Entropy                  | 3.3980 | 0.1990  | 3.4520   | 0.0140 | 0.2900 | 1.2570 | 7.5680 | 7.7810 |
| Variance                 | 8.7320 | 0.4660  | 8.0700   | 0.9950 | 1.5130 | 4.0730 | 16.6670 | 26.7970 |
| Information Measure      | -0.8352| 0.00878 | 0.1521   | -0.9443| -0.8831| -0.8457| -0.8091| 0.9171 |
| Correlation 1            | 0.7475 | 0.0160  | 0.2774   | 0.1377 | 0.5231 | 0.8529 | 0.9943 | 0.9975 |
| Information Measure      |        |         |          |        |       |        |       |        |
| Correlation 2            | 0.7475 | 0.0160  | 0.2774   | 0.1377 | 0.5231 | 0.8529 | 0.9943 | 0.9975 |
| Leaf Canopy Area         | 1312979| 98930   | 1713512  | 16741  | 127533| 519330 | 1879725| 8310300|

Fig. 3. System architecture for thresholding, feature extraction and model optimization
Ronnie S. Concepcion II et al.: A Method of Measuring Lettuce Leaf Canopy Area

Development of the Leaf Canopy Area Measurement Model

In region of interest (ROI) image segmentation, the scientific RGB, HSV, YCbCr, and the scientific CIELab color spaces are used for thresholding the lettuce pixels from the background pixels. For image texture feature extraction, Haralick, and gray level co-occurrence matrix (GLCM) is implemented. For the development of leaf canopy area measurement models, four static supervised machine learning models are used namely, fitting function neural network (FFNN), radial basis function neural network (RBFNN), exact radial basis function neural network (RBEFNN), and generalized regression neural network (GRNN).

Color Space Thresholding

Thresholding transforms grayscale image to a binary image in the simplest form of segmenting the focal image from the occluded and complicated background. The constant threshold, \( T \), is used to countercheck if the certain image intensity \( I_{i,j} \) is lower than the \( T \) value, then all included pixels are replaced with a black pixel. Otherwise, it is replaced with white pixels.

In this study, multiband thresholding was used using the AND operator for each color space. The Matlab color threshold toolbox was used to determine the exact range of the multiband spectrum in discriminating the lettuce pixels from the mid- and background pixels. The RGB color space characterizes the blend of several intensities of red, green, and blue to form other color spaces. The first derivative is the hue-saturation-value (HSV) color space in which \( H \) corresponds to the color transition from red to black with the numerical value of from 0 to 1, \( S \) corresponds to unsaturated to fully saturated with values of 0 to 1.0, and \( V \) correspond to brightness with values of 0 to 1.0. The second derivative is the YCbCr color space that corresponds to brightness, blue-yellow spectrum, and red-green spectrum for \( Y \), \( Cb \) and \( Cr \) components respectively. The CIELab color space is a derivative of the CIE XYZ tristimulus components that corresponds to luminosity, red-green chromaticity, and blue-yellow chromaticity for \( L \), \( a \), and \( b \) components respectively.

The small unconnected pixels of size less than 500 derived from the first-hand segmentation are further eliminated using erosion and dilation on structuring element (SE). The resulting image is a clean colored image of the lettuce plant. It is then processed through morphological operations based on decision boundary feature extraction (DBFE). The phytomorphological leaf canopy area is computationally identical to the image region property of biomass area using blob analysis. The performance indicators used are sensitivity or the true positive rate (TPR), specificity or the true negative rate (TNR), precision, or positive predictive value (PPV), accuracy or negative predictive value (NPV), and f-measure.

Image Textural Feature Extraction

Content-based image retrieval such as the automatic measurement of lettuce canopy area is one of the most widely known applications of texture feature extraction. It is very different from morphological features as it deals more with the boundaries of the structuring elements of ROI and requires a grayscale image input. In this study, combined Haralick and gray level co-occurrence image textural features are used. A total of eight texture features are labeled to provide regression in measuring the corresponding leaf canopy area.

There are fourteen Haralick features available but only four were considered in this study namely, entropy \( (H) \), variance \( (\sigma) \), and information measure of correlations 1 \( (IMC1) \) and 2 \( (IMC2) \) which are mathematically defined by Equations 1 to 4 respectively. By using the developed haralickTextureFeatures, the image is read into the Matlab workspace and computed with the symmetric occurrence matrix. Entropy corresponds to the randomness measure in which is the pixel-value vector for rows and columns. The parameter is the mean value of vector , and are similar to entropy but computed on per axis basis.

\[
H = -\sum_{i,j=1}^{n}(P_{ij})(\log_{2} P_{ij}) \tag{1}
\]
\[
\sigma = \sum_{i,j=1}^{n}(1-\mu^2)( P_{ij}) \tag{2}
\]
\[
IMC1 = \frac{H-HXY1}{\max (HXY,HY)} \tag{3}
\]
\[
IMC2 = \sqrt{(1-\exp(-2(HXY2-H)))} \tag{4}
\]

The gray level co-occurrence matrix is a statistical approach in determining how often a certain gray-level intensity pixel appears to its horizontal adjacent neighbor pixels, thus, can provide ROI spatial pixel characteristics. In this study, four GLCM texture features are used namely, contrast (CT), correlation (CR), energy (E) and homogeneity (HO) which are mathematically defined by Equations 5 to 8 respectively. Contrast
corresponds to local variations of gray-intensity pixels, correlation is to the probability of occurrence of gray-level intensity pixel to neighboring pixels, energy resembles uniformity and homogeneity describes the closeness of distribution. By using the built-in Matlab functions of graycomatrix and graycoprops, the spatial matrix is created, and the features are extracted.

\[ CT = \sum_{i,j=1}^{n} (i - j)^2 (P_{ij}) \]  
\[ CR = \sum_{i,j=1}^{n} \frac{(i - \mu_i)(j - \mu_j)(P_{ij})}{\sigma_{ij}} \]  
\[ E = (P_{ij})^2 \]  
\[ HO = \frac{(P_{ij})}{1 + |i-j|} \]

**Machine Learning**

Machine learning models are used for classification, prediction, regression, and other different purposes. Four regression approaches of static supervised neural networks namely, FFNN, RBFNN, RBEFNN, and GRNN have experimented in this study. All of these models are subjected to one hidden layer model.

Fitting function neural network is practically used in regression problems. It forms a generalization model of the input-output relationship based on the training data. The process starts in loading the data with associated target output values. The network is then created using fitnet function and is trained using the trainbr function for the Bayesian regularization (BR) algorithm. To assess the performance of the trained network, perform function is used for mean square error (MSE) basis with an objective value of 0. Moreover, the learning time and regression value were used to determine the least-computational cost network that can provide the optimum root mean square error in contrasting the computed area.

Radial basis function neural network is used in time-series prediction, approximation, and classification that create the network per neuron at a time. It has a radial basis function (RBF) as an activation function on its hidden layer with a transfer function described by Equation 9 in which \( \text{radbas}(n) = e^{-n^2} \). Exact radial basis function neural network is similar to RBFNN but with the exception of modeling goal, MN, and DF hyperparameters. This ensures that the hidden layer only responds with the changing value of spread making this network to produce zero error on training vectors. The process starts in uploading the training input and output vectors separately and inversely, then configuring the spread value with a default value of 1. The newrb function is executed to create the preliminary network. Then, the testing input vector is uploaded inversely and was used in sim function to determine the approximation yields of the developed network. Comparably, RBEFNN models the network based on changing the values of the spread parameter only in which RMSE was used the performance indicator.

Generalized regression neural network is a reformed RBFNN that is used in classification, prediction and regression problems both for static and dynamic systems. It employs nonparametric regression on its radial basis neuron with Gaussian function in the hidden layer. The process starts in uploading the training input and output vectors separately and inversely, then configuring the value of spread hyperparameter one at a time. The newgrnn function is executed to construct the GRNN network. The number of hidden neurons present at the hidden layer is equal to the number of row samples of the input training vector. Likewise, the performance indicator for this network-problem case is RMSE.

**RESULTS AND DISCUSSION**

**Results of Thresholding for Image Segmentation on Lettuce**

Cultivation of vegetable crops inside a controlled environment chamber and extracting leaf canopy signatures that holds essential information for crop phenotyping has captivated agriculturist and scientist for quite a few generations (Burgos-Artizzu, Ribeiro, Guijarro, & Pajares, 2011; Calangian et al., 2018; de Luna, Dadios, Bandala, & Vicerra, 2019; Hang, Lu, Takagaki, & Mao, 2019;
Loresco, Valenzuela, Culaba, & Dadios, 2019; Zou et al., 2019). In this study, it is shown that indoor hydroponic lettuce canopy area can be measured based on numerical image textural feature analysis of Haralick and gray level co-occurrence matrix (Table 1) as compared with morphological pixel feature (Calangian et al., 2018), leaf shape (Saleem, Akhtar, Ahmed, & Qureshi, 2019) and point cloud analysis (Berk, Stajnko, Belsak, & Hocevar, 2020). Instead of using LIDAR technology (Berk, Stajnko, Belsak, & Hocevar, 2020) and a multispectral camera (Fan et al., 2018), a consumer-grade digital camera was used in an image capturing in order to be more available for the general public.

The lettuce images passed through chromatic adaptation enhancement to preserve the true appearance of chromatic intensity in the object due to illumination variations. It is necessary to employ chromatic adaptation so that the erroneous chromatic intensity affected by changes in illumination is corrected and the true ridge of lettuce pixels will come out for effective segmentation. The multi-band color space thresholding for image segmentation is shown in Fig. 4 using the image of ready to harvest lettuce. Based on the original colored image, the ground truth was extracted through segmentation and binarization. And then, the segmented foreground and background pixels using RGB, HSV, YCbCr, and CIELab thresholding was determined using the mean color markers of each color space shown in Table 2, Table 3, Table 4 and Table 5. The color band markers specify the distinction of thresholds of significant pixels for classification.

### Table 2. HSV color band marker mean values

| Pixels    | H   | S   | V   |
|-----------|-----|-----|-----|
| Lettuce   | 0.1385 | 0.386 | 0.373 |
| Non-lettuce | 0.1045 | 0.114 | 0.0695 |

### Table 3. YCbCr color band marker mean values

| Pixels    | Y   | Cb  | Cr  |
|-----------|-----|-----|-----|
| Lettuce   | 146 | 100 | 103.5 |
| Non-lettuce | 21   | 140.5 | 137   |

### Table 4. RGB color band marker mean values

| Pixels    | R   | G   | B   |
|-----------|-----|-----|-----|
| Lettuce   | 43.5 | 177.5 | 53.5 |
| Non-lettuce | 171 | 50   | 176.5 |

Table 6 shows the performance measures for each color space. CIELab has the highest sensitivity, specificity, precision, accuracy, and f-measure. RGB color space always performed the least for each metric. With these results, it is logical that the application of chromatic adaptation minimizes the illumination gradient problem that results to more accurate thresholding as this process is based solely on color intensity. Since CIELab performed best among the color spaces, it was used in phytomorphological and numerical image textural feature extraction. The CIELab color map is shown in Fig. 5. The combination of extracted texture features of the lettuce mask corresponds to the specific numerical value of phytomorphological leaf canopy area or technically the surface area of the lettuce plant. Homogeneity and energy have a strong positive correlation with each other, whereas variance and entropy have a strong inverse correlation. Information measure of correlation 1 has both weak correlations with other texture features but still considered for as part of modeling input to furtherly improve the stability of computational characteristic of each neural network model. Fig. 6 shows the lettuce leaf canopy area values for 300 samples that is unevenly divided into three: 60 samples for vegetative lettuce, 150 samples for head development lettuce, and 90 samples for harvest lettuce. The uneven partition is based on the number of weeks considered per the actual and scientific growth stage of lettuce. It is noticeable that the average area for vegetative, head development, and harvest lettuce is 44,751.28 pixels, 579,112.19 pixels, and 3,381,575.11 pixels respectively. The harvest lettuce leaf canopy area is almost sextuple of the value for head development. RGB color space exhibited the poorest performance in segmenting vegetative pixels from non-vegetative pixels among HSV, YCbCr and CIELab (Table 6). CIELab colorspace with 95.94% accuracy in segmentation was thoroughly used to annotate phenotypic images. It was similarly observed that the a* component of the vegetative pixels is significantly greener compare to the complicated background (Calangian et al., 2018).
Fig. 4. Multiband segmentation through color space thresholding (a) original image, (b) ground truth (c) RGB, (d) HSV, (e) YCbCr; (f) CIELab

Table 6. Performance measures for different color space

| Color Space | Sensitivity (%) | Specificity (%) | Precision (%) | Accuracy (%) | F-Measure |
|-------------|-----------------|-----------------|---------------|--------------|-----------|
| RGB         | 20.02           | 20.80           | 19.75         | 20.41        | 0.20077   |
| HSV         | 87.32           | 91.98           | 92.46         | 89.52        | 0.90962   |
| YCbCr       | 45.75           | 45.73           | 45.86         | 45.74        | 0.45798   |
| CIELab      | 94.77           | 97.16           | 97.24         | 95.94        | 0.96583   |

Fig. 5. CIELab color map indicating lettuce and non-lettuce pixels
Results of Machine Learning for Leaf Canopy Area Measurement

Table 1 summarized the descriptive statistics of phytomorphological leaf canopy area and numerical image textural features of the 300 sample images. The Q1 parameter corresponds to the threshold value on each extracted feature for vegetative to head development growth stage. The Q3 parameter corresponds to the threshold for head development to the harvest growth stage. The surface area of the whole lettuce plant is a strong determinant to discriminate each lettuce growth stage. There are three static supervised machine learning models, namely, fitting function neural network, radial basis function neural network, exact radial basis function neural network, and the generalized regression neural network. The same dataset was used for each model and data splitting was standardized to 80%-20%. Model optimization was done through varying the hyperparameters supported by each model. RBFNN, RBEFNN, and GRNN were all optimized based on fine-tuning the value of spread factor. Fig. 7 separately shows the performance of each optimized model on measuring the leaf canopy area based on eight selected texture features. The FFNN model performed with the highest RMSE by measuring 604,500 pixels instead of 19,023.36 pixels for the vegetative lettuce samples. The RBFNN and RBEFNN models performed least accurate by measuring 1,270,000 pixels and 1,572,600 pixels instead of 71,211 pixels for the head development lettuce sample. The GRNN model garnered poor results by measuring 426,000 pixels instead of 35,469 pixels for the head development lettuce sample. On the other hand, the lowest RMSE yielded by FFNN was recorded on measuring 615,900 pixels compared to 624,000 pixels for head development lettuce sample. For RBFNN, RBEFNN, and GRNN it was by measuring 2,507,500 pixels instead of 2,500,000 pixels for harvest lettuce sample, 333,800 pixels instead of 328,000 pixels for head development lettuce sample, and 350,000 pixels instead of 346,000 pixels for head development lettuce sample, respectively. The RMSE value of 0.641, 0.673, 0.626, and 0.588 was yielded for FFNN, RBFNN, RBEFNN and GRNN models respectively.

![Graph showing leaf canopy area values for 300 images](image-url)

Fig. 6. Lettuce leaf canopy area values for 300 images
Fig. 7. Comparison of computed leaf canopy area for each static supervised model (a) FFNN, (b) RBFNN, (c) RBEFNN, (d) GRNN

Fig. 8. Developed GRNN model with 2 hidden layers
It has been confirmed that the optimized GRNN performed best in deriving the lowest leaf canopy area difference to the theoretical ground truth area that is comparatively shown in Table 7. Fig. 8 shows the developed GRNN model with 1 input layer, 2 hidden layers, and 1 output layer. The dimension of numerical weight elements, sample time, and the number of hidden artificial neurons in the first and second hidden layers are 2400, 1, 240, and 1 respectively. The optimizing spread value is adjusted to 0.09 which is still supported by Matlab framework. The network connections were configured to [1; 0] for bias connect, [1; 0] for input connect; [0 0; 1 0] for layer connect and [0 1] for output connect. The derivative function was set to the default that ensured Jacobian errors based on network biases and weights. The performance function and parameter were set to mean squared error, and regularization and normalization. Using simple linear regression (SLR) for optimization, the first-order degree characterizing the spread value and RMSE relationship was developed and shown in Equation 10. Based on the optimization experiment, as the value of the spread (S) factor increases so as the RMSE. Equation 11 was developed using a multi-objective fitting regression model which corresponds to the relationship of each independent texture features namely, contrast, correlation, energy, homogeneity, entropy, variance, information measure of correlation 1, and information measure of correlation 2, to the response factor that is the leaf canopy area.

For vegetative lettuce samples, the GRNN model bested the other models with an 18.94% error. The FFNN yielded an accumulated 128.07%. For head development, the GRNN model measures closest to ground truth with 14.11% error, and the RBF-FNN model responded the worst with 18.82%. For harvest growth stage samples, RBFNN bested all other models with 5.08% and GRNN performed the least with 7.57%. Moreover, among the three lettuce growth stages, the optimized machine learning models garnered profound difficulty in measuring leaf canopy area for vegetative lettuces and with precision for the harvest samples. GRNN bested other included feature-based machine learning models in predicting canopy area with $R^2$ of 96.66%. It is slightly lower to the $R^2$ of 98% of a straight-forward linear regression utilizing phytomorphological pixels as the dependent variables (Calangian et al., 2018). However, the developed GRNN model has a great advantage as it resolves canopy area using multiple leaf texture signatures whereas the accuracy and sensitivity of the pixel-based regression model can be easily disrupted when other materials with closed same chromaticity with lettuce leaf are present in its background. Moreover, the developed leaf texture- based GRNN model was trained using leaf signatures from vegetative, head development, and up to harvest stage unlike with just a single stage of the lettuce life cycle (Calangian et al., 2018; Loresco, Valenzuela, Culaba, & Dadios, 2019).

It was also analyzed that there is a 127,600% increase in canopy area in terms of phytomorphological pixel area from the first week of germination (vegetative) to the tenth week after germination (harvest). Hence, the lettuce vegetative stage rendered an average of 44751.3 area pixels, $5.79 \times 10^5$ area pixels for head development, and $3.38 \times 10^6$ area pixels for harvest lettuce as a measure of growth. This evident growth of lettuce crops signifies that the configured controlled environment is sufficient in providing the required environmental stressors in promoting plant growth.

### CONCLUSION AND SUGGESTION

The phytomorphological feature extracted is surface area and considered as the leaf canopy area. It has been confirmed that the optimized GRNN performed best in deriving the lowest leaf canopy area difference to the theoretical ground truth area that is comparatively shown in Table 7. Fig. 8 shows the developed GRNN model with 1 input layer, 2 hidden layers, and 1 output layer.
area. Model optimization was done by finetuning the hyperparameters particularly the spread factor. In multiband thresholding for color space-based segmentation, CIELab performed best based on sensitivity, specificity, precision, accuracy, and f-measure. For optimized machine learning models, the developed two-hidden layer GRNN with 0.09 spread value bested FFNN, RBFNN, and RBEFNN with an 18.94% error, 14.11% error, and 7.57% for vegetative, head development and harvest lettuce samples. GRNN was also characterized by stability from training to the testing stage without overfitting. Future work involves applying algorithms for multidimensional reduction and feature selection that will furthermore improve the computational cost of the network.

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