INTRODUCTION

Philippines is an agricultural country having a 30 million ha land area which 47% of it is agricultural land. Conventional way of farming is still being practiced by farmers in the country as they toil the soil, plant the seeds, water the plant and harvest the crop according to their observation and calendar. According to International Labor Organization in 2018, the employment percentage in agriculture in the country declined from 35.28% to a value of 25.96% in the span of 10 years. Due to the declining percentage of the agricultural workforce, it is naturally considered as a physically challenging work which involves extensive periods of bending, stooping, standing, and incorporates out tedious movements in awkward positions for the body. In addition, the danger of hazards is increased by poorly designed tools, body fatigue, difficult terrain, exposure to the different chemicals and deprived overall health.

Tomato, as one of the commonly grown vegetables, is widely cultivated as a subordinate produce (Lesaca, 2019, February 15). Indeed, tomatoes are considered the fourth most sought-after commercial vegetable next to potatoes, lettuce, and onions (Ware, 2017). PSA (2019) conducted a survey during the period of April to June of 2018. The production of the tomato in the country increased by 1.8%, from last year's record of 72.19 thousand metric tons to 73.50 thousand metric tons. In spite of that, the biggest challenge is in what way to deliver the required quantity and quality of tomatoes through the whole year-round (Lesaca, 2019, February 15). The very challenging season for the growing of tomatoes is the rainy season because the production is focused on dry season that causes market oversupply during this season and shortage during rainy season. Throughout rainy season, tomato production is low which corresponds to supply resulting to high price

ARTICLE INFO

Keywords:
Deep learning
Flower and fruit detection
Maturity classification
Regional-based convolutional neural network
Single shot detector

ABSTRACT

The tomato farming industry needs to adopt new ideas in applying the technology for its growth monitoring and main. Machine vision and image processing techniques have become useful in the increasing need for quality inspection of fruits, particularly, tomatoes. This paper deals with the design and development of a computer-vision monitoring system to assess the growth of tomato plants in a chamber by detecting the presence of flowers and fruits. The system also provides maturity grading for the tomato fruit. Two pre-trained deep transfer learning models were used in the study for the detection of flowers and fruits, namely, the Regional-based Convolutional Neural Network (R-CNN) and the Single Shot Detector (SDD). Maturity classification of tomato fruits are implemented using the Artificial Neural Network (ANN), K-Nearest Neighbors (KNN), and the Support Vector Machine (SVM). Evaluation results show that for the detection of flowers and fruits, the over-all accuracy of the R-CNN is 1.67% for flower detection and 19.48% for the fruit detection while SSD registered 100% and 95.99% for flower and fruit detection respectively. In the machine learning for maturity grading, SVM produced the training-testing accuracy rate of 97.78%-99.81%, KNN with 93.78%-99.32%, and ANN with 91.33%-99.32%.

ISSN: 0126-0537 Accredited First Grade by Ministry of Research, Technology and Higher Education of The Republic of Indonesia, Decree No: 30/E/KPT/2018

Cite this as: de Luna, R.G., Dadios, E.P., Bandala, A.A., & Vicerra, R.R.P. (2020). Tomato growth stage monitoring for smart farm using deep transfer learning with machine learning-based maturity grading. AGRIVITA Journal of Agricultural Science, 42(1), 24–36. http://doi.org/10.17503/agrivita.v42i1.2499
The availability and inadequate supply of quality fresh tomato results to market price hikes during off season. Tomato production throughout regular planting season is affected by diseases leading to production losses.

Several studies on how to ensure the quality of growth of tomato were conducted already like the one performed by Islam, Mele, & Kang (2018). They used silcon treatment to maintain the firmness, shelf life and microbial activity of cherry tomatoes. Potassium and biopesticide were also used in increasing the resistance of the tomato in bacterial disease (Prihatiningsih, Djangkiko, & Rochminarsi, 2011). Daily monitoring of the growing tomatoes is also a problem because abnormalities of the plant should be observed. Conducting regular maintenance means preventing the occurrence of pests. Problems can be corrected when identified early by having regular check-up around for anything unusual because alertness saves tomatoes (Burpee, n.d.).

Machine vision plays a significant role in the classification and identification of plants (de Luna et al., 2017), growth monitoring and assessment (Dimatira et al., 2016; Valenzuela et al., 2017). Mobile devices can be used to perform augmented reality (AR) to increase productivity in a workplace. The study of Siriborvornratatukan (2018) provided hardware designs and architectures for projector-based AR to enhance user experiences. Research related to object detection and object classification using image processing and machine and deep learning techniques has been available for many years and applied for plant monitoring especially in the detection of flowers, fruits, yield, and diseases. The study of Yamamoto, Guo, Yoshioka, & Ninomiya (2014) developed a tomato fruit detection system utilizing color, shape, and size as features in the machine learning. Similarly, Mohammed & Amer (2017) focuses on an automated segmentation and calculation of yield fruit based on the color and shape analysis. The color transformation from RGB to YCBCR was used in the segmentation of fruits in an input sectional tree image. Mostly fruit recognition techniques which combine different analysis method like color-based, shaped-based, size-based and texture-based (Ninawe & Pandey, 2014). The study of Oppenheim, Edan, & Shani (2017) utilized the HSV shading space to segment the tomato flower from the contextual. In the study of Malik et al. (2018), new mature tomato detection algorithm based on the improved HSV color space watershed segmentation was proposed to guide a robot to pick up red tomatoes automatically. Same utilization of HSV features was used by Kandi (2010) designed for automated defect detection and sorting of single-color fruits such as banana, tomatoes, and mangoes. Together with neural network, Yossy, Pranata, Wijaya, Hermawan, & Budiharto (2017) used image processing involving RGB to HSV transformation to classify mango for sorting.

The machine learning regarding the ripeness of the tomato fruit was developed by El-Bendary, El Hariri, Hassanien, & Badr (2015). The system used color features for classifying tomato maturity. It uses Principal Components Analysis (PCA) for sustaining the SVM and Linear Discriminant Analysis (LDA) algorithms for feature extraction. Different approach was made by Semary, Tharwat, Elhariri, & Hassanien (2015) as the system is allocated to a feature fusion method adding with some color and texture features in tomato grading. The system also used a color moment, GLCM and Wavelets energy and entropy.

On the other hand, deep learning also paved its way in applications for detection and recognition tasks. The study conducted by (de Luna R. G., Dadios, Bandala, & Vicerra, 2019) used machine learning and deep learning for tomato fruit size classification. Deep Convolutional Neural Networks are commonly used in the detection of objects. The study of Sa et al. (2016) presents a new approach for fruit detection using deep convolutional neural networks which aims to build a reliable, fast, and accurate fruit detection algorithm, which is a vital component of a self-governing agricultural robotic system; it is a key element for fruit yield approximation and automatic harvesting. Another research work by Rahmoenofar & Sheppard (2017) proposed a deep convolutional neural network for counting tomato fruits. Wherein, the architecture used is based on Inception-ResNet because of two reasons; a better accuracy and lesser the calculation cost. The study of Sun et al. (2018) provided an improved deep learning-based tomato organ detection method. Faster R-CNN algorithm and Resnet-50 were used as feature extractors instead of the VGG16 in the model’s training.

In this paper, researchers developed a computer-vision system that can be used in the monitoring of the tomato plants inside the chamber with the capability of monitoring the growth of the tomato plants through detection of flowers and fruits.
The system is developed using Python programming with libraries intended for image processing, machine learning, and deep learning.

**MATERIALS AND METHODS**

**Image Acquisition**

Images are obtained using the image capturing device designed to capture the tomato plant inside the controlled chamber. Captured image has a uniform dimension of 680 x 480 with horizontal and vertical resolution of 96 dots per inch (dpi) and has the bit depth of 24 and in the Joint Photographic Experts Group (JPEG) format. Capturing of tomato plants is done by the system at 8:00 am, 12:00 noon, and 5:00 pm in order to obtain a dataset of the tomato plant under different natural lighting conditions. Camera is placed in 0.65 meters from the targeted plant to be able to capture the fruits with better quality. Researchers provided the ground truth in every gathered image regarding the presence of flower and fruit, total number of tomato fruits, and the maturity grade of every fruit whether green, turning, or red. Fig. 1 shows the sample captured images of the tomato plant inside the chamber.

**Dataset Organization**

The datasets obtained from the growth chamber will be utilized for the training of the deep learning algorithms. This data sets will be processed based on the ground truth using the software which is named as “LabelIMG”. It is an object labelling tool used for annotations of image datasets. Annotations is done in order to determine the location of the classes (flower and fruits) to be detected in the image. Wherein, during the annotation of the images, each flower and each tomato, whether green, turning, or red is enclosed in a box which will dictate its location when it is saved as an .xml file. Table 1 shows the distribution of the dataset for deep learning training.

| Item                                    | Quantity |
|-----------------------------------------|----------|
| Number of Gathered Image Datasets       | 277      |
| Number of Sample Images Used for Training | 231     |
| Number of Samples Images Used for Validation | 46      |
| Number of Tomato Fruits in the Training Dataset | 1,193   |
| Number of Tomato Flowers in the Training Dataset | 421     |

The generated images are also been utilized for the training of the different machine learning models for maturity grading. From the images, green, turning, and red tomatoes are identified and cropped. The first class (green tomatoes) is derived from the green until breaker maturity stage of a tomato which is generally green in color. The second class (turning tomatoes) is derived from the turning until the pink maturity stages of a tomato which is generally orange in color. The third and last class (red tomatoes) is derived from the light red until the red maturity stages of a tomato which is generally red in color. After the sorting of the extracted tomato images according to their actual classes, the Hue-Saturation-Value (HSV) color space are extracted from the samples of each. The mean data of the HSV color space of the image will be used in the training of different machine learning algorithms. From this, a csv file containing 450 rows x 7 columns is generated. Table 2 shows the content distribution of the csv file.

Fig. 1. Sample of plant images captured inside the chamber
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System Overview

The system utilized the use of Python programming in a console that contains libraries that include the Open Source Computer Vision Library (OpenCV) and the scikit-learn. Those libraries are essential image processing, machine learning, and deep learning. Fig. 2 depicted the process of flower and fruit detection in the tomato plant image. It is subdivided into three different processes which is the candidate region generation, the feature extraction, and the category judgment. In the candidate region generation stage, an input image is being investigated using the Selective Search Algorithm where a series of small areas or candidate regions that are more likely to be a tomato or fruit is to be extracted. While the main idea of the Selective Search Algorithm is that there can be a two thousand candidate boxes to split the input image into small areas. Also, selective search is responsible for the repeated merging of the two most likely adjacent areas to form a possible object that is guided accordingly by the merge rule. The merge rule encompasses the color similarity or the color histogram, the texture similarity or gradient histogram, size similarity, and shape compatibility.

In the second stage, feature extraction is done using the retrained convolutional neural network (CNN) specifically, VGG16, which is based from the PASCAL VOC Datasets. In which, during transfer learning, the last three classification layers are replaced with new layers that are specifically tomato fruits and flowers to the object classes that want to be detected. Finally, for the category judgment stage, the region proposal bounding boxes are refined by a support vector machine (SVM) that is trained using CNN features.

Table 2. Dataset for the training of the machine learning algorithms

| Item | Quantity |
|------|----------|
| Number of Samples (No. of Rows) | 450 |
| Number of Samples for the Green Tomato Maturity (No. of Rows) | 150 |
| Number of Samples for the Turning Tomato Maturity (No. of Rows) | 150 |
| Number of Samples for the Red Tomato Maturity (No. of Rows) | 150 |
| Number of Columns | 7 |
| Column Label | Red, Green, Blue, Hue, Saturation, Value, Maturity |

Fig. 2. Flower and fruit detection algorithm
Fig. 3 illustrates the process of tomato ripeness classification algorithm. For the pre-processing of the bounding box that contains the image of the tomato fruit, the color space values RGB and HSV will be extracted. After this, image segmentation will take place. Color image segmentation which is constructed on the feature of a color in the pixels of an image adopts the similar colors of an image resemble to dispersed groups and hereafter specific areas in the image. Which means, every cluster represents a group of pixels that match in terms of the similarity in the color property.

Scaling is the next process to convert the image into a 16 x 16 pixel dimensions. It will result to a reduced time of computation and for the adjustment of filter parameters utilized in the next pre-processing process. After the scaling, the conversion pixel values to an array in accordance to the HSV Color Map Array, which will undergo the process of function fitting with utilization of machine learning algorithms. In which, three machine learning algorithms will be tested for the function fitting which can be defined as the procedure of selecting values for the parameters in a function to finest designate a set of data. In which in this study, it will specifically test the use of feed-forward neural network, support vector machine, and K-Nearest Neighbors for the function fitting or the classification of the detected tomato fruits according to its ripeness categories.

**Fig. 3.** Tomato fruit maturity grading algorithm

**Fig. 4.** Annotation of images (A) flowers only, (B) fruits only, (C) both flowers and fruit
RESULTS AND DISCUSSION

Dataset Generation and Preparation for the Object Detection and Maturity Grading Algorithm

The preparation for the datasets that will be used for the training of the object detection algorithm is done using LabelIMG, a graphical image annotation tool. Sample annotation for the plant images containing flowers only, fruits only, and both flowers and fruits are presented in Fig. 4. Annotated images generated an xml file which serve as the ground truth for the detection of fruit and flowers during the deep learning training.

Dataset for maturity grading came from the extracted RGB and HSV values from the cropped images of tomato fruits classified as green, turning, and red. With the aid of Minitab, Table 3 summarized the descriptive statistics of the generated dataset.

### Table 3. Descriptive statistics generated in Minitab

| Variable | Count | Mean  | SE Mean | St. Dev | Minimum | Q1     | Median  | Q3     | Maximum |
|----------|-------|-------|---------|---------|---------|--------|---------|--------|---------|
| Red      | 450   | 127.90| 0.96    | 20.33   | 83.54   | 112.05 | 124.67  | 141.37 | 188.46  |
| Green    | 450   | 90.61 | 1.05    | 22.31   | 29.60   | 74.55  | 91.70   | 106.51 | 145.28  |
| Blue     | 450   | 62.08 | 0.74    | 15.63   | 17.79   | 51.79  | 60.54   | 72.80  | 107.52  |
| Hue      | 450   | 24.24 | 0.32    | 6.71    | 6.65    | 20.52  | 24.35   | 28.01  | 48.59   |
| Saturation | 450 | 153.11| 1.28    | 27.14   | 86.13   | 132.78 | 150.88  | 176.42 | 218.49  |
| Value    | 450   | 128.04| 0.96    | 20.29   | 83.65   | 112.27 | 124.84  | 141.45 | 188.46  |

Remarks: Q1 is the median of the lower half of the data and Q3 is the median of the upper half of the data

### Table 4. Region-based convolution neural network (RCNN) training details

| Epoch   | Training Result |
|---------|-----------------|
| Epoch 10/20 10th Epoch Results | Mean number of bounding boxes from RPN overlapping ground truth boxes: 3.231277559157
Classifier accuracy for bounding boxes from RPN: 0.9991875
Loss RPN classifier: 1.4436373786
Loss RPN regression: 0.0.3421450123
Loss Detector classifier: 0.801223601844
Loss Detector regression: 0.8074852079856
Elapsed time: 1614.69676898
Total loss decreased from 1.65390185239 to 1.6355656360, saving weights |
| Epoch 15/20 15th Epoch Results | Mean number of bounding boxes from RPN overlapping ground truth boxes: 2.90748189863
Classifier accuracy for bounding boxes from RPN: 0.9899625
Loss RPN classifier: 1.47523356582
Loss RPN regression: 0.0020390051111
Loss Detector classifier: 0.04851523774135
Loss Detector regression: 0.043897300803
Elapsed time: 1697.18015313
Total loss decreased from 1.68111493465 to 1.58847548055, saving weights |
| Epoch 20/20 20th Epoch Results | Mean number of bounding boxes from RPN overlapping ground truth boxes: 3.05162364696
Classifier accuracy for bounding boxes from RPN: 0.99610125
Loss RPN classifier: 1.59288279586
Loss RPN regression: 0.0.015164809952
Loss Detector classifier: 0.8397018341873
Loss Detector regression: 0.0.3490001405741
Elapsed time: 1685.48926337
Training complete, exiting. |
Results of Deep Learning for Object Detection (Flower and Fruit)

The training process was performed with Python 3 on Google Colaboratory with TensorFlow backend and GPU-enabled environment. This is to address the hardware requirements of the training since images are used in the deep learning.

Region-based Convolution Neural Network (R-CNN)

For the development of the region-based convolutional neural network, 231 training samples and 46 validation samples that contains 421 flowers and 1, 193 fruits are used. The training is executed with 20 epochs to acquire the needed accuracy in the training for the detection of the tomato fruit and tomato flower. Table 4 tabulates the epoch accuracy about the RCNN.

Trials are performed to show the results of using the trained model in the detection of tomatoes in different test images. Percent accuracy are then computed to calculate how accurate the trained model is in providing its expected outputs. Table 5 presents sample output obtained for detection for an image which contains a flower only while Table 6 presents for fruit only and Table 7 for an image that contains flower and fruits.

Table 5. Sample detection for presence of tomato flower of the RCNN model

| Trial | Model's Determination | Machine Detection | Ground Truth | Remarks |
|-------|-----------------------|-------------------|--------------|---------|
| 1     | Presence of Flower: No | Presence of Flower: Yes | Failed |

Table 6. Sample detection for presence of tomato fruit of the RCNN model

| Trial | Model's Determination | Machine Detection | Ground Truth | Remarks |
|-------|-----------------------|-------------------|--------------|---------|
| 1     | Fruit Count: 3        | Fruit Count: 6    | Fruit Count: 50% |

Table 7. Sample detection for presence of tomato flower and fruit of the RCNN model

| Trial | Model's Determination | Machine Detection | Ground Truth | Remarks |
|-------|-----------------------|-------------------|--------------|---------|
| 1     | Presence of Flower: No | Presence of Flower: Yes | Presence of Flower: Failed |

| Fruit Count: 0        | Fruit Count: 5    | Fruit Count: 0% |

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### Table 8. Single Shot Detector (SSD) training details using Tensor Board

| Metrics                                                                 | Training Result |
|-------------------------------------------------------------------------|-----------------|
| Mean Average Precision (mAP) for (small) objects which Area < 32²       | ![Graph](image1) |
| Mean Average Precision (mAP) for (medium) objects which 32² < Area < 96² | ![Graph](image2) |
| Mean Average Precision (mAP) for (large) objects which Area > 96²       | ![Graph](image3) |
| Total Loss                                                              | ![Graph](image4) |
Single Shot Detector (SSD)

For the development of the Single Shot Detector, 231 training samples and 46 validation samples that contains 421 flowers and 1,193 fruits are used. The training is executed with 10,000 step size to acquire the needed accuracy in the training for the detection of the tomato fruit and tomato flower. The training was done in Google Colab, aided by a Tensor Board which present graphs during training. These graphs show if the training of the object detection algorithm is under fit, over fit, or good fit. Over fitting is a condition where a model has learned the training dataset too well. While, underfit graph shows that the model cannot learn the data sets which was input in the training. Lastly, good fit is a training which is between an overfit and an under fit model. Shown in Table 8 are the mean average precision, losses, and learning curves that means that the system is in a good fit.

Table 9 presents sample output obtained for detection for an image which contains a flower only while Table 10 presents for fruit only and Table 11 for an image that contains flower and fruits. Green bounding box presents detection of flower while blue bonding box for the detection of fruits.

Performance Evaluation for R-CNN and SSD

The RCNN and SSD models are evaluated in the following conditions: flower alone, fruit alone, and both flower and fruit. Every condition has 30 images to be evaluated. Table 12 presents the summary of the characteristics of both RCNN and SSD for detection and assessing the correct number of detections. It can be inferred that SSD performed better in comparison with the RCNN for both flower and fruit detection.

Results of Machine Learning for Maturity Grading

For the classifiers which will be responsible for the classification of the detected tomato fruit, the ANN, KNN, and SVM, are trained and evaluated. Different training-testing dataset distribution are considered in the training phase. Models are created using the 60%-40%, 70%-30%, and 80%-20% train-test dataset splitting.
The training accuracy performance was evaluated using 10-fold stratified cross-validation per model. Optimization was also performed using GridSearchCV in finding optimal values for hyperparameter tuning. Models were tested using the testing dataset to establish the best dataset splitting and machine learning model. Table 13 summarized the accuracy percentage of every model in different dataset splitting both during training and testing.

| Trial | Model’s Determination | Machine Detection | Ground Truth | Remarks |
|-------|-----------------------|-------------------|--------------|---------|
| 1     | Presence of Flower: Yes | Presence of Flower: Yes | Presence of Flower: 100% | |
|       | Fruit Count: 9         | Fruit Count: 9    | Fruit Count: 100%    | |

Table 12. Summary of accuracy performance for RCNN and SSD in flower and fruit detection

| Image Features         | RCNN’s Accuracy (%) | SSD’s Accuracy (%) |
|------------------------|---------------------|--------------------|
| Image with Flower Only | 0.00                | 100.00             |
| Image with Fruit Only  | 26.98               | 96.62              |
| Image with Flower and Fruit | Flower: 3.33  | Flower: 100         |
|                         | Fruit: 11.98        | Fruit: 95.35       |
| Over-all Accuracy       | Flower: 1.67        | Flower: 100         |
|                         | Fruit: 19.48        | Fruit: 95.99       |

Table 13. Accuracy performance of size classification models using machine learning

| Model | Splitting | No. of Samples | Default Parameter Accuracy (%) | Optimized Parameter Accuracy (%) | No. of Samples | Correct | Incorrect | Accuracy (%) | Over-all Accuracy (%) |
|-------|-----------|----------------|-------------------------------|---------------------------------|----------------|---------|-----------|--------------|-----------------------|
| SVM   | 60-40     | 270            | 7.78                          | 97.78                           | 180            | 179     | 1         | 99.44        | 99.81                 |
|       | 70-30     | 315            | 7.78                          | 97.78                           | 135            | 135     | 0         | 100.00       | 99.32                 |
|       | 80-20     | 360            | 7.78                          | 97.78                           | 90             | 90      | 0         | 100.00       |                       |
| KNN   | 60-40     | 270            | 90.44                         | 93.78                           | 180            | 179     | 1         | 99.44        | 99.32                 |
|       | 70-30     | 315            | 90.44                         | 93.78                           | 135            | 133     | 2         | 98.52        |                       |
|       | 80-20     | 360            | 90.44                         | 93.78                           | 90             | 90      | 0         | 100.00       |                       |
| ANN   | 60-40     | 270            | 85.11                         | 91.33                           | 180            | 179     | 1         | 99.44        | 99.32                 |
|       | 70-30     | 315            | 85.11                         | 91.33                           | 135            | 133     | 2         | 98.52        |                       |
|       | 80-20     | 360            | 85.11                         | 91.33                           | 90             | 90      | 0         | 100.00       |                       |

There is significant increase in all machine learning models once optimization is performed as compared to the performance using the default value of parameters. Result also depicted that regardless of whatever combinations of data splitting is used, every model has consistent performance in the training phase. The accuracy result from cross-validation is the same, which is 91.33% for ANN, 93.78% for KNN, and 97.78% for SVM.
In Fig. 5, testing accuracy revealed that the performance of all the models using independent dataset for testing is high also consistent with its performance during the training phase. Comparison of the three model’s performance revealed SVM as the best optimized machine learning model with training performance of 97.78% accuracy and overall testing accuracy of 99.81%.

CONCLUSION

Two deep learning models are implemented in the detection of flowers and fruits in the image of a tomato plant. These are the Region-based Convolutional Network (R-CNN) and the Single Shot Detector (SDD). Both models are trained using the gathered images of tomato plants inside the growth chamber. Due to heavy specification requirement of deep learning, the training is implemented in the on-line infrastructure of Google through the Google Colab. Results revealed that after several test of the two models, SSD performs very well in the detection of flowers and fruits with outstanding performance of 100 and 95.99%, respectively, compared to the R-CNN’s 1.67 and 19.48%. For the maturity grading, three machine learning classification models are trained to classify the ripeness of the tomato fruit into green, turning, and red. SVM produced the training-testing accuracy rate of 97.78-99.81%, KNN with 93.78-99.32%, and ANN with 91.33-99.32%. All three models performed very well and are robust not just because of obtaining an accuracy of over 90%. The model is also trained from the RGB and HSV Color space features that are comparable representation to human eye’s behavior in observing the fruit color of the tomato plant with different lighting conditions. SVM model is considered the best model due to its best performance in maturity classification.

ACKNOWLEDGEMENT

The authors would like to acknowledge the Engineering Research and Development for Technology (ERDT) under the Department of Science and Technology (DOST) for funding this research. The authors also recognized the assistance and technical expertise of the members of the Intelligent Systems Learning (ISL) Laboratory group of De La Salle University (DLSU).

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