Sugar Cane Red Stripe Disease Detection using YOLO CNN of Deep Learning Technique

Inchaya Kumpala*, Nontawat Wichapha and Piyawat Prasomsab

Department of Computer Engineering, Rajamangala University of Technology Khon Kaen Campus, Muang District Khon Kaen, 40000, Thailand

Inchaya.ku@rmuti.ac.th*, Nontawat.wi@rmuti.ac.th and piyawat.pr@rmuti.ac.th

Abstract. *The objective of this research is to apply the deep learning technology based on the Convolutional Neural Network (CNN) algorithm YOLO, creating a simulation for image recognition. The technology was used to recognise the sugar cane disease with specified images. The Sugar cane-Leaf Disease Diagnosis System was designed and developed to enable the user to recognise sugar cane disease automatically. Sugar cane-Leaf Disease Diagnosis System consisted of two parts: the first part was the disease detection and diagnosis. This was where the Convolutional Neural Network learning-teaching import 4,000 images divided into 2,000 images of sugar cane leaves with disease and 2,000 images of sugar cane without disease for the comparison. The other part was the system for displaying response or disease diagnosis system interface. This part contained the Convolutional Neural Network used to categorize and analyzing the leaf condition that would be diseased and non-diseased. The tool used for sugar cane leaf recognition and analysis in this research was the Deep Learning technique based on a Convolutional Neural Network consisting of image classification, image analysis, and image processing. This tool was used to test 3 sample groups, which were selected from 9 promotional staff from Mitrphol sugar factory, Thailand, 3 operative agricultural academic experts from Khon Kaen Field Crop Research Center, Thailand, 2 system developers, and 30 local agriculturists. The average accuracy score of processing of the first and the second group was 95.90 % and 91.30% with the highest accuracy of 98.45% and 97.26%, respectively, while the average estimated time duration was 1.46 and 1.53 seconds, respectively.*

Received by	9 June 2021
Revised by	31 March 2022
Accepted by	4 April 2022

Keywords:

YOLO, image processing, deep learning, Convolutional Neural Network, CNN, sugar cane, leaf-disease, image classification

1. Introduction

Convolutional Neural Network (CNN) is a class of neural networks. This algorithm set recognises essential correlation in data pack through procedures that simulate the function of the human brain, processing specific imagery to identify pixels. CNN is powerful visual imagery, a deep learning artificial intelligence designed for generative and descriptive function, using full vision to recognise image and video together with user and natural language processing [1]. In computerised vision, object detection has always been a challenging problem. There are many different object detections based on deep convolutional neural networks in classifying and identifying objects in the same plane, demonstrating the object detection that outstand other methods [2]. Convolutional Neural Networks (CNN) for remote detection in plants has become a significant technology that demonstrates plants in area-based and global based. Convolutional Neural Network (CNN) deep learning is the most efficient in the regional-based. It can identify various plant properties from remote image recognition, intelligently detecting plant species, or classifying plants in pixel mode.

YOLO algorithm is a tool used for fast and precise object identification, suitable for computerised vision. We connect YOLO to a camera and ensure the real-time response, including the image retrieved from the camera and display of object recognition [4]. YOLO is a deep learning based on a neural network simulating human vision, which contains object identification, real-time response, and image detection. The principle is to divide an image into frames. Then run the perception algorithm in parallel for every object frame. YOLO minimises localisation error, learning object representation, giving better performance for object detection than another method, including DPM and R-CNN [5]. To study, design, and develop a sugar cane disease diagnosis system using deep learning of the Convolutional Neural Network YOLO algorithm. The simulation is created to recognise an image, detecting sugar cane disease with the Colab program. The sugar cane disease diagnosis system is based on a deep learning technique for Sugar cane Red Stripe Disease. Developers must develop sugar cane disease diagnosis system with visual imagery, sending into the system and give result to minimise time and ensure a correct solution. With the design based on python linked with API to exchange data from Flask, the system detects sugar cane disease on time. The Google Cloud is processed with a python flask framework for web applications with a virtual environment [6].

2. Material and Method

2.1 Study Locations

The research locations were in Sri Thad district, Udon Thani province, Mittraparp road, Sila sub-district, Mueang Khon Kaen District, Khon Kaen province and Chiang Yuen sub-district, Chiang Yuen district, Maha Sarakham province, Thailand, as shown in Fig. 1. These locations have had sugar cane red stripe disease.

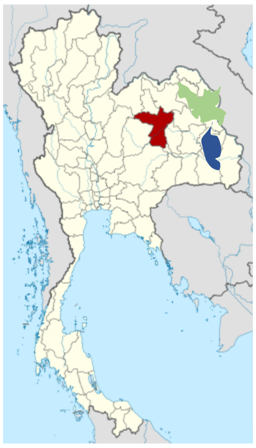

Fig. 1 The study locations: Udon Thani province, Khon Kaen province and Maha Sarakham province, Thailand

2.2 Field Data Collection

The photograph data for this study were gathered from three different places as shown by the examples in Fig. 2 after isolating the germs from the leaves as shown in Fig. 3, in Hua Na Kham sub-district, Sri Thad district, Udon Thani province, Mittraparp road, Sila sub-district, Mueang Khon Kaen District, Khon Kaen province; and Chian Yuen sub-district, Chiang Yuen district, Maha Sarakham province, Thailand.

(a) without disease (b) with desease

Fig. 2 Example of sugar cane classification

Fig. 3 The researcher isolated the germs from the sugar cane leaves

2.3 YOLO Object Detection

Faster-YOLO inherits the characteristics of YOLO end-to-end operation and directly predicts the bounding box and object class. Faster-YOLO mainly includes four parts: input image, feature extraction network, bounding box prediction and final detection result [2].

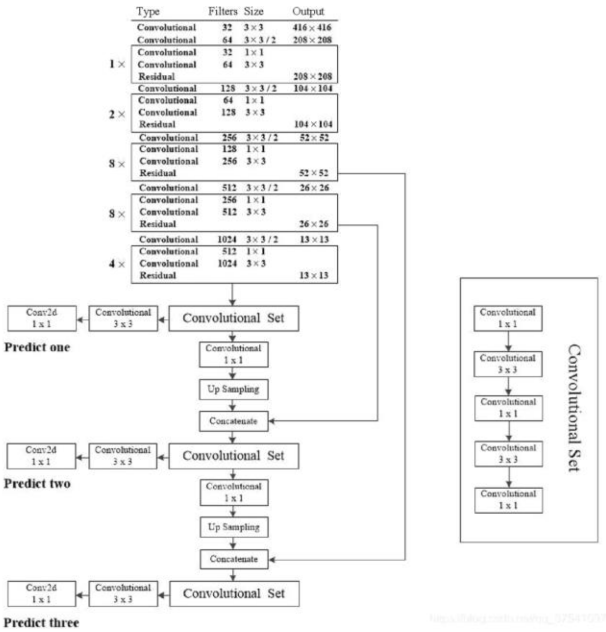

Fig. 4 Network structure of Yolo V3 [2]

The efficiency measurement of this model is calculated in percentage (%) of accuracy, as (1):

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

; where TP is True Positives
TN is True Negatives
FP is False Positives
FN is False Negatives

2.4 CNN Training

The CNN training consisted of 2 steps. The first step was the training for creating the simulation and the second step was the testing of the created simulation. Before creating the simulation, the original images were adjusted to have the same scale with 500x500 pixels using the

Pycham program [11]. The training dataset, which was a part of the learning process, there were 4,000 pictures of sugar cane leaves were classified into 2 groups, namely ‘with disease’ and ‘without disease’. Additionally, 200 pictures of each group were allocated for the testing dataset process. The YOLO object detection algorithm was applied to identify disease in sugar cane leaves based on the Convolutional Neural Network (CNN) [3] via Colaboratory or "Colab” written and operated by Python in a browser without any settings YOLO-v3-spp and YOLO-v3 models were applied in the Google Colab [8].

The test program environment was utilized the python programming language in accompanying with the access to the GPU Colab. The Python library was used for analysing and displaying the resultant information as an image. The NumPy library was used to create the random data. Then, the percentage of accuracy was calculated for the ingot image in comparison with the trained image. The Keras's reference was used to process the model and the TensorFlow was used to get varied API and that to create deep learning architecture [11]. This setting supported the OpenCV to accelerate the outcome and enhance resultant accuracy [10]. The deep learning technique was used to distinguish the feature between the leaf with and without disease, which was processed by importing all framed images for training and comparing them with the data submitted. The training part was divided into two groups, namely diseased and non-diseased [6].

The OpenCV was applied to accelerate the outcome and enhance result accuracy [10]. This research contained the K-Fold Cross Validation; where k = 10 was used to create the training and learning data, which were categorised into 2 model groups; 200 images were used for the data validation.

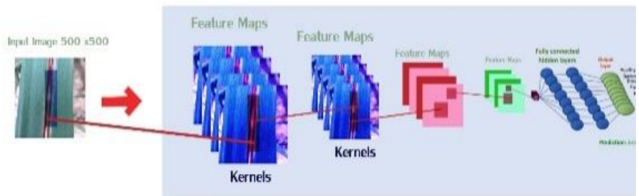

Fig. 5 Overall architecture of the proposed system

3. Methodology

3.1 Modeling

In this research, the Deep Learning of the Convolutional Neural Network based on the YOLO algorithm was used, which was by creating a simulation of visual imagery to detect disease in sugar cane. The system then classified, analysed and processed the images to identify and diagnose sugar cane disease. The samples were sent to the relevant authority to identify the disease; taking at least two weeks to obtain the results.

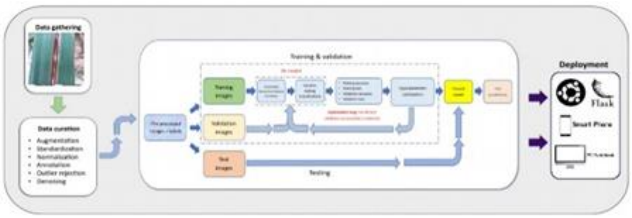

Fig. 6 Overall architecture of the proposed system in this research

The Convolutional Neural Network pictures were collected from 3 different locations: Hua Na Kham sub-district, Sri Thad district, Udon Thani province, Mittraparp road, Sila sub-district, Mueang Khon Kaen District, Khon Kaen province; and Chian Yuen sub-district, Chiang Yuen district, Maha Sarakham province, Thailand. The photos of the sugar cane leaves collected were adjusted into the same scale of 500x500 pixels. According to the information from the agricultural academic experts at Khon Kaen Field Crop Center, the sugar cane leaves were divided into disease and non-disease ones, as shown in Fig. 2. The samples from the 3 locations were sent to Khon Kaen Field Crop Center for identifying the disease, by certifying the samples and pictures used in training with the results. The sugar cane disease diagnosis system with visual imagery was developed, which was by sending into the system and obtaining the results to minimise time and ensure the correct solutions. With the design based on python linked with API to exchange data from Flask, the system could detect the sugar cane disease promptly.

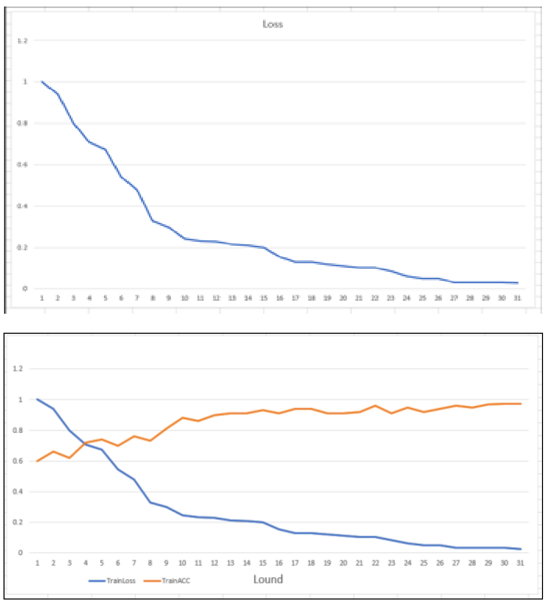

Fig. 7 Accuracy and Loss function in training for model creation

3.2 Experimental Design

The proposed system consisted of the Convolutional Neural Network used for categorising and analysing the leaf condition, which was diseased or non-disease. The program tool used for sugar cane leaf recognition and analysis was the Deep Learning technique based on Convolutional Neural Network. In addition, with the use of the OpenCV, TensorFlow pandas, NumPy, matplotlip, and Keras, the sugar cane leaf disease diagnosis system could perform its function accordingly. The library function was summarised as follows:

1) Apply YOLO to detect disease in sugar cane leaves based on Convolutional Neural Network. [4]

2) OpenCV was the library in the Deep Learning technique used in classifying the leaf with disease and without the disease. To proceed, total framed images were imported for training purposes. Eventually, the images were compared with the information submitted. The training was divided into two parts: diseased and non-disease [6].

3) Tensorflow was the library applied to accelerate the outcome and enhance result accuracy [10].

4) Pandasis was the library used in coupling with NumPy for data management within the system [8].

5) NumPy was the library used for calculating accuracy percentage from the imaged being compared to the trained images [7].

6) Matplotlip was used for drawing or framing an image. In the training process, the user must frame an area for comparison. The frame was classified into two parts: diseased and non-disease [9].

7) Keras enhances model running efficiency. The Keras was the high-level neural network API, written in Python language and capable of running on top of either TensorFlow or Theano. It was developed with a focus on enabling fast experimentation. Being able to go from idea to result with the least possible delay is key to doing good research. [11]

Fig. 8-13 show the photographs of the pages and features of the proposed sugar cane leaf disease diagnosis system.

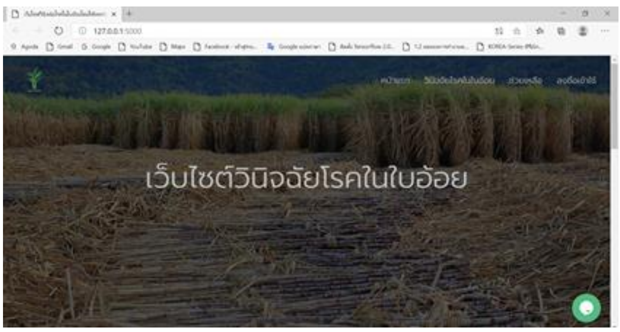

Fig. 8 Home Page of Sugar cane leaf disease diagnosis system (https://lib-decv.kku.ac.th/)

Fig. 9 Sugar cane leaf disease diagnosis system page

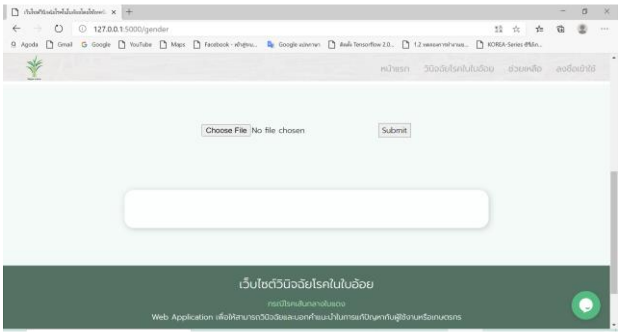

Fig. 10 Uploading the image for disease diagnosis

Fig. 11 Diagnosis results

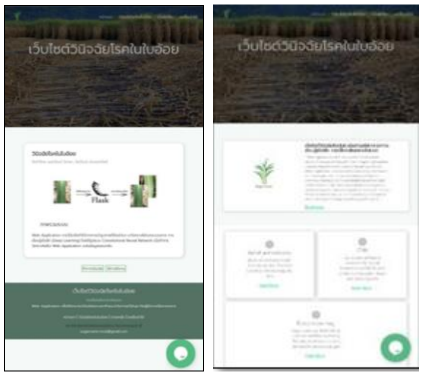

Fig.12 Using diagnosis system on mobile device

Fig. 13 Diagnosis System function on a mobile device

4. Results

This research proposed the sugar cane red stripe disease detection using YOLO CNN of Deep Learning technique. The accuracy and speed obtained from the tests of the system showed high consistency as designed. The evaluation obtained from the comparison with the results from the general users and system experts/developers showed that the proposed system achieved high accuracy of 95.90% and 91.30%, with diagnosis time of 1.46 and 1.53 seconds, respectively.

5. Discussion and Conclusions

In this study, the operation platform was carried out on the Google Colab cloud service. The algorithm took from the YOLO of weights that were trained by using 4,000 training images. The proposed system ran using the open source artificial neural network called as Numply library. The result was recorded as per user types, which included the general users and the system developers. The proposed system could distinguish images from the two groups. Further details are shown bellows:

1) The average duration of sugar cane red stripe disease diagnosis system based on the deep learning technique for the general users was 1.46 seconds while the system developers was 1.53 seconds which meet the criteria set forth.

2) The average diagnosis score of the diagnosis system for sugar cane red stripe disease passed the accuracy measurement criteria. The general users achieved the average accuracy of 95.90%, while the system developers achieved average accuracy of 91.30%. Both are above the set threshold.

YOLO algorithm was suitable for real-time vehicle detection. With the data set suitable for the targeted study [12] You Only Look Once (YOLO) method that was used for creating a simulation for image recognition. The technology would recognise the sugar cane disease detection with an image real-time object detection, which was quickly performed using a single convolutional neural network [4] to estimate the paddy rice plant height (PH) using UAV remote sensing for evaluation of the growth status of the rice in fields [13]. to monitor rice growth by using the reflectance relation of (R-B)/(R+B) and R/(R+G+B) to predict rice biomass before and after the heading stage. UAV-derived aerial imagery was obtained from an RGB camera attached on the UAV [14].

Acknowledgements

The authors would like to extend my sincere thanks to dad, mom, teachers and those providing data to support this study and for making this work possible and The Faculty of Engineering, Rajamangala University of Technology Isan Khon Kaen Campus, Thailand, for the experimental equipment, as well as, the technical supports.

References

[1] Y. Liu, H. Pu and Da-WenSun, "Efficient extraction of deep image features using convolutional neural network (CNN) for applications in detecting and analysing complex food matrices," *Trends in Food Science & Technology*, vol. 113, pp.193-204, 2021.

[2] Y. Yin, H. Li and W. Fu, "Faster-YOLO: An accurate and faster object detection method," *Digital Signal Processing*, vol.102, July, 102756, pp.1-11, 2020.

[3] T. Kattenborn, J. Leitloff, F. Schiefer and S. Hinz, "Review on Convolutional Neural Networks (CNN) in vegetation remote sensing," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 173, March, pp. 24-49, 2021.

[4] J. Redmon and A. Farhadi, "YOLOv3: An Incremental Improvement," *IEEE Conference on Computer Vision and Pattern Recognition* (*CVPR*), Las Vegas, NV, USA, 2016.

[5] X. Han, J. Chang and K. Wang, "You Only Look Once: Unified, Real-Time Object Detection," *Procedia Computer Science,* vol. 183, pp. 61-72 ,2021

[6] B. Aakash and A. Srilakshmi, "MAGE: An Efficient Deployment of Python Flask Web Application to App Engine Flexible Using Google Cloud Platform," *Inventive Communication and Computational Technologies*, pp. 59-68

[7] Ihsan Ali, Aftab Khan, Muhammad Waleed "A Google Colab Based Online Platform for Rapid Estimation of Real Blur in Single-Image Blind Deblurring" , *International Conference on Electronics, Computers and Artificial Intelligence (ECAI),* 2020

[8] Introduction to Keras. [Online]: https://colab.research.google.com/drive/1R44RA5BRDEaNxQIJhTJzH_ekmV3Vb1yI#scrollTo=ggBJHZ3Z6E11 [Accessed Jan. 18, 2021].

[9] Tutorials point, Google Colab Introduction, [Online]: https://colab.research.google.com/notebooks/intro.ipynb?utm_source=scs-index [Accessed Jan. 18, 2021].

[10] M. Swain and S. Dhariwal, "A Python (Open CV) Based Automatic Tool for Parasitemia Calculation in Peripheral Blood Smear," *International Conference on Intelligent Circuits and Systems (ICICS)*, pp.445-448, 2018.

[11] C. Xianbao, J. Q. Guihua and Y. Z. Zhaomin, "An improved small object detection method based on Yolo V3," *Pattern Analysis and Applications.*, 3 May, 2021.

[12] S. Ray, K. Alshouiliy and D. P. Agrawal, "Vehicle Detection Using Different Deep Learning Algorithms from Image Sequence," *Baltic J. Modern Computing*, vol. 8, no. 2, pp. 347-358, 2020.

[13] P. Bunruang and S. Keawplang, "Evauation of Sugarcan Plant Height Using UAV Remote Sensing," *Engineering Access*, vol.7, no.2, pp. 102, 2021.

[14] P. Suphan, S. Kaewplang and W. Sa-Ngiamvibool, "Monitoring of Rice Growth with UAV-Derived Aerial Imagery, " Mahasarakham International Journal of Engineering Technology, vol.5, no.1, pp. 28-32, 2019.

Biographies

Inchaya Kampala is a Lecturer at the Computer Engineering, Faculty of Engineering at Rajamangala University of Technology Isan, Khon Kaen Campus, Thailand. She received her Master of Science in Industrial Education Program in Computer and Information Technology from King Mongkut's University of Technology Thonburi, Thailand in 2012. Her researcher interests include interactive design, user experience design, user interface and web application.

Nontawat Wichapha was born in 1998. He received his Bachelor degree in Computer Engineering, Faculty of Engineering, Rajamangala University of Technology Isan Khon Kaen Campus, Thailand, in 2021. His researcher interests include web application, deep learning, and YOLO.

Piyawat Prasomsab was born in 1998. He received his Bachelor degree in Computer Engineering, Faculty of Engineering, Rajamangala University of Technology Isan, Khon Kaen Campus, Thailand, in 2021. His researcher interests include web application, deep learning, and YOLO.