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A Framework for Chili Fruits Maturity Estimation using Deep Convolutional Neural Network

***Abstract**. An agriculture robot has been demanded in recent years. Inaccurate in estimating the maturity of the chili always happens since the human eyes are tend to prone to errors. Serving an effective, innovative, feasible chili recognition system would help farmers as economical alternative by reducing the workloads while increasing fruit yield. Hence, a comprehensive framework of chili maturity estimation using deep learning is carried out.*

Streszczenie.** W ostatnich latach pojawił się popyt na robota rolniczego. Niedokładne oszacowanie dojrzałości chili zawsze się zdarza, ponieważ ludzkie oczy są podatne na błędy. Dostarczenie skutecznego, innowacyjnego i wykonalnego systemu rozpoznawania chili pomogłoby rolnikom jako ekonomiczna alternatywa, zmniejszając obciążenie pracą przy jednoczesnym zwiększeniu plonów owoców. W związku z tym przeprowadzane są kompleksowe ramy szacowania dojrzałości chili z wykorzystaniem głębokiego uczenia..* (Szacowanie dojrzałości owoców chili przy użyciu głębokiej konwolucyjnej sieci neuronowej***)

Keywords: agriculture, chili, maturity, deep learning.
Słowa kluczowe: robot rolniczy, dojrzałość owoców, sieci neuronowe.

Introduction

Agriculture has always been a noteworthy economic and social sector in any country [1]. Worldwide, agriculture is a $5 trillion industry for its importance of providing food, raw materials and also employment opportunities within the social community. As the economy grows, so did agriculture. Since agriculture is evolving, the procedures and techniques are also changing. The previous harvesting system does not have the recognition ability as a human does. A slow harvesting process leads to an inaccurate and inefficient result, while increasing the production cost. Hence, the process of detection and classification of maturity are bound to be different in comparison to the approach that has been done previously. Two essential variables need to be considered when classifying agricultural products; the weight and the size. Researcher starts to undergo their study by improving the current practice in agriculture industries including the process of farming, fertigation supplies, harvesting and categorizing. Such information is crucial by creating a documentation and management record for farmers to undergo further analysis [3]. The invention of Internet of Things (IoT) has been broadly utilized for improving fertigation and pesticide purposes. Somehow, some industries have started to implement an autonomous or semi-autonomous robot for practicing the harvesting process. However, the process of categorizing the fruits still remain unchanged. Manual process of classification of the fruit’s class still be conducted by workers.

By using traditional approach, it's difficult for farmer or manpower to detect the size of chili for estimating the maturity level. Small mistakes or missteps are usually unavoidable, especially for estimating the maturity of the chili because human eyes are prone to errors and inaccurate. Thus, the use of automated classification of maturity level is take into consideration. This approach represents an innovative, feasible, and economical alternative for farmers who require the accurate size of chili for maturity classification. In consequences, this approach is able to solve the problem mentioned by replacing Artificial Intelligence (AI) towards the Industrial Revolution (IR 4.0) such as deep learning method such CNN. To date, few numbers of related works reported for measuring the quality or categories of the fruits. Most reported works is able to prove its ability to define the fruit’s quality for certain types of fruits based on the captured images. Fruits images with small in sizes and having a complex characteristic such chili still remain unanswered for further investigations. Practically, the size of chili fruits is measured by calculating the length between the tip (calyx) and the end of the structure (apex).

In addition, when analyzing the pixel size of an image, it tends to a difficult situation for converting from 2D image into 1D vector. It might lose their characteristics as spatial features of the picture space when the first generation of Artificial Neural Network (ANN) used. Spatial features refer to the arrangement of pixels in an image as vector files which consisting locations or spatial information. In such circumstances, the files do not always have data connected to them. Spatial features often offer various natural or artificial boundaries or shapes to aid in visualizing spatial data and network manipulation [2]. For instance, when the system tries to distinguish between dogs and cats, nose width and ear length must be explicitly stated as data points. However, by using Convolutional Neural Network (CNN), these spatial features are automatically extracted from the image. To make CNN more ideal, thousands of parts need to be extracted. The main advantage of CNN is that it is automatically detects the important features without any human supervision which made CNN would be an ideal solution to computer vision and image classification problems.

This study aims to group the chili categories according to the point calculated from calyx and apex. Afterwards, CNN is used to categorized the extracted chilis into its maturity levels. The algorithm will start tracking the number of samples that has been collected from the farms. Then, it will categorize the number of pictures based on the different chili sizes. After classifying the size of the chili, the analysis needs to be done to measure the accuracy of size classification. CNN with the three-layer operation which is the conventional layer, max-pooling layer, and fully connected layer is used during this experiment.

Artificial intelligence

AI is a branch of computer science that focuses on the development of intelligent machines to function and respond in the same way that humans do. One of AI's goals is to create machines that can communicate with humans and understanding human intelligence as well as how events and the world affecting people's emotion [4]. Alan Turing proposed in 1950 that a machine's intelligence could be determined by its ability to exhibit intelligent behavior that is indistinguishable from an intelligent human. The computer is considered to have passed the test if the human was unable to decide whether or not the machine was an individual [5]. AI in the public sector attempts to replicate human problem-solving practices to achieve more efficient solutions. A unique feature in the replication of human thinking, learning and problem-solving capabilities are intended to enhance performances by incorporating AI technology into a computer application with human-computer interaction and data interaction which is also referred as AI application [6]. Nowadays, AI technology are widely used around the world in different sectors and its influence can be seen especially in healthcare, manufacturing, and agriculture. Agriculture is an extreme sector in the industry consisting 30.7 percent of the world's population directly working on 2781 million hectares of agricultural land [7]. In terms of accuracy and robustness, the systems in the agriculture sector that using AI are the best performers. Agriculture is a dynamic domain where situations cannot be generalized to suggest a standard solution.

Machine learning

Machine learning is a branch of computer science originating from pattern recognition and computational learning theory. Machine learning is the analysis and design of algorithms which can learn from data for making predictions. It is used in various computational tasks where explicit algorithms are impossible to design and programmed. Data mining and machine learning are often confused, but data mining focuses mainly on exploratory data processing [8]. The fundamental difference between humans and machines in performing their work is intelligence. The neural system sends the data collected to the human brain for perception and action. The data then is structured and remembered by comparing it to previous experiences stored in the brain, and interpreted during the perception process [9]. Learning method in machine learning can be categorized into; supervised, unsupervised and reinforcement learning.

Supervised learning

Supervised learning are divided into two sorts which is classification and regression. Classification employs an algorithm to reliably assign test results to specified groups, whereas regression is used to investigate the relationship between dependent and independent variables [10]. When dealing with supervised learning problems, one has a set of measured inputs, which affect one or more outputs. Input variables can either be qualitative, quantitative or both. Depending on the distinction between input variables, one will use different prediction methods [11]. Qualitative variables are also called categorical, discrete or factors. Supervised learning aims to create an artificial system that can learn how to map inputs to outputs and anticipate the system's output given new inputs [12].

Unsupervised learning

Marr in 1970 made early unsupervised learning about the goal of learning the model of neocortex. Geoffrey Hinton and Terrence Sejnowski introduce a model of learning called the Boltzmann machine in 1986 [13]. Unsupervised learning is the second type of machine learning, in which unlabelled data are used to train the algorithm, which means it used against the data that has no historical labels. The purpose is to explore the data and find some new structure in it. According to the data segments, the algorithm figures out the data and clusters technique with new labels [14]. It teaches the model to learn about the data and work on it right away. Then, the model can also label the data in distinct categories once it has been clustered and categorised because the data has already been solved. Cluster analysis is a type of machine learning groups that are unlabelled, unclassified, or uncategorized data into clusters. Cluster analysis, rather than responding to input, discovers commonalities in the data and reacts to the existence or lack of such commonalities in each case. The new piece of information for this method aids in detecting out-of-place data points [15].

Reinforcement learning

It aids in determining which activity gives the most significant benefit over time. This method focuses on interacting with the environment because learning decisions in the reinforcement earning approach are dependent. Dependent decisions should be labelled and it also helps and works better in AI, which involves a lot of human interactions [16]. An autonomous parking for example, learning the road map by the car is handled by training algorithm. The training algorithm is in charge of fine-tuning the agent's policy based on the sensor readings, actions, and incentives that have been collected. Thus, the vehicle's computer should park using only the tuned policy and sensor readings after the training is completed.

Deep learning

Deep neural networks have been analyzed by scientists since 1979. However, it became a new machine learning research field in 2006 when it was used for unsupervised reducing data dimensionally [17]. Deep learning refers to a group of machine learning algorithms which use multiple layers that contain nonlinear processing units [18]. It enables a program to construct complex concepts from simpler ones. A deep learning system can reflect the idea of a person’s image by incorporating more straightforward concepts like corners and contours, which are represented in terms of edges. Neural networks can be trained to perform the same tasks on data as human brains do in identifying patterns and classifying various types of knowledge. Individual layers of neural networks may also be thought of as a kind of filter that operates from the most obvious to the most subtle, raising the probability of detecting and producing a correct result [20].

Supervised learning

In supervised learning, it divides two sorts of problems for pattern classification and regression. The model tries to learn the differences between the data items belonging to different classes based on the labels provided with the data. The model also learns to link input to predicted output in both classification and regression tasks. The method for supervised learning includes ANN, CNN, and Recurrent Neural Network (RNN) [21]. ANN is a component of a computing system supposed to assess and make decisions in the same way as the human brain does. ANN is a deep learning building block that solves problems that humans find impossible or extremely tough and function similarly to the human brain. The input layer, hidden layer, and output layer are the three layers of ANN. Each layer is made of interconnected adaptive processing units called neurons. Each neuron in the human brain is made of a cell body which is responsible for computing information by passing forward information to hidden neurons and providing final output. ANN learns to discover patterns based on inputs given to the input layer during the training phase [22].

CNN are AI systems based on multi-layer neural networks that learn significant features from images and perform various tasks such as object classification, detection, and segmentation. The CNN method has four types of layers which is Convolutional Layer, Activation Layer, Max Pooling Layer, and Fully Connected Layer. The fundamental advantage of CNN over its predecessors is that it discovers essential traits without human intervention. RNN is an artificial neural network that works with time series or sequential data. Language translation, Natural Language Processing (NLP), speech recognition, and image captioning are examples of challenges in deep learning techniques. This method made its way into popular apps like Siri, voice search, and Google Translate [24].

Unsupervised learning

In unsupervised learning, we have the input data only and no corresponding output to map. Though algorithms may be able to uncover the data's fascinating structure. The unsupervised learning algorithms such as the K-means algorithm is used in clustering problems [20]. K-means clustering is particularly valuable in exploratory data analysis and data mining. As computer power has increased, so has the prevalence of big data sets. Compared to the alternative clustering approaches, k-means clustering has remained popular due to its ease of implementation, computational efficiency, and low memory usage [25].

Convolutional neural network

The foundation of the CNN started from the discovery of Hubel and Wiesel in 1959 [26]. A particular type of multilayer neural network for spatial data is CNN amongst different deep learning architectures. The visual perception of living beings inspires the architecture of CNN. CNN is mostly employed in image recognition and face recognition [19] and has an excellent feature extraction capability [27]. The different CNN architectures include LeNet, AlexNet, VGGNet, GoogleNet, ResNet and ZFNet [28]. CNN is a particular classes of neural networks and best suited for the intelligent processing of visual data. It is a multilayer neural network architecture variation and includes convolution layers, sub-sampling layers, and fully connected layers [29] as shown in Fig. 1.

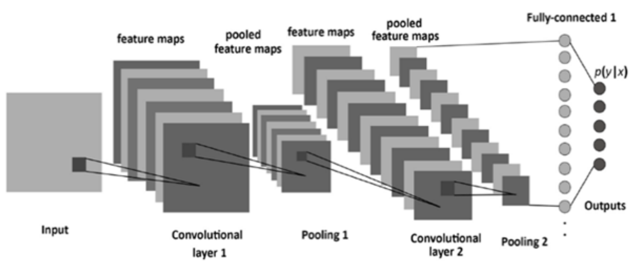

Fig.1. CNN architecture [30]

Table 1. Comparison of previous related work on fruit detection

Author(s)	Title	Features/Accuracy
Shiv Ram Dubey and Anand Singh Jalal	Fruit and vegetable recognition by fusing colour and texture features of the image using ML [31]	Colors, texture/88.7%
T.Ishikawa, A.Hayashi, S.Nagamatsu,Y.Kyutokn, I. Dan,T.Wada, K. Oku, Y.Saeki, T. Uto	Classification Of Strawberry Fruit Shape By ML [32]	Shape/70.0%
M. Atas, Y.Yardimci, A. Temizel	A new approach to aflatoxin detection in chili pepper by machine vision [33]	Texture/83.3%
O. Cruz-Domínguez, J.L. Carrera-Escobedo, C.H. Ortiz-Rivera,	A novel method for dried chilli pepper classification using Artificial intelligence [34]	Size, colors/82.7%
Mandeep Kaur, Reecha Sharma	Quality Detection of Fruits by Using ANN Technique [35]	Shape, colors, size/80.0%
A Taofik, N Ismail, Y A Gerhana, K Komarujaman and M A Ramdhani	Design of Smart System to Detect Ripeness of Tomato and Chili with New Approach in Data Acquisition [36]	Colors/80.0%
S.Deepika, Dr.R.Punidha	Fruit Maturity And Disease Detection Using Artificial Neural Network [37]	Size, shape/83.0%
Norasyikin Fadilah,Junita Mohamad Saleh, Haidi Ibrahim,Zaini Abdul Halim	Oil Palm Fresh Fruit Bunch Ripeness Classification Using Artificial Neural Network [38]	Colors/86.7%

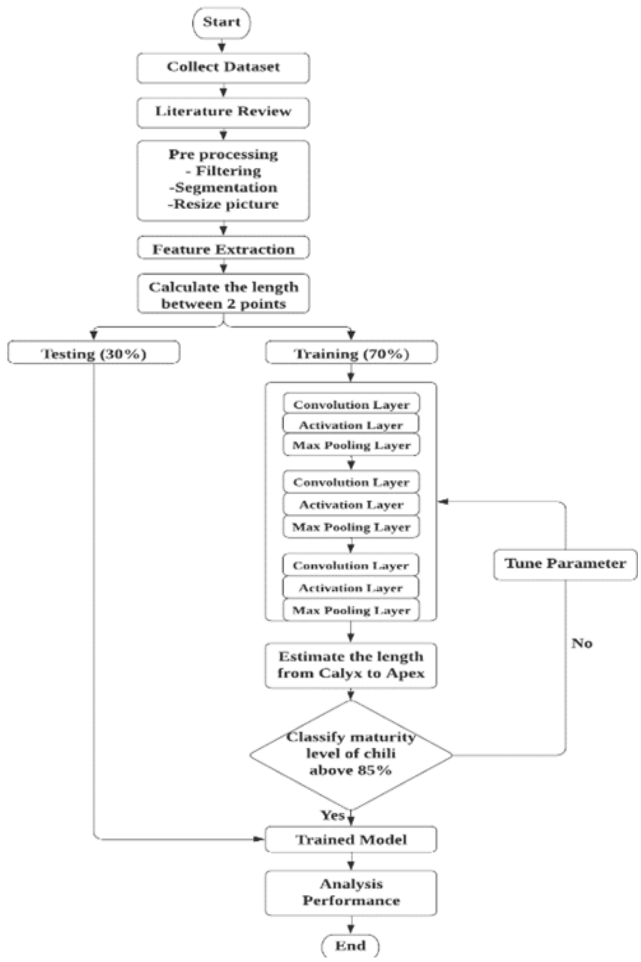

Fig. 2. Proposed framework for chili maturity estimation using deep learning

Framework for chili fruits maturity estimation

The chili dataset is considered to be tough to collected due to some criteria such as camera position, clutter, lighting for taking a photo for each chili according to its size. Then, the dataset will undergo the preprocessing including filtering, segmentation and resizing. The noise or unwanted features need to be removed before pursuing any further process. Filtering could improve the image to highlight certain elements while removing others. The technique of converting one image into several segments or group of pixels for identifying items and pertinent information is known as picture segmentation for simplifying or changing its representation [39]. Then, the image pixel has to resize from 4160x3120 to 195x260 for easier processing. Next step is extracting the chili feature by calculating to its length from the calyx and apex while dividing and reducing large datasets into smaller groups. The important characteristic of these data sets is generated and a large number of variables is produced. Feature extraction aids for extracting the meaningful feature from input data by selecting and combining variables into set of features while reducing the size of data. The measured images later are divided into its categories according to its maturity. The entire subset is divided into two different sizes of subsets; training and testing before it passes through a series of convolution layers with filters such pooling layers, activation layer, fully connected layers. Softmax activation function is applied as activation function in this experiment. In this work, we set the desire accuracy as 85% by classifying the chili according to its maturity levels. Hyperparameter tuning need to be undergone until the model reaches the desired or beyond desired performance.

Overview of entire system

Fig. 3 show the block diagram of system operation for this study. This study uses a deep learning model using Convolution Neural Network (CNN). First, take the photo of green chili to collect the dataset. Next, image pre-processing needs to be undergone to resize the picture making the process classification in MATLAB Software easier. Feature Extraction is used extract the features to measure the length between calyx and apex. CNN is used to detect the size and to classify the maturity level. Lastly, the performance for recognition accuracy is analyzed. Overall system overview as shown in Fig. 3.

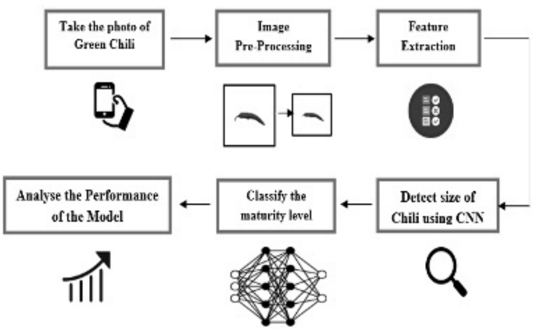

Fig. 3. Overall system overview

Data collection

In this work, we are collaboration with our industrial partnership Solok Fertigasi, MSJP Enterprise located at Bukit Baru Duyung Melaka, Malaysia. There are about 1000 chili plant has been planted in the polybag. The total of chili's images used is 600 where 420 used for training and 180 for testing. All the images are categorized into three categories: unmatured, moderately matured, and matured. The pictures are made of frames which the position has been rotated. Table 3.2 indicates the number of instances of each class that were utilized for training and testing with some sample images for each category. Size of each image set to be 195 x 260 pixels.

Table 2. Category of chili maturity level

Maturity level	Size	Training	Testing
Unmatured 	< 6 cm	140	60
Moderately matured 	7 cm – 11 cm	140	60
Matured 	> 12 cm	140	60

Preliminary experimental result

For this preliminary result, we have conducted a number of experiments by extracting the images by calculating the sizes of the chili fruits. Then, those images have been fed into CNN model to experience and learn the pattern into its categories; unmatured, moderately matured and matured. In this pre-experiment, we choose learning rate as 0.0001 and number of epochs is 200. Adam optimizer has been chosen for optimization algorithm by adaptively changing the learning rate accordingly by combining stochastic gradient descent algorithm. Fig. 4 shows the experimental results for categorizing the level of chili maturity. Total 240 images have been utilized in this experiment with the size of 195 x 260 pixel of each.

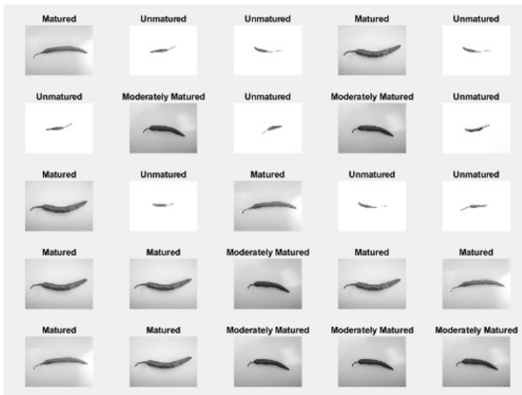

Fig. 4. Preliminary result of maturity classification

Conclusion

This article proposed a comprehensive framework for measuring maturity level of chili fruits using CNN. An initial result is reported from our preliminary experiment shows that the proposed model is able to produce an outstanding performance to classify the chili fruits into unmatured, moderately matured and matured. For further experiment, we are planning to expand our experiment with more images and compare the performance of our outcome with several other deep learning methods.

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