Computer Engineering Senior Project Proposal

B. Eng. Computer Engineering

Academic Year 2559

Project title: Sugar Cane Grading from photo using machine learning

Group number: 2559:39

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**Introduction**

## **Keywords:** sugar cane grading, machine learning, image processing, convolutional neural network

## **Problem Statement, Motivation, and Potential Benefits**

Sugarcane is an important crop in Thailand. In order to produce high quality sugar, sugar companies need detailed information on the cane conditions in different fields. Features such as color and size of the leaves are some indicators of cane conditions (cane health).

A field’s condition, such as soil properties, seed quality or irrigation system, has some important consequences for those features. However, not every field is identical. Thus, the features and the resulting can quality vary from one field to another. This will cause a problem in collecting data: there are too many fields and it is too complicated for sugar companies to do exhaustive surveys to get the information that they need.

To address to this problem, this project will work in co-operation with staff from Mitrphol Sugar Company to create a software test bed for improving cane quality control over a large area. The test bed will be able to analyze the sugar cane health from mobile phone photos. The project will use machine learning to train the software to discriminate photos based on cane quality. The results obtained from this project will be useful for developing a real world system to allow individual farmers to send photos of their fields, which can be analyzed and classified to get more detailed information about cane health over a wide area. This project is thus important because it will help sugar companies gain better information with a lower surveying cost.

## **Project Types**

## This is a research - real world stakeholder project.

## 

## **Proposed Method**

The goal of this project is to develop a software test bed (not a final system) for experimenting with sugar cane images using supervised machine learning technique. The test bed will first extract the sugar cane crucial features from mobile phone photos. This test bed will then classify the cane photos into different health categories based on extracted features using supervised machine learning.

The project is expected to contain the following steps:

1. Research basic image processing concepts, machine learning concepts and algorithms with a focus on convolutional neural network
2. Collect, create and understand training/testing data
3. Write pre-processing software to standardize images
4. Extract desire features from input images (could be combined with ML frameworks, depending on which framework will be chosen)
5. Research and test/create prototypes for various ML frameworks (Potential libraries to look at: Caffe, Tensorflow, CUDA) on order to make a decision about which learning framework to use
6. Create experimental design - details of what parameters will vary; how to select training and test images (there are various strategies); how to analyze the results
7. Write scripts to control the experiments
8. Train the learning system
9. Test and analyze the result
10. Repeat training/testing (possibly) with 1) different framework; 2) different parameters.

## 

## **Original Engineering Content**

The main issue of this project is to classify mobile phone images into different classes using machine learning. There are already some existing works on this topic (i.e. recognizing images using machine learning). However, the problem of this project is more complicated because sugar cane photos are almost identical. Thus our test bed must be able to tell the difference between two slightly varied details such as two close color tones. Additionally, the choice of machine learning techniques varies depending on the problem. Therefore, we will need to choose and implement a proper machine learning technique that is able to classify the input images into the correct category. Furthermore, if we have time, we will produce a design for a system to receive photos sent from mobile phones, classify them and save the results.

## **Task Breakdown and Draft Schedule**

### **Task breakdown**

1. Analyze and determine the requirements of the project
2. Plan the project schedule
3. Work on introduction chapter of the report (chapter 1)
4. Research emphasizing on the following topics:

Work by other researchers on discriminating between similar images using machine learning

Machine learning methods for image classification and the available libraries

Basic image processing concepts

1. Create the project proposal and get feedbacks
2. Test prototypes for various learning frameworks and make a decision on which learning framework to use
3. Collect and create dataset
4. Study and understand the dataset
5. Create experimental design
6. Complete progress report for the first semester
7. Work on theory and background chapter of the report (chapter 2)
8. Work on methodology chapter of the report (chapter 3)
9. Prepare for presentation for the first semester
10. Write pre-processing software to standardize images
11. Write scripts to control the experiments
12. Test the system and fix bugs
13. Train and test the system with different parameters
14. Analyze the results
15. Complete final report for the second semester (Result + conclusions, chapter 4 and 5)
16. Create poster and prepare for presentation for the second semester

### **Draft Schedule**

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
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| **Step** | **Operation** | **Project Duration** | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| **2016** | | | | | | | | | | | | | | | | | | | | **2017** | | | | | | | | | | | | | | | |
| **August** | | | | **September** | | | | **October** | | | | **November** | | | | **December** | | | | **January** | | | | **February** | | | | **March** | | | | **April** | | | |
| 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 | 1 | 2 | 3 | 4 |
| 1 | Analyze and determine the requirements of the project |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 2 | Plan the project schedule |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 3 | Work on Introduction chapter of the report |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 4 | Research emphasizing on the following topics: |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  | 1. Work by other researchers on discriminating between similar images using machine learning |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  | 2) ML method for image classification especially CNN and the available libraries |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  | 3) Basic image processing concept |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 5 | Create the project proposal and get feedbacks |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 6 | Test prototypes for various learning frameworks and make a decision on which learning framework to use |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 7 | Collect and create dataset |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 8 | Study and understand the dataset |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 9 | Create experimental design |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 10 | Complete progress report for the first semester |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 11 | Prepare for presentation for the first semester |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 12 | Work on Background and Theory chapter of the report |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 13 | Work on Methodology chapter of the report |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 14 | Write pre-processing software to standardize images |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | H | H | H |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 15 | Write scripts to control the experiments |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 16 | Test the system and fix bugs |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 17 | Train and test the system with different parameters |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 18 | Analyze the results |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 19 | Complete final report for the second semester |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 20 | Create poster and prepare for presentation for the second semester |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |

\*\* H:holiday

## **Deliverables for Term 1**

* Experimental data set
* Experimental design
* Some prototype using the selected framework
* Decision on what learning framework(s) to use, with justification

## **Deliverables for Term 2**

* Complete experimental design of the test bed
* Software test bed with desirable results
* Results and data analysis

**Background and related theories**

1. **Data Augmentation**

Overfitting describes the problem when the model is tailored to fit the random noise in one specific sample rather than reflecting the overall population. The easiest and most common method to reduce overfitting on image data is to artificially enlarge the dataset using label-preserving transformations [1,2]. To each of the sampled batch, we will apply n ∈ [1, 100] random transformations. Each of these random transformations is a combination of several elementary forms transformation, which we will describe shortly [1,7]. The benefit of using little computation is that we will not have to store the pre-processed image on the disk.

Image transformation contains two major approaches: point operators (sometimes called 1-to-1 pixel transforms) and neighborhood (or area-based) operators. In point operators, each output pixel value is strictly a function of the corresponding input pixel value. Brightness and contrast adjustments are two examples of such transformation. Techniques like convolution, which we will discuss later on in part 2.1, are not 1-to-1 transform [6]. Here we will discuss brightness and contrast adjustments as the first and the second form of data augmentations.

The first form of data augmentations is to adjust the image brightness. We add or subtract a constant amount of light to all input pixel in order to change an image brightness, as suggested in the following function:

g(i,j)= f(i,j)+β (1)

Where f(i,j) is the pixel located in the *i-th* row and *j-th* column of the input image, g(i,j) is the pixel located in the *i-th* row and *j-th* column of the output image and β is a bias parameter which is used to control the image brightness. Brightness adjustment is equivalent to shifting the contents of the histogram left (subtraction) or right (addition).



Figure 1.2.1. brightness

The second form of data augmentations is to adjust the image contrast. Contrast is the different between the maximum and the minimum pixel intensity of an image. To change the contrast of an image, we change the range of the luminance value presented in the input pixels. It is mathematically suggested by the following function:

g(i,j)= α f(i,j) (2)

Where f(i,j) is the pixel located in the *i-th* row and *j-th* column of the input image, g(i,j) is the pixel located in the *i-th* row and *j-th* column of the output image and α is a weight parameter which is used to control the image contrast.



Figure 1.2.2. contrast

We can combine the brightness and contrast control in a single operation. It is mathematically represented as:

g(i,j)= α f(i,j) + β (2)

Where f(i,j) is the pixel located in the *i-th* row and *j-th* column of the input image, g(i,j) is the pixel located in the *i-th* row and *j-th* column of the output image, α and β are weight and bias parameter respectively which are used to control the image contrast and brightness.

The third form of data augmentations is scaling. This can be done easily by multiply the scale of the patch by a factor between 0.7 and 1.4 (as suggested by Alexey Dosovitskiy, Jost Tobias Springenberg and Thomas Brox) [7]. Two other possible forms of data augmentation are horizontally flipping and random cropping.

Artificially enlarge the dataset using the combination of these three forms of image translation in image pre-processing has two extra benefits. Firstly, it allows the network to “look at” the seed image at different perspectives. Secondly, it allows the CNN model to work properly, because CNN often require to be fed with a considerably large dataset [1,4]. Notice that data augmentation is different from image pre-processing.

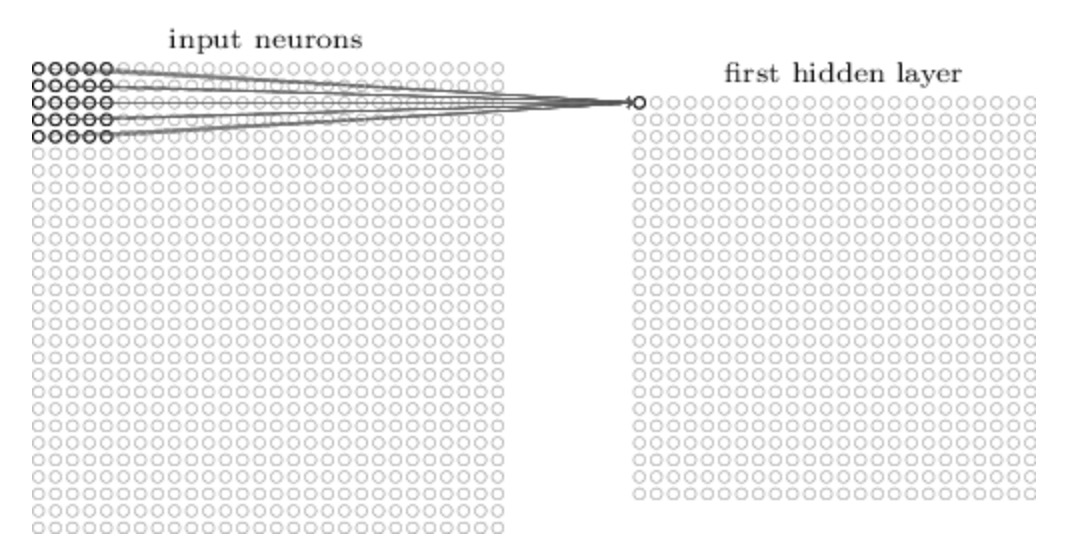
1. **Data preprocessing**
2. **Data processing** 
   1. **Convolutional Neural Networks (CNN)** 
      1. **The architecture**CNN is a state-of-the-art technique for image recognition [1,2,3,4,5]. It is a multilayer neural networks, consists of one or more convolutional layers, followed by subsampling layers (sometimes called pooling layers), and one or more fully connected layers.

Figure 3.1.1. a convolutional neural networks

* + 1. **Convolutional layer**

Four parameters are required in convolutional layer: the number of layer K, receptive field size F, the stride S and the amount of zero padding P. This layer accepts input of volume size and produces an output of volume size [(.

Think of the input image as a square of n x n neurons. The value of each neuron is the corresponding pixel intensity of the input image. We will map a localized region of the input neurons to a neuron in the hidden layer. These localized regions of input neuron are called local receptive fields.



n x n input neurons

Figure 4.1.2.1. local receptive fields

Each mapping from input layer to a hidden neuron at the hidden layer next to it learns a weight , and each corresponding hidden neuron leans a bias b. This weight and bias together make up a kernel (sometimes called a filter). The kernel value is shared among all neurons in the same hidden layer. The output generated by the , hidden neuron is a convolutional function between an input neuron , ’s value and its weight:

(3)

Where

is neural activation function

b is the shared value for the bias

the weight of the connection at the row and the column of the receptive field

is the input pixel value at the ( row and the column of the receptive field where j is row position of the hidden layer and k is the of the hidden layer

x is the total number of row in the receptive field

y is the total number of column in the receptive field

The combination of outputs generated by a hidden layer is called a feature map. To calculate the value of the next pixel in the feature map, will move our kernel k pixel along both width and height consequently (in which case we would say a stride length of k is being used) and re-apply the convolution function (3), until we run out of input neuron.



Figure 4.1.1.2.1 convolutional process - An input image of size 7x7x3 is filtered by 2 3×3x3 convolutional kernels with stride 2 which create 2 feature maps.

Each feature map can detect one feature at different locations of the same input image. To detect many features from one input image, we need several features maps. To generate several feature maps, we will need several kernels. A complete convolutional layer consists of several different features maps.

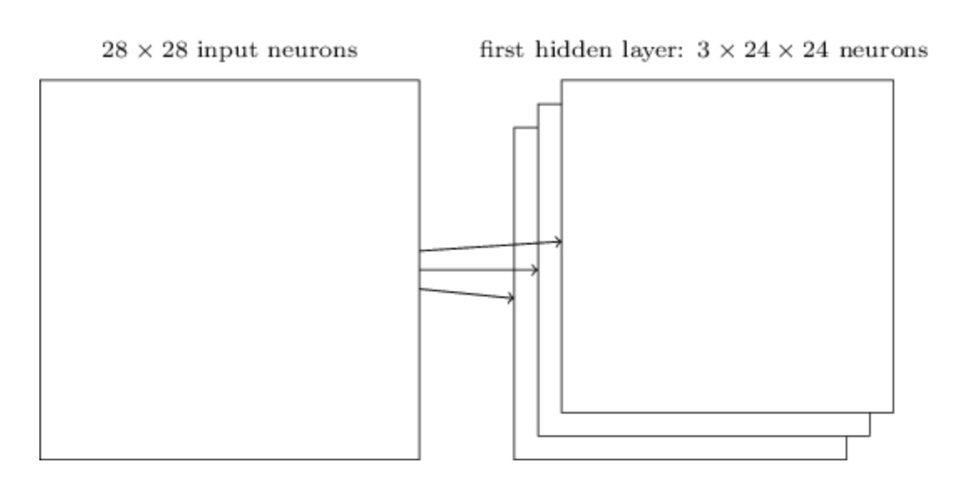


Figure 4.1.2.3. the first hidden layer consists of several features maps

* + 1. **The use of zero-padding**
    2. **Pooling layer**

Pooling layer requires two parameters: filter size F and stride S. It accepts input with volume size and produces an output of volume size [(.

A convolutional layer is usually followed by a pooling layer. Its function is to simplify every feature map in the previous layer at every depth slide spatially. The benefit of performing this step is to reduce the amount of parameters, computation in the network and therefore overfitting. A successful pooling layer should be able to preserve critical information while being invariant to troublesome deformations [9].

Pooling is done via a summary statistic over a region of neurons in the preceding layer. The summary statistic in is defined by the norm of inputs in the pools. If node are in the pool, the output of the pooling process can be mathematically represented as:

(4)

Two widely used pooling techniques can be derived from function (4). The first one is max pooling. This is when p → ∞

(5)

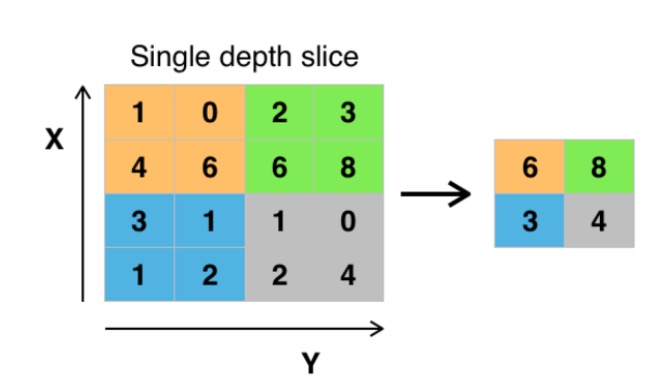


Figure 4.1.4.1. pooling layer – An input single depth slice of size 4 x 4 is filtered by a 2x2 kernel with stride 2 which results in a pooling feature map of size 2 x 2

When p = 2, we have pooling:

(6)

A filter size of 2x2 and a stride of length 2 are often applied with these two pooling techniques. Average pooling (when P = 1) was often used historically but has recently fallen out of favor because it gives less competitive results than the other two.

An another known pooling technique is called subsampling [10]. The output of subsampling function is given by:

β + b)

Where

β is a trainable scalar

b is a bias

n x n is the size of the receptive field

There is no best pooling technique. We will need to try applying several pooling techniques to our problem to see which one yields the best result.

A. Krizhevsky et al. has taken a step further to the traditional pooling [1]. Suppose a pooling layer consists of a grid of pooling units, each summarizes a neighborhood of size z x z and stride s. Traditionally, we set z = s, where we obtained non overlap pooling. Now we will set s < z to obtain overlap pooling. A. Krizhevsky et al. has pointed out this is a more effective pooling technique as it reduces the top-1 error rate by 0.4% and top-5 error rate by 0.3%.

* + 1. **Cyclic pooling**
    2. **ReLU non-linearity**
    3. **Fully connected layer**
    4. **Back propagation**
  1. **CNN vs. Fine Grained recognition**
  2. **Training on multiple GPUs**

1. **Data post-processing** 
   1. **Dropout**

**Reference**

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