A decision support system for hybrid corn classification

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Abstract: High yielding corn is primarily derived from a cross-pollination among superior appearing male and female plants. Cross-pollination is closely linked at the tasseling/flowering stage, marked by the emergence of tassel for 5-10 days. With the advancement of machine learning, there are opportunities to apply deep learning models to control the purity of plants. The research aims to develop a decision support system based on deep learning to enable earlier identification and removal of contamination/off-type plants during seed production. The datasets containing 1,587 tassel images taken by high resolution camera. The results of the training and the validation sequence indicated a highly correlated accuracy score. A quite contrasting tassel morphology makes it easier for the model to distinguish on and off-type plants. The loss value during the training and the validation stages was 0.05 and 0.1 respectively. A stand-alone graphical user interface (GUI) was deployed to support the early detection of tassels in the field. This tool can be used to support national corn seed production programs.

1. Introduction
The “Special Effort Program” launched by the Ministry of Agriculture recently aims to provide a breakthrough in increasing national corn production through the introducing of hybrid seeds [1]. The focus on shifting local corn to modern/hybrid varieties was carried out by various methods including dem-farm managed by Indonesian Agency for Agricultural Research and Development (IAARD) and local/regional private sectors in major corn production areas in East Java, South Sulawesi, Lampung, East Nusa Tenggara, and North Sulawesi [2]. At the same time, the demand for hybrid seed increased as the Government’s seed provision program was expanded.

In the phenology of hybrid seed production, tasseling is among the critical stage for gaining acceptable yield. During the tasseling, cross-pollination should be well prepared among male and female plant [3]. Pollen age affects the grain filling on the corn cob. Too older and hot weather condition will inhibit the growth of the pollen tube and subsequently enable empty cob. Severe heat and dry weather have a detrimental effect on pollen production. Pollen has a moisture content of approximately 57% and will lose very quickly under low humidity [3]. Although male flowers release pollen gradually, the synchronization timing between pollen spread and the silking phase should be taken into consideration. Most of the inbreds and hybrids are protandrous, meaning to disperse pollen a few days before the cob initiations [4]. These relationships are diverse and are hereditary. In some inbreds, the hair/silk is released late until all the pollen has been scattered.

In agriculture, the application of image recognition technology has been reported extensively to deeper understand mechanism in any field. The objective of the research was to develop a desktop-based decision support system by involving Densenet-201 deep learning convolutional neural network (CNN) to support earlier identification and removal of contamination/off-type corn plants.
2. Research Methodology

Much of the valuable work on corn hybrids has been conducted by Indonesian Cereals Research Institute. The research on the detection of parental lines during hybrid maize (F1 seeds) production was conducted in January-April 2020 at the Indonesian Cereals Research Institute’s experimental farm. As many as two types of parental lines were planted namely female parents (Mal 03) and male parents (G102612). The number of datasets collected during the observation included 529 images of female parent lines, 579 images of male parent lines, and 479 images of mixed / contamination lines. Image capture is done using a Samsung A70 mobile phone with high-resolution image capture. The model developed adopted the principle of feature extraction to make predictions based on the type of features of tassel [5].

2.1 Densely Connected Network (Densenet-201)

The development of a classification model for hybrid maize lines uses a Multilayer Perceptron (MLP) which is designed to process two-dimensional data. CNN is included in the Deep Neural Network classification type because of the network depth used for image information classification. More specifically, the entire tassel classification process was carried out using the Dense Connected Network (Densenet) developed by Huang [6].

The Densenet model has an architecture that connects each layer to another by feed-forward. Furthermore, the feature map X l on the lth layer can be projected by all layer features, , X 0, … , X l-1 on the previous layer in the form as follows:

\[ X_l = H_l ([X_0, \ldots, X_{l-1}])X_0 \ldots X_{l-1} \]

Where [X 0, … , X l-1] is the map feature on the 0th…, l-1th. Hl(.) layer. Hl(.) is a composite function of three operations, namely batch normalization, a rectified linear unit (ReLU), and 3 x 3 convolution. The Densenet network architecture consists of an input layer, a convolution layer, a pooling layer, a dense block, a transition layer, a global pooling layer, a fully connected layer, softmax layer, and a classification layer (Figure. 1).

![Figure 1. Densenet-201 model used in the study](image-url)
The structure of the Densenet-based hybrid corn tassel classification model is shown in Figure 2. The typical network architecture of this model is the interconnection between each block including the reuse of features to support the decision-making system. There are various kinds of Densenet architectures including Densenet-121, Densenet-169

3. Results and Discussion

The architecture of the Densenet-201 based hybrid corn tassel classification model indicated the existence of four connectively dense blocks. The input model consists of 529 images of the female parent, 579 images of the male parent, and 479 images of mixed / contamination lines with various image size, so that it requires to resizing all images to 224 x 224 x 3. To reduce the size of the matrix, a pooling layer operation was performed. Based on the pooling results, a new matrix measuring 56 x 56 x 64 will be generated. After completed the pooling process, the model was divided into four dense blocks with the dimensions of the map feature fixed in one block. The difference between each dense block is the number of image filters used.

Each dense block is connected to a transition layer for down sampling activity by using batch normalization. Before the flatten, where only one hidden layer was contained in the multilayer perceptron network, global pooling was carried out based on average pooling. The flatten process then converts the output pooling layer into a vector. The function used in this study is the softmax activation function.

Table 1. Structure of densenet-201 classification model

| Parameters     | Size of layer |
|----------------|---------------|
| Input          | 224x224x3     |
| Convolution    | 112x112x64    |
| Pooling        | 56x56x64      |
| Dense bl (1)   | 56x56x256     |
| Transm layer (1)| 28x28x128    |
| Dense bl (2)   | 28x28x512     |
| Transm layer (2)| 14x14x256   |
| Dense bl (3)   | 14x14x1792    |
| Transm layer (3)| 7x7x896     |
| Dense bl (4)   | 7x7x1920      |
| Global pooling | 1x1x1920      |
| Fully connected| 1x1x2         |
| Softmax        | 1x1x2         |
| Classification | 1x1           |

The model iteration will produce accuracy and loss values for the train data and validation datasets. The accuracy value is used to determine the level of success of the model that has been made, while loss shows a measure of an error made by the network, and the final goal is to minimize it. The image above shows a graph of the movement of the accuracy (acc) value and the loss (loss) value for the train data and test data generated at each iteration (epoch).

During the training process, the network architecture was able to recognize the features of the image and passed to each dense block of each image, indicated by higher accuracy in which exceeded 80%. During the training process, there was a trend of accuracy increase in recognizing objects and feature mechanisms mostly by intuitive ranked. As the running end at 800 iterations, the value of the accuracy obtained approximately > 96%. Furthermore, during the validation stage, the remaining 20% of samples were tested for model accuracy and loss. The accuracy resulted from the validation was slightly lower
than the accuracy of the trained model, i.e. >92%. This shows that the model has a deeper understanding of image patterns including visualization changes in each feature for generating true classification.

The method used to calculate the loss was softmax function loss. During the training process models, the value of loss continues to experience fluctuations but a loss on average still below 0.4. Upon the completion of the training at 800 iterations, the model loss achieved was less than 0.05. Thus, the model created can capture the features of each image and provide the best prediction output.

Furthermore, at the validation stage, the more achieved good predictions with loss value were lower than <0.1. Low loss value indicates the model is not experiencing overfitting, especially at the stage of validation. [7] reported that Dense Neural Network produced a higher accuracy than CNN as more dense features involved in the modeling process.

A deeper assessment into the overall datasets indicated that there was a tendency of misclassification mostly among female and contaminant plant. In addition, misclassifications were also found among the old tassel as the morphological characteristics change rapidly. Furthermore, illumination and background image was also a challenge as these factors affect the proper detection at random moments. In addition, [8] also mentioned that overlapping images and the background were some of the obstacles in the detection of the corn tassel. The technique commonly used in the detection of the tassel on corn is using global regression [9], [10] as well as regression of local regression [11] and [12].

Visualization of the training process in each block was done by projecting back feature activation to the beginning of the training process the network. Image visualization in the processing layer among male and female parent in the dense block is shown in Figure. 2-4. The initial extraction of information from an image was generated from the curves and colour characteristics. Although the process of visualization of the training has been done, because of differences in the morphology of tassel including varied off-type tassels shapes made it complicated to analyse although by visual sight. Several false-negative cases were found in the classification process, especially in tassels that had similar shapes.

![Figure 2. Layer visualization of female plant](image)

To improve the accuracy of tassel type classification, another challenge that can be carried out is through rearranging the input image in the relevant region of interest and forced the network to identify the tassel from the entire relevant focused region.
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Figure 3. Layer visualization of male plant

Figure 4. Layer visualization of contamination plant

The GUI was developed and deployed to stand-alone software for practical use. The field test indicated that the GUI which is operated in a stand-alone Windows-based program can perform data processing and generate prediction rapidly (less than 5 seconds) and the classification results will appear in the button bar below the Figureure. Field test results indicated that GUI can predict with an accuracy of > 95%. For technical operations, field workers can take tassel photos and store them in their cellphone memory for later processing.

However, because it is not real-time, the use of a GUI based on the desktop is a bit less convenient. Furthermore, it takes a longer time for data transfer from the field to the Desktop PC. Further research is needed for real-time model-based programming using tools such as TensorFlow, PyTorch, and Keras so that prediction results can be generated in real-time in the field. In-field tassel detection face additional challenges due to mainly unpredictable environment conditions and self-changing tassel morphology after heading.
4. Conclusion and Suggestion

The detection and classification model for hybrid corn parental lines was developed and evaluated using CNN Densenet-201. The results indicated that the model produced an accuracy of higher than 96% during the training stage. Furthermore, analysis and model validation was carried out with accuracy exceeded 92%. The loss value during the training process was <0.05 and <0.1 during the training and validation stages respectively. A GUI was developed to facilitate the desktop-based corn tassel classification. However, as the model was developed in a desktop environment, various limitations were found such as difficulty to use in the field and delayed data transfer process. Further research is needed for real-time model-based programming using tools such as TensorFlow, PyTorch, and Keras so that real time prediction can be done in the field. In-field tassel detection faces also additional challenges due to mainly unpredictable environment conditions and self-changing tassel morphology after heading.

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