Classification of Haploid and Diploid Maize Seeds based on Pre-Trained Convolutional Neural Networks

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Received: 26 May 2020  
Accepted: 14 September 2020  
DOI: 10.18466/cbayarfbe.742889

Abstract

Analysis of agricultural products is an important area that is widely emphasized today. In this context, with the development of technology, computer-aided analysis systems are also being developed. In this study, a system has been proposed for classifying maize seeds as haploid and diploid using pre-trained convolutional neural networks. For this purpose, AlexNet, GoogLeNet, ResNet-18, ResNet-50, and VGG-16 pre-trained models have been used as feature extractors for the haploid and diploid seed classification process. In the first stage, the deep features of haploid and diploid maize seeds have been obtained in these models. The features have been taken from different layers of network architecture. Instead of softmax classifier in the last layer of the network, classifiers based on decision tree, k-nearest neighbor, and support vector machine have been used. According to the classification results with these features, the achievements in network architectures and classifier methods have been observed. The experiments have been carried out on a publicly available dataset consisting of 3000 haploid and diploid maize seed images. The experimental results revealed that the developed classification systems demonstrate a remarkable performance.

Keywords: Haploid Maize Seed Identification, Deep Features, Artificial Learning, Convolutional Neural Networks, Image Processing

1. Introduction

The researches have focused on computer-aided agriculture systems in terms of providing advantages such as growing healthy products, increasing production efficiency, and reducing costs in recent years. The main contribution of these systems is that they save time and labor. Computer-aided agricultural researches have gradually gained momentum [1, 2]. These systems are utilized extensively in most of the agricultural processes. The agricultural tools supported by these systems as well are commonly developed today. These systems prevent product havoc caused by human errors and ensure maximum efficiency.

In vivo maternal haploid breeding method has become the standard method in modern maize breeding because of its advantages compared to traditional methods [3]. In this maize breeding method, artificial chromosome folding is performed by treating haploid individuals with single chromosomes with colchillin and 100% pure lines can be obtained in 1-2 years [4]. Haploids must be separated from diploids after hybridization in order to increase the effectiveness of the method and to be successful. Depending on the characteristics of the inducer line used, haploid individuals in the range of 2-15% are obtained [5]. Separation of haploid individuals during the seed period is of great importance in terms of reducing greenhouse area, labor, and planting costs [4].

Although different genetic markers have been proposed to differentiate haploid maize seeds from diploids, the most common and successful method is the R1-nj color marker. In this method, which has been first used by Nanda and Chase [6], the inducer line carries the dominant R1-nj gene, which causes red-purple coloration in the embryo and endosperm. Since diploid seeds obtained as a result of crossbreeding carry chromosomes belonging to the inducer line, this coloration occurs in both embryos and endosperms. Haploid seeds, on the other hand, carry the chromosome of the inducer line in their endosperms, their embryos with single n chromosomes consist only of the chromosomes of the donor parent. Therefore, R1-nj coloration is seen in the endosperms of haploid seeds, but R1-nj coloration does not occur in their embryos.
This coloration difference occurring in embryos enables the visual separation of haploid and diploid seeds [7]. This separation is done manually today. In addition to this, it causes separation with high error rates; costs increase and separation takes a long time. Computer-aided classification methods are developed to overcome these problems. Today, with the advances in machine learning methods, deep learning methods based on convolutional neural networks (CNN) are widely used for computer-aided classification studies.

CNN aims to calculate the features of an object in image data based on multiple processing layers of artificial neural networks without using an external method [8]. Image processing techniques are used for the detection of the features (color, shape, texture, pattern, etc.) of the objects, segmenting the related objects properly and/or classification of the objects in the image data. Feature inputs used for traditional machine learning methods are obtained by processing image data. In the CNN method, the image data feeds the network input layer directly. Features are acquired from these layers without using additional image processing methods. More data may be required to train the network comparing to traditional methods. On the other hand, the transfer learning approach can be utilized to retrain classification part of a pre-trained CNN model to speed-up the training phase.

In summary, the CNN approach can provide great flexibility and remarkable achievements in the classification of object images. In this context, different CNN models have been used to classify images of maize seeds as haploid and diploid.

Related studies are given in the second part of the study. In the third section, the dataset and recommended methods are mentioned. The experimental findings obtained on the dataset are given in the fourth section. In the fifth section, the results obtained within the scope of the study are discussed and future studies are mentioned. In the last part, the references for the study are given.

2. Related Studies

There are some prominent studies using computer-aided methods and approaches to facilitate the separation of maize seeds. Some studies have focused to identify seed characteristics by using special imagining equipment or software tools. Recently, a remarkable number of studies have investigated the machine learning (ML) methods to extract features of the maize seeds. Then these features are used to train classification algorithms based on ML. Moreover, electro-mechanical systems have been also developed to classify the maize seeds. Based on all these studies, literature have been deeply investigated and state-of-the-art studies have been analyzed.

Wang et al. [13] aimed to investigate a fast and accurate method to identify haploid maize kernel using infrared hyperspectral imaging technology. This technology has been utilized to overcome the current automatic haploid identification limitations and provide a more accurate screening of haploid. Fuente et al. [14] focuses on defining the haploid lineage. In the study, six inbred lines have been developed with the maternal haploid inducer ‘RWS / RWK-76' and a seed sample has been manually aligned for each line.

Wang et al. [15] have carried out the selection model design of high accuracy maize haploid seeds from diploid ones based on optimum waveband selection of the LSTM-CNN algorithm with deep learning and hyperspectral imaging technology. As a result of the experiments, it has been claimed that the accuracy rate reached 97% in the optimum waveband of 1367.6-1526.4nm. Altuntaş et al. [7] have proposed a method to classify haploid and diploid maize seeds using image processing and classification methods. Firstly, five different features are obtained from each maize seed image. Then the feature vectors are classified using a support vector machine classifier. In the study [16], texture features of maize seed embryos have been used. These features are derived from the gray level co-occurrence matrix. In another of their study [17], it is inspired by the latest achievements of deep transfer
learning, they address this problem as a computer vision task to present a non-destructive, fast, and low-cost model. To achieve this goal, CNN have been used to automatically recognize haploid and diploid maize seeds with a transfer learning approach. Altuntas and Kocamaz [18] have proposed a computer-based method for the identification of haploid maize seeds. Maize seed embryos have been segmented by the k-means clustering method. In RGB, HSV, and Lab color spaces, the first four-degree color moments have extracted for each color channel. The obtained features then have been classified with SVM.

Song et al. [19] have designed an automatic separation system that can separate the haploid maize seeds from hybrid seeds marked with the R1-nj label, in their study. The system includes seed feeding, image acquisition, sorting, and system control units. The seed feeding unit distributes the maize seeds on a synchronous belt. The image acquisition unit acquires images of maize seeds on a synchronous belt. The image acquisition unit acquires images of maize seeds and separates the heterozygous from the haploid nuclei depending on the color property of the endosperm. Finally, the separation unit performs physical separation with mechanical arms and solenoid valves that can select the heterozygous seeds using air intake.

3. Materials and Methods

3.1. Dataset

The dataset consisting of 3000 maize seed images in total [17] contains 1230 haploid and 1770 diploid maize seed images. The dataset occupies 49.3 MB of disk space. Each image obtained is in RGB color space and format is JPEG. Since the resolutions of the images in the dataset vary between 300x289 pixels and 610x637 pixels depending on seeds size, the images have been resized to the appropriate resolution according to the input layer of each CNN model. In this context, when 227x227 resolution is used for the AlexNet model, 224x224 resolution is used for GoogleNet, ResNet18, ResNet50, and VGG16 models. Sample maize seeds have been demonstrated in Figure 1.

![Figure 1. Sample diploid (top) and haploid (bottom) maize seed images from the dataset.](image)

3.2. Deep Feature Extraction

A deep feature in the context of deep learning is that a unit (layer) within a hierarchical model responds consistently to an input, where this response contributes to the model's decision. Deep features are obtained from pre-trained CNN models. In other words, pre-trained CNN models can be used as feature extractors to feed any classifiers. Depending on where the model is located along with its hierarchical structure, one layer can be considered deeper than the other. Each of the network layers has deep features. Deep features are used in the network layers of the CNN model like convolution, pooling, etc. Their values/weights vary depending on the filter and mathematical operations applied in the layers. Deep features are expected to represent the highest level of images of objects intended to be classified.

AlexNet [20] is one of the pioneering deep learning algorithms. It has been introduced for the first time in 2012 as part of the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). In this competition, it has attracted attention to the CNN architecture by providing a remarkable high performance. AlexNet is a CNN architecture with a total of 25 layers: input, convolution, ReLU (Rectified Linear Unit: it simply changes all the negative activations to 0. It is a basic layer for all CNN architectures), normalization, pooling, fully connected layer, drop-out, classification, and output. The AlexNet model has a total of 60 million computational parameters. The architecture takes 227x227 colored images as input.

ResNet [21] is a CNN architecture that uses the residual learning framework module to facilitate network training. The focus of this architectural model is the degradation problem. The novelty of the model is the use of residual blocks and the depth in its architecture. In a conventional convolutional deep learning model, stacked layers fit a desired underlying mapping, while the ResNet model allows these layers to be seated in a residual mapping. In this study, Resnet-18 and ResNet-50 have been used.

GoogLeNet [22] is another deep learning network that has managed to attract attention. Similarly, it has been revealed in the ILSVRC competition held in 2014. The most important difference in this architecture is the inception module added to the layers as a new block. This module consists of branching to more than one depth that works like a shortcut between layers. The most prominent feature of this CNN architecture is that the architecture increases width and depth while keeping the computational cost constant. It makes this possible with the newly added inception module. The module has improved the level of utilization of computing resources within the network architecture. GoogLeNet consists of 22 layers in total and 7 million computational parameters.

VGGNet [23] is a CNN architecture presented for the first time in the ILSVRC competition held in 2014. The most unique property about VGG16 is that instead of having many hyper-parameters, it is focused on having the convolution layers of a step-1 (stride-1) and 3x3 filter, and use always the same fill and maxpool layer of
the 2x2 step-2 (stride-2) filter. The convolution and maximum pool layers have been maintained consistently throughout the entire architecture. VGG16 is a fairly large network, it consists of 41 layers in total and has about 138 million (approximately) parameters.

3.3. Classifier Methods

A classification method uses a learning algorithm to define the model that is optimal to the relationship between the feature set of input data and the class label/tag. Therefore, the primary goal of the learning algorithm is to create a smart model that accurately predicts class tags of previously unknown records. The classifier method is employed to determine the label data of different classes in the utilized data set in this study.

Support Vector Machine (SVM) [24] are supervised learning models used for classification and regression analysis, analyzing data, with associated learning algorithms in machine learning. An SVM is a separator classifier that is formally defined by a separator hyperplane. In other words, when labeled training data is given, the algorithm produces an optimal hyperplane that categorizes new samples. The general SVM function dual version is given below (1). The second-order (quadratic) SVM classifier has been used to avoid the local minimum, in the study.

\[ f(x) = \sum_{i=1}^{N} a_i \cdot y_i \cdot K(x, x_i) + b \]  

The equation simply calculates the distance between the pairs \((x, y)\) in 2d Cartesian space. Unlike most algorithms, SVM is a non-parametric model, meaning it makes no assumptions about the dataset. This makes the algorithm more effective as it can process realistic data. SVM is a lazy algorithm, which means that it memorizes the training dataset rather than learning a distinctive function from the training data. In this study, weighted KNN will be used as a classifier. Unlike the traditional KNN method, \(K\) is weighted with the nearest neighbor \(1/k\) in weighted KNN, while the weight of other data is considered to be 0. For this purpose, the closest neighbor ‘i’ is weighted for n samples with the following equation (3).

\[ \sum_{i=1}^{n} w_{ni} = 1 \]  

Decision Tree (DT) [26] is a simple and widely used classification technique. It applies a simple approach to solve the classification problem. The DT classifier performs a series of specially crafted branching about the features of the test data. If a result is reached about the class label of the data as a result of the branching, the algorithm is terminated; otherwise, the next branching continues until a result is reached. Within the scope of the study, the maximum deviation reduction (MDR) has been used as the division criterion. It is also known as the entropy function and found by the following equation (4).

\[ I_E(N) = -K \sum f(N,j)logf(N,j) \]  

Here, \(K\) is the proportion of observations, function \(f\) is the frequency of class \(j\) in node \(N\). The purpose of MDR is to reduce uncertainty until a pure leaf node is established. In DT, root and internal nodes contain feature test conditions to separate data with different features. All terminal nodes are assigned a class label ‘Yes’ or ‘No’. Once DT is created, it is quite easy to classify a test record. Starting from the root node, the test condition is applied to the data and the appropriate branch is monitored according to the result of the test. The branching then takes place towards another inner node or a leaf node to which a new test condition is applied.

4. Results

The computer used in the experiments within the scope of the study has an i7 6700HQ CPU, 8GB RAM, 2GB GTX950 GPU, and 240GB SSD HDD. Experiments have been carried out using MATLAB (2019b) environment.
The features of 3000 maize seed images have been obtained on the CNN models within the scope of the study. For this purpose, it is provided to extract features from 9 different layers in total over five different CNN models. Obtained features have been given to the classifier algorithms as input to perform the classification process. SVM, KNN, and DT classifiers have been used for this process. Regarding the classifiers used; in the DT classifier, the maximum split parameter (max split) value has been set to 20. The partition criterion is made according to the MDR technique. In the KNN classifier, a weighted tree method predicts as diploid. Finally, the method predicts as haploid in the dataset, it is the true negative (TN) data that the proposed methods have been handled as false negative (FN). Among the samples labeled as haploid, what the method predicts as diploid is handled as false positive (FP). Mathematical calculation formulas for performance metrics are as follows:

\[ \text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \]  

Table 1. Feature acquiring times.

| CNN Model | Feature Number | Feature Acquiring Time |
|-----------|----------------|------------------------|
| AlexNet FC6 | 4096          | 382,86s                |
| AlexNet FC7 | 4096          | 422,20s                |
| AlexNet FC8 | 1000         | 212,50s                |
| GoogLeNet   | 1000          | 332,08s                |
| ResNet18    | 1000          | 324,89s                |
| ResNet50    | 1000          | 310,17s                |
| VGG16 FC6   | 4096          | 1101,48s               |
| VGG16 FC7   | 4096          | 1121,74s               |
| VGG16 FC8   | 1000          | 958,94s                |

In the study, 10-fold cross-validation method has been used to divide the dataset into training and test sets for obtain more generalized results. The effects of deep features obtained from fully connected layers on classification performance have been analyzed. Accuracy, precision, sensitivity, F-score, and classification times have been used as performance metrics to evaluate these effects. Accuracy, precision, sensitivity, and F-score performance metrics are calculated based on confusion matrix. The classification times refer to the time elapsing to classify the maize seed types according to the features.

In the AlexNet model feature extraction has been made from three layers: 'FC6', 'FC7', and 'FC8' layers. In the GoogLeNet model, features have been obtained from the fully connected layer named "Loos-3". In ResNet-18 and ResNet-50 models, the features have been obtained from the "FC1000" fully connected layers. Finally, in the VGG16 model, it has been provided to obtain features from 'FC6', 'FC7', and 'FC8' layers which are fully connected layers similar to the AlexNet model. The number of features obtained and the elapsed times of obtaining the features are given in Table 1. The elapsed time of acquiring the features vary according to the number of layers of the models, processes like the applied mathematical filter, convolution and etc. In a low-complexity CNN model, features can be obtained more quickly.
Feature classification experiment results performed with
the SVM classifier are given in Table 2. The values
given in the table are: confusion matrix (TP, FP, FN,
and TN), accuracy (Acc.), precision (Prec.), sensitivity
(Sens.), F-Score, and runtime of the SVM classifier.
According to the acquired results, the CNN model with
the highest performance of the SVM method is
ResNet50 with an accuracy rate of 91.4%. While the
network with the second-highest performance is VGG16
with 91% accuracy, this performance has been achieved
with the obtained features from the FC6 fully connected
layer of the network. While the third-highest accuracy
model is VGG16, 89.6% accuracy has been achieved
with the features acquired from the FC7 layer of this
network. While the highest precision is 0.91 in the
ResNet50 model, the highest sensitivity is in the
VGG16 model with 0.93. The F1-Score used to
eliminate extreme situations that occurred on the
ResNet50 model has been determined by about 0.90.
When the classification working times of SVM
classifier according to the obtained features from the
models are examined; in layers where 1000 features are
obtained, the elapsed time is less than 1 minute, while in
layers where 4096 features are obtained, this time is
over 2 minutes.

Table 2 Classifier Results with SVM Method.

| CNN Model   | TP   | FP   | FN   | TN   | Acc. | Prec. | Sen. | F-Score | Time  |
|-------------|------|------|------|------|------|-------|------|---------|-------|
| AlexNet FC6 | 1120 | 110  | 214  | 1556 | 89.2%| 0.88  | 0.91 | 0.87    | 148.39s |
| AlexNet FC7 | 1104 | 126  | 230  | 1540 | 88.1%| 0.87  | 0.90 | 0.86    | 154.82s |
| AlexNet FC8 | 1083 | 147  | 255  | 1515 | 86.6%| 0.86  | 0.88 | 0.84    | 38.59s  |
| GoogLeNet   | 1076 | 154  | 254  | 1516 | 86.4%| 0.86  | 0.87 | 0.84    | 45.64s  |
| ResNet18*   | 1103 | 127  | 209  | 1561 | 88.8%| 0.88  | 0.90 | 0.87    | 32.04s  |
| ResNet50*   | 1136 | 94   | 165  | 1605 | 91.4%| 0.91  | 0.92 | 0.90    | 27.51s  |
| VGG16 FC6   | 1139 | 91   | 178  | 1592 | 91.0%| 0.90  | 0.93 | 0.89    | 139.54s |
| VGG16 FC7   | 1116 | 114  | 198  | 1572 | 89.6%| 0.89  | 0.91 | 0.88    | 133.91s |
| VGG16 FC8   | 1093 | 137  | 198  | 1572 | 88.8%| 0.89  | 0.89 | 0.87    | 32.60s  |

*1, 2, 3: top three CNN models and layers with the highest performance.

Figure 3. SVM classifier and performance metrics of
CNN models.

Accuracy, precision, sensitivity, and F-Score values
obtained in the pre-trained CNN models with the SVM
classifier are given graphically in Figure 3.
Table 3. Classifier Results with KNN Method.

| CNN Model       | TP     | FP     | FN     | TN     | Acc. | Pre. | Sen. | F-Score | Time  |
|-----------------|--------|--------|--------|--------|------|------|------|---------|-------|
| AlexNet FC6     | 1048   | 182    | 382    | 1388   | 81.2%| 0.78 | 0.85 | 0.79    | 92.07s|
| AlexNet FC7     | 1001   | 229    | 382    | 1388   | 79.6%| 0.78 | 0.81 | 0.77    | 83.75s|
| AlexNet FC8     | 955    | 275    | 379    | 1391   | 78.2%| 0.79 | 0.78 | 0.74    | 51.49s|
| GoogLeNet       | 1021   | 209    | 360    | 1410   | 81.0%| 0.80 | 0.83 | 0.78    | 54.00s|
| ResNet18""""    | 1096   | 134    | 337    | 1433   | 84.3%| 0.81 | 0.89 | 0.82    | 51.99s|
| ResNet50""""    | 1130   | 100    | 276    | 1494   | 87.5%| 0.84 | 0.92 | 0.86    | 51.51s|
| VGG16 FC6""""   | 1162   | 68     | 385    | 1385   | 84.9%| 0.78 | 0.94 | 0.84    | 93.08s|
| VGG16 FC7      | 1106   | 124    | 384    | 1386   | 83.1%| 0.78 | 0.90 | 0.81    | 83.08s|
| VGG16 FC8      | 1104   | 126    | 371    | 1399   | 83.4%| 0.79 | 0.90 | 0.82    | 18.26s|

*1, 2, 3: top three CNN models and layers with the highest performance

Accuracy, precision, sensitivity, and F-Score values obtained through KNN classifier and pre-trained CNN models are graphically given in Figure 4.

Feature classification experiment results performed with the DT classifier are given in Table 4. The highest accuracy in the DT classifier is again in the ResNet50 model with a rate of 82.5%. The second and third best accuracy rates have been obtained from ResNet18 and VGG16 FC6 models as 80.5% and 79.8%, respectively. The best sensitivity value is realized in the ResNet50 model as 0.82. The best sensitivity value has been found as 0.84 in the ResNet50 model. In F-Score values, the best value has been obtained as 0.80 with the ResNet50 model. When the obtained values according to the classification times of the DT classifier are examined; it has been observed that classifiers took less than 1 minute in all models. However, in layers containing 1000 features, this time is around 30 seconds at most, while in layers containing 4096 features, it is quite close to 1-minute.

Table 4. Classifier Results with DT Method.

| CNN Model       | TP     | FP     | FN     | TN     | Acc. | Pre. | Sen. | F-Score | Time  |
|-----------------|--------|--------|--------|--------|------|------|------|---------|-------|
| AlexNet FC6     | 894    | 336    | 407    | 1363   | 75.2%| 0.77 | 0.73 | 0.71    | 59.79s|
| AlexNet FC7     | 958    | 272    | 429    | 1341   | 76.6%| 0.76 | 0.78 | 0.73    | 58.79s|
| AlexNet FC8     | 920    | 310    | 430    | 1340   | 75.3%| 0.76 | 0.75 | 0.71    | 12.47s|
| GoogLeNet       | 962    | 268    | 380    | 1390   | 78.4%| 0.79 | 0.78 | 0.75    | 31.47s|
| ResNet18""""    | 933    | 237    | 335    | 1435   | 80.5%| 0.81 | 0.80 | 0.77    | 30.97s|
| ResNet50""""    | 1031   | 199    | 326    | 1444   | 82.5%| 0.82 | 0.84 | 0.80    | 30.51s|
| VGG16 FC6""""   | 984    | 246    | 360    | 1410   | 79.8%| 0.80 | 0.80 | 0.76    | 57.84s|
| VGG16 FC7      | 954    | 276    | 373    | 1397   | 78.4%| 0.79 | 0.78 | 0.75    | 56.89s|
| VGG16 FC8      | 956    | 274    | 345    | 1425   | 79.4%| 0.81 | 0.78 | 0.76    | 12.57s|

*1, 2, 3: top three CNN models and layers with the highest performance
In future studies, in order to increase the performance, it is aimed to give embryo areas on the maize seed by segmenting them instead of giving all maize seed images as input directly to the models. On the other hand, based on the knowledge gained from this study, it is aimed to increase the performance to higher levels with the fusion of the features obtained from different CNN models. In other words, deep features from different CNN models will be used together. Fusion approaches will be developed to improve overall performance by readjusting these features.

Author’s Contributions

Emrah Dönmez: Drafted and wrote the manuscript, proposed a CNN based classification approach for maize seeds. He has performed the experiment and analyzed the classification results.

Ethics

There are no ethical issues after the publication of this manuscript.

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