Seed Quality Prediction using Computer Vision and Convolutional Neural Networks

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Abstract— **Knowing the quality of the seeds is the most important thing for a farmer. The quality of the seed is critical for obtaining a good yield. Farmers typically purchase seeds from companies. They will ensure that the seeds are of high quality. However, because they use manual force to collect good quality seeds, there is a chance that they will replace good quality seeds with damaged ones. The precaution to be taken is to predict the seed quality. Our goal is to provide a solution that eliminates the need for manual seed quality checks in commercial farming. Without human intervention, the detection of pure and damaged seeds requires the use of computer vision and deep learning techniques. The proposed model employs OpenCV to detect every seed grain in the seed lot, as well as a convolutional neural network to predict the quality of the detected seed grain. The model's output is a prediction of the seed lot's purity percentage. This paper suggests a solution that reduces the amount of manual labor and time required to filter out damaged seeds.**

Keywords —*Seed Quality, Computer Vision, Deep Learning, OpenCV, Convolutional Neural Networks.*

I. INTRODUCTION

Seed cultivation in the commercial sector is a time-consuming process since it is impossible to separate damaged seeds and foreign materials from a large batch of seeds. Among all seed technologies, the most important is effective and automated seed testing [1]. Every year, seed testing organizations must assess thousands of seed batches. To make the procedure easier, there must be some sort of effective seed automation technique for seed separating in all seed sectors. All of these issues encouraged to apply deep learning to increase efficiency and introduce automation.

Computer vision is a system that teaches how images and videos are stored, as well as how to modify and retrieve data from them. OpenCV is a library for computer vision, image processing, and machine learning which is now important in real-time applications. Image processing technologies are used to extract the most obvious features and perform operations on images in order to enhance them.

Deep learning techniques can handle enormous amounts of data and have therefore been proven to be a highly beneficial approach. These techniques have been widely used in pattern recognition. Convolutional Neural Networks(CNN) are among the most often used deep neural networks. It implements a novel method called as convolution. Convolution is a mathematical operation performed on two functions that results in a third function indicating how the form of one is impacted by the other. CNN is used to categorize the data to its best. It is composed of many layers that work together to finish the categorizing process[2]. The convolutional layer is the initial layer that is utilized to extract the feature map from the training set's images. The dominant features are retrieved from this feature map using the Max-pooling layer. The matrix produced by the max-pooling layer is sent into the flatten layer, which lowers the matrix to a single vector. Finally, all of these layers are linked by a dense layer, which is a fully-connected layer as shown in Fig 1.

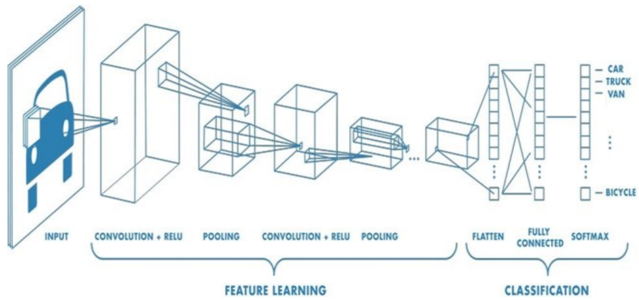

Fig . 1. Layers of CNN Architecture[3]

II. LITERATURE SURVEY:

Xu et al.[4] developed a model for rapid detection of maize seed classification using machine vision and machine learning based on variety purity. Halogen lights were employed to illuminate the laboratory, and a high-resolution RGB camera was used to acquire photos of maize seeds. To extract key properties from photos, an image processing algorithm was proposed. The performance of several machine learning techniques such as multilayer perceptron, decision tree, linear discrimination, naive bayes, support vector machine, k-nearest neighbor's, and AdaBoost algorithms were compared. Among all of these methods, the support vector machine classification achieved the best accuracy.

Basol et al.[5] created a CNN-based model to categorize 15 different types of seeds, including anise, sunflower, broad bean, pea, rosemary, bean, poppy, spinach, pumpkin, black pepper, flax, maize, chickpea, fennel, and clover. They updated the pre-trained CNN models Xception, InceptionV3, InceptionResnetV2, and Resnet50 to meet their needs. When the findings of each model were compared, InceptionV3, InceptionResnetV2, and Xception were all 99% accurate, whereas Resnet50 was just 98% accurate. A smartphone application was created to anticipate the seed and give the user with information on the morphological qualities and usage of seeds.

Sheng Huang et al.[6] used Convolutional Neural Networks and transfer learning to develop a model for seed quality classification. In addition, they were compared to typical machine learning techniques. This model, which has three classifiers, was created using the Googlenet method. The results reveal that Googlenet had a 95 percent accuracy rate, whereas the machine algorithm support vector machine only had a 79.2 percent accuracy rate. They created the feature map with visualization software and represented the probability distribution of inference results with a heat map.

Javanmardi et al.[7] proposed a novel method for classifying maize seed types that use a Convolutional Neural Network as a general feature extractor. Artificial Neural Networks, weighted k-nearest neighbor's, cubic support vector machine, boosted tree, bagged tree, and linear discriminant analysis were used to classify the retrieved features. When CNN extracted features were used instead of basic features, classification accuracy was higher. This study demonstrates that a CNN-ANN classifier is a useful tool for classifying corn seed variants.

Gulzar et al.[8] used Convolutional Neural Networks with transfer learning to create a system for categorizing corn seeds. Using enhanced deep learning techniques, the proposed model identifies 14 well known seeds. This work used symmetry when sampling images during data collection to ensure image uniformity in order to extract their attributes. The accuracy for both the test set and the training set was 99 %.

Keling Tu et al. [9] suggested a deep learning-based method for detecting the uniqueness of single maize seeds. To acquire a huge number of images for the training and testing sets, data augmentation techniques were applied. After supplementing the data, the VGG16 network was utilized for transfer learning to detect the seed images and uniqueness of maize variety "JINGKE 968."

III. METHODOLOGY

This paper proposed a system for detecting the quality of seed lots using Convolution Neural Networks(CNN). This system makes use of Keras, Tensorflow, OpenCV, Otsu Thresholding and Python. The Fig 2. represents the process flow of the proposed model.

- The systemtakes image of maize seed lot as input.
- Otsu thresholding is applied to the image to segregate each seed in the seed lot.
- The obtained individual seed images were passed to the CNN model.
- The model identifies the class of each seed to which it belongs to.
- The count of number of pure seeds is to be obtained from prediction results.
- The percentage of purity is calculated.
- Percentage purity of seed lot is displayed.

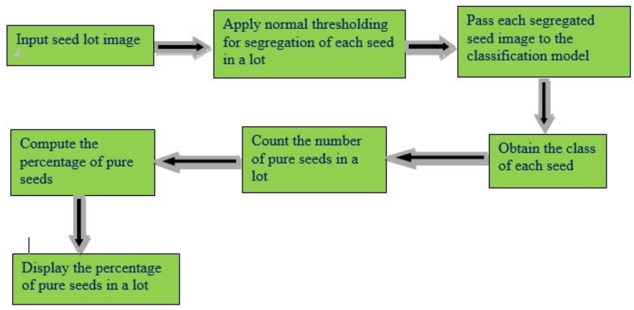

Fig . 2. Process Flow Diagram

The model has been developed in 3 stages: Dataset Collection, Segregation and Classification using CNN.

A. Dataset Collection

In this model the dataset considered is collected by the research team of IIIT Hyderabad[10]. It consists of three classes of corn seeds namely pure, discolored, and broken. The training set comprises 5,800 images of pure, 4,500 images of broken, and 2,500 images of discolored corn seeds, and the validation set consist of 1500 images of pure, 1200 images of broken, and 600 images of discolored corn seeds.

B. Segregation

For processing the image of the seed lot, segmentation is the first step to extract the individual seed for further analysis. In the segmentation technique, Otsu's method is widely used[11] because it dynamically computes the optimal threshold value based on the lighting conditions of the input image. It is best used for bimodal images which is when the histogram has two distinct peaks such as foreground and background. So, to separate the seed from its background this method is highly preferable. Each seed has been segmented out from the seed lot to test whether it is pure, broken, or discolored.

Binary Thresholding involves comparing each pixel value of the image with a mentioned threshold value that divides all the pixels into two groups. One with intensity lower than the threshold value and the other with greater than the threshold value. This method works well in controlled lighting conditions where there will be high contrast between background and foreground. In this study, Otsu Thresholding is considered where the threshold value is not predefined but a histogram of a bimodal image that contains two peaks is considered. The value that lies in the middle of both these peaks is considered the threshold value.
In the process of image segregation using Otsu Thresholding, the image has been preprocessed by both filtering the image and converting it into grayscale. The image has to be filtered to increase the contrast in the image

and also for noise reduction. This paper used OpenCV mean shift pyrMeanShiftFiltering to achieve color image segmentation. For optimal mean shift, the drift physical space radius (sp) has been defined as 21 and the radius of the drift color space as 51. The shifted image is then converted into a grayscale image. After converting the image into grayscale, we compute the thresholded image. Otsu Thresholding requires defining a few parameters such as the input image source, the thresh value which has been defined as 0, the maxval parameter which is the maximum value to use with the THRESH_BINARY thresholding type, and finally the type parameter which is the thresholding type. This paper defined THRESH_BINARY logically OR'd with THRESH_OTSU as the thresholding type. Fig. 4 shows the thresh image for the seed lot in Fig. 3. Thus, the foreground and background are separated with the help of thresholding. Now, we find the contours in the thresholded image. From Fig. 5 the contours can be observed clearly. Based on these contours we can separate each seed for classification. The number of unique contours observed in Fig. 5 is 21. Based on this we can obtain the seeds as in Fig. 6.

Fig. 3. Sample Seed lot

Fig. 4. Thresh image for sample seed lot

Fig. 5. Contours identified for sample seed lot

Fig. 6. Segmented maize image

C. *Classification*

Classification is performed after segregating each seed from the seed lot to determine whether they are pure, discolored, or broken. The CNN model has been trained using the dataset [10]. The training process involved reshaping each training image into the size 120*120 and then rescaling each image by dividing each pixel of the image by the value 255.0. The model uses CNN layers to classify the image of maize into three classes. The layers used in the model are two Conv2d layers each followed by a max-pooling layer. There are many parameters in this Conv2d layer but many of them are used as usual with default values, some of them need to be modified according to our CNN model. The first parameter that needs to be considered is the number of filters depending on the complexity of the dataset and the depth of the neural network. 64 filters were considered in this model. And the next one to be considered is kernel_size. It is a tuple that specifies the width and height of the 2D convolution window. The size of the image considered in this paper is 120*120 which is less than 128*128. we consider a kernel_size as (3,3). The kernal_size 3*3 indicates that the size of the convolution window is a 3*3 matrix for framing the feature map from these kernels.

The activation function is the next parameter in the Conv2d layer. The activation function is the one that decides whether the signal from a particular neuron should be transferred to another neuron in the next layer. It is used both at the hidden layers and at the output layer. The decision of the activation function at the output layer leads to the back-propagation which is the process of updating the weights and biases of the neurons. ReLU is the most generally used activation function for multi-class classification. It is a non-linear activation function. ReLU does not saturate, the gradient is always high if the neuron activates. The function can be written as f(x)=max(0,x).This function tells us that the ReLU function returns the value if it is positive otherwise zero, which happens in the case of negative numbers. Fig. 7 represents the ReLU graph[12]. The Rectifies Linear Unit function is used to make the network learn complex patterns.

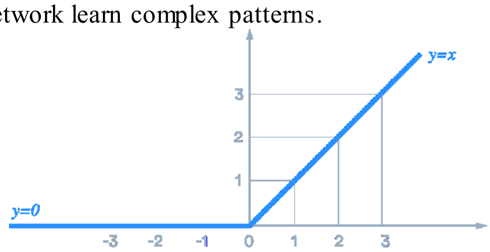

Fig. 7. ReLU Graph

We have to extract the prominent features from the feature map obtained from the Conv2D layer. Here comes the role of pooling. There exist two kinds of pooling, average pooling, and max-pooling. Max-pooling is a process that obtains the maximum area where it convolves. There might be some unwanted features in the detected feature map which can be reduced with the help of max-pooling. The pool_size is the parameter that needs to be mentioned in the max-pooling layer. In this study, it is considered as a 2*2 output matrix.

The output obtained was a feature map which is a 2*2 matrix. But we need to feed in fully connected layer as a single vector. This can be done with the help of a flattening layer. Flattening is the process of converting the feature map into a 1-D array to pass it to the output layer.The outputt obtained from the pooling layer is passed as input for the flattening layer which produces a single feature vector as output. This flattening layer is connected to all the other layers which is then called a fully-connected layer or dense layer.

And the final layer in the CNN model is the dense layer which receives input from each layer used for connecting all the layers, hence dense layer is called a fully connected layer. The dense layer performs matrix-vector multiplication where each row vector of previous layers is a column vector of the dense layer. The matrix product is as shown:

$$\mathrm{Ax} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

$$= \begin{bmatrix} a_{11}x_1 + a_{21}x_2 + \cdots + a_{1n}x_n \\ a_{21}x_1 + a_{22}x_2 + \cdots + a_{2n}x_n \\ \vdots \\ a_{m1}x_1 + a_{m2}x_2 + \cdots + a_{mn}x_n \end{bmatrix}$$

These values considered in the matrix are trained parameters in previous layers. This layer produces the correct class to which the image belongs.

In this study, a problem of overfitting was observed. To overcome this problem a dropout layer is added to the model. Overfitting is the case where the model learns some extra unwanted features which need to be removed[13]. Some of the neurons are removed by adding the dropout layer. A dropout layer with 0.5 probability is added to the CNN model. After overcoming the problem of overfitting, all the layers need to be connected with the help of a fully-connected layer.

The CNN model in this study was compiled with the following factors in mind: loss function, optimizer, and evaluation metric. During the training of the CNN model, a loss occurs at each iteration of each epoch, which is the difference between the actual value and the value predicted by the model using the loss function. It is critical to minimize this loss in order to improve the model's accuracy. The loss of our multi-class classification model was calculated using sparse_categorical_crossentropy. The RMSprop optimizer is the most often used adaptive gradient technique for training neural networks[14]. In this study, a RMSprop optimizer with a learning rate of 0.001 was applied. The model was evaluated using an accuracy metric. After 200 epochs of training, the model was 84% accurate.

D. *Algorithm (Model Training)*

Step 1: Start
Step 2: Get the Images
Step 3: Reshape each image of the train and validation to [-1,120,120,-1]
Step 4: Rescale each image (divide each pixel by 255.0)
Step 5: Split the data into Training and Test set
Step 6: Create the Model
Step 6.1: Add Conv2D layer with filters=64, kernel_size=(3,3), activation="ReLu"
Step 6.2: add MaxPooling Layer with pool_size=(2,2)
Step 6.3: add Conv2D layer with filters=64, kernel_size=(3,3), activation="ReLu"
Step 6.4: add MaxPooling Layer with pool_size=(2,2)
Step 6.5: add Flattening layer
Step 6.6: add fully flattening layer
Step 6.7: add a dropout layer with a dropout rate=0.5
Step 6.8: add the final layer
Step 7: Compile the Model
Step 8: Fit the train data, labels
Step 9: Save the model to our device

IV. RESULTS

A sample seed lot image is provided as input to the final prediction model that has been built. Each seed is segregated and passed as an input to the classification model which classifies the seed as pure, discolored, or broken. The overall purity percentage is found from that classification. The final results are shown in the below figures.

The number of pure seeds detected in Fig 8 is 17 out of 21 seeds. As a result, the percentage purity obtained in Fig 8 is 80.9.

Fig. 8. Sample seed lot 1

The number of pure seeds detected in Fig 9 is 1, and the total number of seeds found is 8. As a result, the percentage purity obtained in Fig 9 is 12.5.

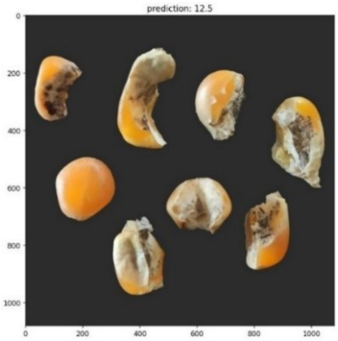

Fig. 9.Sample seed lot 2

The accuracy of a model is generally computed after the model parameters and is expressed as a percentage. It is a measure of how close your model's forecast is to the genuine data. The accuracy graph of the model is shown in Fig 10.

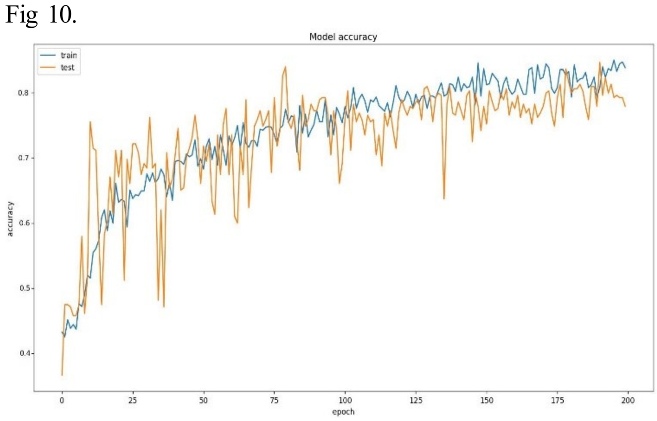

Fig. 10. Accuracy Graph

V. Conclusion and Future Work

In this work, deep learning techniques were used to develop a system for detecting the quality of maize seeds. The dataset consisting of three types of maize seed pictures was obtained and was trained using CNN. The proposed model has given an accuracy of 84%. Thus, the real-world applicability of an automatic system capable of predicting the purity percentage of the seed lot has been proposed. Future research will focus on developing a model that can be trained on other types of seeds.

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