Maize seed variety identification model using image processing and deep learning

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ABSTRACT

Maize is Ethiopia's dominant cereal crop regarding area coverage and production level. There are different varieties of maize in Ethiopia. Maize varieties are classified based on morphological features such as shape and size. Due to the nature of maize seed and its rotation variant, studies are still needed to identify Ethiopian maize seed varieties. With expert eyes, identification of maize seed varieties is difficult due to their similar morphological features and visual similarities. We proposed a hybrid feature-based maize variety identification model to solve this problem. For training and testing the model, images of each maize variety were collected from the adet agriculture and research center (AARC), Ethiopia. A multi-class support vector machine (MCSVM) classifier was employed on a hybrid of handcrafted (i.e., gabor and histogram of oriented gradients) and convolutional neural network (CNN)-based feature selection techniques and achieved an overall classification accuracy of 99%.

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1. INTRODUCTION

Properly utilizing various seed types is one of the most significant aspects of any agricultural development system. This technique has received emphasis in recent times as it is expected to harness food security to the increasing population in the world, for achieving better harvest execution and production yield, the identification of high production yielding seed varieties deprived of vital characteristics such as flooding, breaking obstruction, insects, and diseases. The production of a high-quality seed variety is the basis of any effective agricultural system since agriculture is the economic backbone of most countries worldwide. Basic requirements such as food, clothing, shelter, and medicines increase as the population grows. Advancement in agriculture is needed to meet these needs, especially for countries with large populations [1]. Regarding production output, maize, also called corn, has become the major grain crop worldwide. As mentioned in [2], between 2017 and 2019, the total production of maize worldwide was 1,137 metric tons, which is 39% of all cereals produced in those years. Maize is considered the cheapest calorie source compared to the other grains and now constitutes Ethiopia's highest calorie consumption and production share [2]. Due to the significant variation in price and resemblance in form, the impurity of maize seed varieties creates many challenges. Identification of the type of maize seeds is an essential aspect of the development of the maize industry. In Ethiopia, maize has traditionally been a significant food source for many people. The majority of Ethiopian farmers are known for cultivating maize crops. As a result, maize has become the second dominant crop next to teff (Eragrististeff) among the cereals grown in Ethiopia [3].

Different automation techniques and approaches have been introduced in the agriculture sector to increase the yield of several crops, including deep learning and image processing. Deep learning (DL), extended from machine learning by adding feature learning, is a major technique used for image processing and is becoming popular with machine learning research for agriculture [4].

Image processing is a computational method used to perform some operations on an image. This technique generates an enhanced image based on the given input. Image processing is used to classify and detect different areas of interest. In agriculture, image processing plays a significant role in the category of different varieties of crops. In recent years, various maize seed classification methods have been developed. Some of the ways include morphology method, protein electrophoresis, and Deoxyribonucleic acid (DNA) molecular marker. The problem with most of these methods is that they require specialized instruments and experts, and as such, they are time-consuming, expensive, and complicated to use. As a result, an approach that can quickly and reliably identify maize seeds is needed. This study, therefore, aims to build an image identification model for maize seed varieties using a deep learning approach.

2. RELATED WORK

Several image identification and recognition systems were built for cereal grains, but these systems needed more robustness to identify and recognize the seed varieties for complex seed varities [5]. So far, researchers mainly focused on the identification and quality scrutiny of wheat, chickpea, and rice varieties. So, an imaging classification system for maize seeds has yet to be developed. Therefore, this research aims to implement a technology to aid the visual scrutiny and extrapolation of maize seeds by humans in the process of identifying maize seeds. In the process of farming and harvesting, each production activity may introduce variety mixing, thus making seed identification complex and decreasing production. Extant literature in the area noted that a reduction of purity identification of maize seeds by 1% can lower the production by 9 kg per 667 m^2 [6]. This explains how important is the variety classification or identification of maize seeds before planting. This study is aimed to build a computer vision and image processing model to classify maize seed varieties. Saeed *et al.* [7] presented an identification model built to identify varieties of canola seeds using computer vision and image processing. The study used a K-nearest neighbor classification algorithm to achieve a classification accuracy of 90%. The study deploys a 50% train/test and validation split to train and test the dataset. Since a comparison of different classifiers was not made to choose the optimal classifier by changing the K-values, the classification scheme greatly depended on the nearest distance. A similar study was done on building an identification model of barely seed varieties using a convolutional neural network. The study, presented in [8], classified six barley seed varieties and achieved an acceptable accuracy of 93%. Image preprocessing techniques like segmentation, background removal, and kernel extraction of over 10,000 images per variety class were used in the experiment. Nasirahmadi and Behroozi-Khazaei [9] did research that identified ten bean varieties using the artificial neural network (ANN) classifier. In the study, 1,000 image samples were used for training, testing, and validation. Bean varieties whose neuron has the highest value in the output layer were assigned to the class. The model was limited to extracting more features if the amount of data used to train the model was higher. The study also proposed a combination of CNN and hybrid handcrafted features to fix the gap.

The research presented in [10] is yet another research that used wheat seeds collected at the Institute of Agrophysics of the Polish Academy of Sciences in Lublin and used a new deep neural network model (DNN) for identifying and recognizing wheat seeds [10]. This study used tangent hyperbolic (Tanh) as an activation function for three hidden layers. The study achieved a classification accuracy of 100%, reflecting the model's reliability. In their study, Hemachitra and Lakshmi [11] developed a quality assessment model using computer vision and image processing of beans based on color and size. The authors used skewness, average, and variance parameters. A similar study by Xinshao and Cheng [12] demonstrated how a feature extraction using the principal component analysis (PCA) network and enhanced PCA can classify the resultant seeds [12]. The study used an ANN for classifying seeds using the color quality of the seeds. It classified the bean seeds effectively as white beans, yellow-green harmed beans, dark harmed beans, low harmed beans, and highly harmed beans. The classifier improves the classification accuracy rate of bean seeds significantly and thus can be implemented in agricultural production practice.

Recent research presented in [13] discussed a maize seed identification model built to identify four varieties of maize seeds, including Nongda 108, Zhengdan 958, Ludan 981, and Jingdan 28, each with 200 maize seed images as feature extraction objects. The study used 14 features of shape and color for extraction purposes and achieved a classification accuracy of 94.5%. Based on the characteristics of maize seeds and images captured, the study recommended that an algorithm that could effectively extract features of multi-objects is required. A study conducted on maize seeds to minimize the occurrence of peak subjectivity, recurring error, and impairment of traditional maize seed classification techniques by combining deep learning with machine vision is discussed in [14]. The study's findings showed that the average precision, recall, and F1-values of the MFSwin transformer model on the test set resulted in an accuracy of 96.53%, 96.46%, and 96.47%, respectively. The classification accuracy of the MFSwin transformer was better than previous models [14]. The first research and development work on Ethiopian maize was started in 1952 by Jimma College of Agriculture researchers. Since then, the research and development efforts in the maize sector have shown many improvements, such as launching the national maize research program and various technology transfer approaches [1]. Ethiopia is one of the largest maize-producing countries in Africa, with many farmers engaged in its cultivation. In terms of market, maize is the largest cereal commodity in the country [1]. Maize is also the most significant agricultural product, with high yield and consumption. The farmers in Ethiopia grow maize primarily for subsistence, where 75% of the production is consumed by farming households as it is the cheapest source of calories [15].

As mentioned before, farmers are interested in the variety of the seeds they plant to ensure the correct product is grown and harvested. As far as the majority of Ethiopian farmers are engaged in cultivating maize crops as their primary food, it is required to assess the varieties of maize seeds to be grown in the right farming area and conditions (weather, soil type, and fertility). The visual similarity of maize seeds makes it hard to identify the seed type even by experts. This lack of an identification model for those varieties of maize seeds for their livestock production is a major problem for Ethiopian farmers. So, to overcome the issues mentioned above, an effective maize varieties identification and classification model is required. The study aims to find an answer to the research question: *how to develop a machine learning model to classify maize seed variants?* This study uses image processing and machine learning methods to implement the complex maize seed variety identification for agricultural purposes. This deployment process would reduce time and cost and enhance the exactness of the intricate type of seed variety identification. The rest of this paper is organized as follows: Section three presents the related works. It is followed by the methods and materials section that explains the methods used in developing the maize seed identification model. The experimental results and conclusions are presented in sections five and six.

3. MATERIALS AND METHODS

3.1. Image acquisition

From extant literature, it was noted that many researchers had applied deep learning to develop classification systems for agriculture. Deep learning is a state-of-the-art technique for image processing and data analysis with commendable results in seed identification [16]. The applications of deep learning in agriculture range from identifying herb types and seed varieties to recognizing plants, including fruit counting and classifying crop types. The first step in digital image processing is collecting and organizing the image in an image acquisition format [17]. The photos must be in high resolution and proper form for analysis and import into the electronic device or vision machine using digital cameras, scanners, and other optical devices. Varieties of maize seed images were collected directly from the Amhara region's agricultural and research center found in West Gojjam's Adet town. After the image was captured, the research center experts helped classify the data into the respective types correctly. As all maize crops do not yield good results in farming, farmers must select the most improved and widely cultivated maize type in a particular area. About 160 images were selected for each type for each variety, resulting in 800 images after applying rotation augmentation techniques, as shown in Figure 1. The five most important and widely planted maize as shown in Figures 1(a)-(e) that is AMH851, BH540, BH543, Gibe3, and MH140, were eventually selected for this study.

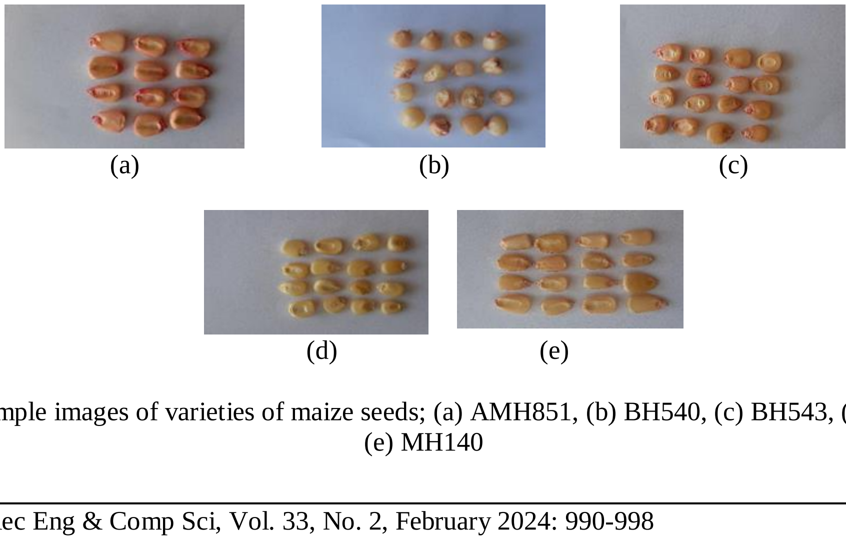

Figure 1. Sample images of varieties of maize seeds; (a) AMH851, (b) BH540, (c) BH543, (d) Gbi3, and (e) MH140

One of the objectives of this study is to determine which classifier is effective for identifying the varieties of maize seeds. The other objective is choosing feature extraction techniques that increase the model's classification performance. The next section discusses the detailed steps followed, including image processing and the identification of kernels to determine orientation. Other aspects, like how image features are used to numerically characterize the image's texture, color, and shapeare also explained. As mentioned, the system uses supervised learning to select attributes that best discriminate maize seed varieties and contribute to high-performance classification.

3.2. Image preprocessing

Any effort in the pre-processing technique must be meticulously adjusted to the particular seed type. Image preprocessing techniques such as image size normalization, noise removal, and other image filtering techniques and methods are used to visualize the required features from the original image [18]. The data set contains images with different image sizes, including (360×360), (256×256), and (224×224). While testing the model, the image size (360×360) achieved a better result. Hence, the size of the images was normalized into (360×360) using OpenCV for image operation and Numpy for array declaration.

One significant critical process in the image and computer vision process is noise removal. Noise comes due to various reasons. As mentioned in [11], "Images are usually degraded by impulsive noise because of noise sensors or channel transmission errors or faulty storage hardware." Noise removal techniques for impulsive noise from images aim at smoothening an image while keepingedges and other information intact. Noise filtering and image enhancement are other essential image processing techniques aimed at improving image quality and interpretability. In this study, an adaptive median filter (AMF) is applied for the noise reduction of varying window sizes mentioned above. As mentioned in [11], AMF works better at low and medium noise densities while disguising the picture at high noise densities. When the window size increases, the noise evaluation measurement will increase, enabling the researcher to think of poor median filter performance. Such problems can be solved using one of the image enhancement techniques by applying the adaptive median filter strategy discussed in [11]. At first, the Image is converted to grayscale for the visual perception of the image. Then, the noises in the images are eliminated using denoising filters like the mean filter to denoise the blur found in the image. The gabor kernel function was also implemented to enhance the texture segmentation and increase image quality. For reliable predictions, rotation augmentation is applied by rotating the image right or left. As indicated in [19], the degree of rotation confirms the rotation augmentation safety. An extensive training data set helps handle the over-fitting problem and increases accuracy. The training images were randomly rotated, flipped horizontally and vertically, and normalized as discussed in [4], [20]. In the proposed model, a 90-degree rotation is applied to increase the size of the dataset. So, the total length of the data after rotation is 1,600 images.

3.3. Feature extraction

After preprocessing the seed image, essential features of the image data were extracted. The CNN algorithm is used to extract features of the image data. CNN is a powerful algorithm for better performance in computer vision applications and image recognition [21]. As part of deep learning algorithms, CNN has powerful self-learning capability, flexibility, and generalizability [22]–[24]. Zhou *et al.* [25] also stated that CNN outperforms other algorithms in feature extraction and is widely used in image processing. Therefore, the study proposed a CNN feature extraction model consisting of convolution layers, pooling layers, filter sizes, and stride numbers selected in the experiment setup based on performance accuracy.

During the setting up of the experiment, a filter size 0f 7×7, a stride number 2 to skip two pixels, ReLU activation function were used. In addition, a max-pooling size of 3×3 is performed after the convolution operation to reduce the dimension of the data maximally. Moreover, the gabor filter is applied for texture feature extraction for texture characterization and multiresolution analysis. As mentioned in [26], image texture can be analyzed in a multiresolution representation using gabor filters. On the other hand, Zhou *et al.* [27] showed that the "histogram of oriented gradients (HOG) technique helps to extract features of objects following a change in intensity." Kok and Rajendran [20] also proposed the application of HOG descriptors for different computer vision tasks [28]. HOG feature is typically "extracted by counting the occurrences of gradient orientation based on the gradient angle and the gradient magnitude of local patches of an image" [29]. The distribution of the intensity gradients is essential to get the edges objects highlighted, which eventually allows features to be extracted and identify the shapes.

3.4. Feature vector concatenation

Combining the handcrafted and deep feature vectors increases the feature discrimination ability of the algorithm. The study used CNN for deep feature extraction and a HOG for handcrafted feature extraction [30]. The details of how the two feature vectors were concatenated are illustrated in Figure 2.

3.5. The proposed model architecture

As mentioned, building a suitable model involves three phases: image preprocessing, feature extraction, and image classification see in Figure 2. The image size was normalized in the preprocessing phase by conducting an experiment. The second phase, i.e., feature extraction, uses deep and handcrafted feature extraction algorithms. As mentioned before, gabor filter extraction was used to clarify the texture of the seed image and enhance the image quality because the gabor filter is the most popular technique for texture feature extraction [31]. Deep and handcrafted features of the image were combined into one feature vector, called a hybrid feature vector. Rahman *et al.* [32] demonstrated how the hybrid model enhances image processing tasks since it has the advantageof less training time, computational cost, and resources, and also the less environmental footprint of training.

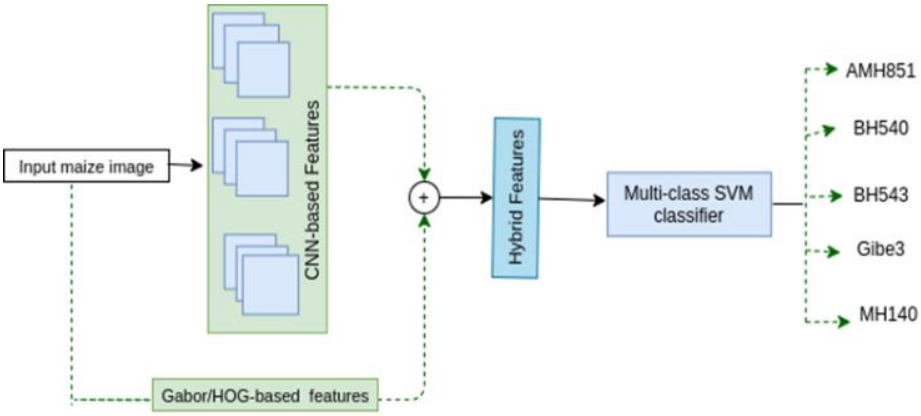

Figure 2. The proposed model architecture

4. RESULTS AND DISCUSSION

Experiments are conducted using a dataset of about 800 maize seed images collected from the Adet agricultural and research centers. Considering the nature of the features we extracted from the maize seed images and the heart of the algorithms selected, we conducted four experiments. (i) end-to-end CNN model, (ii) HOG feature with SVM classifier, (iii) CNN feature with SVM classifier, and (iv) combining both CNN and HOG features. The details of the first experiment are discussed in section 4.1, and the results recorded in each of the other experimental setups are shown in Table 1.

4.1. Experiment on end-to-end CNN model

We have conducted a different experiment on the proposed end-to-end CNN model. Since there are no criteria to select the CNN model parameters, we have tested the experiment on many convolutions and pooling operations, the number of filters and filter size, and activation function. The researchers tested the model on 2, 3, 4, 5, and 6 convolutions see in Table 1.

Table 1. Relation between the number of convolutions and accuracy

Number of convolutions	Accuracy in (%)
2	21
3	78
4	79
5	66
6	45

As can be seen in Table 1, convolution four is selected for its better accuracy. An experiment was also conducted on max pooling and average pooling, and both pooling operations were carried out to choose the max-pooling process. Moreover, the researchers have tested maximum pooling by comparison operation and achieved an accuracy of 76%; average pooling by addition and multiplication operation results in an accuracy of 21%. In contrast, the combined process of average pooling and maximum pooling gives an accuracy of 71%. So, the best pooling operation that fits our model is maximum pooling.

As we did for convolutions, three activation functions were considered to select the best activation function that fits the proposed model. Accordingly, we have tested the sigmoid activation function, which has an accuracy of 50%. RELU activation function has an accuracy of 76%, and Tanh activation function has an accuracy of 74%. So, based on the experiment, the RELU activation function has shown the best performance and fits the model.

As can be seen from Figure 3, the training accuracy is higher than the validation accuracy after epoch number 50. Additionally, the gap between the training and validation curves is narrow. These showed that there is low overfitting, and the model performed well, as supported in the study of [33]. As mentioned in [34], if a model is well-trained, training accuracy is expected to increase with a decreasing loss as per the training iterations. This is seen in Figure 4, which shows the learning curves of the CNN model that is taken from the training phase. The graph shows the curves relating to the change of loss (error) and accuracy. As shown in Figure 4, both training and validation losses increased until epoch 30, but after a while, validation loss increases gradually and become higher than training loss. The gap between training loss and validation loss is high, but it was expected that the proposed model would show a better performance.

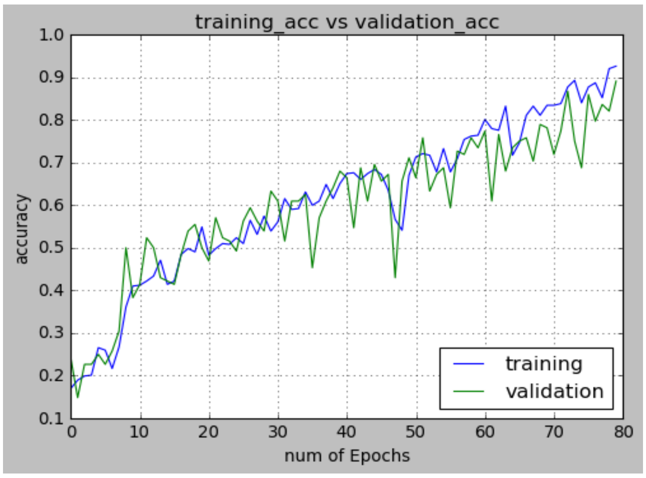

Figure 3. Training and validation accuracy of CNN model

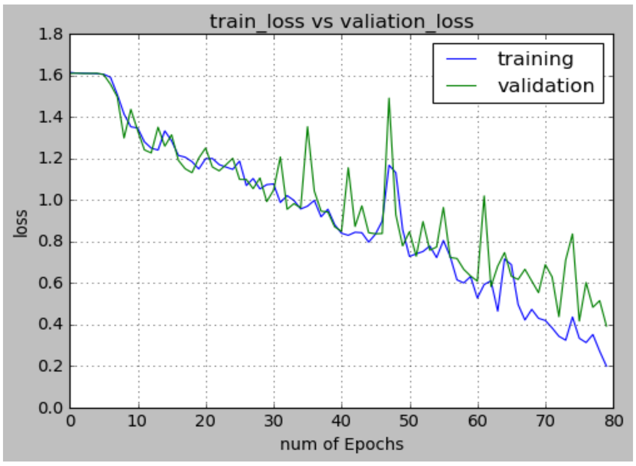

Figure 4. Training and validation loss of CNN model

Following the training phase, the maize seed identification models were tested with the test dataset (unseen data). To have a clear picture, we also created confusion matrices by comparing the models' predictions and the actual data that shows the seed varieties. Table 2 displays the results of the experiments of the various models based on 320 test images and the confusion matrices. An average of F1-scores of each class (the five maize seed classes) was carried out to determine the accuracy rate, as shown in Table 2.

Looking at the results in Table 2, we can conclude that all the models achieved a classification accuracy of over 0.88. Notably, the hybrid model of CNN with HOG produced a maximum rate of 0.99 in identifying maize seed varieties.

Table 2. Summary of the results of the experiment on the varieties of maize seed images

Model	Varieties	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
	MH140	100	97	98	
	Gbi3	82	100	90	
End-to-end-CNN	BH543	89	79	77	89
	BH540	92	82	87	
	AMH851	85	97	91	
	MH140	93	86	89	
	Gbi3	86	96	91	
CNN with SVM	BH543	100	100	100	95
	BH540	100	96	98	
	AMH851	100	100	100	
	MH140	86	86	93	
	Gbi3	92	92	92	
HOG with SVM	BH543	77	74	76	88
	BH540	85	92	88	
	AMH851	86	100	93	
	MH140	100	100	100	
	Gbi3	100	100	100	
CNN, HOG with SVM	BH543	100	100	98	99
	BH540	100	96	100	
	AMH851	95	100	97	
	MH140	92	100	96	
	Gbi3	100	97	92	
Gabor, CNN with SVM	BH543	98	75	94	92
	BH540	86	96	88	
	AMH851	96	100	92	

As shown in Table 2, the study results showed that 99% accuracy is achieved by combining CNN with AMH851, BH543, GBI3, and MH140 are 100% correctly predicted. Whereas BH543 images are 96% correctly predicted, only 4% of the samples are incorrectly classified as BH540. Therefore, the hybrid CNN model with HOG could be accepted as the best classification model with accuracy and prediction performance to identify maize seed varieties. As can be seen from Table 2, precision and recall values for the BH543 maize types are low. From the summary table shown in Table 2, the hybrid model, the result emphasized the class error distribution. Looking at the confusion matrix, we can see that most classification errors occurred for BH543. It can be seen that 74% of the BH453 varieties are correctly classified, while 26% of the sample needs to be correctly classified.

5. CONCLUSION

Developing a maize seed varieties identification model can support experts in the food processing and packaging industry and agricultural institutes. In this paper, an attempt has been made to use a novel dataset and develop an optimal model for identifying Ethiopian maize varieties. Once we prepared the dataset, two feature extraction techniques (automatic and hand-crafted features) were proposed. The CNN extracted the automatic feature, while the HOG and gabor filters were used to remove the hand-crafted features. After extracting the features using these techniques, various experimental steps were employed to select the optimal model. Finally, we achieved 89% on the end-to-end CNN model, CNN with SVM 95% accuracy, HOG with SVM 88%, CNN and gabor filter with SVM 90.62%, and the hybrid of CNN, HOG with SVM 99% accuracy. The study is focused on determining the best models to identify maize seeds. The study’s result showed that identifying maize seed types using deep learning technology is a feasible approach. The methodology also revealed that, for the best performance result, a hybrid model was achieved to identify maize seeds. As a result, the enhanced hybrid model (HOG+CNN) could assist food and agricultural agencies and organizations for maize variety selection and inspection purposes. The work contributes to evaluating the different maize seed varieties to increase maize productivity levels in Ethiopian farmers and transform the current agricultural status into modern production and growth rate. In this work, we only considered maize non-overlapping seed images as part of future work; the proposed model can be extended and redesigned to identify overlapping maize seed images.

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