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Research article

Efficient and Rapid Classification of Various Maize Seeds Using Transfer Learning and Advanced AI Techniques

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Abstract: The classification of maize (Zea mays) is crucial for agricultural efficiency, breeding programs, and market specifications. The EfficientMaize dataset was utilized alongside Google's Teachable Machine to develop a model separating maize varieties into classes: Bhihilifa, SanzalSima, and WangDataa. As a result, the study demonstrated that user-friendly machine learning tools are helpful in agriculture since they delivered high accuracy rates, such as 99% in Bhihilifa, 95% in SanzalSima, and 85% in WangDataa. This paper also emphasizes how modern machine-learning technologies can be accessible to farmers and researchers through tools such as Google's Teachable Machine, which does not require coding knowledge or online expertise. To validate the results obtained with Google Teachable Machine, further analyses were conducted using RESNET-50. These findings add to previous studies on deep learning and hyperspectral imaging, leading to seed classification by increasing the potential of using machine learning to improve agricultural practices and food security.

Keywords: Maize classification; Machine learning; Agricultural technology; EfficientMaize dataset; Sustainable farming.

1. Introduction

Corn is an important nutritional resource for both humans and animals. This product is also quite suitable for agricultural purposes in Türkiye and eligible for commercial animal feeding. Corn has high nutritional value and also has a high portion of yield and a well-adaptation potential [1]. Thus, the production of corn in Türkiye is popular. Although there are many corn varieties, 7 popular corn varieties are produced worldwide [2]. As in other agricultural production, yield and product quality in corn production are indispensable elements for agricultural processes [3]. To ensure seed quality and purity, the categorization of maize varieties is crucial for farming operations and agricultural research [4]. Classification of seed varieties, including maize seeds, is important for producers and farmers to maintain variety purity and product yield [5]. However, classifying corn seeds is not very easy. Maize seeds of different varieties are very similar, with significant overlap in morphology and color characteristics. Thus, it is very important to classify them using machine learning since mechanical classification does not make it possible to distinguish between species. Machine learning has become increasingly important in various technical breakthroughs [6]. Machine learning, a sub-field of artificial intelligence, improves computational algorithms with practice and makes precise analyses and predictions using training data [7].

The subject of machine learning is a very broad field. It involves supervised machine learning to develop predictive models based on the training data. In unsupervised machine learning, it aims to group observations or create simplified representations of the main structures within the data [8]. Each example in machine learning consists of a set of features or expressions that describe the situation in question. The training set is the set of examples the proposed algorithm uses to learn, and the test set is the set of new and never-before-seen cases it uses to see how good it is at classification [9]. Machine learning has become increasingly available in every field. For example, in food classification [10], improving the net yield rate of crops in a particular season [11] or product selection based on geographic information systems (GIS) and multi-criteria decision analysis (MCDA) was achieved [12].

There have been many new approaches to machine learning, and recently, a lot of research, such as herbal plant classification [13], leaf classification [14], plant disease detection [15] or fruit classification [16] has been done with the Google Teachable Machine tool because it enables fast and mobile use. Google Teachable Machine is a machine learning tool. It has a graphical user interface (GUI), and its usage depends on its platform. Teachable Machine is based on TensorFlow[17]. Previous studies have shown that cutting-edge technologies such as deep learning algorithms, machine vision, and hyperspectral imaging can improve the accuracy and speed of maize seed classification [18]. New studies have focused on developing low-cost tools and processes to increase the accessibility of these technologies [19]. Some recent studies have focused on low-cost and fast processing for certain corn varieties, and researchers have developed applied machine learning algorithms [20, 21].

Efficiency is very important in agricultural areas, and one of the important factors affecting productivity is the selection and classification of seeds. In this context, varieties of corn seeds have different growth needs. At the same time, these seeds do not have the same tolerance to pests and diseases. Also, precise classification helps agricultural workers choose the right variety for their specific conditions. This helps improve the management of products and increase technical efficiency [22]. However, classification is also advantageous for breeding programs. Growers must use the right grade of seeds for the R&D and P&D activities they want. Correct classification ensures the use of appropriate genetic materials on the subject. This subsequently aids the reproductive process [23]. Another important classification aspect is delivering the right product to the right buyer. Products with high commercial value suffer financial losses if the correct classification is not made. In other words, farmers working on this issue will not have problems meeting market demand and can increase their profits if their products are classified correctly [24].

As artificial intelligence has become increasingly widespread in recent years, significant progress has been made in agriculture. Classification studies using AI, along with forecasting [25], IoT[26], and prediction studies [27], have gained momentum. Recent works include studies such as "Maize Seed Variety Identification Using Hyperspectral Imaging and Self-Supervised Learning: A Two-Stage Training Approach Without Spectral Preprocessing" [28] and "Maize Seeds Forecasting With Hybrid Directional and Bi-Directional Long Short-Term Memory Models." [24] Additionally, studies like "Maize Seed Variety Classification Using Image Processing" [29] have been conducted in image processing. The growing use of YOLO has also been seen in studies such as "Soft X-ray Image Recognition and Classification of Maize Seed Cracks Based on Image Enhancement and Optimized YOLOv8 Model." [30]

There are different datasets containing corn types. In this study, the dataset named EfficientMaize was used. The main goal in creating the dataset is to classify corn on low-performing devices [31]. This study aimed to separate the seeds into three types: Bhihilifa, SanzalSima, and WangDataa, using artificial intelligence and transfer learning. Transfer learning and artificial intelligence were used to differentiate the seeds by taking advantage of current technological developments, and the study was carried out with the Google Teachable Machine tool, a machine learning tool.

2. Materials and Methods

2.1 Dataset used for the study

In this study, the EfficientMaize dataset was used. This dataset contains 4,846 images as raw and 17,724 images as augmented. The images were randomly rotated by 20 degrees, shifted horizontally and vertically by 20% of the image width and height, respectively. A maximum angle shift transformation of 0.2 radians was applied, and brightness adjustments were made in the range of 0.5 to 1.5. After these transformations, the newly created pixels were filled using the nearest pixel values. The augmented dataset provided by these processes was applied equally to the dataset to ensure the model was trained on a more diverse dataset. As a result, the aim was to increase the model's performance. The dataset creators applied data augmentation techniques. All images had a blue background. Researchers compressed the augmented images to a size of 128 x 128. Total image size 57.82 MB. The images were captured with a 12 MP iPhone 11 Pro Max device. Display features include a Super Retina XDR display, HDR display, 2,688-by-1,242-pixel resolution at 458 ppi, True Tone display, and Triple 12MP Ultra-Wide, Wide, and Telephoto cameras [31]. Details of each class of seeds in the dataset are shown in Table 1.

Table 1. EfficientMaize dataset

Crop	Categories	No. of Classes	Background	No. of Images
Maize	Bhihilifa	1	Blue	6,480
Maize	SanzalSima	1	Blue	5,100
Maize	WangDataa	1	Blue	6,144

2.2 Google Teachable Machine Model

The Google Teachable Machine model used in this study is based on the MobileNet architecture, a lightweight convolutional neural network (CNN) specifically designed for mobile and resource-constrained environments. MobileNet employs depthwise separable convolutions, significantly reducing the computational complexity compared to traditional CNNs. This makes it an ideal choice for real-time applications, such as those in agricultural technology [32]. The architecture consists of the following layers: Input Layer: This accepts image inputs and is resized to 224x224 pixels, as the MobileNet architecture requires. Depthwise Separable Convolutions: These layers break down standard convolutions into two parts: a depthwise convolution (which filters each input channel separately) followed by a pointwise convolution (which combines these filtered outputs). This reduces the number of parameters and computations. Batch Normalization and ReLU Activation Functions: After each convolution operation, batch normalization is applied to stabilize and speed up training, followed by a Rectified Linear Unit (ReLU) activation function to introduce non-linearity into the model. Global Average Pooling: Reduces the spatial dimensions of the feature maps to a single value for each feature, thus minimizing overfitting and reducing the overall model complexity. Fully Connected Layer: The final layer of MobileNet is a fully connected layer that outputs predictions based on the learned features [33]. Additionally, transfer learning was employed using the pre-trained weights from ImageNet, a large dataset used to initialize the model with general image features. This allows the model to adapt quickly to our specific maize classification task by fine-tuning the final few layers while keeping the pre-trained layers fixed, thus leveraging existing learned features from similar image classification tasks [33].

The computational efficiency of the Google Teachable Machine, based on the MobileNet architecture, is one of its primary strengths, especially for practical agricultural applications where real-time or near-real-time inference may be required. Our study found that the inference time for Google Teachable Machine (GTM) was 6 ms, making it exceptionally fast for real-time applications, while ResNet50 had an inference time of 18 ms. Although ResNet50 is still reasonably fast, GTM's lower latency makes it more suitable for mobile and resource-constrained environments where real-time decisions are crucial, such as agricultural fieldwork. The differences in training time are equally significant. ResNet50 required 34 minutes and 19 seconds for training, while Google Teachable Machine only took 4 minutes and 53 seconds, demonstrating the efficiency of GTM in inference and the training phase. The short training time makes GTM more practical and valuable for scenarios where frequent retraining or model parameter updates may be required, such as adapting to changing agricultural conditions or adding new crop species to the dataset, making GTM more practical. Therefore, GTM is suitable for practical agricultural applications where both speed and computational efficiency are critical. The substantial reduction in training and inference times allows the model to be deployed on lower-end devices without compromising performance, enabling widespread use by farmers or agricultural technicians in real-world settings.

2.3 Training the Model

For the training phase of the model, the entire dataset was randomly divided into two main parts: training (85%) and test sets (15%) by default in Google Teachable Machine. There are some optimization possibilities for the training process with the Google Teachable Machine tool. The number of epochs, batch size, and learning rate adjustments for these optimization processes were determined before training, and the relevant settings are shown in Table 2.

Table 2. Model parameters

Model	Epochs	Batch Size	Learning Rate
Teachable Machine	50	16	0.001

There is some preliminary parametric process in determining these parameters, and the relevant parameters are determined as a result of routine experiments in standard machine learning processes [34]. After this optimization process, the images in the dataset were transmitted to the Google Teachable Machine tool with the help of a web tool, as illustrated in Figure 1. Subsequently, the training process was completed for corn seeds belonging to 3 different classes, specific to each class. The interface can update instantly, and the performance of the developed model can also be viewed instantly.

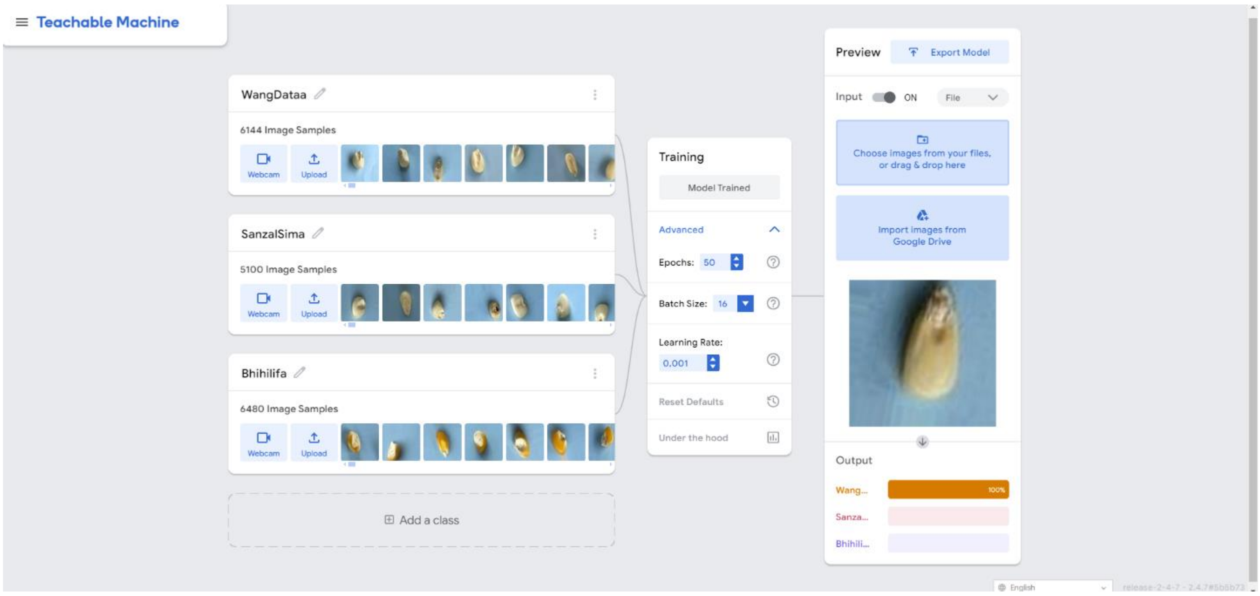


Figure 1. This is a figure. Schemes follow the same formatting.

As a basic machine learning process, the testing process was started in the second stage after completing the training. The model was re-evaluated with the test set. Unlike other machine learning tools, previews were provided at every stage during this process. The most important criterion of the developed model is performance evaluation. The main parameters in this evaluation can be listed as the confusion matrix, per-class accuracy, and overall performance metrics. Data augmentation techniques ensured that the developed model produced more accurate and sensitive results. More specifically, the dataset is digitally and artificially augmented. For the resulting model to produce more universal results, rotations, shifts, translations, and zooms were applied to the raw images [35]. The performance of the results of this model is determined by critical measurements based on accuracy, precision, recall, and F1 score. Accuracy shows the pattern of the prediction made with the actual result. Precision is another metric that measures the model's ability to remove false positives and represents the proportion of positive cases that are correctly and successfully predicted among all expected positives. Recall evaluates the model's ability to identify positive cases accurately. How effectively does it capture actual positive cases? The F-1 score takes the harmonic mean of precision and recall to provide a balanced assessment of the model's predictive performance.

Calculation formulas of the metrics are given in Table 3.

Table 3. Calculation formulas of metrics

Metric	Formula[1]
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{TP+FN}$
F1-Score	$2\frac{Precision*Recall}{Precision+Recall}$

[1] TP: True Positives TN: True Negatives FP: False Positives FN: False Negatives.

2.4 Software and Hardware Specifications

To ensure the reproducibility of the study, the hardware and software features must be known. In this context, this study was carried out on a workstation with the software and hardware information shown in Table 4.

Table 4. Software and hardware information

Name	Value
OS Name-Version:	Microsoft Windows 11 Pro - 10.0.26120
OS Configuration:	Standalone Workstation
Original Install Date:	12.04.2024, 14:09:46
System Boot Time:	18.07.2024, 04:18:02
System Model:	MS-7C71
System Type:	x64-based PC
Total Physical Memory:	32,686 MB
Network Card(s):	[01]: Intel(R) Wi-Fi 6 AX201
	[02]: Realtek PCIe 2.5GbE Family Controller
	[03]: Bluetooth Device (Personal Area Network)
Browser	Google Chrome (Chromium), Version: 126.0.6478.128 (64-bit)

3. Results and Discussion

After training the model with the EfficientMaize dataset and Google's Teachable Machine, the findings showed a high level of accuracy in categorizing maize varieties. The accuracy rates for each class were as follows: Bhihilifa achieved 99%, SanzalSima 95%, and WangDataa 85%, as shown in Table 5.

Table 5. Accuracy for GTM

Model	Class	Accuracy	Samples
Teachable Machine	Bhihilifa	0.99	972
Teachable Machine	SanzalSima	0.95	765
Teachable Machine	WangDataa	0.85	922

The confusion matrix in Figure 2 shows a detailed breakdown of the model's performance, including the number of instances correctly and wrongly classified for each class. For example, WangDataa has 787 correctly classified instances, 132 misclassified as SanzalSima, and 3 misclassified as Bhihilifa. The lower accuracy of WangDataa (85%) compared to Bhihilifa (99%) and SanzalSima (95%) could be due to several factors. One possible reason is the inherent variability in the visual characteristics of the WangDataa class, such as differences in color, texture, or shape, making it more challenging for the model to generalize across all samples.

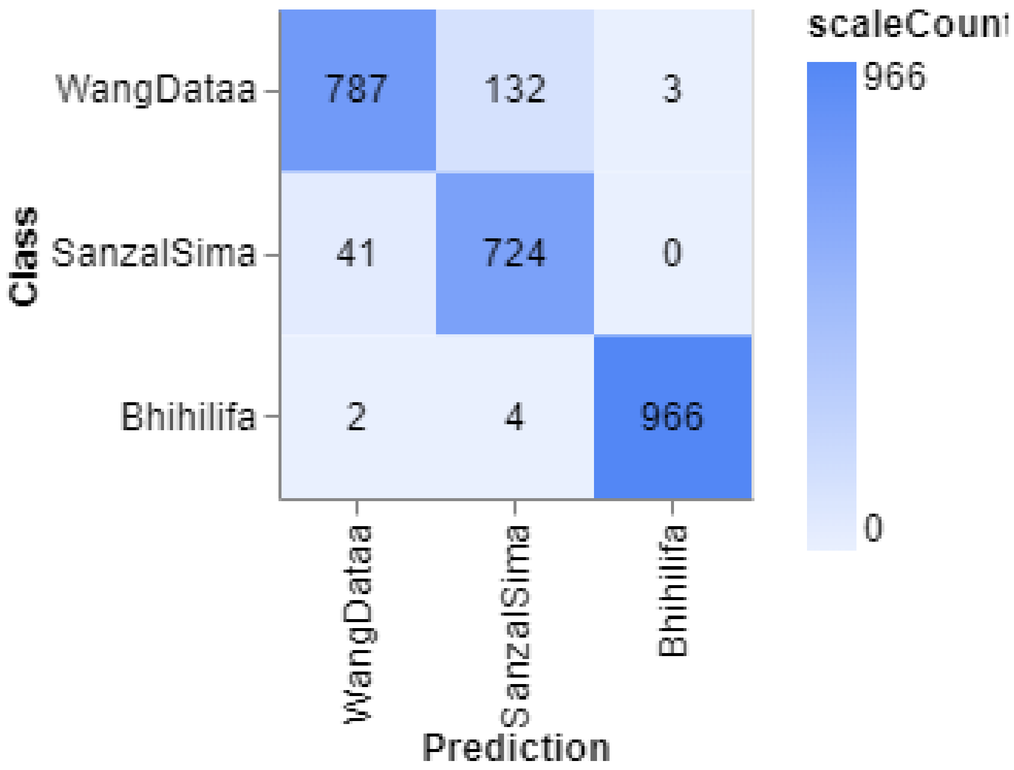


Figure 2. Confusion matrix.

Figure 3 shows the accuracy of training and validation throughout 50 epochs. The orange line depicts validation accuracy, whereas the blue line reflects training accuracy. The model's training accuracy improved steadily, reaching near-perfect levels, while validation accuracy fluctuated but remained excellent overall.

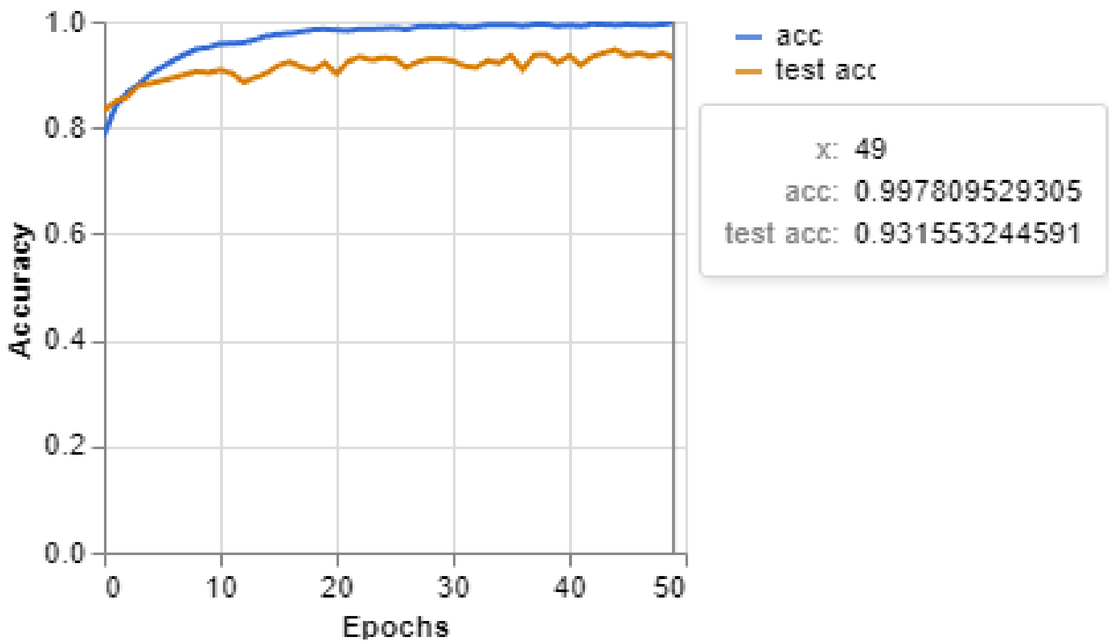


Figure 3. Accuracy per epoch.

Figure 4 shows the training and validation losses over 50 epochs. The blue line represents training loss, which fell in the first epochs before leveling out, showing effective learning from the training data. The orange line depicts validation loss, which fluctuated but decreased, showing that the model was successfully generalizing to new data.

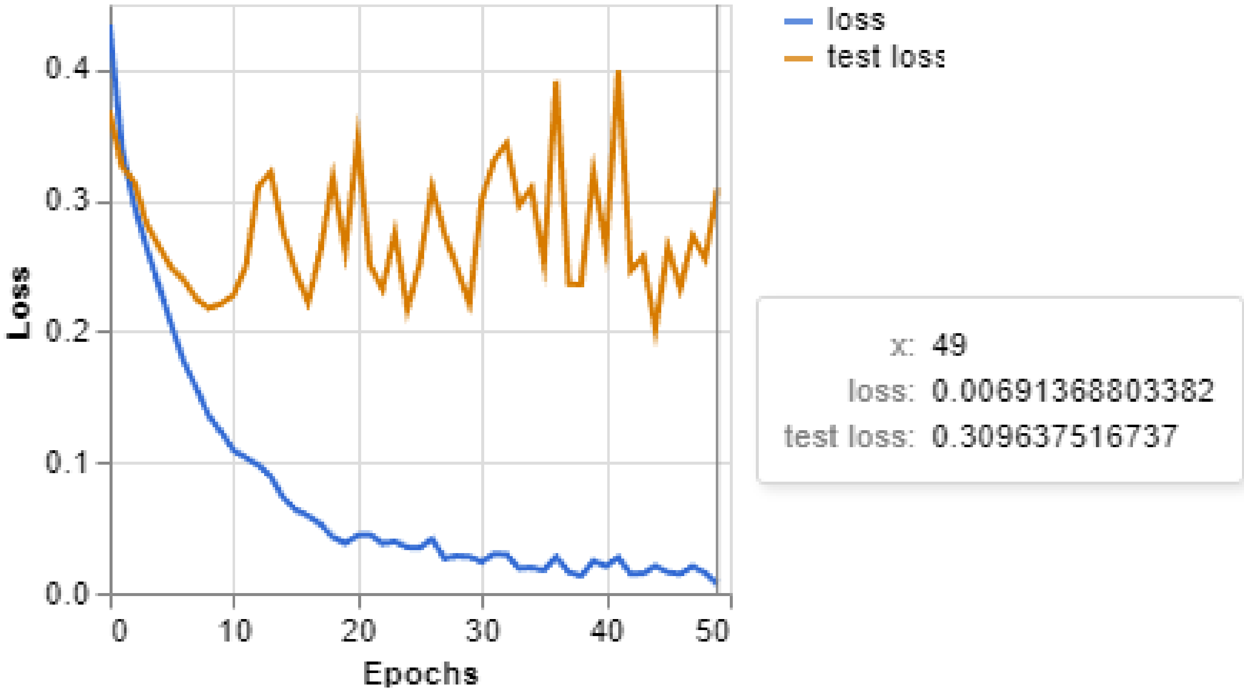


Figure 4. Loss per epoch.

Such evaluations and visual presentations throughout the testing process are critical for verifying the machine learning model's reliability and usability for the entire system. They help ensure the program runs successfully in real-world circumstances, which are critical to user pleasure and safety.

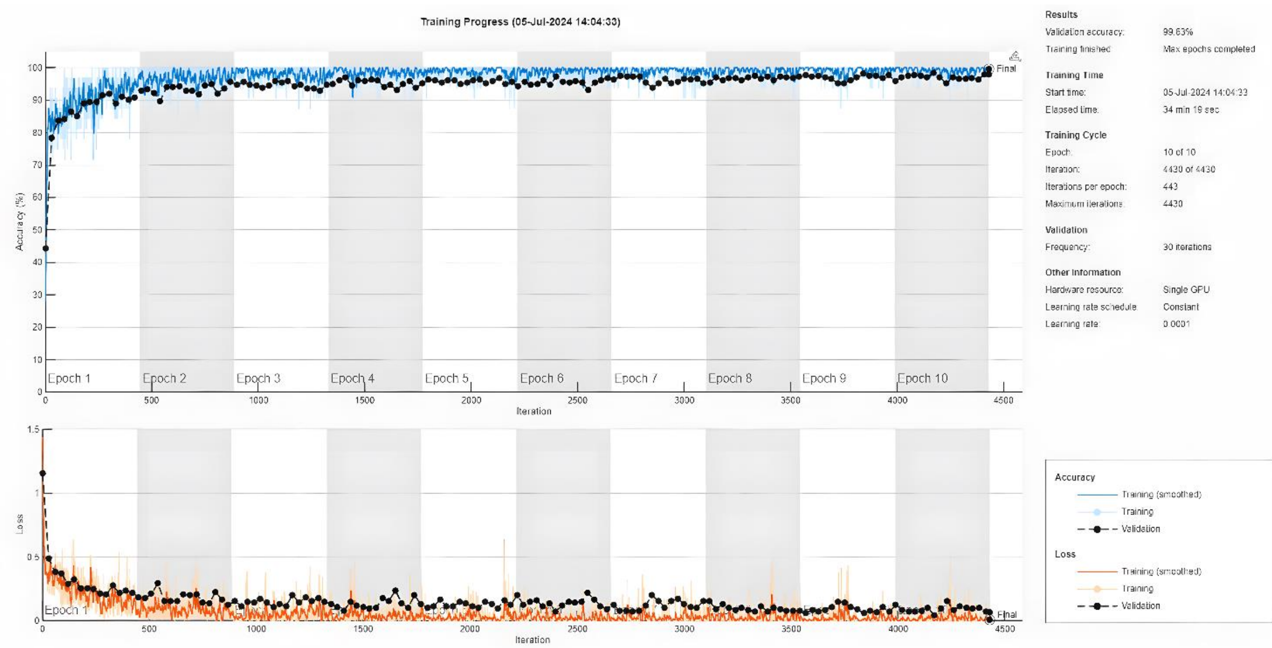


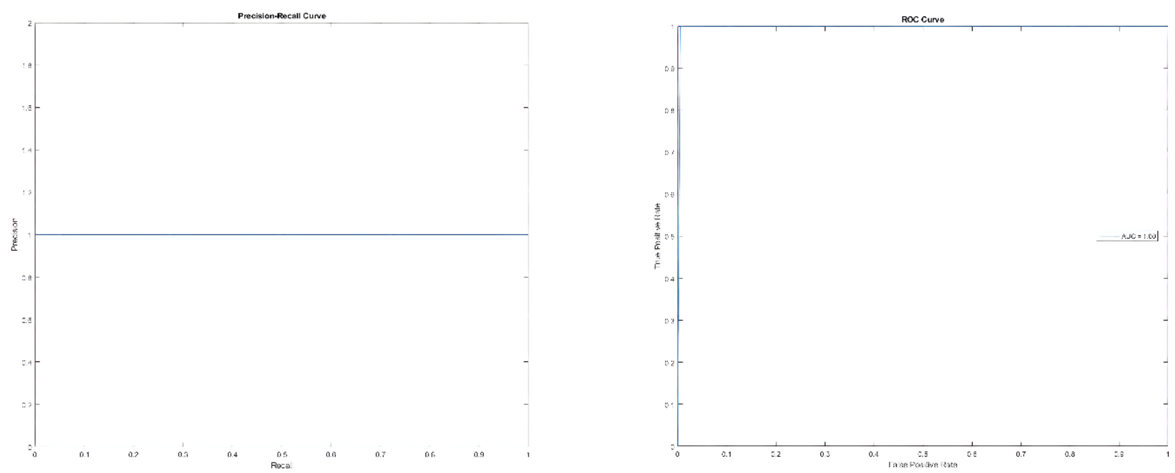
Figure 5. The training progress of ResNet-50.

ResNet-50's distinct architecture, which combines residual connections and a bottleneck structure, allows it to efficiently address the issues of training deep neural networks. Resnet-50 was used to verify the Google Teachable Machine results. For the Resnet-50, the entire dataset was randomly divided into two main parts: training (80%) and test sets (20%). For ResNet-50, the entire dataset was randomly divided into 80% and 20% training and test datasets for each class. For the training of the ResNet-50 model, standard training configurations of MATLAB were used to ensure stable performance. The 'adam' optimizer, known for its efficiency and adaptability in training deep learning models, was used. The mini-batch size was set to 32, a commonly used value, to balance memory efficiency and training speed. The learning rate was initialized at a typical setting of 0.0001 to achieve a stable and effective learning process without straining the convergence ability of the model. The model was trained for 10 epochs, and validation data was provided every 30 iterations to prevent overfitting of the model, thus running an effective learning process to increase the model's generalization ability. The data was shuffled in each epoch to ensure that the training data was exposed to the model in various ways. These choices were guided by standard practices in the machine learning literature and preliminary experiments, ensuring optimal model performance across various applications. MATLAB's default settings were used as they are well-regarded for producing consistent and successful results in deep learning tasks. Figure 5 depicts the training progress of Resnet-50, and Table 6 contains the Resnet-50 results.

Table 6. Software and hardware information

Parameter	Result
Validation accuracy	99.39%
Training finished	Max epochs completed
Training elapsed time	236 min 34 sec
Training epoch cycle	10 of 10
Iteration	9,480 of 9,480
Iteration per epoch	948
Max Iteration	9,480
Validation Frequency	30 iterations
Hardware resource	Single GPU
Learning rate schedule	Constant
Learning rate	0.0001

Figure 6 shows the precision-recall and ROC curves for ResNet-50.



(a) (b)

Figure 6. (a) Precision-Recall Curve, (b) ROC Curve.

Figure 7 shows the confusion matrix of the test dataset for ResNet-50.

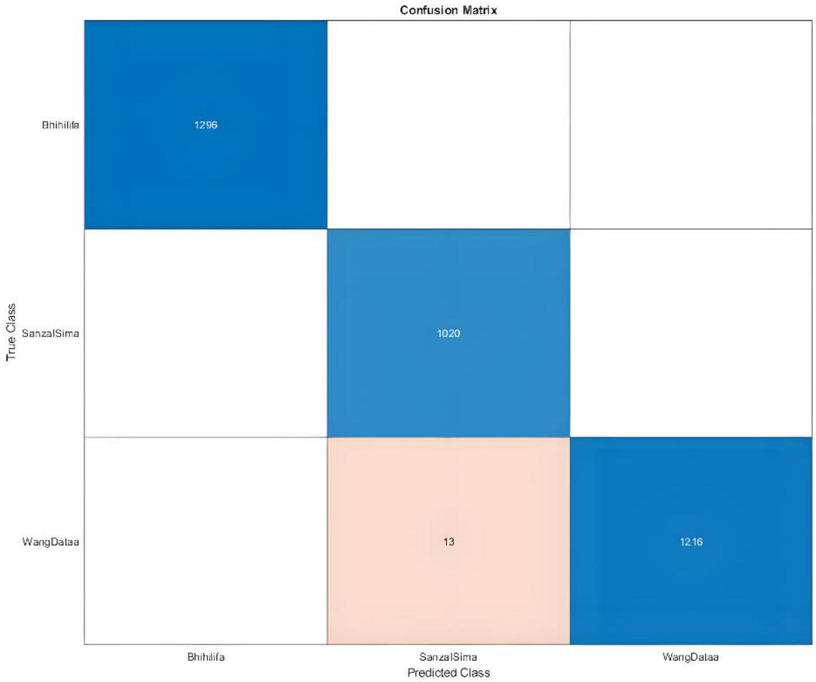


Figure 7. Confusion matrix of ResNet-50.

Table 7 shows the findings from Google Teachable Machine and ResNet-50, highlighting the precision, recall, and F1-score for the classes "Bhihilifa," "SanzalSima," and "WangDataa."

Table 7. Accuracy of ResNet-50

Class	Samples	Precision	Recall	F1-Score	Accuracy
Bhihilifa	1296	1.00	1.00	1.00	1.00
SanzalSima	1020	0.99	1.00	0.99	1.00
WangDataa	1229	1.00	0.99	0.99	0.99

The research shows that both classes' models have exceptionally high-performance metrics. The precision and recall values of classes “Bhihilifa,” “SanzalSima,” and “WangDataa” are consistently higher than 0.99, indicating a high level of classification accuracy. The accuracy, recall, and F1-Score value of the Bhihilifa class was 1.00, the precision and F-1 Score of the SanzalSima class was 0.99, while the recall value was 1.00. The recall and F1 score of WangDataa was 0.99, and the precision value was 1.00. Our results are consistent with recent studies on maize seed classification; [36, 37] however, GTM outperforms all these studies in terms of faster training, testing, and validation times, although its accuracy is slightly lower. However, it is anticipated that as the dataset grows, the learning curve will improve, increasing accuracy. Currently, one of the limitations of this platform is the maximum limit of 10,000 images per class.

When all the results were evaluated, the accuracy rate of the Bhihilifa class was found to be 99%, and this value was also quite high in classification success. Considering agricultural practices, it has been reported that this high-value classification success will also be advantageous to ensure seed quality and purity, which are very important for basic parameters such as yield and sustainability [4]. The accuracy values of the other two classes, SanzalSima and WangDataa, were 95% and 85%, respectively. Although these values were lower than the Bhihilifa class, it was thought that the model could be further improved by using different data augmentation techniques or optimization of preliminary parameter values, as mentioned before.

After a classifier is trained, the confusion matrix is generated by that classifier on a validation set. It can be used to find out which classes present some confusion in the classification, and then a more customized classification structure can be created [38]. When the confusion matrix of this study is examined, it is seen that the matrix values of two classes (WangDataa and SanzalSima) are higher than the other class (Bhihilifa). In other words, there is a possibility of confusion in classifying these two species. To prevent this, further optimization processes can be applied, or the training phase can be strengthened by increasing the source images to improve the model. When the model's training process was examined, it was observed that the training loss was reduced, and the training accuracy was high. These results show that the model is quite successful on the training set side. However, approaches to reduce overfitting should be used when evaluating model performance, validation accuracy, and loss oscillations. These approaches may be validation accuracy, loss oscillations, dropout regularization, or cross-validation [39]. Different machine-learning techniques have been applied to classify corn [40-42], and researchers have emphasized that low-cost devices and procedures should be prioritized when classifying [43, 44].

The implementation of this technology in real-world agricultural settings has the potential to enhance productivity and decision-making efficiency significantly. Farmers can reduce the time and labor required for manual seed sorting by AI-based maize seed classification, leading to more accurate and rapid processing. Using machine learning models like Google Teachable Machine in the field can also enable mobile-based solutions, allowing for on-the-spot classification with minimal infrastructure requirements. Economically, such technology could save costs by reducing the need for specialized labor and minimizing errors in seed selection, ultimately leading to higher crop yields [45]. However, challenges remain in the widespread adoption of this technology, including initial setup costs, the need for reliable internet connectivity in rural areas, and the integration of AI systems with existing farming equipment [46]. Further, it is necessary to ensure that these systems are adaptable to various crops and growing conditions to make them broadly applicable in diverse agricultural environments[47]. Future research could expand the model to classify additional maize varieties or adapt it for other crops like wheat or rice. Incorporating larger, more diverse datasets would enhance the model's generalization. Improvements could also include using more advanced neural networks, such as transformers, and domain-specific augmentations to increase robustness [48]. Additionally, integrating the system with IoT sensors or automated machinery could create comprehensive smart farming solutions, enabling real-time monitoring and decision-making [49]

This study investigated the classification success of different corn varieties with machine learning and transfer learning approaches using the Google Teachable Machine tool, which is low-cost, fast, and highly accurate, as the researchers suggested. There is no statistically significant difference ($p<0.01$) between the two models' weighted accuracies. The analysis and test results showed that these three types of corn seeds could be classified successfully and accurately. At the same time, this has shown that it is applicable in many agricultural applications due to its low costs and flexible structure. The accuracy of the results was evaluated by comparing them with ResNet-50, a well-known and successful method. As a result, this method is thought to be widely used in the classification of corn seeds and will be the basis for future studies that may include more varieties.

4. Conclusions

Maize (Zea mays), known as corn, is one of the world's most important grain crops. Correct classification of corn varieties is important in many areas as it is one of the basic foodstuffs for humanity and an important component of animal feed and various industrial products. This study proposes using Google's Teachable Machine to successfully differentiate maize seeds belonging to Bhihilifa, SanzalSima, and WangDataa species. In this study using the EfficientMaize dataset, it was observed that Bhihilifa was successfully classified with 99% accuracy, SanzalSima with 95% accuracy, and WangDataa with 85% accuracy. These findings suggest that using Google's Teachable Machine will increase the accessibility and usefulness of modern machine learning technology in agricultural applications. It can be run on low-cost devices, thus demonstrating the potential of machine learning techniques to increase precision and efficiency in agricultural applications. The most important findings of the research are high classification accuracy, improvement potential, and usability of machine learning. The model has been highly successful in classifying maize species, especially Bhihilifa. SanzalSima and WangDataa's classification performance has been achieved with relatively lower accuracy than Bhihilifa. Still, it is thought that the performance will be increased by improving the model with new data and various optimizations. It has been evaluated that when the advantages obtained from the model and the new technologies to be developed are paired with user-friendly tools, they can be widely used in agricultural practices by improving seed quality evaluation, breeding program assistance, and marketability of agricultural products.

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