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Tomato Seed Classification with Artificial Intelligence: A SqueezeNet-Based Approach

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***Abstract*— The development of agricultural technologies is of great importance in improving agricultural production processes, enhancing crop quality, reducing production costs, and optimizing resource utilization. Seed quality is crucial in agricultural production in terms of plant development and yield. The use of high-quality seeds supports healthy plant development, thus increasing the productivity and sustainability of agriculture. Traditional methods rely on approaches such as visual inspection, manual sorting, and biological testing. However, these methods have significant limitations due to their time-consuming nature, dependence on human experience, and inability to provide sufficient efficiency in large-scale applications. In this study, an artificial intelligence-based decision mechanism is proposed for the automatic classification of healthy and unhealthy tomato (Solanum lycopersicum) seeds. A dataset of tomato seeds was specifically created for this study. The dataset consists of a total of 200 tomato seed images obtained under different environmental conditions, and the generalization ability of the model was strengthened by applying data augmentation and various preprocessing techniques. A deep learning-based SqueezeNet model, capable of providing high accuracy rates with low memory requirements, was used for feature extraction from the obtained tomato seed images. Model performance was evaluated using a 5-fold cross-validation method, and classification accuracy, precision, sensitivity, and F1 score were analyzed. Furthermore, quantization was applied to assess the model's usability in mobile and field applications, and it was observed that discrimination was achieved without performance loss. In comparative analyses, experiments with a YOLO-based object detection approach revealed that lightweight CNN architectures that perform direct classification are more effective when dealing with small and visually similar objects. In conclusion, this study demonstrates that a SqueezeNet-based deep learning approach offers high accuracy, low computational cost, and practical applicability in the automatic classification of tomato seeds. The proposed method has the potential to reduce human error in agricultural quality control processes and contribute to the rapid and reliable assessment of seed quality.**

***Keywords*— artificial intelligence, classification, deep learning, SqueezeNet, seed separation, seed quality, tomato seeds.**

I. INTRODUCTION

Seed quality has a multifaceted and critical importance in terms of agricultural production and food security. It also directly affects crop yield, agricultural productivity, food security, and nutritional value [1]. High-quality seeds are superior in terms of genetic and physiological purity and are free from seed-borne diseases and defects, which increases productivity [2]. While seed quality is affected by genetic and environmental factors, climate change leads to significant changes in seed characteristics [1, 3]. Studies show that high-quality seeds provide a 25-30% increase in yield in agricultural production [4]. Therefore, accurate and reliable assessment of seed health in agricultural production processes is of great importance.

High-quality tomato seeds contribute to the optimization of fertilization practices, increasing crop yield and also improving nutritional value [5]. Well-managed fields with high-quality seeds provide superior germination and viability, which are crucial for achieving potential yields [6]. In addition, the use of quality seeds reduces the need for excessive agricultural chemicals, promoting sustainable agricultural practices [7]. Studies have also shown that the quality of tomato seeds affects the nutritional content of the fruit [8].

Traditional methods used for seed quality assessment, such as visual inspection, washing tests, and seed soaking methods, rely on the interpretation of visual symptoms and often fail to detect latent symptoms [9]. These methods are time-consuming and may not yield accurate and reliable results, making it difficult to assess the economic suitability of seeds under field conditions [10]. The procedures involved in traditional methods are often lengthy and labor-intensive, making them less efficient for large-scale seed quality assessment. These methods may not accurately detect damage or provide comprehensive information about seed viability and health [9, 11]. This situation increases the need for faster, more objective, and automated systems in seed quality assessment processes.

Computer Vision (CV) systems enable non-destructive, contactless, and objective evaluation of agricultural products, providing consistent quality assessments without human bias [12]. These systems automate labor-intensive tasks such as sorting, grading, and defect detection, significantly reducing manual labor and associated costs [13, 14]. Machine learning and CV techniques, especially when combined with deep learning (DL), provide high accuracy and speed in the detection and classification of agricultural products. DL models demonstrate superior accuracy in identifying defects and classifying products compared to traditional methods [15, 16]. The use of these technologies can automate quality control processes, helping to reduce production costs and improve overall product quality, leading to higher revenues and faster market access. CV systems allow for non-destructive quality assessment while preserving seeds for later use. This is particularly beneficial for tests such as purity analysis and germination tests [17]. Machine learning algorithms can provide a comprehensive assessment of seed quality by analyzing multiple features such as shape, color, and texture. The integration of ML and CV into seed quality control offers significant improvements in accuracy, speed, and reliability, making them invaluable tools in modern agriculture.

This study proposes a SqueezeNet-based deep learning approach for the automatic classification of healthy and unhealthy tomato seeds. In the proposed method, classification is performed by extracting distinctive features from tomato seed images, and model performance is evaluated using a 5-fold cross-validation method. Furthermore, quantization is applied to assess the model's usability in mobile and field applications, and a comparative analysis is conducted using an object detection-based YOLO approach. The main objective of this study is to develop a decision-making mechanism that automatically, accurately, and quickly evaluates the quality of seeds used in agricultural production and to make this process more efficient. It is also aimed that the results obtained will contribute to the automation of quality control in agricultural production processes and to increasing product yield.

The remaining sections of this study present the methods followed and experimental results in detail. The materials and methods section describes the dataset creation process, the image processing techniques used, and the details of the machine learning algorithms. The experimental results section presents the performance results of each algorithm in tables and graphs, and a comparative analysis is conducted. Finally, the conclusions section summarizes the overall findings of the study, discussing the applicability of the proposed methods in agricultural production and potential future improvements.

II. Related Work

This section reviews previously applied methods for classifying tomato seed quality. Areas examined include image processing techniques used in seed analysis, machine learning algorithms used for seed classification, deep learning models used for feature extraction, and computer vision applications in agricultural quality control. Relevant articles and studies are listed below.

Koppad et al. developed a method using deep learning algorithms for the automatic classification of soybean seeds. In the study, seed classification based on quality factors such as shape, size, color, and surface features was achieved using image recognition and deep learning techniques. This process increased accuracy by minimizing human errors and subjective evaluations compared to manual methods. ResNet50, MobileNetv2, DenseNet121, YOLOv5, and YOLOv8 models were used in the research. Among all models, YOLOv8 showed the best performance with an accuracy rate of 91% [18].

Kumari and colleagues conducted a study on the detection, classification, and counting of mixed seeds using the YOLOv5 deep learning model. In the study, deep learning models were applied to detect and count mixtures of various seed types such as flax, fringed vetch, red clover, radish, and rye. Seed images were obtained with a Canon LP-E6N R6 5D Mark IV camera, and dataset annotation was performed with the Robo-flow platform. The generalization power of the model was increased using data augmentation techniques. The YOLOv5 model showed the best performance with 96.96% recall, 94.81% precision, 68.62% mAP, and a CPU time of 28.8 seconds for a test image [19].

Jian Li and colleagues developed a method combining hyperspectral RGB imaging and deep learning techniques for the identification of maize seed varieties. In the study, the aim was to detect seed varieties by reconstructing RGB images with hyperspectral data. Hyperspectral bands with R, G, and B features were selected, and the image set reconstructed with these bands was used. Then, the model was improved by adding a coordinate attention (CA) mechanism to the ResNet50 model. The results showed that the accuracy rate reached 86.28% with the unimproved model, while the accuracy increased to 88.18% with the improved model [20].

Yu Xia and his team developed a method based on a YOLOv5-based deep learning model to detect surface defects in maize seeds. In the study, surface defects of maize seeds were detected quickly and effectively with an image-based information gathering system. Various models were used for surface defect recognition, and the ECA-Improved-YOLOv5S-Mobilenet model yielded the best results. This model combined lightweight architecture and high accuracy to detect surface defects in maize seeds with 92.8% accuracy, 98.9% recall rate, and 95.5% mAP0.5. The model was able to quickly detect surface defects at different levels and improve efficiency in seed classification and planting processes [21].

Basol and Toklu developed a deep learning-based seed classification method and integrated it into a mobile application. In the study, a dataset was created from high-resolution images, taking into account the morphological structures of various seed types, and this dataset was processed using deep learning techniques such as CNN (Convolutional Neural Network). As a result of training using pre-trained models such as ResNet50, InceptionV3, Xception, and InceptionResNetV2, an accuracy of up to 99% was achieved. The highest performing model was converted to a mobile platform, and a mobile application was developed that allows users to quickly and accurately classify seed types by taking photos [22].

When examining studies aimed at determining seed quality, it is seen that deep learning is applied to automate seed separation, classification, and quality assessment. Studies demonstrate the effectiveness of deep learning models such as YOLOv5, ResNet50, MobileNetv2, and CNNs in accurately classifying and identifying seeds based on various quality characteristics, including shape, color, and texture [18, 23, 24]. Deep learning models show high performance in seed quality classification. The high accuracy, recall rates, and F1 scores obtained demonstrate their potential to improve seed quality assessment and disease detection [25, 26]. The use of deep learning techniques such as CNNs can contribute to breeding and yield improvement by leading to the development of automated software for high-yield seed phenotyping, quality assessment, and prediction [22].

In deep learning studies, comprehensive and accurately labeled datasets are needed for successful training of models [25]. However, deep learning models pose challenges in real-time applications on devices with limited resources (e.g., mobile applications or field-use devices), primarily due to their high computational power and storage capacity requirements. Lightweight deep learning models developed to determine seed health and quality should aim to overcome these challenges. In this context, solutions that reduce computational complexity and resource limitations while maintaining high accuracy rates should be emphasized [27]. Furthermore, these models need to be optimized in terms of computational resources, efficiency, and interpretability in practical applications.

Therefore, further research and development of deep learning methods for seed quality classification and prediction will play a significant role in improving the efficiency of agricultural processes [24, 25, 28].

III. Materials and Methods

In this study, a deep learning-based approach was developed to classify tomato seeds as healthy and unhealthy. The proposed method utilizes SqueezeNet, a lightweight convolutional neural network architecture, to extract distinctive features from tomato seed images. The model's performance was analyzed using a 5-fold cross-validation method and various evaluation metrics. The overall flowchart of the proposed method is shown in Fig.1.

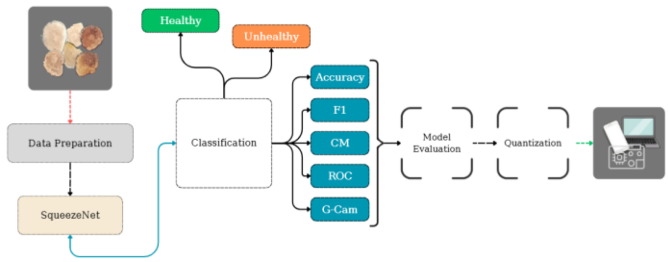

Fig. 1 General workflow of the proposed SqueezeNet-based tomato seed classification model

This section details the dataset used, preprocessing steps, proposed model structure, training process, and performance evaluation methods.

A. *Tomato Seed Data Set*

The dataset used in this study consists of a total of 200 color (sRGB) images of tomato (Solanum lycopersicum) seeds. The images were obtained under different environmental and lighting conditions using a high-resolution Samsung camera. The dataset was divided into two classes: 100 healthy and 100 unhealthy tomato seeds.

The dataset underwent enhancement processes prior to feature extraction and classification. Augmentation techniques such as mirroring and rotation were applied to diversify the images and improve classification accuracy. As a result of this process, the total number of images in the dataset increased to 800. The dataset expansion was carried out primarily to reduce misclassifications between seeds and potential overfitting. In this way, a more balanced and representative dataset was created by increasing visual variation between classes.

Table 1 shows the image distribution of the post-classification dataset. The healthy class generally includes fresh seeds with high germination potential, while the unhealthy class includes seeds exhibiting structural defects, color changes, and low viability. The quality of tomato seeds was determined primarily by surface structure and color changes, and these changes were used as the main criteria in classification.

TABLE I - Distribution of Tomato Seed Dataset Images

Seed Classes	Images	Number of Data
Healthy		100
Unhealthy		100
Total		200

B. *Preprocessing and Data Augmentation*

All images given as input to the deep learning model were rescaled to 227×227 pixels to meet the requirements of the SqueezeNet architecture. During the training process, the images were subjected to various data enhancement operations to improve the model's resilience to different transformations. These operations included random rotation, horizontal reflection, scaling, and translation.

The applied data enhancement techniques aim to enable the model to accurately classify seeds even under varying angles, scales, and positional changes. This approach plays a significant role in improving the model's generalization performance, especially in datasets with a limited number of images.

C. *SqueezeNet-Based Deep Learning Model*

Deep learning-based convolutional neural networks (CNNs) are a powerful artificial intelligence technique widely used in image analysis and processing. CNNs treat each pixel in images as a numerical value and extract meaningful features from images by analyzing the relationships between these numerical values. When an image is fed into the network, the CNN learns the connections between these pixels in layers and extracts features. During this process, various mathematical operations are applied in successive layers to obtain features from the image. In this study, SqueezeNet, a lightweight deep learning model, was chosen for the classification of tomato seeds. This model demonstrates effective performance in extracting different features from images.

SqueezeNet is a lightweight convolutional neural network (CNN) architecture designed to achieve high accuracy with significantly fewer parameters compared to traditional CNNs like AlexNet. The core building block of SqueezeNet is the Fire module, consisting of a compression layer and an expansion layer. The compression layer uses 1x1 convolutions to reduce the number of input channels, while the expansion layer uses a mix of 1x1 and 3x3 convolutions to increase the number of output channels [29]. It is particularly noteworthy for its efficiency, which includes up to 50 times less weight while maintaining comparable accuracy levels [30]. This reduction in parameters makes SqueezeNet highly suitable for applications with limited computational resources, such as mobile and embedded systems [31].

The proposed method adopts a transfer learning approach using a SqueezeNet model previously trained on large-scale datasets. The model's original classification layers have been restructured to be suitable for classifying tomato seeds as healthy and unhealthy. This allows for effective classification with a limited number of images by leveraging previously learned general visual features.

D. Model Training and Cross-Validation

During the model training process, the dataset was evaluated using a 5-fold cross-validation method. This approach allowed for the analysis of the model's performance in different training and testing phases and increased the generalizability of the results. In each cross-validation step, a portion of the dataset was allocated for testing, while the remaining portion was used for training and validation.

The Adam optimization algorithm was used during model training. The training process was limited to a specific number of epochs, and an early stopping mechanism was activated if the improvement in validation loss stopped. This prevented overlearning and made the training process more efficient.

E. Performance Appraisal Criteria

The classification performance of the proposed model was analyzed using commonly used evaluation metrics such as accuracy, precision, recall, and F1 score. Additionally, receiver operating characteristic (ROC) curves and area under the curve (AUC) values were calculated to assess the model's ability to discriminate between classes.

The results obtained during the cross-validation process were combined to create a confusion matrix, and the model's performance for both classes was examined in detail. These evaluations comprehensively demonstrate the effectiveness of the proposed SqueezeNet-based approach in tomato seed classification.

IV. Experimental Results and Discussion

In this study, the performance of the proposed SqueezeNet-based tomato seed classification approach was evaluated using a 5-fold cross-validation method. Model performance was assessed using common performance metrics such as accuracy, precision, sensitivity, F1 score, and ROC–AUC. Additionally, post-quantization performance results were examined to evaluate the model's usability in field and mobile applications.

A. Classification Performance

The complexity matrix, created by combining the results obtained during the cross-validation process, shows that the model offers high and balanced classification performance for both classes. According to the results, 99 out of 100 healthy tomato seed samples were correctly classified, with only 1 sample being misclassified. Similarly, 94 out of 100 unhealthy tomato seed samples were correctly identified, while 6 samples were incorrectly classified as healthy. The combined complexity matrix, obtained to examine the classification performance of the model in detail, is presented in Fig. 2.

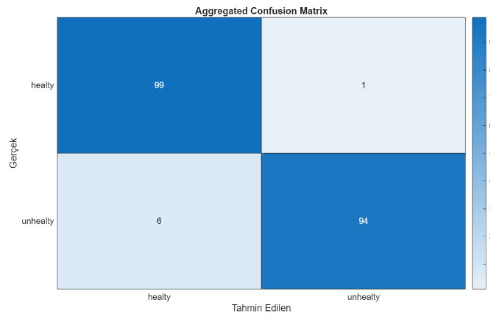

Fig. 2 The combined matrix obtained for the SqueezeNet-based model.

Based on these results, the overall classification accuracy of the proposed SqueezeNet-based approach was calculated as 96.5%. The high sensitivity value obtained, particularly for the healthy seed class, indicates that the model is highly successful in accurately identifying quality seeds. A summary of the performance metrics obtained during the cross-validation process of the proposed model is given in Table 2.

TABLE II - Class-based and overall performance results of the SqueezeNet-based model

Criteria	**Healthy**	**Unhealthy**
Precision	94.3	98.9
Recall	99.0	94.0
F1-score	96.6	96.4
General Criteria	**Value**	
Cross-validation	5-Fold	
Total Sample Size	200	
ROC-AUC (Quantized)	1.00	
Accuracy (%)	96.5	
Average Education Time	~28 sec.	

This is of great importance in agricultural practices, as the accidental discarding of healthy seeds during cultivation can lead to economic losses.

B. ROC Curve and Discrimination Analysis

To evaluate the model's ability to discriminate between classes, ROC curves and AUC values were analyzed. The ROC curve obtained for the quantized SqueezeNet model shows that the model can distinguish both classes with high accuracy. The calculation of the AUC value as 1.00 in the relevant ROC curve reveals that the model retains its discrimination power even after quantization. The ROC curve of the quantized model is presented in Fig. 3.

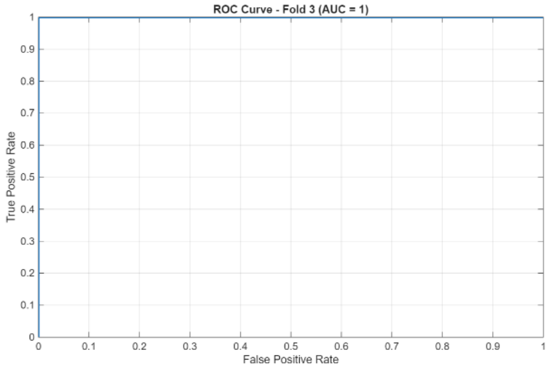

Fig. 3 ROC curve for quantized SqueezeNet model (Fold 3).

This result demonstrates that the proposed approach not only offers high accuracy but can also be used effectively in resource-constrained environments. The negligible performance loss after quantization supports the model's suitability for mobile and field applications.

C. Educational Process and Model Commitment

When the accuracy and loss curves of the training process were examined, it was observed that the model converged stably and did not show any signs of overfitting. With the activation of the early stopping mechanism, the training process was efficiently terminated and the validation performance was preserved. The short training time and the rapid convergence of the model clearly demonstrate the computationally efficient nature of the SqueezeNet architecture. The changes in accuracy and loss during the training and validation process of the model are shown in Fig. 4 for a representative cross-validation layer.

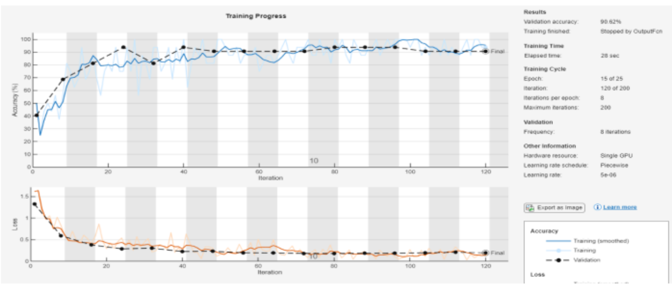

Fig. 4 Change in training and validation accuracy of the SqueezeNet model.

D. Comparison with the YOLO-Based Approach

To evaluate the effectiveness of the proposed SqueezeNet-based classification approach more comprehensively, a comparative analysis was performed with a YOLO-based object detection model trained using the Datature platform [32]. While YOLO-based approaches can provide strong results in object detection problems, they may exhibit some limitations in the analysis of small, singular, and visually similar objects, such as tomato seeds.

Analysis of the training logs obtained from the Datature platform revealed that the YOLO-based model achieved significant improvements in class-based performance metrics in the later stages of the training process. In particular, high precision, recall, and F1 score values were observed for both healthy and unhealthy seed classes during the final evaluation steps of the training. This indicates that the model was able to learn meaningful features after a sufficient training period.

However, when the training process is evaluated overall, it is noteworthy that the performance of the YOLO-based approach fluctuated throughout the training and exhibited low discrimination in the early stages. In particular, the stability of the object detection-based approach decreased in images with small object sizes and dominant backgrounds. This indicates that object detection methods require more precise tuning and larger datasets for small objects.

In contrast, the SqueezeNet-based approach, which focuses directly on image classification, demonstrated more stable performance throughout the training process and achieved higher accuracy values faster. Offering low computational costs thanks to its lightweight architecture, the SqueezeNet model stands out as a more suitable solution, especially for mobile and field applications with limited hardware resources. This comparison shows that the proposed method is based on an architectural choice more compatible with the problem definition and offers a more practical approach for tomato seed classification. This indicates that model selection should be based not only on final accuracy values but also on training stability and compatibility with the problem type. The key features and performance differences between the SqueezeNet-based and YOLO-based approaches are summarized in Table 3.

TABLE III - COMPARISON OF SQUEEZENET-BASED IMAGE CLASSIFICATION APPROACH AND YOLO-BASED OBJECT DETECTION APPROACH

Method	SqueezeNet	YOLO (Datature)
Duty	Classification	Object Detection
Performance Level	High and stable	High (final stage)
Educational Commitment	High	Medium-Low
Small Object Compatibility	High	Medium

E. Discussion

When the experimental results are evaluated overall, it is seen that the proposed SqueezeNet-based approach offers high accuracy, stable class performance, and low computational cost in tomato seed classification. In particular, the accurate identification of healthy seeds provides a significant advantage in terms of quality control processes in agricultural production. Maintaining performance after quantization strengthens the usability of the model in real-time and field applications. The Grad-CAM analysis results, obtained to visualize the image regions that the model focuses on when making classification decisions, are presented in Fig. 5.

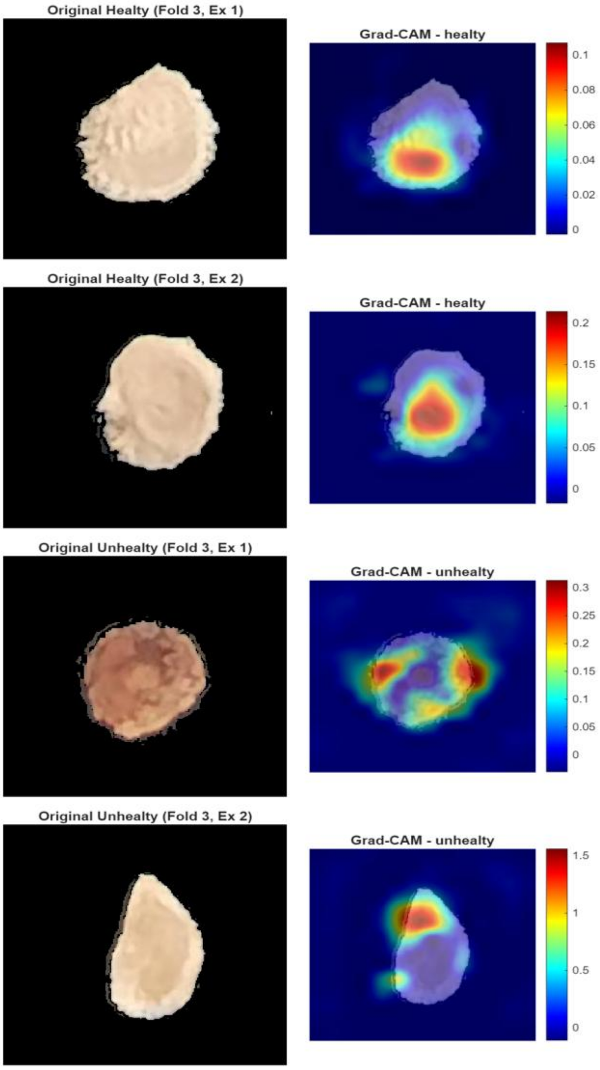

Fig. 5 Grad-CAM visualizations for healthy/unhealthy tomato seed samples.

V. Conclusion and Future Studies

This study proposes a SqueezeNet-based deep learning approach for the automatic classification of healthy and unhealthy tomato seeds. Considering the time-consuming and human-factor-dependent limitations of traditional seed quality assessment methods, an image-based and AI-supported decision-making mechanism has been developed. In the proposed approach, distinctive features are extracted from tomato seed images, and the classification process is performed using SqueezeNet, a lightweight and computationally efficient CNN architecture.

Experimental evaluations using the 5-fold cross-validation method showed that the proposed model achieved an overall classification accuracy of 96.5%. The resulting complexity matrix indicates that the model exhibits balanced performance for both classes and achieves particularly high success in correctly identifying healthy seeds. This offers a significant advantage in preventing economic losses in agricultural practices.

Quantization, performed to evaluate the model's suitability for field and mobile applications, revealed that high discrimination power was maintained. The ROC-AUC values obtained after quantization showed that the proposed approach offers strong classification performance despite its low computational cost. Furthermore, comparative analyses with the YOLO-based object detection approach trained on the Datature platform showed that lightweight CNN architectures based on direct image classification are more suitable and effective for small and visually similar objects such as tomato seeds.

In conclusion, this study demonstrates that a SqueezeNet-based deep learning approach offers high accuracy, low computational cost, and practical applicability in tomato seed classification. The proposed method has the potential to reduce human error in agricultural quality control processes and contribute to the rapid, reliable, and automated assessment of seed quality.

Future studies plan to expand the dataset with different tomato varieties, varying environmental conditions, and larger sample sizes. Additionally, the proposed model is intended to be implemented in a real-time mobile application or embedded system. Comparing different lightweight deep learning architectures and addressing multi-class seed quality assessment scenarios are also among the potential future research activities.

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