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Automatic Quality Assessment of Red Haricot Beans Using Deep Learning

Melkamu Workneh Bishaw [1] , Senayt Molla Ejigu [1] , Sefineh Getachew Tiruneh [2] , Adis Abebaw Dessalegn [1]

1. Computer Engineering, Debre Markos University, Debre Markos, ETH 2. Computer Engineering, Injibara University, Injibara, ETH

Corresponding authors: Melkamu Workneh Bishaw, melkamu_workneh@dmu.edu.et, Senayt Molla Ejigu, senaytmolla@dmu.edu.et

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Abstract

Red haricot bean, also called Boleqe and Red Kidney bean, is one of the most important legume crops in the world. In Ethiopia, it became one of the most exported legume crops in 2020. Due to its many advantages in daily life, ensuring its quality is essential for both producers and consumers. Therefore, we developed an automatic red haricot bean defect detection system using a custom model that utilizes a convolutional neural network (CNN) with skip connections and a SoftMax classifier. Sample images of red haricot beans were collected from the Ethiopian Commodity Exchange at the Bure branch. We took 650 images, each containing a minimum of 15 kernels, and finally obtained 10,093 kernel datasets using an automatic segmentation process. Eighty percent of the dataset was used for training, and the remaining 20% was used for validation and testing. After splitting the dataset, we evaluated the custom model with different image sizes (32 × 32 and 64 × 64) and applied data augmentation to prevent overfitting. Finally, we achieved 98.5% test accuracy and 98.9% training accuracy with augmented data and an image size of 64 × 64. We also compared our best model with a CNN without skip connections, VGG16, and ResNet50, which yielded average accuracies of 96.7%, 97.5%, and 63.0%, respectively. The findings show that custom deep learning models can provide accurate and reliable quality assessments while significantly reducing the time and subjectivity involved in traditional agricultural quality control methods.

Categories: Artificial Intelligence and Machine Learning in the Cloud, Computer Vision, Deep Learning
Keywords: canny edge detection, contour detection, deep learning, defect detection, red haricot bean

Introduction

Today, the world is driven by technological advancements that facilitate the agriculture and food industries in creating smart information systems to increase business competitiveness and enable commodity exchange through international trade, especially in exporting agricultural and food products. Agriculture accounts for 61% of employment and 14% of gross domestic product in developing countries, and 85% of employment and 36% of gross domestic product in least developed countries [1]. Haricot bean is an annual crop originating from both the southern and northern parts of Ecuador and the northern part of Peru [2]. Nowadays, it is one of the most important grain legumes grown in the lowlands of Ethiopia, particularly in the Rift Valley. It also ranks as the largest export commodity among legume crops [3-4]. Red haricot bean has become an important export item in Ethiopia since 2020. During that year, Ethiopia exported approximately 68,183 tons of red haricot beans valued at about 42 million USD (around 369.7 million ETB). This value of export was collected from various countries such as Russia, India, Kenya, UAE, USA, El Salvador, Italy, Germany, Belgium, and the Netherlands [1-3]. To increase the value of red haricot beans produced in agricultural areas and enhance competitiveness in the international market, the Ethiopian Commodity Exchange (ECX) has to certify that the supplied red haricot beans meet the minimum national standards for both domestic and international markets. ECX has established its own integrated warehouse system that accepts red haricot beans based on grades and industry standards. The quality of red haricot beans is assessed by experts at the ECX. However, the number of experts is not enough to cover all agricultural product quality assessment tasks. Therefore, to supply improved quality products to societies and international markets, an enhanced quality monitoring system is needed. Quality assessment is often subjective when performed by human inspectors. Due to high labor costs, inconsistency, and variability associated with human inspection, automatic quality assessment systems should be developed using image processing technologies for sensory analysis of agricultural and food products [5-8]. In this paper, we propose an automatic red haricot bean defect detection and grading system using various image processing techniques.

We have accounted various digital image processing research works focused on grain quality and variety assessment in the literature. These research works use image analysis techniques that utilize grain surface, morphology, and shading highlights to achieve their objectives. Some studies utilize morphological features alone, while others have used a combination of surface, morphology, and shading highlights together to evaluate quality. Numerous studies have been conducted in the field of cereal grain variety recognition. For example, Catanzaro et al. [9] and Goa and Dabala [10] investigated the classification of Ethiopian coffee based on the regions where it is grown. They extracted morphological and color features from images of coffee beans collected from Welega, Limu, Jima, Harar, Sidamo, and Bale. Naïve Bayes and neural network classifiers were used in their experiments, with tests conducted using color, morphology, and a combination of both. The results of this research concluded that morphological features are more effective than color features for classifying coffee beans based on their growing regions, using both neural network and Naïve Bayes classifiers.

Suseendran and Chandrasekaran [11] identified different types of corns using color characteristics and morphology. Here, different varieties of corns were classified using the capacity of multilayer neuronal networks and neuro-fuzzy perceptron based on morphological and mixed characteristics. The researchers achieved average precisions of 94% and 96% for corn classification using multi-layer perceptron and neuro-fuzzy classifiers, respectively.

Daniel [12] developed an automatic maize quality evaluation system aimed at evaluating the quality of corn sample constituents using digital image processing techniques. They used an artificial neural network classifier based on the standard corn setup from the Ethiopian Standards Agency. In this study, the researcher detected seven classes, such as foreign materials, rotten, healthy, broken, discolored, wrinkled, and parasite-damaged kernel. The detection accuracies achieved for foreign, rotten, healthy, broken, discolored, shriveled, and pest-damaged kernels were 100%, 95.2%, 98.6%, 98.8%, 100%, 98.4%, and 94.8%, respectively.

Abeza et al. [1] proposed an automated grading system for white pea beans using an artificial neural network. Their system detects seven classes: foreign, rotten and diseased, healthy, broken, discolored, shriveled, and pest-damaged kernels. They used 70% of the dataset for training and 30% for testing. Finally, they achieved an accuracy of 96.8%. The individual class accuracies for foreign, rotten and diseased, healthy, broken, discolored, shriveled, and pest-damaged kernels were 94.9%, 96.5%, 96.3%, 97%, 97.9%, 97%, and 97.6%, respectively.

Tian et al. [13] detected apple lesions in orchards using deep learning and YOLOv3-Dense, based on two categories of images: healthy and diseased apples. The researchers used around 640 images and achieved better performance using deep learning model CycleGAN.

The research work by Merga [14] focuses on the classification of haricot beans into different grades using digital image processing and convolutional neural networks (CNN). The researchers collected high-resolution images and preprocessed them using median filtering. They used the watershed algorithm for segmentation and added a 16-layer ResNet-50 model for feature extraction, achieving a classification accuracy of 90%. MATLAB was used for algorithm development, and the model was trained with only 300 images, which is not sufficient for ResNet-50 to extract features. The small dataset size led to lower performance of ResNet-50, and no data augmentation was conducted, limiting the model's generalization capability.

Additionally, Suseendran et al. [15] determined whether a given red haricot bean was defective or not by applying Otsu thresholding for global segmentation, CNN for deep feature extraction, and support vector machine (SVM) for classification. They achieved 99% accuracy, as it was a binary classification task. However, the gap in this research was that it did not consider multiple classes like filthy, broken, shriveled, or rotten, and did not use a powerful edge detection technique such as Canny edge detection and contour detection, which are better suited for such multiple classes.

However, the above research works have their own gaps, such as performing thresholding manually, extracting color features from both the image and background using only ImageJ, and applying techniques with weak performance on complex images such as median filtering and watershed segmentation-which may lead to over-segmentation or under-segmentation. The use of ResNet50 on small datasets also limits performance, and some researchers have used only accuracy as the only evaluation metric, which may not provide reliable information. Other researchers did not consider certain types of kernels, such as touched kernels, filthy seeds, and immature kernels. In this paper, we have attempted to address the above-mentioned research gaps by applying different algorithmic techniques and considering all types of defects that exist in the ECX.

Materials And Methods

In this research, we require various tools for image processing, image analysis, image classification, and an application development environment to implement the red haricot bean quality assessment model. To implement the proposed model, we used several open-source libraries on a Windows 10 Pro system with an Intel(R) Core(TM) i5 processor, CPU 2,370 MHz, and 8.0 GB of RAM, as listed below.

Python: We chose Python as the programming language for developing the algorithm. The main reason for selecting Python is its simplicity and readability.

IDE: We used Anaconda 3 and Jupyter Notebook 6.0.3.

OpenCV-Python: This is a Python library essential for solving computer vision problems. It has the cv2 module, which is crucial for performing overall image preprocessing tasks.

NumPy: NumPy is one of the most crucial packages for scientific computing with Python that contains a powerful N-dimensional array object, and it is required for processing images as matrices. NumPy is important for computer vision and AI researchers as it able to provide efficient tools for numerical analysis and array manipulation. It is also crucial for handling image data, preprocessing input images, and also serves as a foundation for libraries like OpenCV, TensorFlow, and PyTorch. Although it does not offer GPU acceleration, it has its own role in data handling and low-level computations.

Scikit-learn: Scikit-learn is a free machine learning library in Python, and it has features of various classification, regression, and clustering algorithms. It is designed to work seamlessly with NumPy and SciPy.

TensorFlow: TensorFlow is also a free machine learning library used for mathematical operations.

Keras: Keras is used to create layers in the CNN model.

The proposed system architecture for assessing red haricot bean samples consists of five main phases, as shown in Figure *1*: preprocessing of raw images, segmentation of the preprocessed images, feature extraction from the enhanced images, and finally classification and grading phases. The first step, preprocessing, includes resizing all images to a same size, removing noise, converting RGB images to grayscale, and applying Gaussian filtering methods. In the segmentation phase, individual red haricot bean sample constituents are separated from the background and from each other using Canny edge detection, which is one of the most important edge detection algorithms, followed by contour detection to detect each cell. Then, we crop each individual red haricot bean kernel. In the feature extraction phase, we developed custom model with skip connections to extract features automatically from segmented image components. We applied SoftMax in the final layer to classify constituents of red haricot bean samples into one of the five classes. Finally, after we determine the class of each kernel and the amounts of kernels in each class, we can determine the grade level of each sample image of red haricot bean. Figure *1* illustrates the overall design architecture of the proposed system.

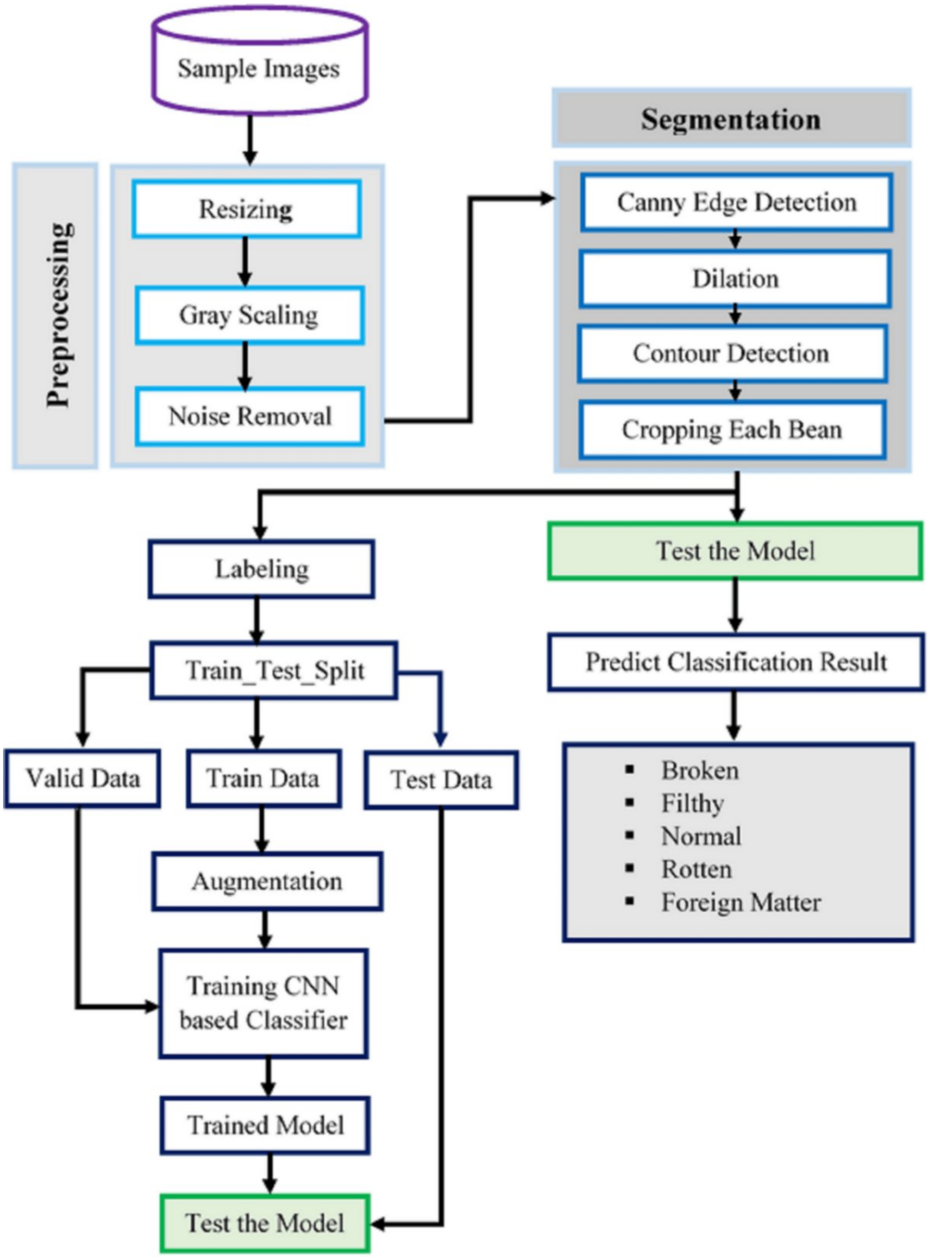

FIGURE 1: Overall Architecture of the Proposed System

CNN, Convolutional Neural Network

Red haricot bean images are required for performing image processing operations to determine the quality and grade level of the beans. The sample should contain enough number of representative kernels for each class type, such as normal, broken, filthy, rotten, and foreign matter. The ECX in Burie town has a red haricot bean storage facility and collects large quantities of red haricot bean products from farmers around Burie town every year. To gather full information about the quality assessment process, the quality manager at the ECX Burie branch was contacted. The manager describes the entire manual quality assessment process by actually dividing each red haricot bean seed with their representative class (normal, filthy, broken, rotten, and foreign matter). The manager provided a carefully selected half-kilogram sample of red haricot beans for quality analysis, instead of a randomly chosen sample. Images of the beans representing each quality category were then captured. All images were taken using an Infinix Hot 8 smartphone and stored in color JPG format, totaling around 100 MB. The number of red haricot bean kernels in each image is different for different classes. During image acquisition, efforts were made to use backgrounds of different colors. However, it was found that white backgrounds under bright lighting provided good contrast with the foreground objects and resulted in better segmentation. As a result, a white A4 paper was used as the background for all images. The beans were randomly spread on the paper, and photos were taken under both dim and bright lighting conditions. After capturing the images, the next step involved image preprocessing to enhance their quality.

The aim of image preprocessing is to improve the quality of the red haricot bean images in order to make it suitable for the model to analyze the image in a better way. Through preprocessing, unwanted distortions and noise can be suppressed, and essential features necessary for image segmentation and feature extraction are enhanced. We used preprocessing to increase the accuracy of the applied algorithms. Various methods, such as grayscale conversion, resizing, and image cropping, were employed to improve image quality. Some deep learning algorithms have specific requirements like the need to resize images to a unified dimension. This implies that all images should be preprocessed and resized to have the same width and height before being fed into the learning algorithm.

Convert Color Images to Grayscale: Converting color images to grayscale is important for removing unnecessary features from our images for reducing space or computational complexity. In this case, converting the colored red haricot bean images to grayscale, as shown in Figure 2, was the first step before applying other image processing techniques such as blurring, edge detection, and contour detection.

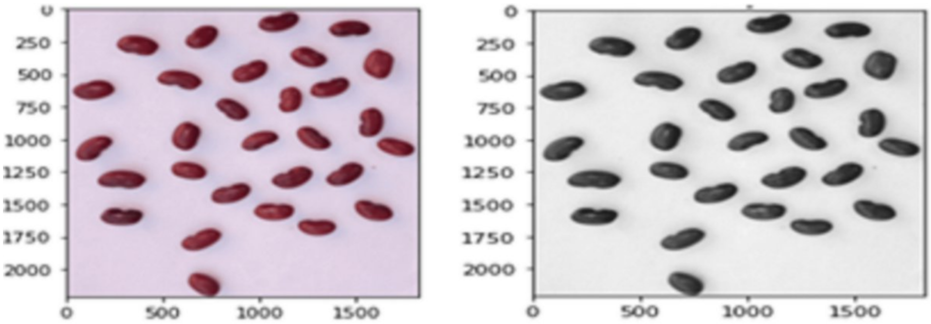

FIGURE 2: Original and Gray Scaling Red Haricot Bean Images

Gaussian Blur Operation: The image is denoised using a Gaussian filter. This filter was selected because it effectively reduces noise while preserving important image details, making it particularly suitable for preprocessing before edge detection.

Data Augmentation: This is a common and important technique used to increase the size of an existing dataset with disturbed versions by using image scaling, rotations, flipping, and other related techniques. Data augmentation is applied to the training dataset after the entire dataset is split into training and testing sets. It helps the model become more efficient at recognizing objects, even when they appear in different forms. In addition to that, data augmentation is used for preventing overfitting problems.

There are different types of segmentation techniques. From those, we tried to get the best-fitted segmentation approaches depending on our dataset. In this research, we used Canny edge detection to detect shape/boundary of each seed. After detecting the boundary of each kernel, we applied morphological operations like erosion and dilation to make the image clearly visible. The dilation is simply adding pixels to object limits in an image, whereas the erosion operation reduces pixels within the limits of objects. In Figure 3, the images represent Canny edge detection and its dilated form.

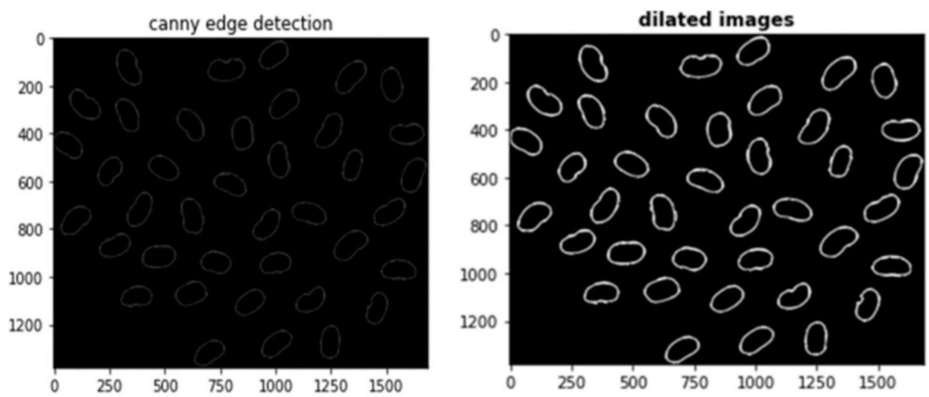

FIGURE 3: Red Haricot Bean Canny Edge Detection With Its Dilated Form

The detection of contours is a process that can be explained as a curve that connects all the continuous points having the same color or intensity. Contours are a useful tool for the analysis of the module and the detection and recognition of objects. An important feature of a region R is the contour (also called edge or limit), which plays a significant role in the analysis of the images. The limit is the set of an internal pixel in the region that has one or more neighborhoods outside R [16-18].

OpenCV provides the findContours function, which is used to detect and extract contours, continuous curves or boundaries of objects, in a binary image, storing the resulting coordinates as NumPy arrays. To manage how contours are organized, OpenCV also offers several retrieval modes such as RETR_LIST, RETR_TREE, RETR_CCOMP, and RETR_EXTERNAL. These modes help to determine the hierarchical relationships between contours, such as nested or parent-child structures. However, in this particular study focused on identifying red haricot beans, only the outer contours are of interest, as each bean is treated as an individual object without hierarchical relationships. Therefore, the RETR_EXTERNAL mode was used. For contour approximation, OpenCV provides two methods: CHAIN_APPROX_NONE, which retains every point along the contour for detailed shape representation, and CHAIN_APPROX_SIMPLE, which compresses the contour by removing redundant points, ideal for shapes like rectangles or triangles. Since red haricot beans generally have smooth, elliptical shapes, the CHAIN_APPROX_NONE method was chosen to preserve full contour detail. Here, we used various contour parameters, such as obtaining the coordinate points of each seed, cropping or segmenting seeds, and labeling beans. Figure *4* shows the bounding box and coordinate points of each kernel, Figure *5* presents the automatically cropped seeds with and without bounding boxes, and Figure *6* illustrates sample image labeling in its class or category.

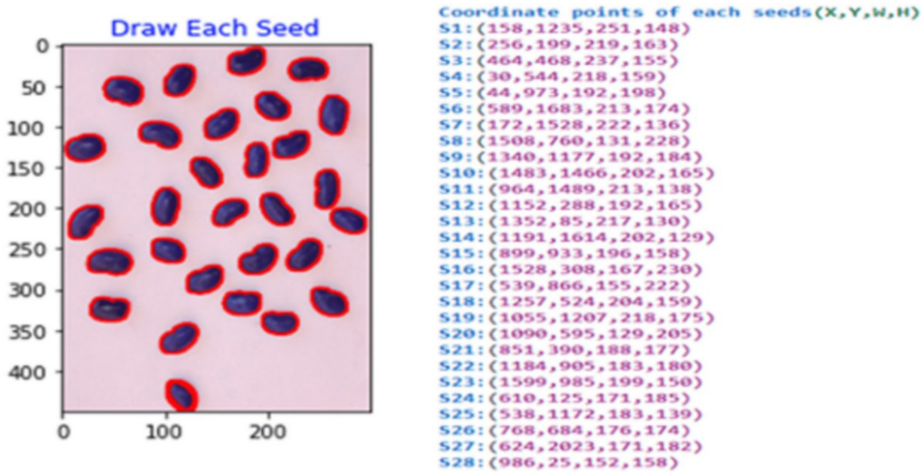

FIGURE 4: The Bounding Box of Each Seed and Its Coordinate Points

FIGURE 5: Cropped Seeds With and Without Contour Bounding

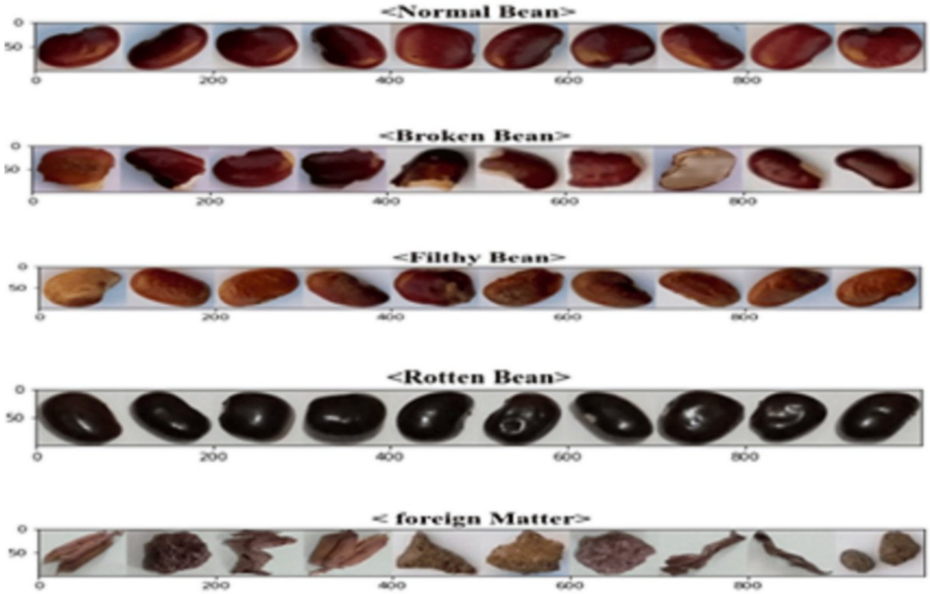

FIGURE 6: Samples of Image Labeling

Feature extraction is the process of identifying key features from a preprocessed image in a reduced way to speed up decision-making mechanisms. In feature extraction, every researcher should gather as much information as possible from available datasets, which gives a solution for the identified problem. Deep learning and CNNs allow us to skip the feature extraction step since they have the ability to extract features automatically. CNN has convolutional layers that consist of filters with a strong capability of learning from the given data by extracting key features from the image. Using CNN to extract and obtain deep features from image data is more effective, as it has feature selector filters. There are different types of CNN architectures such as randomly initialized and pre-trained CNN architectures. Randomly initialized CNN is simply a CNN model that has not been trained before. Pre-trained architectures are a model that is trained before by millions of data and has different types like VGG-16, VGG-19, Inception V3, ResNet-50, etc. Both our custom and pre-trained models are developed either with skip connection or without skip connection. CNN without skip connection is developed without dropping or skipping any block (layer) throughout the process, whereas CNN with skip connection model is developed by skipping or jumping a certain block that may have two or more layers to make the size of input and output image identical. Here, the model learns from both the original input image and the output of a previous block. Due to this, such model provides better performance than the previous one. Therefore, we developed our model using a CNN with skip connections, consisting of 14 layers in total - 12 convolution layers and 2 fully connected layers - as shown in Figure 7. Convolutional layers are crucial to convolve pixel of the image with the kernel. Then, we applied MaxPooling layer to select features with maximum values. Besides, rectifier linear unit activation (ReLU) was applied to introduce non-linearity to our model.
The feature map was then converted into a one-dimensional array using a flatten layer, and the result was passed to the fully connected layer. These fully connected layers were used to combine features from multiple attributes for predicting each class in an improved way. The features of the beans were automatically extracted using the developed model. Our image is resized close to its original size, which is 64×64. A SoftMax classifier with a cross-entropy loss function was employed, as the task involves multiple classes. Classification was done using the knowledge from the learning model designed by using training and validation phases. We used two separate sets of data for the training and validation phases. Hence, the features extracted before by the model were used as input for the SoftMax classifier. By using the knowledge from the learning model, we can classify each image in the testing dataset into a specific or predefined class (broken, filthy, foreign matter, rotten, normal). The overall architecture of the proposed model is illustrated in Figure 7.

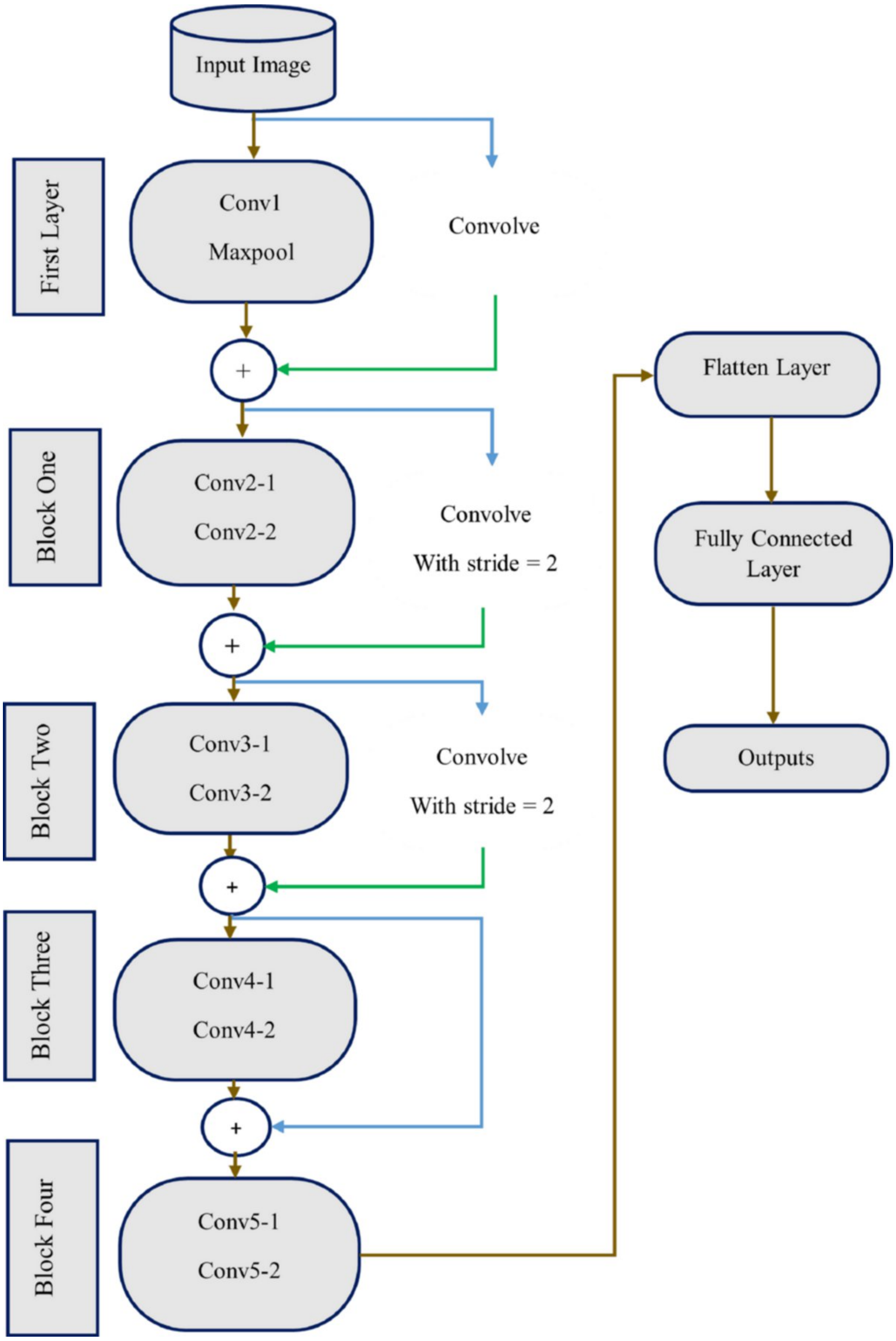

FIGURE 7: Architecture of the Developed CNN Model

CNN, Convolutional Neural Network

We used 20% of the kernels in our red haricot bean image dataset for testing and validation purposes. Specifically, 10% of the dataset was used for testing to evaluate the accuracy of the proposed model, while the remaining 10% was used for validation to fine-tune the hyperparameters of our custom model. These data may be considered as part of training dataset as the model uses the data for evaluation rather than learning from it. We used different measurement metrics such as precision, recall, F1-score, and support, which are important to compute the accuracy of the system.

Results

The proposed CNN with skip connection model was trained using two different image sizes: 64 × 64 and 32 × 32. The model was also evaluated with and without data augmentation, using various learning rates (0.1, 0.001, 0.0001, and 0.0005). Among these configurations, the best performance was achieved with 64 × 64 image size, a learning rate of 0.0005, and with augmentation applied, as shown in Figures 8 and 9. Figure 10 presents the overall confusion matrix and class report of the developed model.

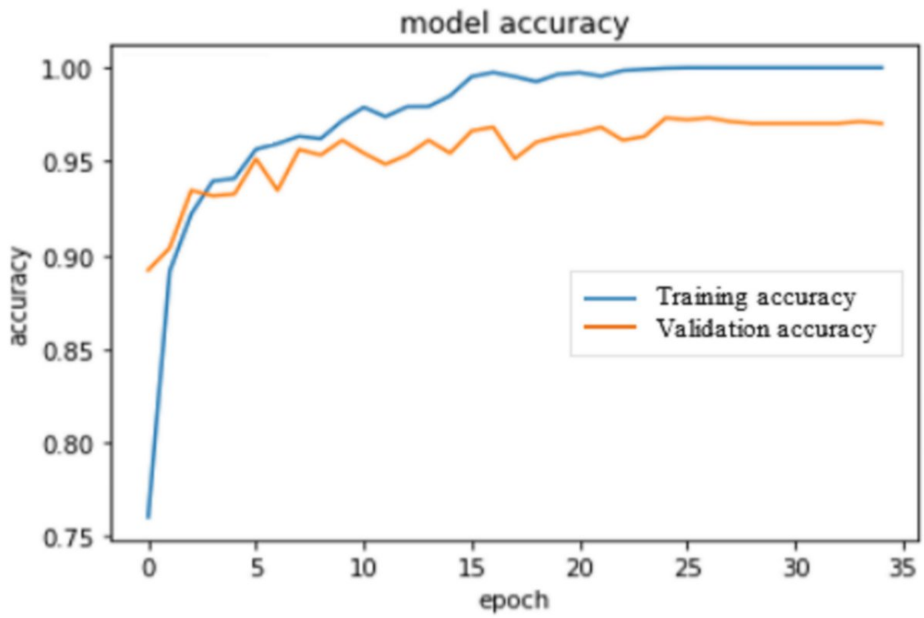

FIGURE 8: CNN Training and Validation Accuracy Without Augmentation and 64 × 64 Image Size

CNN, Convolutional Neural Network

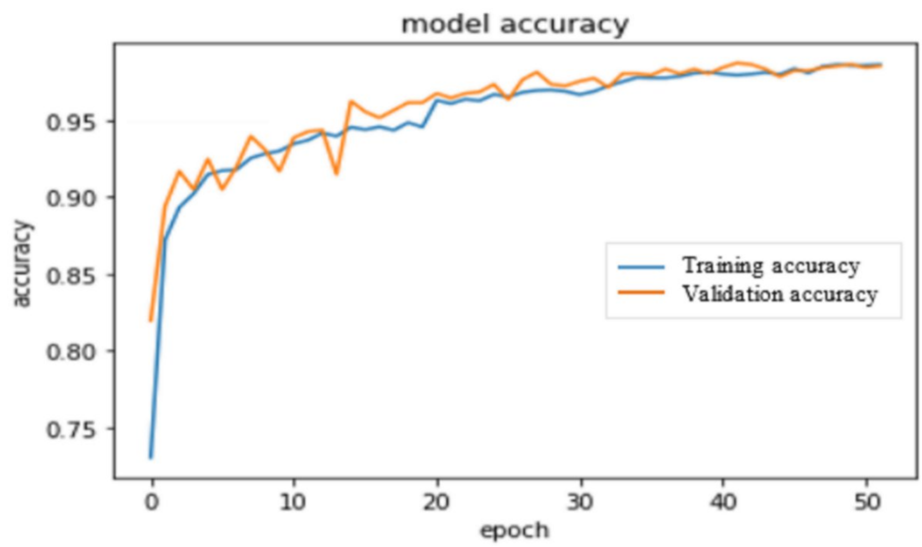

FIGURE 9: CNN Training and Validation Accuracy With Augmentation and 64 × 64 Image Size

CNN, Convolutional Neural Network

	precision	recall	f1-score	support
broken	0.98	0.96	0.97	227
filthy	0.99	0.99	0.99	208
foriegn_m	0.98	0.95	0.97	62
normal	0.97	0.99	0.98	237
rotten	1.00	1.00	1.00	276
accuracy			0.98	1010
macro avg	0.98	0.98	0.98	1010
weighted avg	0.98	0.98	0.98	1010

FIGURE 10: Confusion Matrix and Class Report of the Developed Model

Discussion

We have trained our model by using different optimizer (Adam, SGD, and RMSProp), various learning rates (0.1, 0.001, 0.0001, and 0.0005), and different image sizes with and without augmentation. Among all optimizers, Adam achieved the best performance, resulting in 98.9% and 98.5% accuracies for training and validation, respectively, with a learning rate of 0.0005. SGD achieved its own best result of 98.1% training accuracy and 97.8% validation accuracy with a learning rate of 0.1, and RMSProp performed slightly lower than SGD by achieving 97.6% and 97.1% training and validation accuracies, respectively, using a learning rate of 0.0001. We try to compare our proposed model with other models like ResNet50 that achieved 62.9% training and 62.8% testing accuracies. Another pre-trained model that we tried to compare with our proposed model was VGG16, which achieved training accuracy of 97.8% and testing accuracy of 97.5%. The CNN without skip connection model was also taken into our consideration since its parameters aligned more closely with our model's parameters compared to other models. It achieved 97.7% training and 96.4% testing accuracies. Therefore, we have better results in CNN with skip connection model than other models such as ResNet50, VGG16, and CNN without skip connection models. The superior performance of our model can be attributed to the use of lower number of layers and the use of both the original image and the output of other convolutional layer through skip connection principles. Our model has few layers than ResNet50 and VGG16, which have 50 and 16 layers, respectively. Such a large number of layers requires a huge number of images to improve performance, but the proposed model has only 14 layers. The limited number of datasets used in the developed model is also another reason for lower performance of these pre-trained models (ResNet50 and VGG16) because both models need millions of data with a duration of days or weeks for training to achieve better results. Besides this, skip connection is also another difference between our model and VGG16, because there is no concept of skip connection in VGG16. When comparing the CNN models with and without skip connections, both have 14 layers and use the same datasets. The only difference between them is the presence or absence of skip connections, which plays a vital role in the model's performance. Because of this, the CNN with skip connection model achieves better accuracy than the CNN without skip connection model. A summary of all tested models and their results is provided in Table *1*.

Models	Batch Size	Validation Accuracy	Training Accuracy	Validation Loss	Training Loss
CNN with 32 × 32 and without augmentation	16	97%	100%	26%	0.76%
CNN with 32 × 32 and with augmentation	16	98%	98.5%	6.4%	4%
CNN with 64 × 64 and without augmentation	16	97.6%	100%	25.7%	0.79%
CNN with 64 × 64 and with augmentation	16	98.5%	98.9%	4.9%	3.4%
CNN without skip connection	16	96.4%	97.7%	9.98%	7.10%
ResNet50	16	61.4%	62.2%	93.5%	91.1%
VGG16	16	97.5%	97.8%	6.6%	6%

TABLE 1: The Summary of Overall Models Results

CNN, Convolutional Neural Network

Conclusions

This research work focuses specifically on the quality assessment of red haricot beans, as they are among the most widely harvested crops in Ethiopia. Red haricot beans play a significant role in improving the country's economy because they are one of the most exported legume crops. Therefore, it is our responsibility to ensure and filter the quality of red haricot bean kernels to achieve better results, both in export competition and in contributing to a balanced daily diet. To improve quality assessment, a CNN-based classifier model was developed, capable of detecting, classifying, and grading red haricot bean kernels based on their quality categories. For this purpose, we used image processing techniques such as data acquisition, preprocessing, image segmentation, classification, and counting-based grading. We developed a deep learning CNN-based classifier model with skip connections for feature extraction and classification, using SoftMax as the activation function. The model was trained using RGB images, with and without augmentation, across different image sizes. Finally, we achieved 98% test accuracy using images of size 64 × 64 with augmentation. We also compared our best model with three other CNN models: CNN without skip connection, VGG16, and ResNet50, which achieved average accuracies of 96.7%, 97.5%, and 63.0%, respectively. Based on these results, we can conclude that our model is much better than all the three models. Finally, we can conclude that applying skip connection model and augmentation process are important to give enough information about the original image for inner layers of CNN and to reduce overfitting problem, respectively.

Even though this research has been able to successfully assess the quality of red haricot bean kernels, several aspects remain unexplored and are recommended for future work. The current model uses a single camera that captures only one side of the beans, addresses only loosely or slightly touched kernels, and certain defect types such as immature or insect-damaged beans were not included. Such conditions prevent the system from functioning as a fully automated inspection system, suggesting that future researchers could enhance the model by incorporating these missing aspects.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Melkamu Workneh Bishaw, Sefineh Getachew Tiruneh, Adis Abebaw Dessalegn

Acquisition, analysis, or interpretation of data: Melkamu Workneh Bishaw, Senayt Molla Ejigu

Drafting of the manuscript: Melkamu Workneh Bishaw, Sefineh Getachew Tiruneh, Adis Abebaw Dessalegn

Critical review of the manuscript for important intellectual content: Melkamu Workneh Bishaw, Senayt Molla Ejigu

Supervision: Melkamu Workneh Bishaw

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

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