Ensemble of Deep Convolutional Neural Network Architecture for Classifying the Source and Quality of Teff Cereal

Belayneh Matebie, Michael Melese

***Abstract*—**The study focuses on addressing the challenges in classifying and ensuring the quality of Eragrostis Teff, a small and round grain that is the smallest cereal grain. Employing a traditional classification method is challenging because of its small size and the similarity of its environmental characteristics. To overcome this, the current study employs a machine learning approach to develop a source and quality classification system for Teff cereal. Data are collected from various production areas in the Amhara regions, considering two types of cereal (high and low quality) across eight classes. A total of 5,920 images are collected, with 740 images for each class. Image enhancement techniques, including scaling, data augmentation, histogram equalization, and noise removal, are applied to preprocess the data. Convolutional Neural Network (CNN) is then used to extract relevant features and reduce dimensionality. The dataset is split into 80% for training and 20% for testing. Different classifiers, including Fine-tunned Visual Geometry Group (FVGG16), Fine-tunned InceptionV3 (FINCV3), Quality and Source Classification of Teff Cereal (QSCTC), Ensemble Method for Quality and Source Classification of Teff Cereal (EMQSCTC), Support Vector Machine (SVM), and Random Forest (RF) are employed for classification, achieving accuracy rates ranging from 86.91% to 97.72%. The ensemble of FVGG16, FINCV3, and QSCTC using the Max-Voting approach outperforms individual algorithms.

***Keywords*—**Teff, ensemble learning, Max-Voting, Convolutional Neural Network, Support Vector Machine, Random Forest.

I. Introduction

AGRICULTURE is the science, art, and practice of cultivating the soil, growing crops, and raising animals to produce food, fiber, and other essential resources. It involves managing natural resources sustainably to meet human needs while supporting economic and environmental balance. Agriculture remains a cornerstone of human survival and development, evolving continuously with advancements in science and technology. Agriculture serves as the primary global endeavor for the production of nutritional resources through various agricultural products [1], [2]. It constitutes a foundational element of the world's economy, playing a central role in nations like Ethiopia where 80% of the economy relies on agricultural outputs [3]. Teff stands out among these agricultural products as one of the most popular grains in Ethiopia. Scientifically known as *Eragrostis tef*, its name is derived from "Teffa," meaning "lost," owing to its diminutive size. *Eragrostis tef* is a tiny, spherical grain, holding the distinction of being the smallest cereal grain, measuring approximately 1.0 mm in length and 0.60 mm in width [4]. Functioning as a substitute for gluten-containing flours like regular wheat flour, Teff boasts a nutritional profile comprising 11% protein, 80% complex carbohydrates, and 3% fat [5]. It is widely utilized for baking injera and serves as the predominant grain for nutritional purposes, particularly in Ethiopia and its neighboring country, Eritrea.

In Ethiopia, Teff grain is currently cultivated in numerous regions. However, the area's most commonly recognized for Teff production are East and West Gojjam in Amhara and East and West Shoa in Oromia [6], [7]. Specifically, within the Amhara region, popular Teff production zones include Debre Markos, Dejen, Bichena, and Adet. These regions exhibit variations in environmental conditions and soil fertility, leading to distinct characteristics and qualities of Teff. Even within the same Teff production area in Amhara, the quality of Teff can differ due to the farmers' oversight during the production process. Teff grains that incorporate a mix of gravel, soil impurities, and different Teff varieties are indicative of lower quality. Conversely, Teff grains that are free from such issues are classified as high quality. Consequently, the diverse environmental conditions and farming practices contribute to the unique characteristics and qualities of Teff across different production areas.

In the market, customer interest is influenced by both the quality and cost of Teff cereal. The small size and striking similarities among different Teff cereals make it challenging to accurately distinguish the specific type of Teff cereal desired. Ethiopia has the Ethiopian Commodity Exchange (ECX), an organization facilitating transactions between buyers and sellers, ensuring quality, quantity, delivery, and payment [8]. Despite the ECX's role, challenges persist throughout the value chain, including infrastructure and legal issues, exploitation of farmers at the farm gate, marketing imperfections, systematic rigidity, and traceability problems [8]. The current identification method relies on classical approaches or the naked eye of experts, making it susceptible to misidentification [8]. This vulnerability leads to the inadvertent purchase of the wrong type of Teff cereal, resulting in unforeseen and unaffordable costs.

To tackle the issue of Teff cereal misidentification, this study employed a combination of deep CNN architectures to classify

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both the source and quality of Teff cereal. This investigation utilized an ensemble approach with three CNN architectures: Fine-tuned VGG16 (FVGG16), Fine-tuned InceptionV3 (FINCV3), and the newly devised Quality and Source Classification of Teff Cereal (QSCTC) CNN model architecture designed specifically for categorizing the quality and source of Teff cereal. Parameter tuning is implemented on the existing CNN architectures to improve the model's performance. Additionally, SVM and RF were used.

II. Related Work

Reference [9] presents a method for classifying ten varieties of tef (*Eragrostis tef* (Zucc.) Trotter) grains using image processing and multivariate data analysis. Variety-based classification is employed using Extreme Gradient Boosted Tree Discriminant Analysis (EGBDA). The resulting classification model demonstrated a prediction accuracy of 97% and precision of 99%. A simpler model, employing 18 selected variables that classify the varieties only, achieved comparable classification results.

Classification of Wheat grains using machine algorithms was conducted in [10]. In this study, SVM and the neural network were used for classifying the grain into the appropriate class. Images of the wheat grain are captured using a digital camera to collect the dataset and thresholding is performed. Accordingly, the neural network obtained better accuracy than the other algorithm SVM. Since the accuracy of SVM is 86.8% and of the neural network is 94.5%. This research has a good approach to classifying wheat grain but our problem and study follow different approaches because the nature of the dataset differs in characteristics.

The study investigates and implements a Yirgacheffe Coffee grading model using a deep learning classifier [11]. Image data from Yirgacheffe Coffee Farmers' Cooperative Union, comprising 684 images with 6138 coffee beans, were utilized. Three grade values (grade 1, grade 2, and grade 3) had an average of 228 images each. Employing the CNN deep learning algorithm, coffee bean features were extracted to create a predictive model for classification. Experimental results reveal high accuracy, with 99.51%, 97.56%, and 98.04% for grade 1, grade 2, and grade 3, respectively, culminating in an overall average classification accuracy of 98.38%.

The study successfully implemented an automated maize quality assessment system through image processing techniques [12]. Its goal was to evaluate maize sample quality using digital image processing and an artificial neural network classifier based on Ethiopian Standards Agency criteria. Utilizing 24 features (14 color, 8 shape, 2 size), the system classified grains using a feedforward artificial neural network with backpropagation and a naïve Bayesian Network. It achieved an overall accuracy of 97.8%, although acknowledging limitations in scope and methodology. The study suggests exploring advanced algorithms like CNN for image processing beyond those employed. Additionally, simulating teff and maize structures proves challenging due to their distinct features.

A study [13] employed neural networks to categorize rice grain types based on their distinct features. Samples from each rice variety were examined, capturing seed images. Algorithms were devised to extract thirteen morphological, six-color, and fifteen texture features. Principal component analysis reduced image dimensionality, yielding a 92% accuracy in classifying rice varieties through combined features. However, the research did not extend to examining Teff cereal due to variations in the size, shape, color, texture, and morphology of rice grains.

According to [14], rice grains classification using image processing techniques was done using computer vision. To address this, different features of the grain were taken and have been used different image preprocessing and image segmentation techniques are used such as shape, length, chalkiness, color, and internal damage of rice. Finally, the image processing technique determines the percentage of purity of rice grains based on several characteristics such as grain color and the structure of the grain.

III. Methodology

This research aims to create a combined deep CNN model for the categorization of Teff cereal based on its source and quality. The study consists four main stages. Initially, data are gathered through a digital camera capturing images of the cereal. Subsequently, image preprocessing is carried out, incorporating techniques like scaling, histogram equalization, noise removal, and augmentation. Following preprocessing, a CNN is employed to extract and choose the most significant features from the images. The final phase involves classification, where diverse machine-learning techniques are utilized after the identification of the most representative features in the images.

A. Image Acquisition

Image data are obtained through the use of a digital camera, with a focus on four prominent Teff production regions: Debre Markos, Dejen, Adit, and Bichena. Two distinct qualities of Teff, namely high and low quality, are observed in each production area. The collection process involves physically visiting each area, where merchants and agriculture experts can identify and categorize the Teff based on quality. A 13-megapixel digital camera, with a white paper serving as a backdrop, captures the cereal. This results in a total of eight classes, each representing a combination of production area and Teff quality. The dataset comprises 8 classes, each containing 740 image samples, totaling 5920 images. The accompanying diagram illustrates the distribution of sample image data across different growing areas and qualities.

B. Preprocessing

Preprocessing is used to improve image content by removing unnecessary distortions or increasing specific visual qualities that are important for later processing and analysis. Preprocessing the datasets was applied to eliminate superfluous information, help the model learn the attributes of the images more efficiently, and obtain improved accuracy. Among the preprocessing stages that were used, resizing the image into the standardized image size, removing unwanted noises from the data, equalizing the intensity or brightness of the image, and augmenting the data to make the data size larger and eliminate the overfitting of our model.

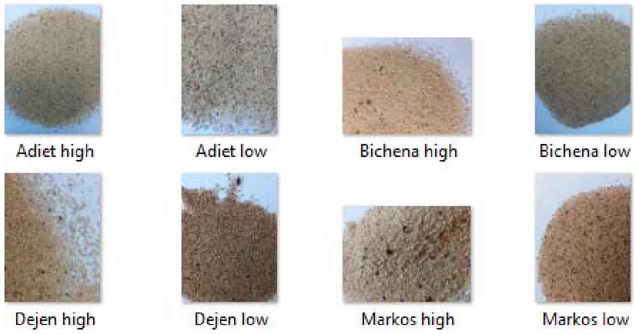


Fig. 1 Sample Teff cereals in each class

The first step in preprocessing is image resizing into its standard size. This is a crucial phase in the process when the images are standardized and scaled to a specified form, which is often 224 by 224. Images come in a variety of forms, thus resizing them to prevent excessive padding is required to aid the model's learning. The image should also be scaled before it can be fed into the models.

Histogram equalization technique was applied for improving the contrast of the image, histogram equalization was used. It performs by distributing the most frequent intensity values of the image, i.e., expanding out the image's intensity range.

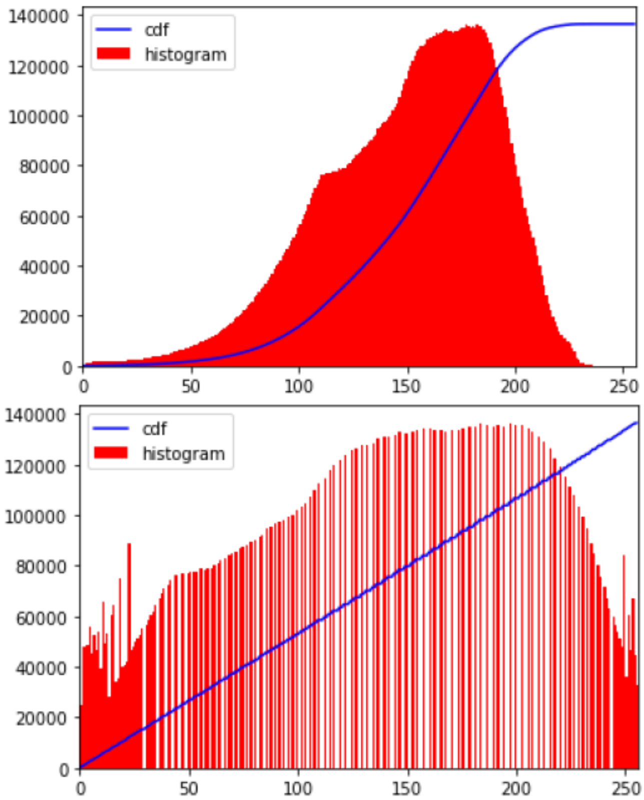


Fig. 2 A pictorial representation of histogram equalization for a sample image

To remove image noise, median filtering was used, which is a nonlinear method for minimizing impulsive noise, sometimes known as salt-and-pepper noise. It can also be utilized to preserve the boundaries of an image while reducing random noise. So, to eliminate the noises in the image, a median filter is applied, which is the most well-known order-statistic filter in digital image processing. Because of its high de-noising power and mathematical precision, a median filter is a common approach for removing impulsive noise [15].

Pseudocode1. Algorithm for noise removal:

INPUT: *sample image*
OUTPUT: *denoised image*
BEGIN
image = imread(sample image)
image = medianBlur (image, 3) // applying a median blur with kernel size 3
imwrite(filename.JPG, image)
END

Fig. 3 The image sample before the median filter and after the median filter

C. Feature Extraction

A neural network initial layer takes all of the pixels in a picture. After all of the data have been put into the network, the image is subjected to several filters, which result in representations of various areas of the image. To extract representative feature of the image, a convolutional and pooling layer are applied.

- *Convolutional Layer:* In a typical neural network, every input neuron is connected to the subsequent hidden layer. In a CNN, the function of our image pixel matrix is multiplied by the function of our filter matrix. This means that the filter slides over the input image and produces the feature map, also known as the activation map.

- *Pooling Layer:* The pooling layer is used to minimize the dimensionality of an image. Its purpose is to reduce the number of parameters and operations in the network by gradually decreasing the spatial dimension of the representation. The pooling layer treats each feature map independently. It helps to avoid overfitting, extracts representative features from the input tensor reduces computation, and thus leads the model to perform efficiently.

A CNN is the best approach for extracting random representative features, reducing the dimension of our image data, and reducing the model computations in the network. After the representative feature vector is selected, the three-dimensional feature vector is converted into one dimensional and this one-dimensional array is fed by the fully connected layer.

D. Classification

Supervised machine learning techniques were used to classify the cereal. Pre-trained CNN architectures such as VGG16, and InceptionV3 by applying fine-tuning, and developed a QSCTC model using CNN. These CNN architectures are ensembled using hard voting to improve the performance of the model. Additionally, machine learning classifiers such as SVM and RF were used.

Fine-tuning was applied to the VGG16 CNN architecture, by replacing the final three fully connected layers with modified dense layers by adjusting the neuron count. To mitigate overfitting, a dropout function with a rate of 0.15 was applied.

On the other hand, a fine-tuned InceptionV3 architecture was used for this study. Inception-v3, with 24 million parameters, succeeds Inception-v1. Therefore, this architectural framework is employed in the study, utilizing transfer learning. To enhance the model's effectiveness, fine-tuning is implemented by incorporating an additional pair of fully connected layers, each comprising 128 neurons.

The study conducted a QSCTC model architecture to classify Teff cereal using CNN using several layers and parameters. The architecture includes six convolutional layers followed by max pooling, with the ReLU activation function employed for feature extraction. The default value of stride of "same" or 1 is used. Additionally, a dropout rate of 0.15 is applied in the fully connected layers. The other parameters include the Adam optimizer, which produces better results than other optimization algorithms, requires less computation time, and has fewer tuning parameters [16]. Additionally, the study employs loss = categorical_crossentropy due to the multiclass nature of this problem. Three fully connected layers are implemented, with the Softmax classifier for the last fully connected layer. Fig. 4 represents the architecture of QSCTC model.

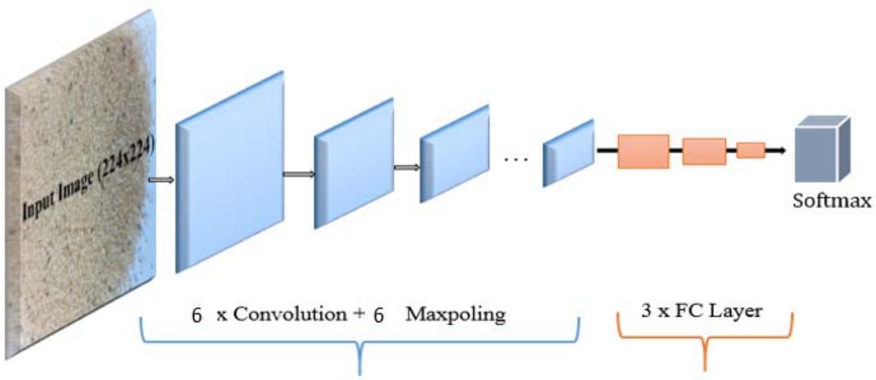


Fig. 4 The architecture of QSCTC representation diagram

Pseudocode2. Algorithm for classification using QSCTC:

INPUT: One dimensional feature vector
OUTPUT: Predicted class label

```
BEGIN
Bring one dimensional feature vector
Apply the 1st fully connected layer // 128 number of neurons
Apply dropout operation //with a dropout value of 0.08
Apply the 2nd fully connected layer // 64 number of neurons
Apply dropout operation // with a dropout value of 0.08
Apply the final fully connected layer // 8 classes and followed by softmax
END
```

Finally, this study employed ensemble method using the hard voting or majority voting approach called Ensemble Method for Quality and Source Classification of Teff Cereal (EMQSCTC). Fig. 5 represents how the max-voting approach works to ensemble the three model architectures (FVGG16, FINCV3, and QSCTC).

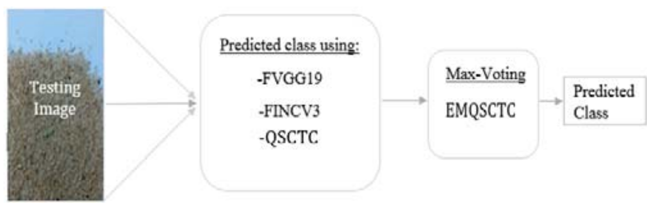


Fig. 5 The architecture of EMQSCTC

Pseudocode3. Algorithm for classification using EMQSCTC:

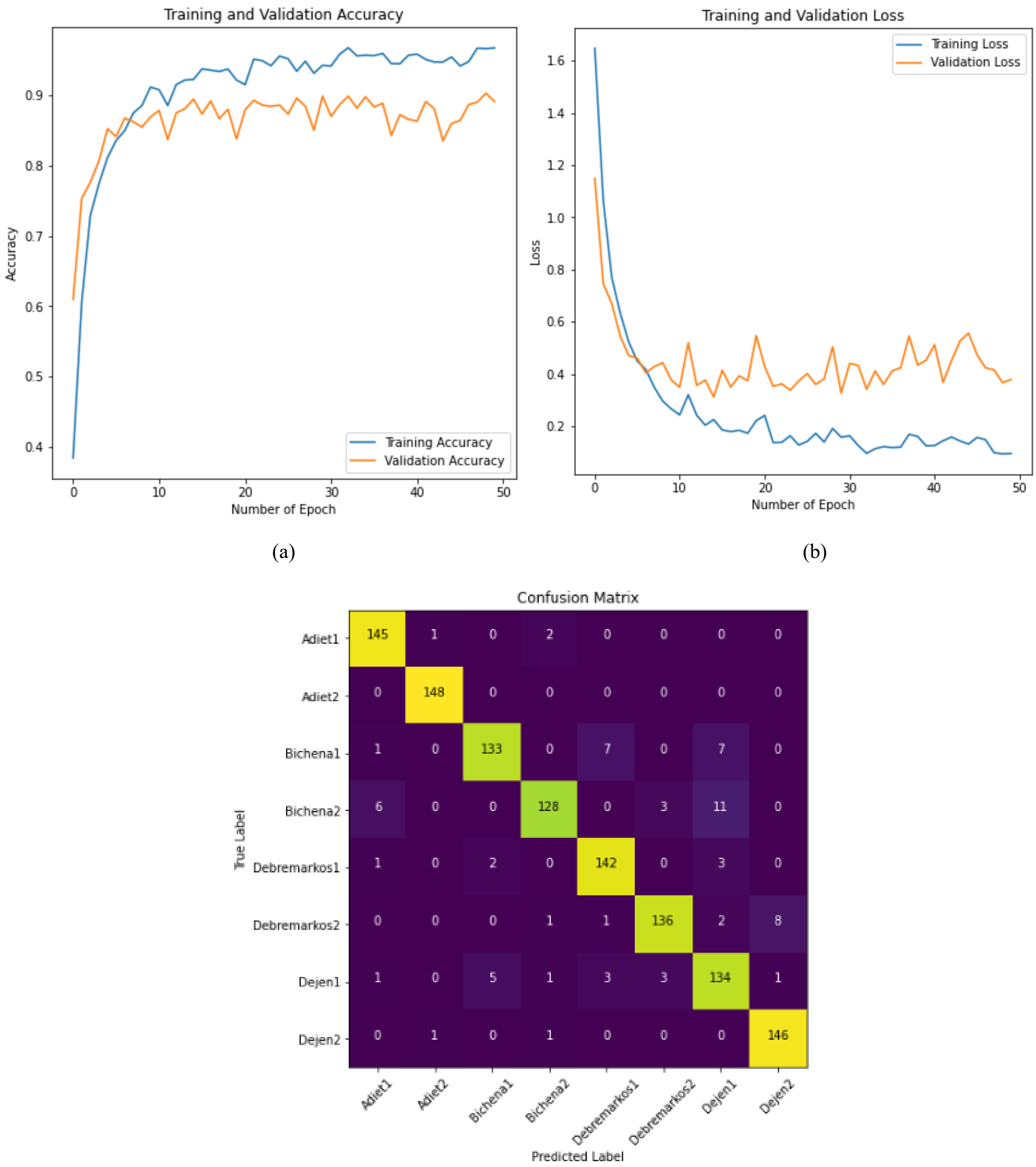
INPUT: Testing image
OUTPUT: A predicted class label for an image

1 BEGIN
2 For each classifier in a testing image
3 Extract convolutional features //128 number of neurons
4 Compute the predicted class label for each image using each model
5 End for
6 Apply Max-voting from (m1, m2, m3) *for image I //for each image in testing data*
7 Return result // using majority vote
8 Predicted class label
9 END

IV. Result and Discussion

A. Experimental Setup

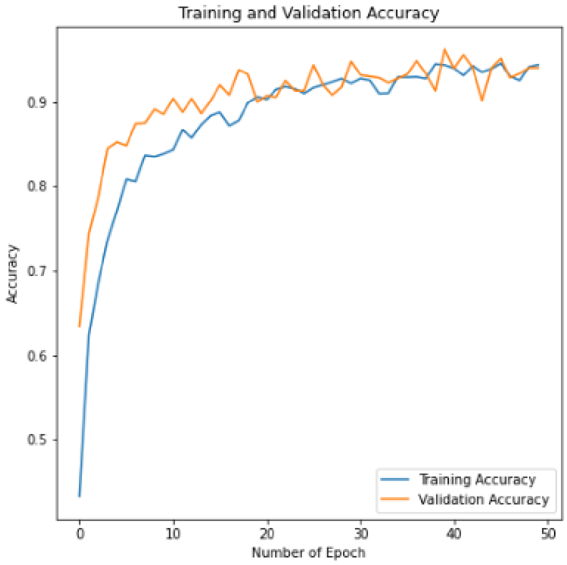
Various tools and techniques were employed to develop the proposed experiment. One such tool is a computer equipped with an Intel® Core(TM) I5-5200U CPU @ 2.20GHz, 4 GB of RAM, and the Python programming language utilizing OpenCV. Additionally, Google Colab, which utilized a single 12 GB NVIDIA Tesla K80 GPU, was used for model training and testing, leveraging its cloud-based Jupyter notebook environment.



(a) (b)

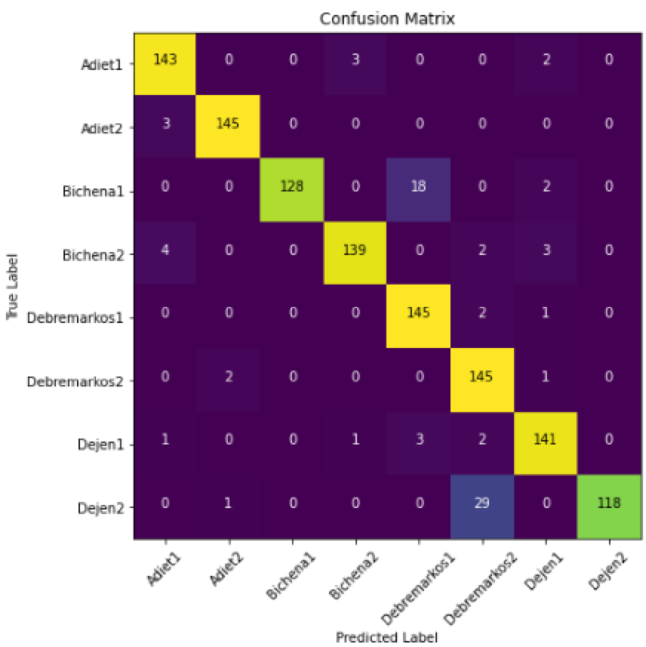
(c)

Fig. 6 The experimental result of FVGG16 model



(a)

(b)



(c)

Fig. 7 The experimental result of FINCV3 model

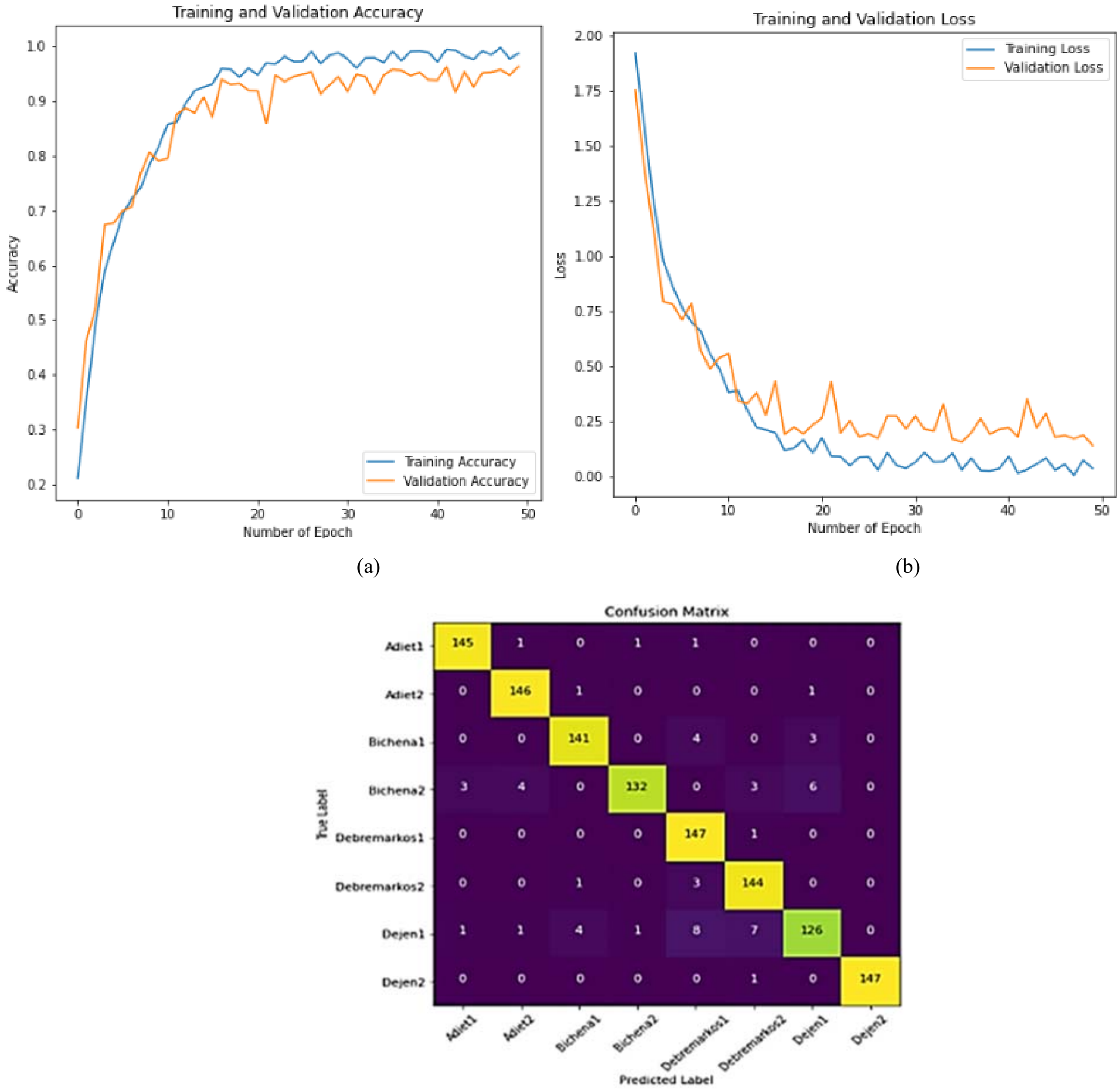
B. Evaluation

Figs. 6-8 represent the training and validation accuracy, as well as the training and validation loss for each individual model at 50 epochs. The results of each model, evaluated using confusion matrix, are also represented in respective training graph (Figs. 6-8 (c)).

When testing the ensemble model, the results of EMQSCTC are represented in the following confusion matrix (Fig. 9), which achieved a testing accuracy of 97.72%.

As a result, the accuracy of each model is evaluated using the testing data. Accordingly, the results of EMQSCTC, QSCTC, FVGG16, FINCV3, SVM, and RF are 97.72%, 95.27%, 93.92%, 93.24%, 90.29%, and 86.91% performance accuracy, respectively. This indicates that the EMQSCTC model achieved better accuracy and outperformed the other individual models.

In this study, an ensemble of deep CNN architectures has been employed to classify both the source and quality of Teff cereal. The results obtained through this approach demonstrate the effectiveness of utilizing a combination of deep CNN models in achieving enhanced classification accuracy. The ensemble of deep CNN architectures presented in this study represents a promising methodology for classifying the source and quality of Teff cereal. The robustness and accuracy achieved through this approach underscore its potential contribution to advancements in automated classification systems, with implications for both agricultural practices and food quality assurance.



(a) (b)

(c)

Fig. 8 The experimental result of QSCTC model

Compared to prior research endeavors, the majority of studies focusing on cereal classification have overlooked Teff cereals. Investigations specifically targeting Teff classification have been notably scarce. While a machine learning and deep learning approach including CNNs are frequently employed in numerous studies for cereal classification utilizing image data [11], [13], [17], [18], their application to Teff classification is not easy because of the cereal's diminutive size and distinct characteristics. Consequently, the study opted for an ensemble approach involving deep CNN architectures. This methodology yielded enhanced accuracy, surpassing the outcomes of alternative methods. The superior performance can be attributed to the ensemble techniques employed to accurately classify cereals into their respective categories.

```
Model Accuracy 0.9771959459459459
              precision    recall  f1-score   support

      Adiet1       0.99      0.99      0.99       148
      Adiet2       0.99      0.99      0.99       148
    Bichena1       0.99      0.97      0.98       148
    Bichena2       0.99      0.93      0.96       148
Debremarkos1       0.95      1.00      0.97       148
Debremarkos2       0.97      0.99      0.98       148
      Dejen1       0.94      0.95      0.95       148
      Dejen2       1.00      0.99      1.00       148

    accuracy                           0.98      1184
   macro avg       0.98      0.98      0.98      1184
weighted avg       0.98      0.98      0.98      1184
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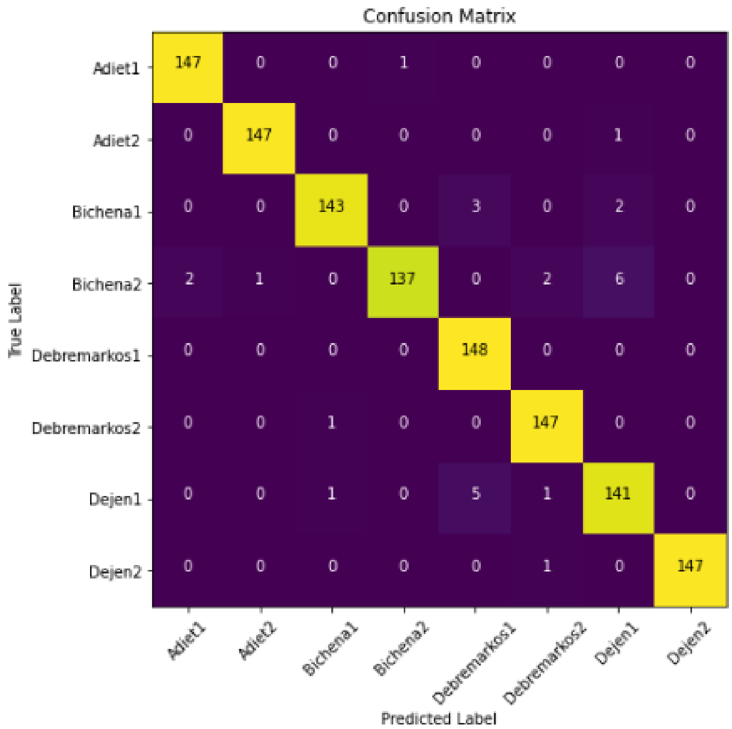

Fig. 9 The experimental result of EMQSCTC model

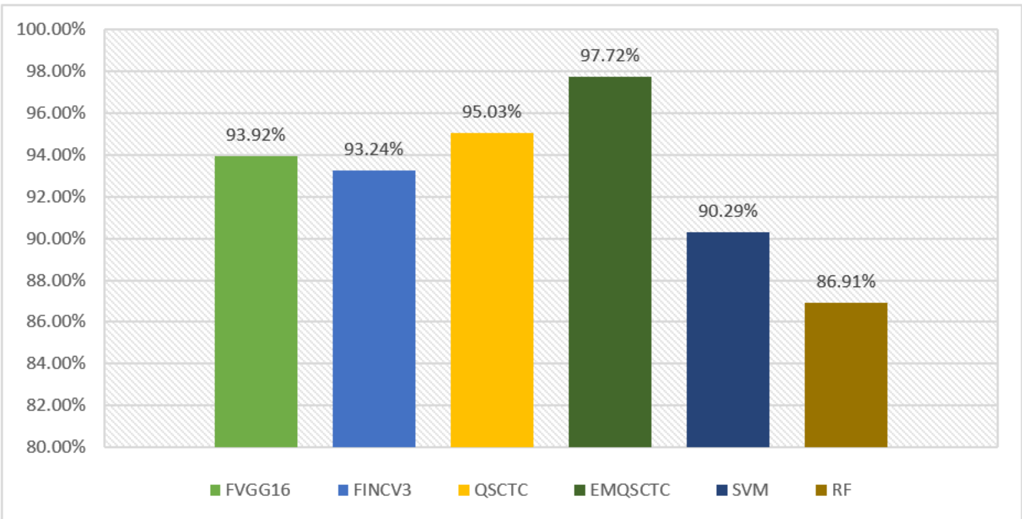

Fig. 10 The accuracy of each model

V. Conclusion

This research aimed to create a production area and quality classification system for Teff cereal through a machine-learning approach. To address this, various pre-trained CNN architectures such as FVGG16 and FINCV3 were utilized. In addition to the pre-trained CNN architectures, a QSCTC model architecture was developed using CNNs and an ensemble method called EMQSCTC was created by combining CNN architectures such as FVGG16, FINCV3, and QSCTC using a majority vote technique. Machine learning algorithms like SVM and RF were also employed, using features extracted from the CNN. So, SVM and RF were used as classifiers. Performance evaluations revealed varying accuracy levels: EMQSCTC achieved 97.72%, followed by FVGG16 at 95.27%, FINCV3 at 93.92%, QSCTC at 93.24%, SVM at 90.29%, and RF at 86.91%.

The Ensemble Method for Quality and Source Classification of Teff Cereal (EMQSCTC) outperformed others, affirming the superiority of ensemble approaches. Our study emphasizes the automated Teff cereal classification's precision and accuracy, surpassing traditional identification methods and highlighting the accuracy of an ensemble model for optimal results.

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