

Classification of Pistachio Nut Using Convolutional Neural Network

Lisda¹, Kusrini², Dhani Ariatmanto³

^{1,2,3}*Informatics Engineering Department, Universitas Amikom Yogyakarta, Indonesia*

¹lisdaa@students.amikom.ac.id

²kusrini@amikom.ac.id (*)

³dhaniari@amikom.ac.id

Received: 2022-12-26; Accepted: 2023-01-18; Published: 2023-01-30

Abstract— The application of innovative technologies in the agricultural industry has the potential to boost yield productivity and affect the well-being of farmers. Pistachio nuts are widely considered among the most precious things agriculture produces. The kirmizi and siirt are the two distinct varieties of pistachio nuts that are available. It is essential to categorize the different types of pistachio nuts to keep the product's quality and worth at a high level. This paper proposes a classified pistachio variety of kirmizi and siirt based on Convolutional Neural Network (CNN) models Inception V3 and ResNet50. The dataset used in this research is 2148 samples of pistachio images. The sample images are divided into 80% training data, 10% testing data, and 10% validation data. First, we pre-process and normalize by wrapping and cropping the images. The next, Inception-V3 and ResNet50 architectures, were trained and tested on the sample datasets. The experimental results show that the accuracy of both models is 96% and 86%, respectively. This can be concluded that the performance of the CNN model using Inception-V3 architecture outperforms ResNet50 architecture.

Keywords— Pistachio, Classification, Convolutional Neural Network, Inception-V3, ResNet50

I. INTRODUCTION

In this century, the agricultural sector is the most significant aspect of a country's development in terms of economic support [1]. As time passes, competition in the agriculture sector will get more intense, as indicated by greater production, quality, and business efficiency [2]. New agricultural inventions are increasingly needed to help the production process so that the quality and quantity produced may be maximized and compete with others. Pistachios are one of the agricultural industries that require fresh ideas.

Pistachio is a type of grain-producing plant that is generally known as pistachio nuts. Pistachios grow best in dry climates with poor soil [3], such as Iran, Turkmenistan, and western Azerbaijan [4][5]. The pistachio plant's vivid green seeds are typically used to adorn cuisine or in various processed delicacies such as ice cream [6]. Pistachios are a type of legume high in nutrition since they include protein, fiber, monounsaturated fatty acids, minerals, vitamins, carotenoids, phenolic acids, flavonoids, and anthocyanins [3].

There is a wide range of diversity among pistachios. Each produced kind has its unique market and pricing point for consumers to purchase. The varieties of Kirmizi and Siirt will be the primary focus of this investigation. Due to its dark green color, distinctive flavor, and aroma, kirmizi is frequently utilized in the confectionery and sweet pastry sectors. In contrast, siirt is well-liked as a snack due to its high cracking rate and round shape. [7].

However, the process used to separate pistachio nuts is still carried out with basic knowledge. Because of this, there is a high potential for mistakes to be made in the classification process because each variety of pistachio nut has a virtually identical form. Innovations are needed to recognize the type of

pistachio nuts so that the packaging process for sales can be right on target.

Previous studies on the subject of classification in agriculture have been carried out in several different ways. Classification and analysis of pistachio species using pre-trained deep learning models [8] is a study that classifies it using the transfer learning approach, namely AlexNet, VGG16, and VGG19. The study used 2148 photos, 916 of the Siirt type and 1232 of the Kirmizi type, divided by an 80:20 ratio for training and testing data. Classification using the AlexNet, VGG 16, and VGG 19 transfer learning algorithms yielded 94.42%, 98.84%, and 98.14%, respectively. The metrics sensitivity, specificity, accuracy, and F-1 score are employed to assess model performance. The ROC curve and AUC values are also employed in performance evaluation. VGG16 achieved the greatest classification success rate of 98.84% [8].

Researchers [9] used machine learning and deep learning architecture to categorize pistachios into three categories: open-shell pistachios, rotten-shell pistachios, and garbage or wood chips. The classification was performed on 1000 photos using the AlexNet and GoogleNet architectures, yielding an accuracy of 98% and 99%, respectively. Another study in which they used image processing and machine learning to perform a classification method for different varieties of pistachios that had been peeled. The peeled pistachios are classified into five classes (SVM) using support vector machines and Artificial Neural Networks. The classification accuracy of ANN and SVM was 99.4% and 99.8%, respectively [10].

The study, Using an Improved K-NN Classifier, Pistachio Species are Classified, uses the KNN technique Siirt using 2148 pictures. KNN implementation for classification is carried out in three scenarios: KNN, Weighted KNN, and PCA-based k-NN. The results of the three situations were 83%, 87%, and

94%, respectively. With an accuracy of 94%, PCA provided the best categorization success [7].

The study, Detection of contaminants in pistachios using multiple Short-wave infrared hyperspectral pictures are classified using algorithms, examined four classification models to find which one was best suited for automatic quality control of edible pistachio nuts. In this investigation, four alternative classification models were utilized, including PLS-DA, which had an effectiveness of 0.86% for edible and 0.80% for inedible. PCA-DA has an efficiency of 0.87% edible and 0.85% inedible, PCA-kNN has an efficiency of 0.93% edible and 0.92% inedible, and CART has an efficiency of 0.82% edible and 0.82% inedible [6].

Another study, prediction of pistachio kernel size and mass using Random Forest Machine Learning, employed Using Random Forest Machine Learning to predict the mass and size of kernels of pistachios. An image processing algorithm calculates one's size and surface area unripe Pistachio in pixels. The pixels are then transformed into feature vectors that reflect the dimensions and surface area of one unripe Pistachio. These feature vectors are used to forecast the length and mass of an unripe pistachio or kernel. The average length measured from 100 pistachio seeds is 18.00 mm, while the image processing system's estimated length is 18.60 mm [5].

This study aims to create a classification system for different types of pistachio nuts to assist farmers in improving the efficiency of the post-harvest process by classifying different types of pistachio nuts quickly and efficiently and handling market needs appropriately. Based on existing problems and previous research literature, this study aims to create a system that can categorize various pistachio nut varieties.

The methods from the fields of computer vision and image processing were hybrid with being used in this research. The Convolutional Neural Network (CNN) is a method for identifying the varieties of Kirmizi and Shiirt pistachios. CNN combined with the Inception-V3 and ResNet50 architectures. We chose these two architectures because they have not been used in previous studies on the pistachios' classification. We then compared the results of the previous architecture with those of the architecture we used, which is expected to classify different variations of Pistachios using images quickly and effectively. This helps classify pistachios in a way that is both effective and efficient.

II. RESEARCH METHODOLOGY

Each study has a research design model or workflow that will be used to describe the research flow. This research has several stages: data collection, pre-processing, training architecture, and evaluation. The workflow in this study is depicted in Figure 1.

A. Research Method

The research method and kind is quantitative research. This study uses mathematical computations to analyze the research data. The research is of the experimental variety. In this study,

learning about the classification of pistachio images was done using two types of Convolutional Neural Network architecture with two experimental scenarios. The learning outcomes were evaluated to assess accuracy in classifying pistachio images from each scenario to learn the facts from the research results.

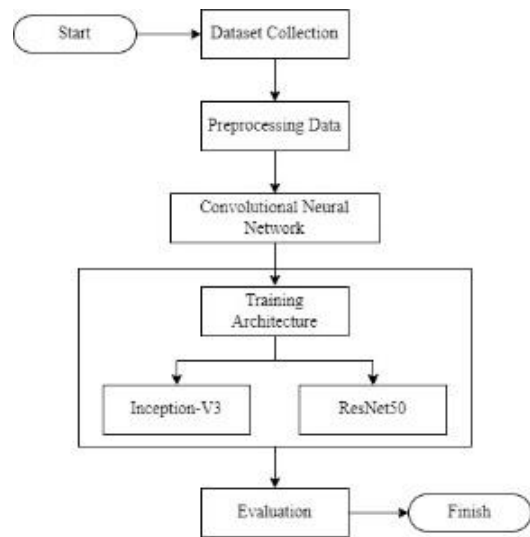


Figure 1. Research Workflow

B. Dataset Collection

The pistachio Image Dataset from Kaggle was used in this investigation [11]. Two prior studies also looked at pistachio nuts have highlighted it. Classification will be performed using 2148 example photos of two varieties of pistachios, the Kirmizi type shown in Figure 2 and the Shiirt type shown in Figure 3. The training dataset contains 2148 pictures, with information on 1232 Kirmizi and 916 Shiirt kinds. Table I contains information on the dataset.

TABLE I
 PISTACHIO DATASET DETAILS

Pistachio Type	Total
Kirmizi	1232
Shiirt	916
Total	2148

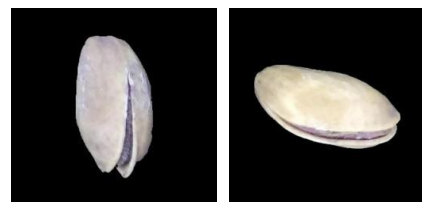


Figure 2. Pistachio Kirmizi Type

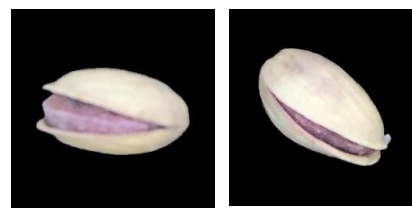


Figure 3. Pistachio Shiirt Type

C. Pre-processing Data

At this point, the collected dataset will be readied for system processing. This pre-processing stage prepares the obtained dataset for usage in the model[12]. Several operations will be performed. This step includes image scaling, image array conversion, and dataset division for future classification processes using the architecture to be employed. Figure 4 depicts a detail of the pre-processing procedure that will be followed.

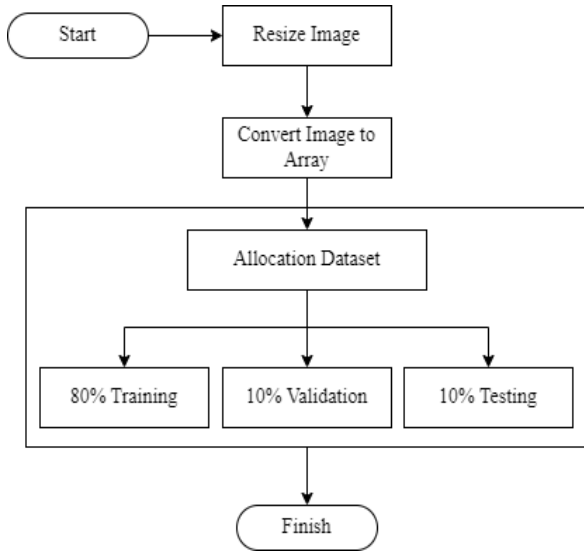


Figure 4. Pre-processing Stages

1) *Image Resize*: Resize is reorganizing the image size so the model can read it[12]. The picture sizes used in this study are 150×150 for the Inception-V3 model and 224×224 for the ResNet50 model. As a result, the resize will be set to that size for each model later trained.

2) *Convert Image to Arrays*: Each image will be stored as an array, with each integer representing a black-and-white value ranging from 0 to 255.

3) *Dataset Allocation*: At this stage, a random selection technique is used to divide the data into two parts, training data and testing data from the existing dataset. This is accomplished by dividing a library folder into 80% of the data will be used for training, 10% for validation, and 10% for testing. Table II shows the dataset's detailed distribution.

TABLE II
 ALLOCATION DATASET

Pistachio Type	Allocation Dataset		
	Train (80%)	Validasi (10%)	Testing (10%)
Kirmizi	980	126	126
Shiirt	736	90	90
Total	1726	216	216

D. Concept of Convolutional Neural Network

Deep learning is a method with several layers for extracting and identifying characteristics from massive amounts of data that has attracted much interest in recent years [13]. It has

different layers with different roles, such as a flattened layer, a pooling layer, an activation layer, a convolution layer, and link layers [14]. A useful layer for extracting attributes from incoming data is the convolution layer. The input vectors are filtered using a locally weighted sum aggregation, and the resulting data is translated to feature space [24]. This layer, the initial convolution layer related to the image collection, may extract basic features like colors and borders [15].

The layer that applies a nonlinear function to each pixel in the image is known as the activation layer (Non-linearity Layer) [16], in contrast to the more popular sigmoid and hyperbolic tangent activation functions. The rectified linear units (ReLu) activation function was used in a recent study [17].

1) *Pooling (Down-sampling) layer*: The pooling layer, another element of the CNN architecture, minimizes the amount of processing and the number of parameters in the network, which has two benefits. Reduced processing for the subsequent layer is one goal, while preventing the network from retaining information is another. The most popular pooling techniques for the layer are average, maximum, total, and mean [18].

2) *Flatten layer*: The only objective of this layer is to prepare the incoming data for the following layer. This layer converts matrix-type data from preceding layers into one-dimensional arrays because neural networks only accept one-dimensional arrays as input. Because a single line represents each image pixel, this process is known as smoothing [19].

3) *Fully connected layers*: The fields of the preceding layer are all required by this layer. This layer's count may vary between architectures. At these nodes, the features are kept, and the learning is done by changing the weight and bias values. This layer accepts input from all feature extraction stages, reviews the outcomes of all processing levels, and does the actual processing. [20].

E. Pre-trained CNN Models

The literature describes a wide variety of CNN architectures. When determining which architecture to use, classification success, model size, and speed are all considered. The study's model was chosen after multiple experiments.

1) *Inception-V3*: Inception typically has three different convolution layer sizes, with the unification layer being the smallest of the three. This architecture has numerous layers, including the convolution layer, which partitions the mass into small disagreements. This shift is an operation to process various features from the given input by speeding up computation and reducing overfitting. The pooling layer aids in reducing the dimensions of the folder function [22]. The concatenation layer connects the previous module with the next. The completely functional layer consists of all neurons from the module layer to the fully functional layer, and the activation layer employed is SoftMax activation, which aids in resolving some class categorization issues. The architecture of the Inception-V3 model is seen in Figure 5.

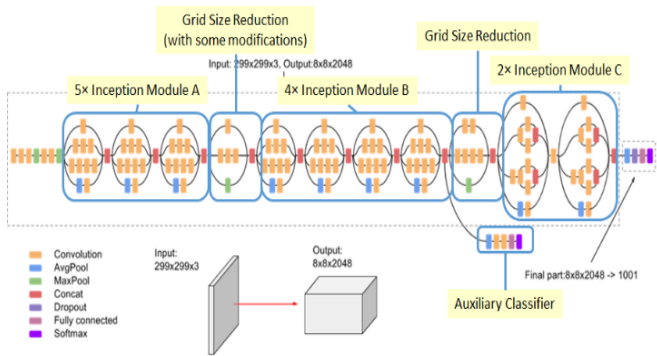


Figure 5. Architecture Inception-V3

2) *ResNet50*: During the training step of ResNet50, 5 types of convolutions are applied by normalizing the image to 224 x 224 pixels [23]. The activation used in the fully connected layer is a flatten function that produces the softmax activation function as input by converting the multidimensional array output from the training process into a one-dimensional array and then calculating the probability of training data on the objects consisting of the 5 classes [24].

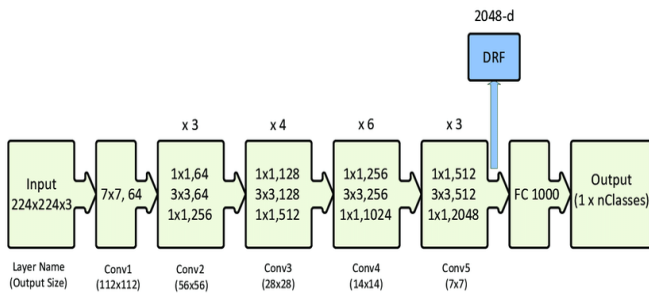


Figure 6. Architecture ResNet50

F. Evaluation

The testing procedure is the final step in the research system. The testing procedure is used to evaluate the classification's accuracy by evaluating the index created by the trained CNN model. The capacity of training and test data to predict is assessed using the complexity matrix. The matrix Values are frequently used to assess the effectiveness of classification issues such as kernel size, stride, pooling model, optimizer, epoch, iteration, and learning [23]. The complex matrix of a two-class classification problem in the study is shown in Table III.

TABLE III
 TWO CLASS CONFUSION MATRIX

		True class	
		Positive (P)	Negative (N)
Predicted class	True (T)	TP	TN
	False (F)	FP	FN

- TP stands for True Positive. Examples are where the model's true value is 1, and the projected value is 1.
- TN stands for True Negative. Examples are when the model's true value is 0, and the forecasted value is 0.
- FP stands for False Positive. For example, where the model's true value is 0 and the projected value is 1.

- A false Negative is referred to as FN. Examples include the case where the projected value is 0, and the model's true value is 1.

The evaluation will be presented in the form of a Confusion Matrix. The confusion matrix displays the number of photos from various classifications and prediction classes. The number on the main diagonal represents the number of right predictions based on the architectural model [25].

III. RESULT AND DISCUSSION

The classification technique was used to determine the architectural model that obtained the highest accuracy by using 2148 pistachio image data separated into 80% training data, 10% test data, and 10% validation data. The Inception-V3 and ResNet 50 models were used for classification, with each model using the same approach with a batch size of 32 and epoch 100. Each of the two architectures obtains different accuracies, as shown in Figure 7 obtained during the training iteration phase with the Inception V3 model. Based on the graph, the accuracy of the training data is 95%, and the accuracy of the validation data is 99%. The loss value for training data loss is 0.12, and the loss value for loss validation is 0.05, as shown in Figure 8.

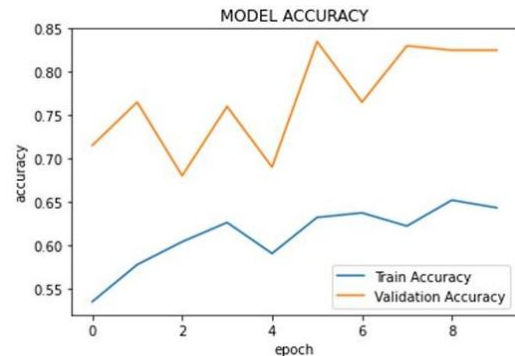


Figure 7. Accuracy Inception-V3

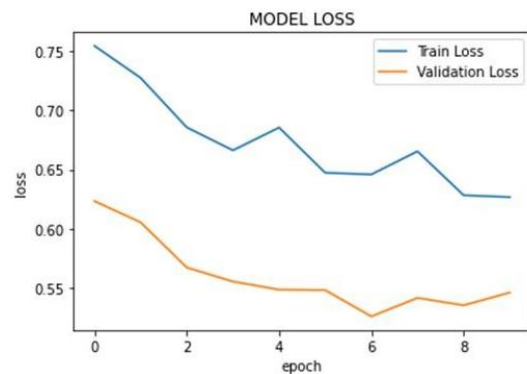


Figure 8. Loss Inception-V3

While the results of the accuracy and loss graphs using the ResNet50 model are shown in Figures 9 and 10. The training data is carried out in the same way. Using ResNet 50, the accuracy of the data train is 98%, and the data validation is 20%, with a loss value of 0.37 and a validation loss of 0.78. It was found that the ResNet50 model has a much larger loss value than the Inception-V3 model.

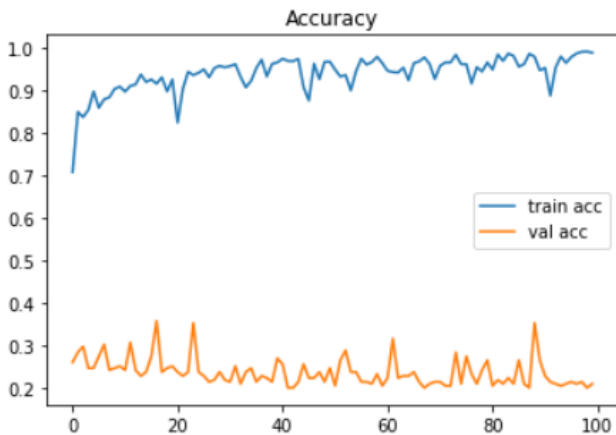


Figure 9. Accuracy ResNet50

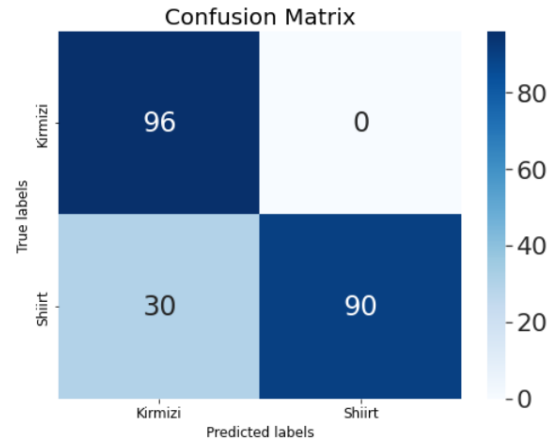


Figure 12. Confusion Matrix ResNet50

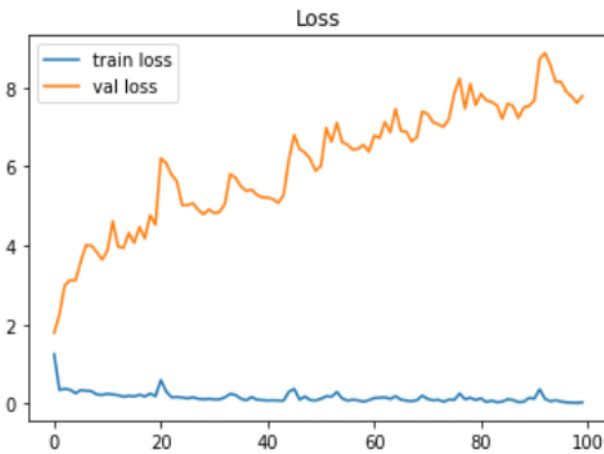


Figure 10. Loss ResNet50

After determining the accuracy and loss values from training and validation data, the data testing is done during classification to determine the extent to which the algorithm utilized can provide sufficient accuracy. The confusion matrix for data testing using the Inception-V3 model is shown in Figure 11, whereas the confusion matrix for data testing using the ResNet50 model is shown in Figure 12.

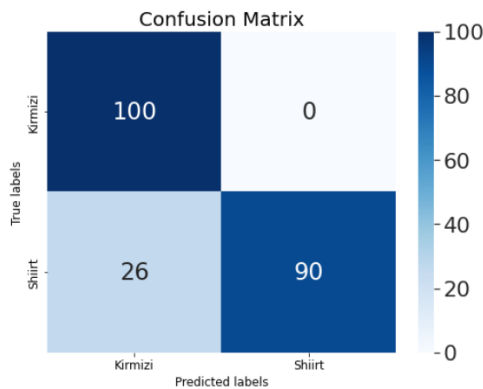


Figure 11. Confusion Matrix Inception-V3

According to the results of the confusion matrix with Inception-V3 in Fig 11, 190 pistachio picture data are accurately identified, with details of 100 data for the Kirmizi type and 90 data for the Shiirt type. Meanwhile, the Inception-V3 model predicted that 26 data were incorrect, with details of 0 data for Kirmizi and 26 data for Shiirt. While the confusion matrix employing Resnet 50 in Fig 12 yielded 186 pistachio image data that were accurately identified with 96 details for Kirmizi and 90 Shiirt kinds. In comparison, 30 image data are expected to be incorrect, with details of 0 for Kirmizi and 30 for Shiirt.

A classification report is used to evaluate the model based on the findings obtained from the confusion matrix. The accuracy value achieved from the report categorization using the Inception-V3 model was 96%, whereas the result using ResNet50 was 86%. The qualification report results with Inception-V3 are shown in Fig 11, while the results with ResNet50 are shown in Figure 12. Compared to the previous study [8] using the AlexNet, VGG16, and VGG19 architectures, using the same dataset amount, and process, the Inception architecture is superior to AlexNet and VGG19. Still, of the 5 CNN architectures used in the classification, Pistachio uses the same dataset, so VGG16 gets the highest accuracy.

TABLE IV
 CLASSIFICATION REPORT INCEPTION-V3

	Precision	Recall	F1-Score	Support
Kirmizi	0.97	0.96	0.96	126
Shiirt	0.95	0.96	0.95	90
Accuracy			0.96	216
Macro avg	0.96	0.96	0.96	216
Weighted avg	0.96	0.96	0.96	216

TABLE III
 CLASSIFICATION REPORT RESNET50

	Precision	Recall	F1-Score	Support
Kirmizi	0.79	1.00	0.86	96
Shiirt	1.00	0.75	0.86	120
Accuracy			0.86	216
Macro avg	0.88	0.88	0.86	216
Weighted avg	0.89	0.86	0.86	216

REFERENCES

The highest accuracy obtained using the Inception-V3 model is 96% in the classification of pistachio nuts. Compared with previous research [8] using the same number of datasets and the same epoch with three CNN architectures, namely AlexNet with an accuracy of 94.42%, VGG19 at 98.14%, and VGG16 at 98.84%. The VGG16 architecture obtained the highest accuracy with an accuracy of 98.84%, then VGG19 at 98.14%, and Inception-V3 at 96%. The architectural model we use is quite low compared to previous research. We suggest you try another architectural model and add it to the dataset for further research on the same object.

IV. CONCLUSION

This research aims to categorize pistachio nut images using the CNN method with two different architectures, inception-V3 and ResNet50. The research data set has 2148 Kirmizi pictures and Siirt pistachio types. CNN architecture pre-training includes successfully classifying pistachio nut pictures in the build model. With epoch 100 and batch size 32, the dataset was divided into portions with 80% training, 10% testing, and 10% validation. As a consequence of the classification, the Inception-V3 model achieves 96% accuracy, and the ResNet50 model achieves 86% accuracy, indicating that the Inception-V3 model achieves the highest classification achievement. A wide range of confusion matrices and performance measurements were applied to conduct an in-depth analysis of the performance model. Once more, the Inception-V3 architecture came out on top with the highest score after these measurements were taken.

In the CNN design, the sum layer is not necessarily directly proportional to classification success. A model with the optimal number of layers on the data set can achieve high classification success. The Inception-V3 architecture has been identified as the best CNN for pistachio datasets. As a result, the Inception-V3 architecture receives the highest classification. The confusion matrix image conclusions contain the article's major points and can be used to see which pistachios are categorized properly or erroneously. The digest portion should not be repeated in the conclusion. The conclusion should discuss what was written in the digest portion. In this area, you should also show whether or not. It is possible to achieve the aims of the research. The findings are provided as a paragraph description, with occasional instances of bulleted lists scattered throughout the text.

The study's methodologies serve as a model for future research in this sector. On the other hand, one can accomplish various levels of categorization by utilizing a wide variety of AI-based classification algorithms. The number of photographs in the dataset can influence the categorization accuracy of various models, leading to various success rates. Pistachios can be recognized very promptly and without any difficulty. Collecting several types of pistachio photos allows for a diverse classification investigation. The application can be made mobile and utilized in an agricultural area to determine the type of Pistachio.

- [1] F. R. Moeis, T. Dartanto, J. P. Moeis, and M. Ikhsan, "A longitudinal study of agriculture households in Indonesia: The effect of land and labor mobility on welfare and poverty dynamics," *World Dev Perspect*, vol. 20, Dec. 2020, doi: 10.1016/j.wdp.2020.100261.
- [2] F. N. Cahya, R. Pebrianto, and T. M. Adilah, "Klasifikasi Buah Segar dan Busuk Menggunakan Ekstraksi Fitur Hu-Moment, Haralick dan Histogram," *IJCIT (Indonesian Journal on Computer and Information Technology)*, vol. 6, no. 1, pp. 57–62, 2021, doi: <https://doi.org/10.31294/ijcit.v6i1.10052>.
- [3] G. Mandalari *et al.*, "Pistachio nuts (*Pistacia vera* L.): Production, nutrients, bioactives and novel health effects," *Plants*, vol. 11, no. 1, Jan. 2022, doi: 10.3390/plants11010018.
- [4] C. Saglam and N. Cetin, "Prediction of Pistachio (*Pistacia vera* L.) Mass Based on Shape and Size Attributes by Using Machine Learning Algorithms," *Food Anal Methods*, vol. 15, no. 3, pp. 739–750, 2022, doi: 10.1007/s12161-021-02154-6.
- [5] S. K. Vidyarthi, R. Tiwari, S. K. Singh, and H. W. Xiao, "Prediction of size and mass of pistachio kernels using random Forest machine learning," *J Food Process Eng*, vol. 43, no. 9, Sep. 2020, doi: 10.1111/jfpe.13473.
- [6] G. Bonifazi, G. Capobianco, R. Gasbarrone, and S. Serranti, "Contaminant detection in pistachio nuts by different classification methods applied to short-wave infrared hyperspectral images," *Food Control*, vol. 130, Dec. 2021, doi: 10.1016/j.foodcont.2021.108202.
- [7] I. A. Özkan, M. Köklü, and R. Saraçoğlu, "Classification of pistachio species using improved k-NN classifier," *Progress in Nutrition*, vol. 23, no. 2, Feb. 2021, doi: 10.23751/pn.v23i2.9686.
- [8] D. Singh *et al.*, "Classification and Analysis of Pistachio Species with Pre-Trained Deep Learning Models," *Electronics (Switzerland)*, vol. 11, no. 7, Apr. 2022, doi: 10.3390/electronics11070981.
- [9] Farazi Mohammad, Abbas-Zadeh Mohammad Javad, and Moradi Hadi, "A machine vision based pistachio sorting using transferred mid-level image representation of Convolutional Neural Network," 2017.
- [10] M. Omid, M. S. Firouz, H. Nouri-Ahmadabadi, and S. S. Mohtasebi, "Classification of peeled pistachio kernels using computer vision and color features," *Engineering in Agriculture, Environment and Food*, vol. 10, no. 4, pp. 259–265, Oct. 2017, doi: 10.1016/j.eaef.2017.04.002.
- [11] "Pistachio Image Dataset".
- [12] E. G. Winarto, Rahmayati, and A. Lawi, "Implementasi Arsitektur Inception Resnet-V2 untuk Klasifikasi Kualitas Biji Kakao," *Konferensi Nasional Ilmu Komputer (KONIK) 2021*, 2021.
- [13] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," *Commun ACM*, vol. 60, no. 6, pp. 84–90, Jun. 2017, doi: 10.1145/3065386.
- [14] E. Dandil and R. Polattimur, "Dog behavior recognition and tracking based on faster R-CNN," *Journal of the Faculty of Engineering and Architecture of Gazi University*, vol. 35, no. 2, pp. 819–834, 2020, doi: 10.17341/gazimmfd.541677.
- [15] H. Chen *et al.*, "A deep learning CNN architecture applied in smart near-infrared analysis of water pollution for agricultural irrigation resources," *Agric Water Manag*, vol. 240, Oct. 2020, doi: 10.1016/j.agwat.2020.106303.
- [16] D. M. S. Arsa and A. A. N. H. Susila, "VGG16 in Batik Classification based on Random Forest," 2019.
- [17] B. Bayar and M. C. Stamm, "A deep learning approach to universal image manipulation detection using a new convolutional layer," in *IH and MMSec 2016 - Proceedings of the 2016 ACM Information Hiding and Multimedia Security Workshop*, 2016, pp. 5–10. doi: 10.1145/2909827.2930786.
- [18] X. Glorot, A. Bordes, and Y. Bengio, "Deep Sparse Rectifier Neural Networks," 2011.
- [19] N. Akhtar and U. Ragavendran, "Interpretation of intelligence in CNN-pooling processes: a methodological survey," *Neural Computing and Applications*, vol. 32, no. 3, Springer, pp. 879–898, Feb. 01, 2020. doi: 10.1007/s00521-019-04296-5.
- [20] G. Habib and S. Qureshi, "Optimization and acceleration of convolutional neural networks: A survey," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 7. King Saud bin Abdulaziz

- University, pp. 4244–4268, Jul. 01, 2022. doi: 10.1016/j.jksuci.2020.10.004.
- [21] N. Dong, L. Zhao, C. H. Wu, and J. F. Chang, "Inception v3 based cervical cell classification combined with artificially extracted features," *Appl Soft Comput*, vol. 93, p. 106311, Aug. 2020, doi: 10.1016/j.asoc.2020.106311.
- [22] M. Nour, Z. Cömert, and K. Polat, "A Novel Medical Diagnosis model for COVID-19 infection detection based on Deep Features and Bayesian Optimization," *Appl Soft Comput*, vol. 97, Dec. 2020, doi: 10.1016/j.asoc.2020.106580.
- [23] N. D. Miranda, L. Novamizanti, and S. Rizal, "CONVOLUTIONAL NEURAL NETWORK PADA KLASIFIKASI SIDIK JARI MENGGUNAKAN RESNET-50," *Jurnal Teknik Informatika (Jutif)*, vol. 1, no. 2, pp. 61–68, Dec. 2020, doi: 10.20884/1.jutif.2020.1.2.18.
- [24] X. Ou *et al.*, "Moving Object Detection Method via ResNet-18 with Encoder-Decoder Structure in Complex Scenes," *IEEE Access*, vol. 7, pp. 108152–108160, 2019, doi: 10.1109/ACCESS.2019.2931922.
- [25] S. Yeshwanth Chaganti Test Engineer, T. GNRSN Prudhvith, N. Kumar, and K. Rao Pandi, "Image Classification using SVM and CNN," in *2020 International Conference on Computer Science, Engineering and Applications (ICCSEA)*, 2020.

This is an open-access article under the [CC-BY-SA](https://creativecommons.org/licenses/by-sa/4.0/) license.

