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Vegetable and Fruit Image Classification with SqueezeNet based Deep Feature Generator

Mehmet BAYGIN[1*]
[1] Bilgisayar Mühendisliği Bölümü, Mühendislik Fakültesi, Ardahan Üniversitesi, Ardahan, Türkiye
[*1] mehmetbaygin@ardahan.edu.tr

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Abstract: Automatic classification of food products according to their types is one of the most common problems in computer vision. In this paper, automatic classification was performed using two different vegetable and fruit datasets. A deep learning-based transfer learning approach is used for the automatic fruit and vegetable classification problem. The first dataset (DB1) used in the study consists of 21000 images and the second dataset (DB2) consists of 980 images. In addition, the first dataset contains 15 classes and the second dataset contains 20 classes. SqueezeNet architecture is used for feature extraction in the developed deep learning-based machine learning model. In addition, the ReliefF method was used for feature selection and the most significant features were determined by eliminating negative features. In the classification phase of the developed application, Linear Discriminant Analysis (LDA) method was preferred. In this study, hold-out and 10-fold cross validation techniques were used for DB1. Also, 10-fold cross validation was used for DB2. An accuracy value of over 99% was obtained for both DB1 and DB2. The obtained results of the study show that the proposed method can be used successfully in automatic vegetable and fruit classification.

Key words: Vegetable and fruit classification, SqueezeNet, ReliefF, Linear Discriminant Analysis.

SqueezeNet tabanlı Derin Öznitelik Oluşturucu ile Sebze ve Meyve Görüntü Sınıflandırması

Öz: Gıda ürünlerinin türlerine göre otomatik sınıflandırılması bilgisayarlı görme alanında sıklıkla karşılaşılan problemlerden biridir. Bu çalışmada, iki farklı sebze ve meyve veri seti kullanılarak otomatik sınıflandırma yapılmıştır. Otomatik meyve ve sebze sınıflandırma problemi için derin öğrenme tabanlı öğrenme aktarımı yaklaşımı kullanılmıştır. Çalışmada kullanılan birinci veri seti (DB1) 21000 görüntüden oluşmaktadır ve ikinci veriseti (DB2) 980 görüntüden meydana gelmektedir. Ayrıca, ilk veri seti 15 sınıftan ve ikinci veri seti 20 sınıftan oluşmaktadır. Geliştirilen derin öğrenme tabanlı makine öğrenmesi modelinde özellik çıkarımı için SqueezeNet mimarisi kullanılmaktadır. Ayrıca özellik seçimi için ReliefF yöntemi kullanılmış ve bu sayede negatif özellikler elimine edilerek en anlamlı özellikler belirlenmiştir. Geliştirilen uygulamanın sınıflandırma fazında Lineer Diskriminant Analizi (LDA) yöntemi tercih edilmiştir. Bu çalışmada, hold-out ve 10-katlamalı çapraz doğrulama teknikleri DB1 için kullanılmıştır. Ayrıca, 10-kat çapraz doğrulama tekniği DB2 için kullanılmıştır. Hem DB1 hem de DB2 için %99 üzerinde bir doğruluk değeri elde edilmiştir. Çalışma kapsamında elde edilen sonuçlar, önerilen yöntemin otomatik sebze sınıflandırmada başarılı bir şekilde kullanılabileceğini göstermektedir.

Anahtar kelimeler: Sebze ve meyve sınıflandırma, SqueezeNet, ReliefF, Lineer Diskriminant Analizi.

1. Giriş

Vegetable is the name given to the part of the plant that is consumed by humans and animals [1]. Vegetables are produced in almost many parts of the world and these vegetables are consumed by humans and animals. With this type of food in the food pyramid, people can meet their various vitamin and mineral needs [2,3].

Nowadays, computer vision is actively used in many fields [4]. Areas such as mass production sites, automobile factories and textiles are among these sectors [5,6]. Another area where computer technology is actively used is the food industry [7]. Various tasks such as automatic quality control, product counting, product classification can be performed with these approaches [8]. In this way, food products can be evaluated in many ways [9]. At this point, vegetable and fruit classification is seen as a very important issue. Because vegetable and fruit food groups contain some manual processes from the production stage to the delivery stage. The similarities between vegetables and fruits, also various parameters such as color, texture, size can sometimes challenge automatic classification approaches [10]. For this reason, automatic classification of these and similar foods according to their types becomes a very important issue.

The topic of automatic vegetable classification in the literature is a problem that has been studied for a long time and continues to be studied. Some studies on this subject are summarized in Table 1.

[*] Corresponding author: mehmetbaygin@ardahan.edu.tr. ORCID Number of authors: [1] 0000-0002-5258-754X

Table 1. Literature review on vegetable and fruit classification

Author(s)	**Year**	**Method**	**Dataset Information**	**Type (Vegetable/Fruit)**	**Result(s)**
F. Yuesheng et. al. [11]	2021	GoogleNet based CNN	6 class and 6600 image	Mixed	Accuracy=98.82
J. K. Bhavya et. al. [12]	2021	CNN	24 class and 3924 images	Mixed	Accuracy=95.5
R. S. Latha et. al. [13]	2021	Custom design CNN	12 class and 6783 images	Mixed	Accuracy=97.4
M. I. Ahmed et al. [14]	2021	Custom design CNN	15 class and 21000 images	Vegetable	Accuracy=97.5
O. Patil and V. Gaikwad [15]	2018	Image preprocessing and InceptionV3	4 class and 1200 images	Vegetable	Accuracy=99
H. Kuang et. al. [16]	2018	Fused HOG, Local Binary Pattern (LBP) and GaborLBP	5 class and 20433 images	Fruits	Accuracy=99.5
Z. Yuhui et. al. [17]	2021	Custom designed deep CNN	20 class and 10756 images	Mixed	Accuracy=95.67
J. L. Joseph et. al. [18]	2021	Custom designed CNN	131 class and 90483 images	Mixed	Accuracy=94.35

As can be seen from Table 1, there are various studies in the literature for automatic fruit and vegetable classification. Although recent studies are summarized in Table 1, there are previous studies on this subject. In this table, only fruit and vegetable classification is focused on. Studies carried out for the food industry are not only about classification. There are also studies on various subjects such as sorting vegetables and fruits according to their quality, freshness control, and whether there is a disease in foods.

The automatic classification problem is one of the hot topics studied in many different areas in the literature [19,20]. The approach that is frequently used in this type of problem is deep learning and machine learning methods [21,22]. In this paper, automatic vegetable classification was investigated. In developed model for this purpose, deep feature extraction based on SqueezeNet [23,24], feature selection based on ReliefF [25] method and classification with LDA [26] method were performed. The main motivation of this study is to develop a high-performance, easy-to-use and easy-to-apply model on large datasets. For this purpose, a vegetable and fruit dataset consisting of 21000 and 980 images was used and the developed model was validated on these datasets. In addition, most of the methods developed in the literature use deep learning methods and the designed deep networks are trained end-to-end. In this study, deep network architectures are used as a feature extractor. Transfer learning approach is used for this process and a feature vector is obtained from each image. In the next phase of the model, the feature selection process is applied, and the most significant features are selected and the feature vector is reduced. In this way, it is aimed to reduce computational complexity. In the last phase of the model, the classification process was carried out with the LDA algorithm, which is a well-known and fast-running method in the literature. Some contributions of the proposed method in this study are given below:

- Deep learning approaches are very popular in the literature. Pre-trained deep networks and custom designs are frequently used, especially in image-related fields. Although these approaches produce successful results, they are methods with high computational complexity. In particular, end-to-end training of a deep network architecture consumes a lot of time. In this study, contrary to the literature, pre-trained deep network architectures were used as feature extractors. In this way, a new feature extractor with low computational complexity is provided.
- The proposed model in this study has been tested with a large dataset. Three different cases were created for the test process and all the images in the dataset were used in the test process. In addition, two different validation methods were used in the study. These are hold-out and k-fold cross validation, respectively. The model developed in both validation methods and datasets has achieved 99% and above accuracy. In terms of dataset size (class and number of images), the proposed method produced quite good results compared to the literature.

The remainder of the paper is organized as follows. In the second section, the used datasets to test the developed model are examined. In the third section of the study, the details of the model developed for automatic vegetable and fruit classification are shared. In the fourth section, the obtained results from the proposed method are given. In the fifth and final section, conclusions and future works are given.

2. Material

Two data sets (DB1 and DB2) were used to test the developed model. Details of these datasets are given in the subsection.

2.1. First Dataset (DB1)

In this paper, a new deep learning-based vegetable classification model was developed. In the model developed, an open access dataset was used and this dataset consists of 21,000 images [14,27]. In addition, the dataset contains 1400 images of 15 different vegetable species in total. Some information about the dataset is presented in Table 2.

Table 2. Detailed features of DB1

Features	Values
Number of classes	15
Class names	Bean, Bitter Gourd, Bottle Gourd, Brinjal, Broccoli, Cabbage, Capsicum, Carrot, Cauliflower, Cucumber, Papaya, Potato, Pumpkin, Radish, Tomato
Total number of images	21,000
Number of images in each class	1400
Image type	JPG
Images of size	224x224

This dataset, which is shared as open access, is divided into three as training, testing and validation. The training group contains 15,000 images, the test group contains 3,000 images, and the validation group contains 3,000 images. In this paper, the developed model was tested in two different ways. In the first test phase, all of these groups were combined and classified using the hold-out validation technique. In the second test phase of the developed model, 10-fold cross validation was applied to the test and validation groups, separately. Some sample images used in the testing phase of the study are shown in Figure 1.

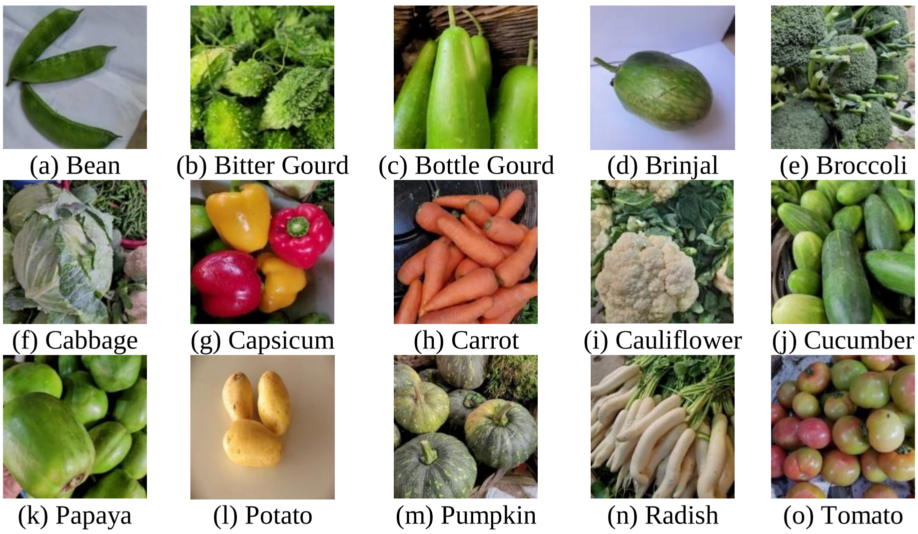


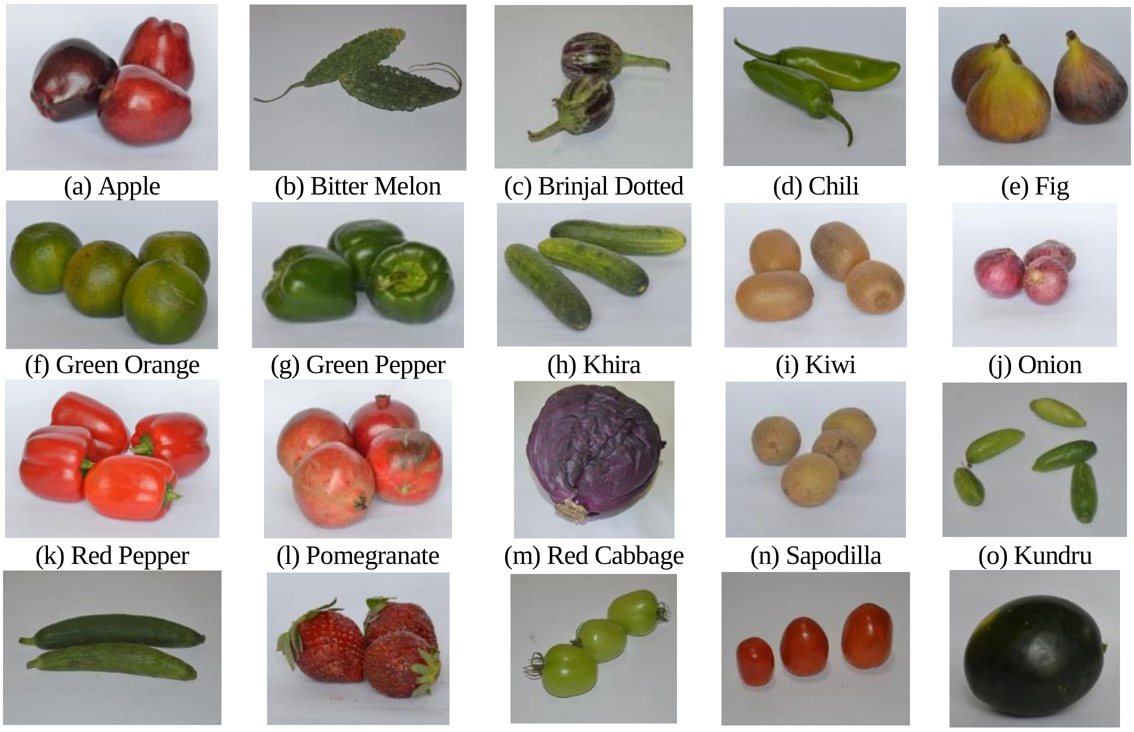
Figure 1. Vegetable images in the DB1

2.2. Second Dataset (DB2)

Another dataset used in the study is named DB2 [28]. This dataset contains various vegetable and fruit images belonging to 20 classes. There are a total of 980 images in the DB2 and available as open access. Details of this dataset are presented in Table 3. Since DB2's data size is small, only 10-fold cross validation technique is used on this dataset in testing phase. Some sample images from this dataset used in the test phase are given in Figure 2.

Table 3. Detailed features of DB2

Features	Values
Number of classes	20
Class names	Apple, Bitter Melon, Brinjal Dotted, Chili, Fig, Green Orange, Green Pepper, Khira, Kiwi, Onion, Red Pepper, Pomegranate, Red Cabbage, Sapodilla, Kundru, Sponge Gourd, Strawberry, Green Tomato, Red Tomato, Watermelon
Total number of images	980
Number of images in each class	50 (Only green orange is 30)
Image type	JPG
Images of size	Various sizes



(a) Apple (b) Bitter Melon (c) Brinjal Dotted (d) Chili (e) Fig
(f) Green Orange (g) Green Pepper (h) Khira (i) Kiwi (j) Onion
(k) Red Pepper (l) Pomegranate (m) Red Cabbage (n) Sapodilla (o) Kundru
(p) Sponge Gourd (r) Strawberry (s) Green Tomato (t) Red Tomato (u) Watermelon

Figure 2. Vegetable and fruit images in the DB2

3. Automatic Vegetable Classification Model based on SqueezeNet

In this study, a deep learning-based automatic vegetable classification model was developed. The developed model basically consists of 3 steps. These steps are feature extraction, feature selection and classification, respectively. In the first step of the developed model, features were extracted from the images using the pre-trained SqueezeNet deep network architecture. In the second phase of the model, the most significant features were selected using the ReliefF approach. In the classification phase of the application, the LDA method was used. The steps of the developed model are shared in the subsections. In addition, the flowchart of the proposed method is presented in Figure 3.

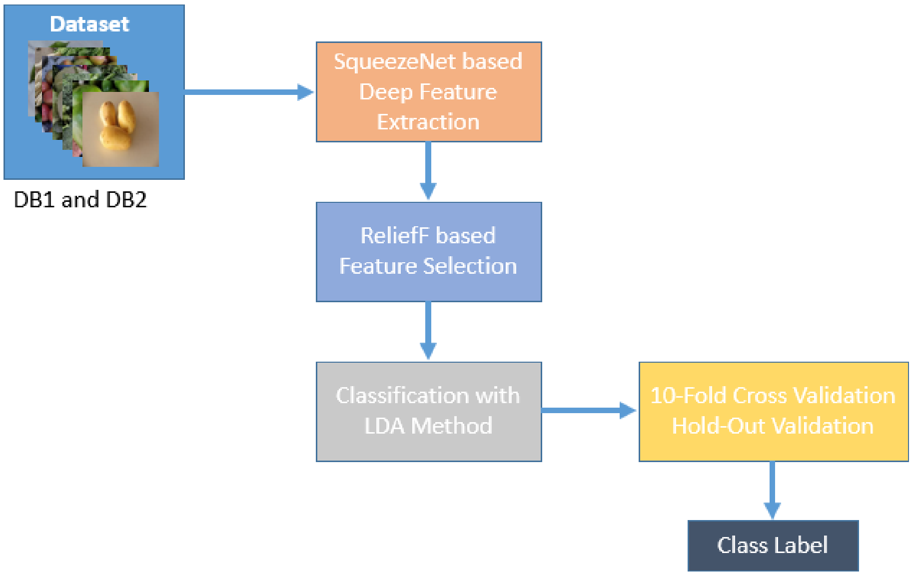


Figure 3. Flowchart of the proposed method

3.1. Deep Feature Extraction with SqueezeNet

In the developed model, feature extraction was carried out with the transfer learning approach. For this purpose, the pre-trained SqueezeNet deep learning model was used and a feature matrix was obtained using this model. For this process, the "GlobalAveragePooling" layer of the SqueezeNet architecture was used, and 1000 features were obtained for each image from this layer. With this approach, features are acquired without the need for retraining the network. A block diagram summarizing the feature extraction step of the developed model is given in Figure 4.

Step 1: Extract deep feature from vegetable images using SqueezeNet architecture

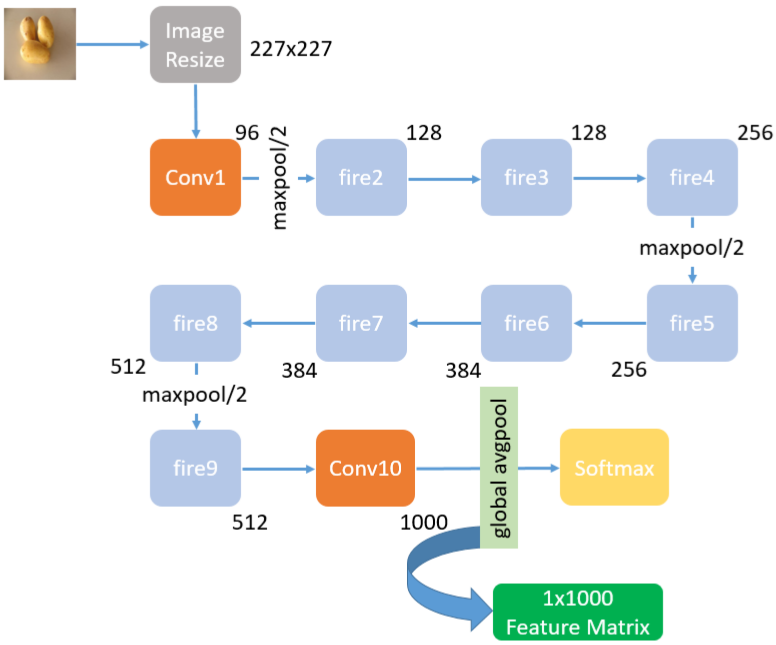


Figure 4. Feature extraction with SqueezeNet architecture

3.2. Feature Selection

The second step of the developed model is feature selection. Feature selection is an approach frequently used in machine learning methods. Thanks to this step, the performance of the classification process is increased by selecting the most meaningful features. In addition, as meaningless features are eliminated, computational complexity is reduced. ReliefF feature selection method is utilized in this step of the developed model. In this method, a weight value is calculated for each feature in the feature vector. Calculated weight values can be positive or negative. Positive weight value represents the most significant feature, while negative values represent meaningless features. For this reason, a threshold value was set in order to eliminate features with negative weight in the study and this threshold value was determined as 0.01. In other words, the features with a weight of 0.01 and above, which were calculated during the feature selection stage, were taken into account. A pseudocode for the ReliefF algorithm used in the developed model is given in Algorithm 1.

Step 2: Select feature with ReliefF algorithm using Algorithm 1

Algorithm 1. ReliefF algorithm based feature selection

```
Input: Feature vector (fv) with size of 1000 and labels (lbl)
Output: Selected features (sf) with the size of L

[idx,weights]=relieff(fv, lbl, 10);
count = 1;
for i=1 to 1000 do
    if weights(i) > 0.01
        sf (:,count) = fv (:,i);
        count = count + 1;
    end if
  i=i+1;
end for i
```

3.3. Classification

The last step of the automatic vegetable and fruit classification model implemented in this study is classification. LDA algorithm was utilized in the classification phase of the model. LDA algorithm is a very simple, fast and a classification method that produces good results. MATLAB Classification Learner Toolbox (MCLT) was used in the classification phase. In addition, hold-out and k-fold cross validation methods were used as validation techniques for DB1. In the hold-out validation technique, the train/test ratio was determined as 80:20. In the k-fold cross validation method, the k value was determined as 10. In the test process for DB2, only the 10-fold cross validation technique was applied.

Step 3: Classify selected features using the LDA method

4. Performance Analysis

In this study, an automated deep learning approach is developed to distinguish vegetables and fruits. The developed model uses the SqueezeNet deep network architecture and extracts deep features with this network. In addition, the most significant features were selected using the ReliefF algorithm and these features were classified with the LDA algorithm. Hold-Out (80:20) and 10-fold cross validation methods were used to validate the developed model on DB1 and DB2. The model was coded on the MATLAB 2021b platform and features were classified using MCLT. The features of the computer used in the development and testing phases of the model are given in Table 4.

Table 4. PC features used in the study

Features	Values
CPU	Intel Xeon 2.70GHz
RAM	256 GB
Harddisk	512 GB SSD
Operating System	Windows Server 2019
Platform	Matlab 2021b

4.1. Results

In this paper, the two open access vegetable and fruit dataset was used. The first dataset, DB1 contains 21,000 images of 15 different species. This dataset is basically divided into three groups. These are training, testing and validation, respectively. Three different tests were performed on this dataset. First, all groups are combined and a single test set with 21000 images is obtained. The model developed for this group was tested with the hold-out (80:20) method. In the second test phase, the test set in the dataset was used and test process was carried out with 10-fold cross validation method. In the third test performed in the study, the validation set was used and the 10-fold cross validation method was preferred. Another dataset used in the study is DB2 and contains 980 images. This dataset has 20 classes. 10-fold cross validation technique has been applied for DB2. As a result of each test process, a confusion matrix was obtained and performance metrics were calculated using this matrix. These calculated metric values are accuracy, recall, precision and f-measure, respectively. The mathematical equivalent of these performance metric values are given in Equation (1)-(4) [29].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$F_{Measure} = \frac{2 * precision * recall}{precision + recall} \tag{4}$$

In this paper, three test cases for DB1 and one test case for DB2 were created. Detailed explanation of these tests and the results obtained from the test procedures are given in the subsections.

4.1.1. Case 1: Hold-Out (80:20) validation by using all images in DB1

Three different test procedures for DB1 were applied in the test phase of the developed model. The first of these tests was carried out using the hold-out (80:20) technique. In this test process, images divided into three groups (training, testing and validation) in the dataset were collected in a single group and all 21000 images were taken into account in the test process. In this test approach, 80:20 hold-out validation was utilized and the obtained confusion matrix is given in Figure 4. The calculated performance metric values are presented in Table 4.

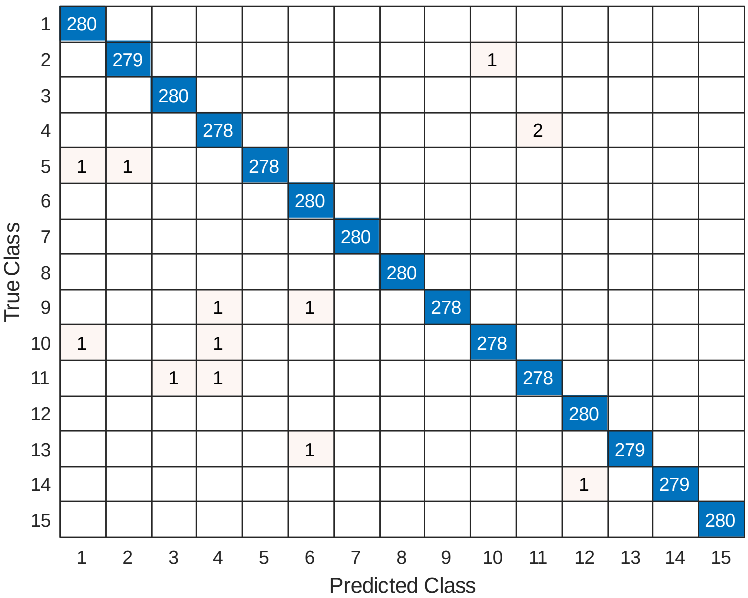


Figure 4. Confusion matrix for hold-out (80:20) validation on DB1

Table 4. Performance metric results for hold-out validation on DB1

Class No	Class Label	Recall	Precision	F-Measure	Avg. Accuracy
1	Bean	1	0.9929	0.9964	0.9969
2	Bitter Gourd	0.9964	0.9964	0.9964	
3	Bottle Gourd	1	0.9964	0.9982	
4	Brinjal	0.9929	0.9893	0.9911	
5	Broccoli	0.9929	1	0.9964	
6	Cabbage	1	0.9929	0.9964	
7	Capsicum	1	1	1	
8	Carrot	1	1	1	
9	Cauliflower	0.9929	1	0.9964	
10	Cucumber	0.9929	0.9964	0.9946	
11	Papaya	0.9929	0.9929	0.9929	
12	Potato	1	0.9964	0.9982	
13	Pumpkin	0.9964	1	0.9982	
14	Radish	0.9964	1	0.9982	
15	Tomato	1	1	1	
	Avg.	0.9969	0.9969	0.9969	

4.1.2. Case 2: 10-fold cross validation for "test" set in DB1 dataset

In the second test of the developed model, the test set in the dataset was used. The test set in the dataset contains 200 images for each label. This set consists of a total of 3000 images. In this test phase, 10-fold cross validation technique was utilized and obtained confusion matrix is given in Figure 5. The performance metric values calculated for this test process are shared in Table 5.

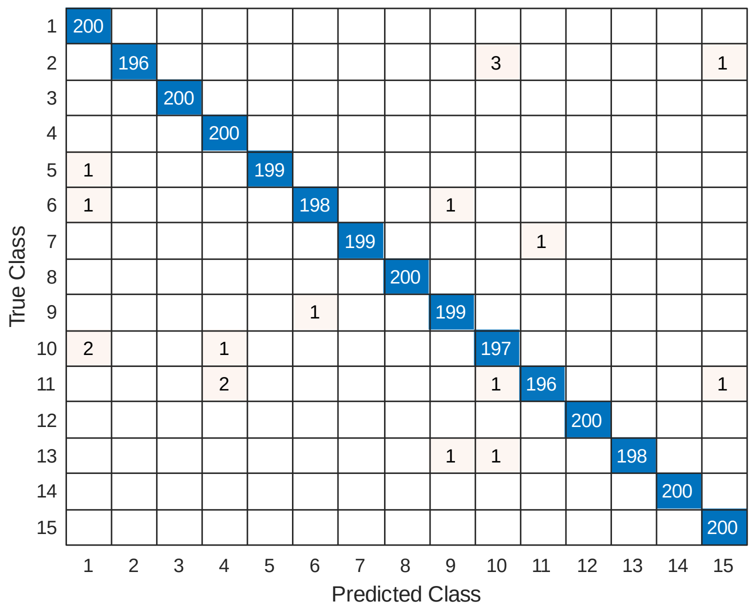


Figure 5. Confusion matrix for 10-fold cross validation (test set in DB1)

Table 5. Performance metric results for 10-fold cross validation (test set in DB1)

Class No	Class Label	Recall	Precision	F-Measure	Avg. Accuracy
1	Bean	1	0.9804	0.9901	0.9940
2	Bitter Gourd	0.9800	1	0.9899	
3	Bottle Gourd	1	1	1	
4	Brinjal	1	0.9852	0.9926	
5	Broccoli	0.9950	1	0.9975	
6	Cabbage	0.9900	0.9950	0.9925	
7	Capsicum	0.9950	1	0.9975	

8	Carrot	1	1	1	
9	Cauliflower	0.9950	0.9900	0.9925	
10	Cucumber	0.9850	0.9752	0.9801	
11	Papaya	0.9800	0.9949	0.9874	
12	Potato	1	1	1	
13	Pumpkin	0.9900	1	0.9950	
14	Radish	1	1	1	
15	Tomato	1	0.9901	0.9950	
	Avg.	0.9940	0.9941	0.9940	

4.1.3. Case 3: 10-fold cross validation for “validation” set in DB1 dataset

In the third test of the model, the validation set in the dataset was used. This group contains 200 images for each vegetable type and a total of 3000 images. As in Case 2, the 10-fold cross validation method was used in this test phase as well. The confusion matrix obtained as a result of test is given in Figure 6 and the performance metric values are given in Table 6.

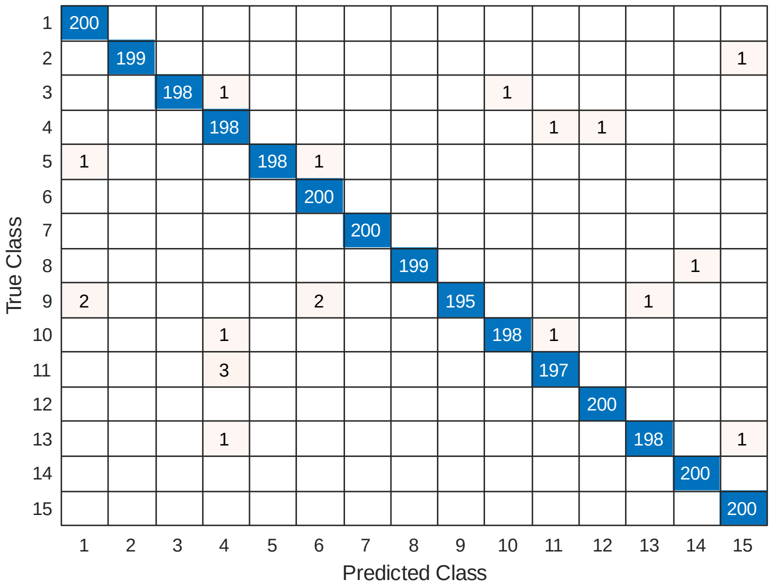


Figure 6. Confusion matrix for 10-fold cross validation (validation set in DB1)

Table 6. Performance metric results for 10-fold cross validation (validation set in DB1)

Class No	Class Label	Recall	Precision	F-Measure	Avg. Accuracy
1	Bean	1	0.9852	0.9926	0.9933
2	Bitter Gourd	0.9950	1	0.9975	
3	Bottle Gourd	0.9900	1	0.9950	
4	Brinjal	0.9900	0.9706	0.9802	
5	Broccoli	0.9900	1	0.9950	
6	Cabbage	1	0.9852	0.9926	
7	Capsicum	1	1	1	
8	Carrot	0.9950	1	0.9975	
9	Cauliflower	0.9750	1	0.9873	
10	Cucumber	0.9900	0.9950	0.9925	
11	Papaya	0.9850	0.9899	0.9875	
12	Potato	1	0.9950	0.9975	
13	Pumpkin	0.9900	0.9950	0.9925	
14	Radish	1	0.9950	0.9975	
15	Tomato	1	0.9901	0.9950	
	Avg.	0.9933	0.9934	0.9933	

4.2.1. Case 1: 10-fold cross validation for DB2 dataset

The developed model was validated using 2 different datasets. The second dataset used in the study is named DB2 and contains 980 images and 20 classes. Since the size of this dataset is small, validation was performed using the 10-fold cross validation technique. The confusion matrix obtained using this dataset is given in Figure 7. In addition, the calculated performance metric values using the confusion matrix are presented in Table 7.

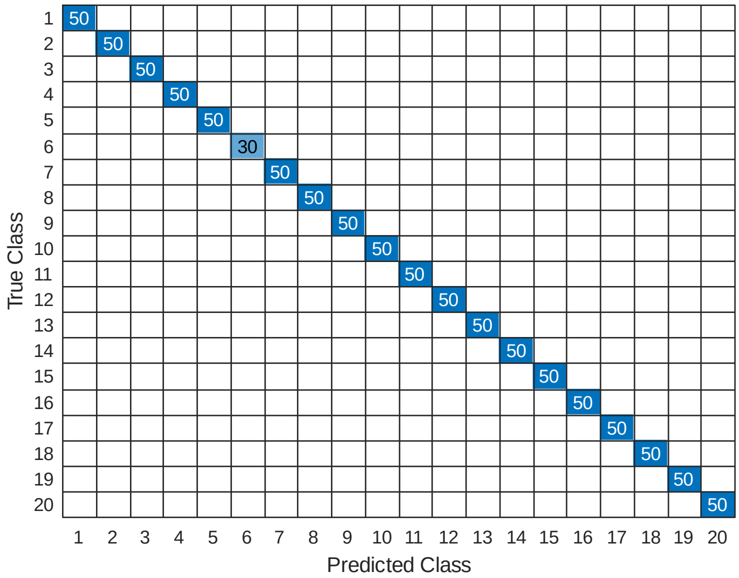


Figure 6. Confusion matrix for 10-fold cross validation (DB2)

Table 6. Performance metric results for 10-fold cross validation

Class No	Class Label	Recall	Precision	F-Measure	Avg. Accuracy
1	Apple	1	1	1	
2	Bitter Melon	1	1	1	
3	Brinjal Dotted	1	1	1	
4	Chili	1	1	1	
5	Fig	1	1	1	
6	Green Orange	1	1	1	
7	Green Pepper	1	1	1	
8	Khira	1	1	1	
9	Kiwi	1	1	1	
10	Onion	1	1	1	
11	Red Pepper	1	1	1	1
12	Pomegranate	1	1	1	
13	Red Cabbage	1	1	1	
14	Sapodilla	1	1	1	
15	Kundru	1	1	1	
16	Sponge Gourd	1	1	1	
17	Strawberry	1	1	1	
18	Green Tomato	1	1	1	
19	Red Tomato	1	1	1	
20	Watermelon	1	1	1	
	Avg.	1	1	1	

4. Discussion

Nowadays, computer-based automatic classification is actively used in many different fields. In this study, two different datasets were used for automatic classification of vegetables. In addition, a new machine learning model based on deep learning has been developed. In the first stage of the developed model, deep feature extraction was applied. At this stage, SqueezeNet architecture is used. Before choosing this architecture, other pre-trained deep network architectures were also tested on DB1. In the test process, the feature vector obtained from each deep network was tested with SVM and the highest accuracy was achieved with the SqueezeNet architecture. The tested other deep network architectures and the obtained accuracies are shown in Figure 7.

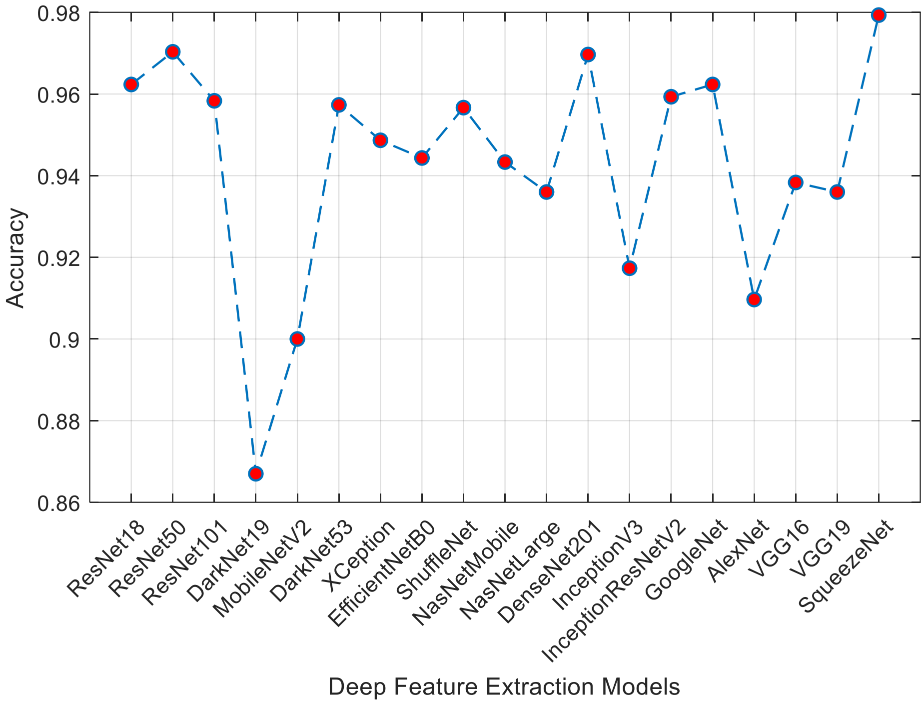


Figure 7. Performances of deep feature extractors

As can be seen from Figure 7, the best accuracy value was obtained with the SqueezeNet architecture. For this reason, this architecture was preferred in the study and the application was developed using this architecture. In addition, 5 different classification algorithms were tested to determine the best classifier in the developed model. These are Tree, LDA, Support Vector Machine (SVM), k-Nearest Neighbor (kNN) and Neural Network (NN), respectively. The accuracy values obtained using these methods are shown in Figure 8.

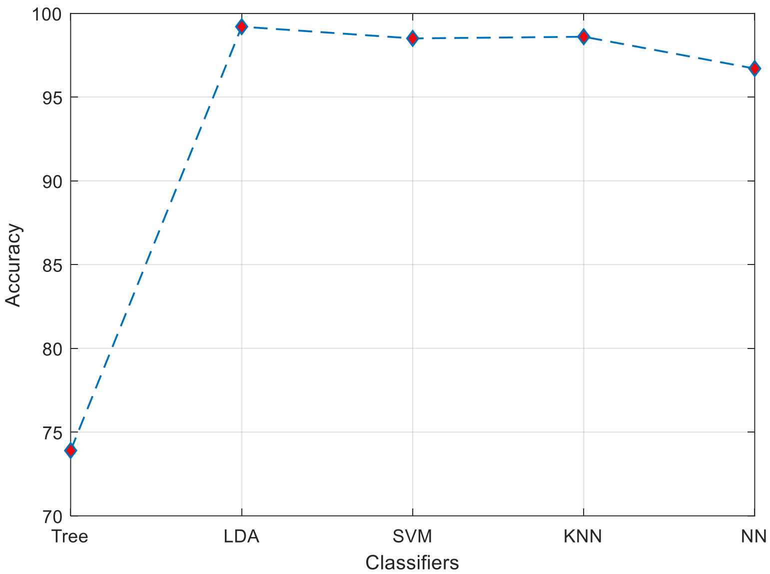


Figure 8. Performances of classifiers

As can be seen from Figure 8, the best accuracy was obtained with the LDA algorithm. After all the methods were determined in this way, the test phase of the developed model was started. Two different datasets were used in the test phase. These are DB1 and DB2 respectively. Two different validation techniques have been used for DB1, these methods are hold-out and 10-fold cross validation, respectively. Three cases have been created for DB1. In the first case, all images were used and validation was made with the hold-out method. In the second and third cases, test and validation sets were used, respectively, and classification was made with the 10-fold cross validation method. Accuracy of 99.69%, 99.4% and 99.33% was achieved for Case 1, Case 2 and Case 3, respectively. In addition, another dataset named DB2 was used in the study. In this dataset, classification was made with 10-fold cross validation method and 100% accuracy value was obtained. The obtained results reveal the success of the proposed method. A comparison of the studies performed for automatic vegetable and fruit classification is given in Table 7.

Table 7. Comparisons of state-of-the art on automatic vegetable and fruit classification

Author(s)	**Year**	**Method**	**Validation(s)**	**Result(s)**
M. I. Ahmed et. al. [14]	2021	Custom CNN	Hold-out (70:15:15)	Accuracy=97.5%
H. Kuang et. al. [16]	2018	Fused HOG, Local Binary Pattern (LBP), GaborLBP	5-fold cross validation	Accuracy=%98.5
Z. M. Khaing et. al. [30]	2018	Custom CNN	---	Accuracy=%94
M. S. Hossain et. al. [31]	2019	VGG-16 Fine tuning	Hold-out (85:15)	Accuracy=%99.75
S. Jana et. al. [32]	2020	Otsu threshold, fractal dimension calculation, gray-level co-occurrence matrix and Naïve bayes	---	Accuracy=%98.33
S. W. SideHabi et. al. [33]	2018	K-Means clustering, RGB and A features and artificial neural network	5-fold cross validation	Accuracy=%90
D. Hussain et. al. [34]	2022	Deep CNN	---	Accuracy=%96
R. S. Latha et. al. [13]	2021	Custom CNN	---	Accuracy=%98
L. Rajasekar and D. Sharmila [35]	2019	Color, shape and texture features, k-Nearest Neighbor	10-fold cross validation	Accuracy=%97.5
O. I. Alvarez-Canchila et. al. [36]	2020	Data augmentation, AlexNet based custom CNN	Hold-out (80:20)	Accuracy=%98.12
This study		Deep feature extraction (SqueezeNet), ReliefF and LDA	Case 1: Hold-Out (80:20) Case 2: 10-fold cross validation Case 3: 10-fold cross validation	DB1-Case 1: 21000 image
				Accuracy: 99.69 Recall: 99.69 Precision: 99.69 F-Measure: 99.69
				DB1-Case 2: 3000 image
				Accuracy: 99.40 Recall: 99.40 Precision: 99.41 F-Measure: 99.40
				DB1-Case 3: 3000 image
				Accuracy: 99.33 Recall: 99.33 Precision: 99.34 F-Measure: 99.33
			Case 1: 10-fold cross validation	DB2-Case 1: 980 image
				Accuracy: 100 Recall: 100 Precision: 100 F-Measure: 100

As given in Table 7, the proposed method produced better results than other studies in automatic fruit and vegetable classification. Studies carried out in the literature have been tested on different datasets. In many studies, the dataset was collected by the authors. In this study, two different datasets shared as open access were used. The developed model is easy to implement and has low computational complexity. In addition, the obtained accuracy value shows the usability of the proposed method. The developed model has been tested with two different validation techniques and datasets. The results obtained for all cases are over 99%, proving the performance of the developed model.

5. Conclusions

This study proposes a new deep feature extraction model for vegetable and fruit classification using vegetable images. In this paper, the performance of deep feature extraction in classifying vegetable images was investigated. For this purpose, different deep network architectures have been tested on the dataset. In addition, feature selection was made with the ReliefF algorithm and the selected features were classified by the LDA method. Two datasets were used in the study. DB1 contains 21000 images and 15 classes. In addition, DB2 includes 980 images and 20 classes. Three cases were created in the study for DB1 and tests were carried out on these cases. For DB1-Case 1, which has the largest data, 99.69% accuracy was achieved. When compared with the studies [14] using the same dataset in the literature, the proposed method has achieved a very high success rate. Another dataset used to verify the success of the proposed method, DB2, has reached 100% accuracy. The most important advantage of the proposed method is that it is simple, applicable and fast. In this study, deep features are obtained by using pre-trained networks instead of end-to-end training of deep network architecture. In addition to this approach, feature selection and classification methods, which are well known and frequently used in the literature, are used. Considering all these methods, the proposed approach in this study has very low computational complexity. In order for the proposed method to be used in real time, it should be tested on datasets with larger size and higher number of classes. This situation constitutes the limitation of the study.

The results show that the proposed method is very successful in automatic vegetable and fruit classification and produces satisfactory results. With future studies, it is planned to increase the number of classes and to achieve similar results in higher class numbers.

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