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U2-NET SEGMENTATION AND MULTI-LABEL CNN CLASSIFICATION OF WHEAT VARIETIES

[1,*] **Mustafa Şamil ARGUN**, [2] **Fuat TÜRK**, [3] **Zafer CİVELEK**

[1] *Selçuk University, Akşehir Engineering and Architecture Faculty, Food Engineering Department, Akşehir, Konya, TÜRKİYE*
[2] *Kırıkkale University, Engineering Faculty, Computer Engineering Department, Kırıkkale, TÜRKİYE*
[3] *Çankırı Karatekin University, Engineering Faculty, Electrical and Electronics Engineering Department, Çankırı, TÜRKİYE*
[1] msargun@selcuk.edu.tr, [2] fturk@kku.edu.tr, [3] zafercivelek@karatekin.edu.tr

Highlights

- The two-stage system has been successfully tested in wheat classification and this is a prelude to more staged systems.
- Wheats have been successfully classified according to both their vitreous/yellow berry status and their varieties.
- Experimental results showed that the accuracy for binary classification was 98.71% and the multi-label classification average accuracy was 89.5%.
- This proposed system can be successfully used in wheat trade and breeding studies to help experts.
- The proposed U2-Net architecture is an example that can be easily used in all grain groups, especially wheat images.

***Corresponding Author**: Mustafa Şamil ARGUN, msargun@selcuk.edu.tr

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[2] *Kırıkkale University, Engineering Faculty, Computer Engineering Department, Kırıkkale, TÜRKİYE*
[3] *Çankırı Karatekin University, Engineering Faculty, Electrical and Electronics Engineering Department, Çankırı, TÜRKİYE*
[1]msargun@selcuk.edu.tr, [2]fturk@kku.edu.tr, [3]zafercivelek@karatekin.edu.tr

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ABSTRACT: There are many varieties of wheat grown around the world. In addition, they have different physiological states such as vitreous and yellow berry. These reasons make it difficult to classify wheat by experts. In this study, a workflow was carried out for both segmentation of wheat according to its vitreous/yellow berry grain status and classification according to variety. Unlike previous studies, automatic segmentation of wheat images was carried out with the U2-NET architecture. Thus, roughness and shadows on the image are minimized. This increased the level of success in classification. The newly proposed CNN architecture is run in two stages. In the first stage, wheat was sorted as vitreous-yellow berry. In the second stage, these separated wheats were grouped by multi-label classification. Experimental results showed that the accuracy for binary classification was 98.71% and the multi-label classification average accuracy was 89.5%. The results showed that the proposed study has the potential to contribute to making the wheat classification process more reliable, effective, and objective by helping the experts.

Keywords: *Wheat Segmentation with U2-NET, U2-NET Architecture, Multi-Label CNN Classification, Wheat Classification*

1. INTRODUCTION

Wheat ranks second after corn with a production of around 780 million tons worldwide [1]. A large number of wheat varieties are produced in the world. Feldman [2] reports that there are 25,000 different forms of cultivated bread wheat worldwide and the total number available is likely to be at least twice this estimate [3]. In Türkiye alone, there are hundreds of local wheat varieties and as of 2016, there are 198 registered varieties for bread and 61 for durum [4]. In the buying and selling transactions of wheat, which has so many varieties, only the experts make a wheat classification. Of course, such a classification can be subjective and there is a possibility of personal errors.

Yellow berry is a physiological condition that affects the quality and commercialization of wheat. In the grain, this situation is characterized by starchy or floury spots [5, 6]. It is stated that yellow berry grains have higher moisture and lower protein content compared to vitreous grains. [7]. Presence of yellow berry grains in durum and bread wheat is an important factor in terms of pasta cooking quality, grinding and baking quality [8]. Compared to non- vitreous grains, vitreous grains generally have better cooking quality, better pasta color, coarser granulation, higher protein content, higher hardness, and are sold at a higher price [9, 10]. For these reasons, it is important to detect the yellow berry grains in bread and durum wheat.

U2-NET is an architecture used in image processing. This architecture is a deep learning network used to obtain high quality and accurately parsed images. U2-NET is designed for salient object detection. The U2-NET architecture is specifically optimized for parsing high resolution images. U2-NET, unlike previous U-NET architectures, has more depth and expansion paths. It also has a dual-output architecture, meaning the same network is used to obtain detailed and extended outputs [11, 12].

***Corresponding Author**: Mustafa Şamil ARGUN, msargun@selcuk.edu.tr

Classification processes are carried out successfully in agriculture with artificial intelligence models. Classical CNN models from artificial intelligence models, architectures such as DenseNet, NasNet Mobile, VGG16, VGG19 are widely used in classification problems [13, 14]. In the literature, applications such as the recognition of plant diseases [15], classification and grading of fruits [16, 17], classification of flowers [18], classification of hazelnut varieties [19], classification of green coffee beans [20], classification of cherry varieties [21], classification of lemons [22], weed detection in wheat fields [23], image-based quality analysis of strawberries [24], detection of impurities in wheat [25] and image-based wheat grain classification using CNN [26] have been carried out successfully. Shen et al. [25] using terahertz spectral imaging and CNN, classified straw from impurities in wheat with 96-97% precision, weed with 95-96% precision, wheat leaf with 96-98% precision, wheat grain with 97-99% precision, ladybug with 97-98% precision, and wheat husk with 95-97% precision. Lingwal et al. [26] classified 15 different wheat varieties with 98% accuracy with their proposed model based on CNN. In their studies, they stated that the image resolution over 256*256 reduces the system performance. Yasar [27] classified 5 varieties of wheat using Inception-V3, Mobilenet-V2 and Resnet18 CNN models with an accuracy of 97.37%, 97.07% and 97.67%, respectively.

In the literature, no study has been found in which wheat grains are distinguished according to both vitreous/yellow berry grain status and cultivar differences. In our study, it is aimed to create a two-stage CNN architecture that will classify wheat according to both variety and vitreous/yellow berry grain status. Thus, a reliable, effective, and objective system will be obtained to assist experts in wheat classification.

2. MATERIAL AND METHODS

2.1. Dataset Description

In our study, the varieties of Bayraktar 2000, Bezostaja-1, Delabrad, Ekiz, Esperia, Lucilla, Odeska, Rumeli and Selimiye, which are the most produced bread wheats in Konya Akşehir region, and the durum wheat variety Kızıltan were used (Figure 1). Wheats were obtained from Turkish Grain Board in Akşehir (Konya/Türkiye). The collected wheat images were first positioned in 224*224 dimensions and with the objects in the center. At this stage, the images were first cropped and then the resize process was applied. Then, blurring and sharpening errors in existing images were minimized. Finally, the Contrast, Brightness and Color parameters of the images were arranged with the image enhance class, and the image preprocessing steps were completed. At these stages, the PILLOW library in the Python programming language was used. Some examples of original and image preprocessing of images are shown in Figure 1.

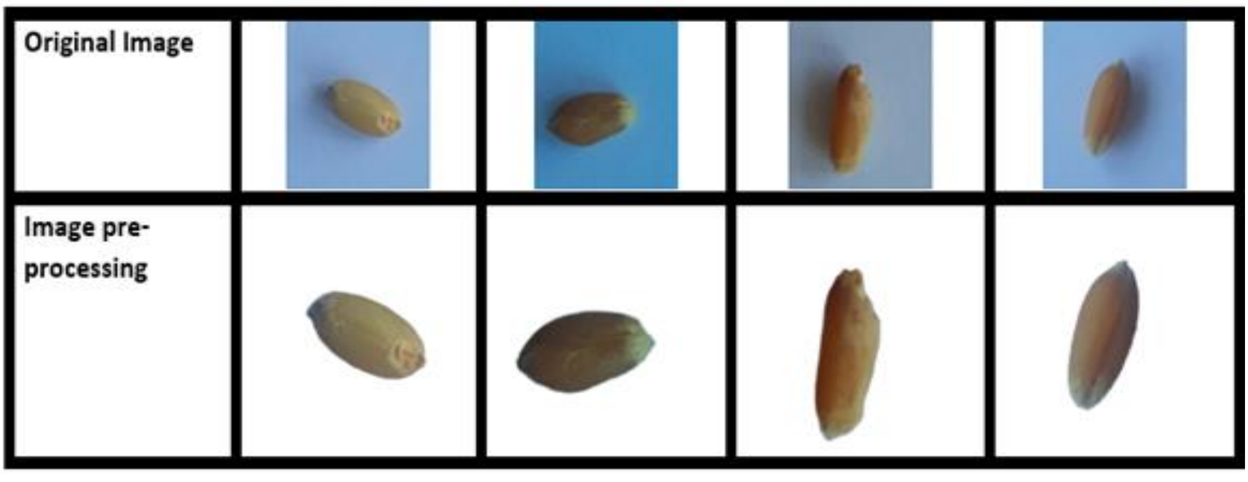

Figure 1. Vitreous and yellow berry grain images of the wheat varieties used and the first image processing stage.

2.2. U2-Net Architecture with Wheat Segmentation

The U2-Net model was proposed by Qin and its structure is shown in Figure 2 [27]. In this study, the U2-Net architecture was arranged for a clear detection of wheat images. In addition, the U2-Net architecture can analyze the curves of the image edges better than a classical segmentation. In this way, the separation of wheat varieties will be more successful. In general, U2-Net model consists of a total of 11 layers including encoder and decoder.

This study, sigmoid function was used in the merging phase, and Adam optimizer was prefered in the other layers. In the proposed U2-Net architecture, batch-size: 4, mask-size: 600, threshold:140, trimap-dilation:4 and trimap-erosion-iters are set to :10 for segmentation. These hyperparameters given are the result of the training process until the best results are obtained. The values given in the tables are an average of 10-fold cross validation. Figure 3 shows the wheat images obtained as a result of the U2-Net segmentation process.

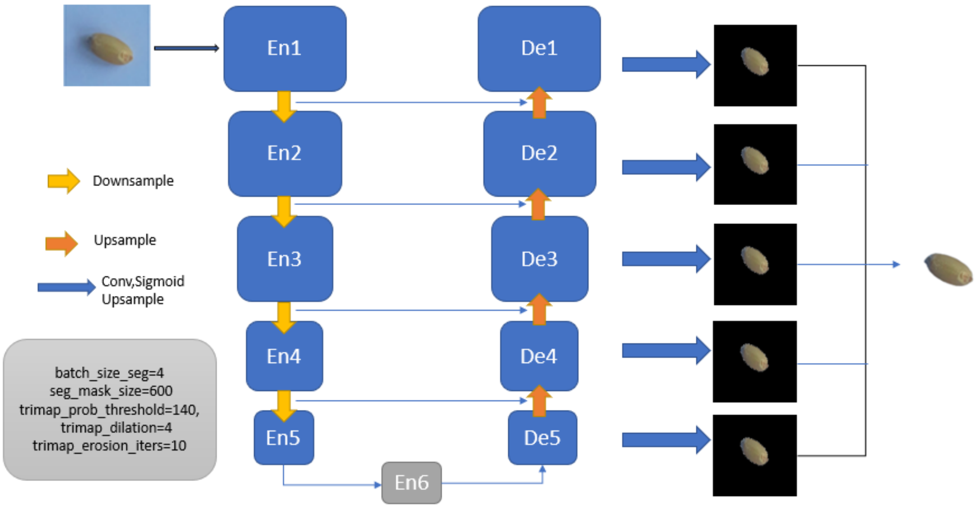

Figure 2. Proposed U2-Net architecture.

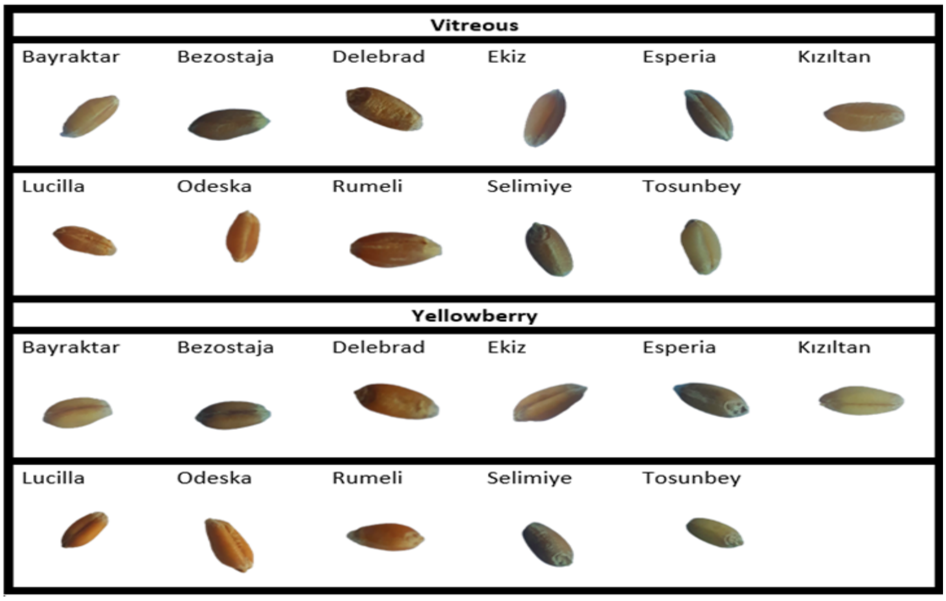

Figure 3. Images of wheat after U2-Net segmentation

While the images are being pre-processed, 196 images collected from each of the vitreous and yellow berry groups in the first place have been increased to a total of 1160 pieces, with the number of each subclass being equal, with the data augmentation process (Table 1). Finally, the train, validation, and test processes were randomly divided into 80%, 10%, and 10%, respectively. Figure 4 shows the train, validation, and test stages for the data set. Here, it is aimed to increase the accuracy of the training process with the cross-validation application. In order to evaluate the model success more effectively and to measure the accuracy of the results they gave; it was preferred to use the cross-validation technique. Thus, it is aimed to increase the success of the test data. The values given in the tables are an average of 10-fold cross validation.

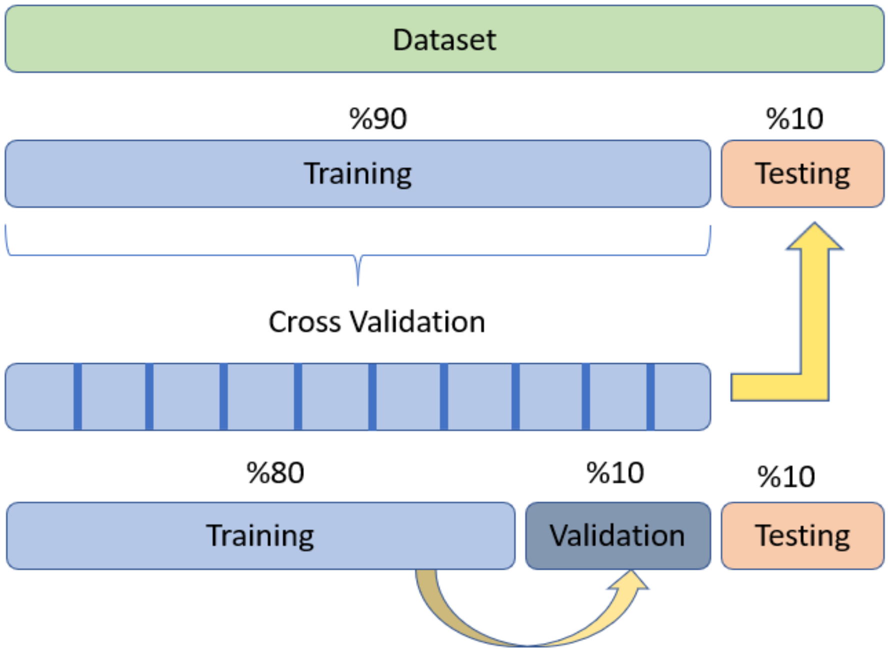

Figure 4. The train, validation, and test stages for the data set

In Table 1, the number of images obtained because of data augmentation is given. During data augmentation, the images were rotated by 45 degrees angles, but no shift (left/right) operation was applied. During the data augmentation phase, the zoom range ratio was set to 0.25. While rotation was applied on the horizontal axis, rotation on the vertical axis was not preferred.

Table 1. Total number of images before and after data augmentation

	Vitreous image	Yellow berry image
Total image	196	196
Total image after data augmentation	1160	1160
Train/Val/Test image	928/116/116	928/116/116

2.3. Proposed CNN Architecture

In the proposed CNN architecture, the input image size is set to 224×224 and then it is aimed to determine the features of the images in the feature extraction stage. At this stage, 4 convolutional layers were used in CNN architecture. The image was scanned with a 3×3 filter around the image. In the decoder phase, max pooling layer, ReLU as activation function and Adam optimizer as optimization method were chosen. At the binary classification stage, the vitreous/yellow berry separation of wheat was made. A multi classification pipeline was then executed with the same subclass names. The proposed CNN model is shown in Figure 5.

The tensorflow 2.0 library was used during the training of the CNN network. In addition, the training and testing processes of the proposed architectural structure were carried out with Nvidia GTX 1060 graphics card.

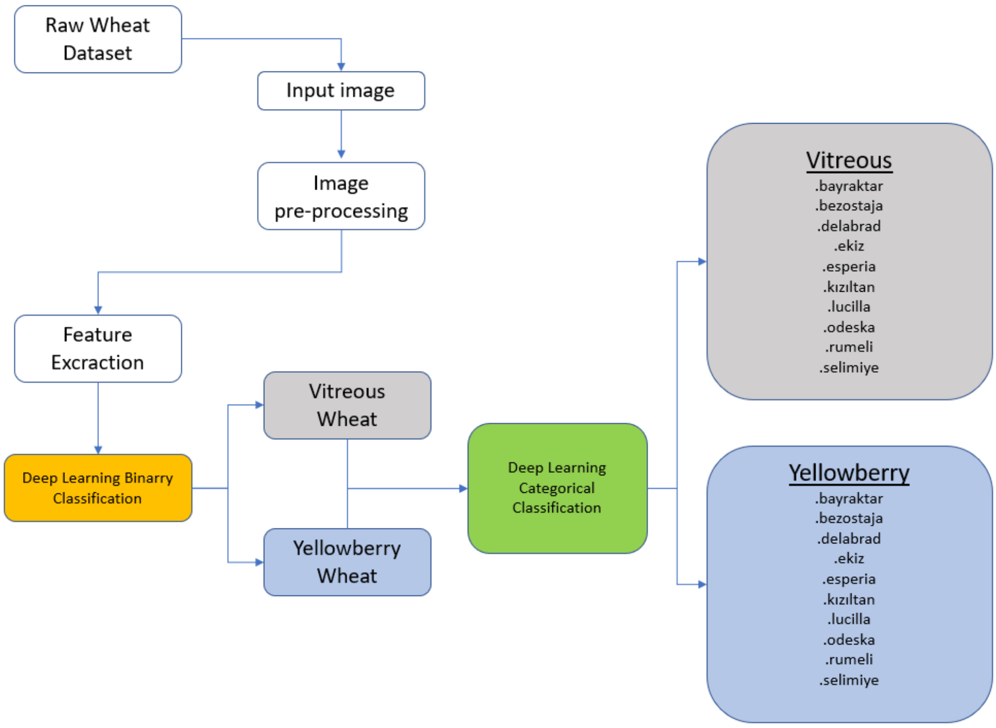

Figure 5. Proposed CNN architecture.

The artificial intelligence model used in our study was designed in two stages and operated differently from previous wheat classification studies. Accordingly, in the first stage, a binary classification output system was implemented that detects the vitreous/yellow berry state of the wheat images. In the second stage, the vitreous/yellow berry labeled data were determined by the multi-label classification output system. Even though the architectural structures used are similar to previous studies, there are differences in terms of choices such as the selection of hyperparameters, the use of activation functions, and filter sizes.

2.4. Performance Evaluation Criteria

Precision, Recall, Accuracy, and F1 score are the main criteria for evaluating the performance of classification algorithms. Precision refers to how many of the values predicted as Positive actually turn out to be Positive. Recall shows how many of the transactions that should have been predicted as Positive were predicted as Positive. Accuracy value is calculated by the ratio of the areas we predict correctly in the model to the total data set. The F1 Score value shows the harmonic mean of the Precision and Recall values. True Positive and True Negative are areas that the model predicts correctly, while False Positive and False Negative are areas that the model predicts incorrectly [13, 28].

The calculations of these metrics were made with the following Equations, respectively;

$$Accuracy = (TN + TP)/(TP + FP + TN + FN) \quad (1)$$

$$Precision = TP \ / \ (TP + FP) \quad (2)$$

$$\text{Recall} = TP/(TP + FN) \quad (3)$$

$$F1 - Score = 2 \times (Recall \times Precision) \ / \ (Recall + Precision) \quad (4)$$

3. RESULTS AND DISCUSSION

3.1. Binary Classification

In the first stage, the accuracy and loss values obtained as a result of the training process are shown in Figure 6. In Figure 6, the vertical axes correspond to the accuracy and loss values for train/validation operations, while the horizontal axes represent the number of epochs. When the graph is examined in detail, it is observed that the train and validation curves are close to each other. This showed us that the training was successful, and that there was no overfitting or memorization. In addition, the training and test results were found to be very close to each other.

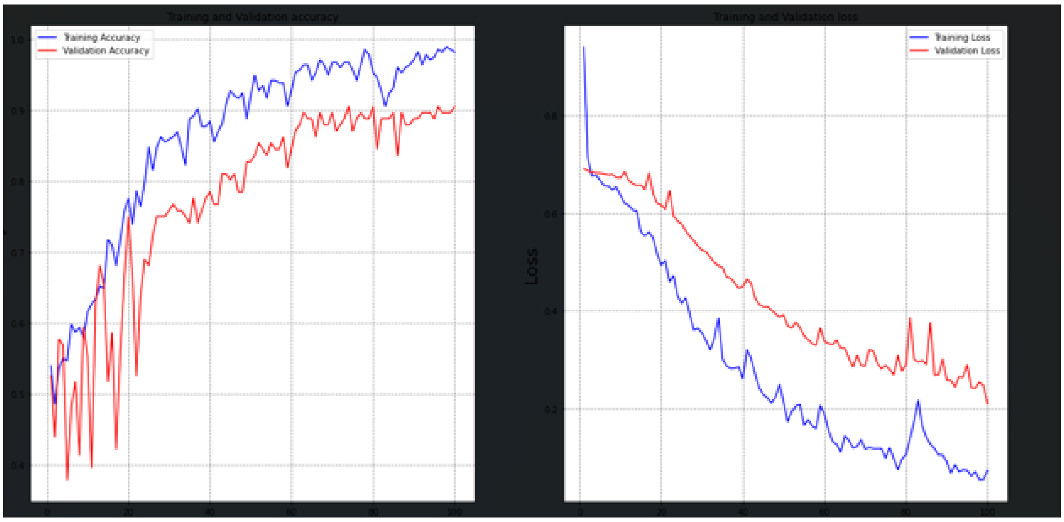

Figure 6. Train/validation accuracy/loss graph for binary classification

The confusion matrix graph calculated because of the test process in determining the vitreous and yellow berry classes is shown in Figure 7. Here, only 2 of the vitreous class and 1 of the yellow berry class were mislabeled, and the average accuracy was calculated as 98.71%.

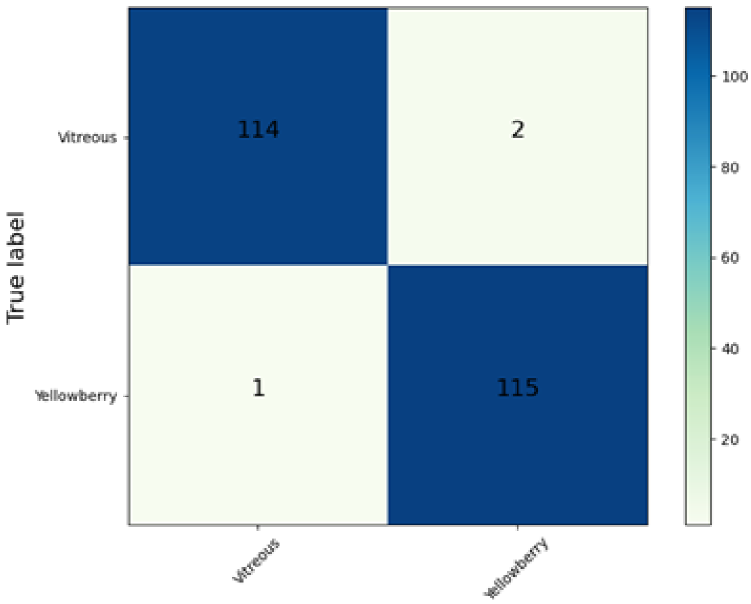

Figure 7. Confusion matrix graph for vitreous and yellow berry classes

The calculated performance metrics of the vitreous/yellow berry groups as the last step of the first phase are shown in Table 2. Looking at the confusion matrix in Figure 7, the accuracy for the vitreous class was calculated as 98.28% and the accuracy for the yellow berry class was calculated as 99.14%.

Table 2. Performance metrics of vitreous/ yellow berry groups

n(classified)	Accuracy(%)	Precision(%)	Recall(%)	F1-Score(%)
Vitreous:116	98.28	99.13	98.28	98.71
Yellow berry:116	99.14	98.29	99.14	98.71
Avg. Acc.	98.71			

3.2. Multi-Label Group Classification

In the Yellow berry/Vitreous group training, after the incorrectly labeled data was detected in the binary classification phase and transferred to the correct groups, the training process was started.

3.2.1. Yellow berry group class

The second stage was run separately for yellow berry and vitreous classes. The accuracy and loss values obtained because of the multi-class training process for the yellow berry class are given in Figure 8. Unlike the first stage, it is an acceptable situation that the validation/loss curves show a fluctuating state in the initial stage but are compatible with the train curve in the advancing epochs. Towards the end of the training, the curves again converged and there were no overfitting events or non-learning cases in the network.

Table 3. Yellow berry group multi-label classification evaluation results

Group No	Wheat variety	Precision (%)	Recall (%)	F1-Score (%)	Support (%)
0	Bayraktar2000	100	100	100	14
1	Bezostaja1	100	86.03	92.21	14
2	Delabrad2	80.13	86.34	83.34	14
3	Ekiz	100	100	100	14
4	Esperia	60.21	86.26	71.44	14
5	Kızıltan	100	100	100	14
6	Lucilla	100	100	100	14
7	Odeska	100	100	100	14
8	Rumeli	85.08	79.27	81.47	14
9	Selimiye	64.11	50.11	56.15	14
10	Tosunbey	100	93.28	96.37	14
	Accuracy (avg): 88.96%				154

The evaluation results of the yellow berry group are shown in Table 3 together with the class label names. Although some images were confused in Selimiye yellow berry classes due to its close resemblance to Esperia yellow berry, other class evaluation criteria were found to be quite good.

The confusion matrix graph calculated because of the yellow berry multi-class test process is shown in Figure 9. When the confusion matrix table is examined, it is observed that there is an acceptable level of mislabeling in a few classes where the test process was successful for most classes. In addition, we can say that performance metrics and average accuracy are very successful for a group of 11 classes.

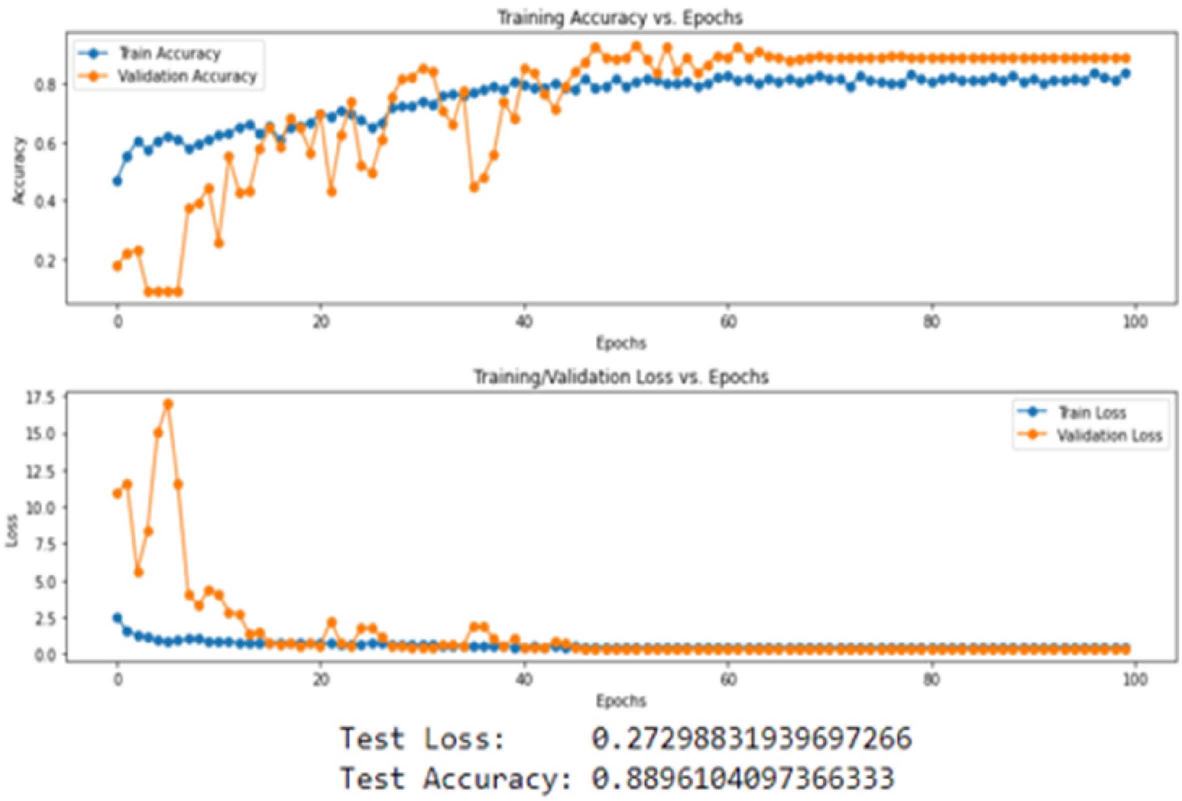

Figure 8. Train/validation accuracy/loss graph for yellow berry group multi-label classification

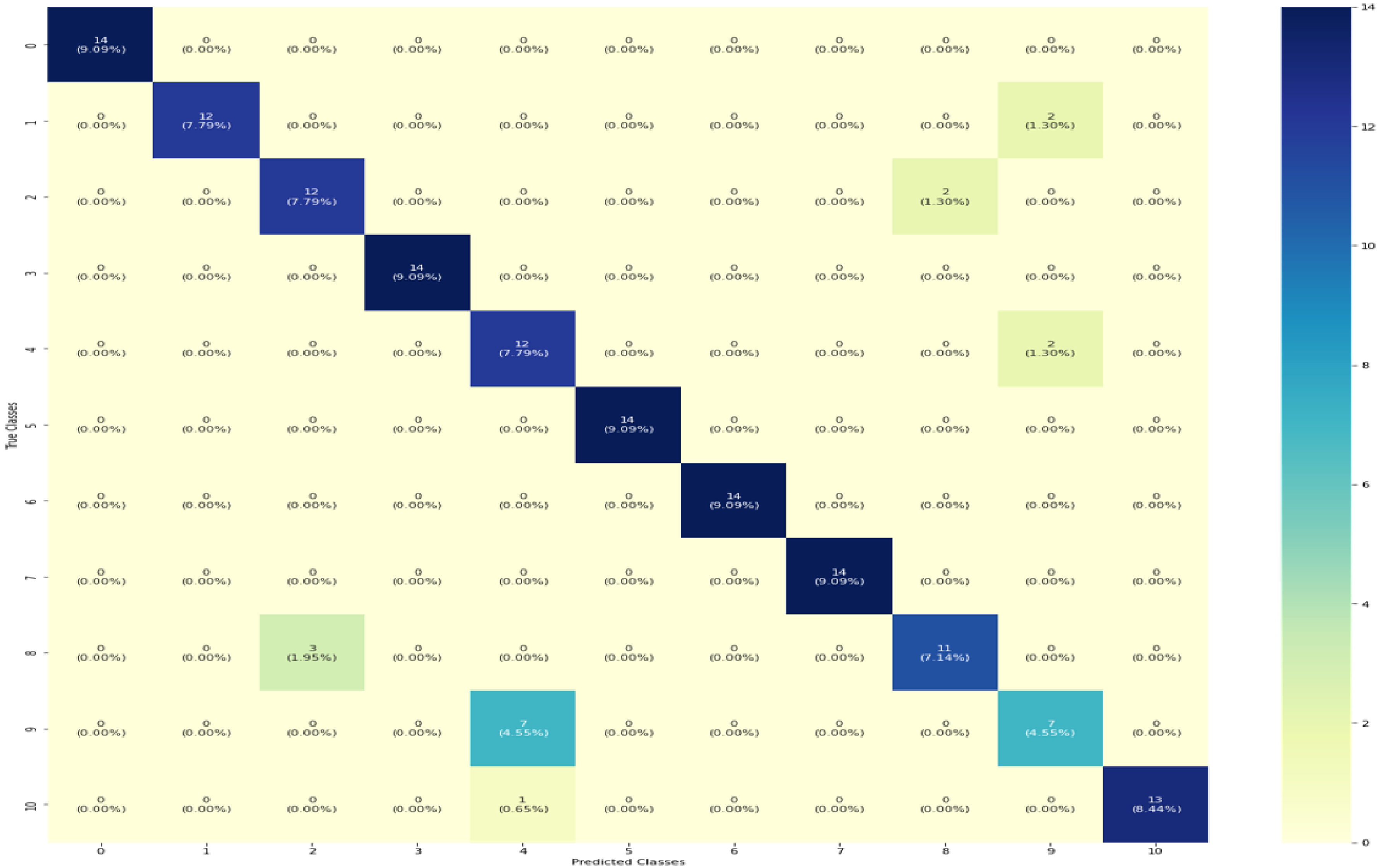

Figure 9. Yellow berry group confusion matrix and evaluation metric

3.2.2. Vitreous class

The accuracy and loss values obtained because of the multi-class training process for the vitreous class are given in Figure 10. It is an acceptable situation that validation/loss curves show a fluctuating state in the initial phase but are compatible with the train curve in the advancing epochs, as in the yellow berry multi-class. As a result of the training, yellow berry was slightly more successful than the classes and no over fitting was observed.

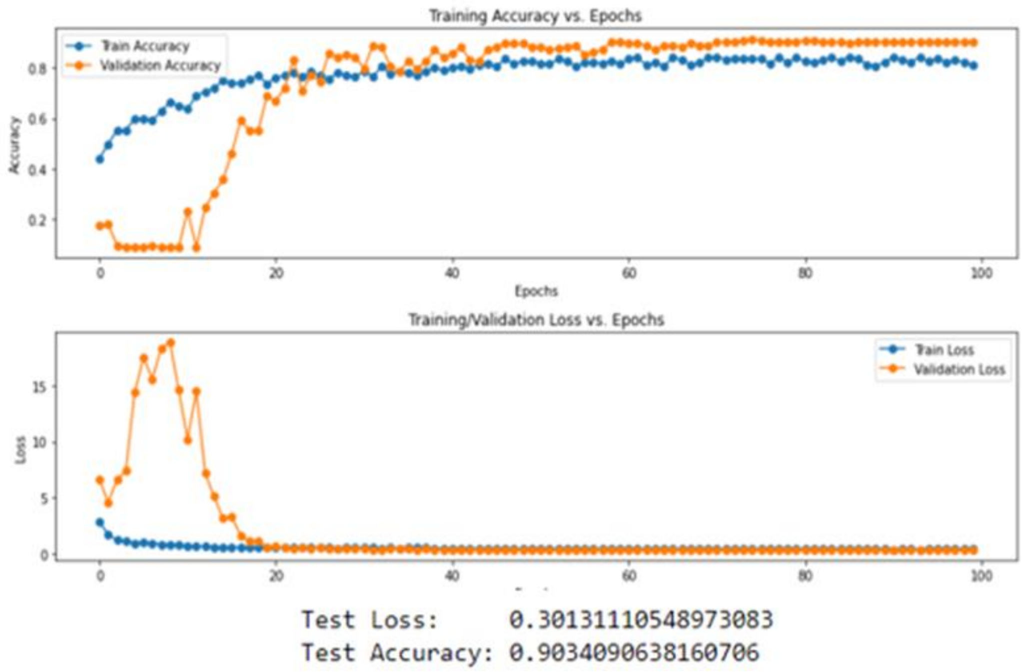

Figure 10. Train/validation accuracy/loss graph for vitreous group multi-label classification

The evaluation results of the vitreous group are shown in Table 4 together with the class label names. As in the yellow berry group, although the Selimiye and Esperia classes were somewhat confused due to their close similarity, the other class evaluation criteria were determined at a very good level.

Table 4. For vitreous group multi-label classification evaluation results

Group No	**Wheat variety**	**Precision** (%)	**Recall** (%)	**F1-Score** (%)	**Support**
0	Bayraktar2000	100	100	100	16
1	Bezostaja1	100	69.17	81.03	16
2	Delabrad2	100	100	100	16
3	Ekiz	100	100	100	16
4	Esperia	73.27	100	84.14	16
5	Kızıltan	100	100	100	16
6	Lucilla	76.05	94.33	84.41	17
7	Odeska	92.16	71.07	80.00	17
8	Rumeli	100	100	100	17
9	Selimiye	67.32	62.21	65.23	16
10	Tosunbey	100	100	100	13
		Accuracy (avg): 90.34%			176

The confusion matrix graph calculated because of the vitreous multi-class test process is shown in Figure 11. When the confusion matrix table is examined, it can be easily said that the test process was successful, as in the yellow berry group. Performance metrics were calculated slightly higher than the yellow berry group.

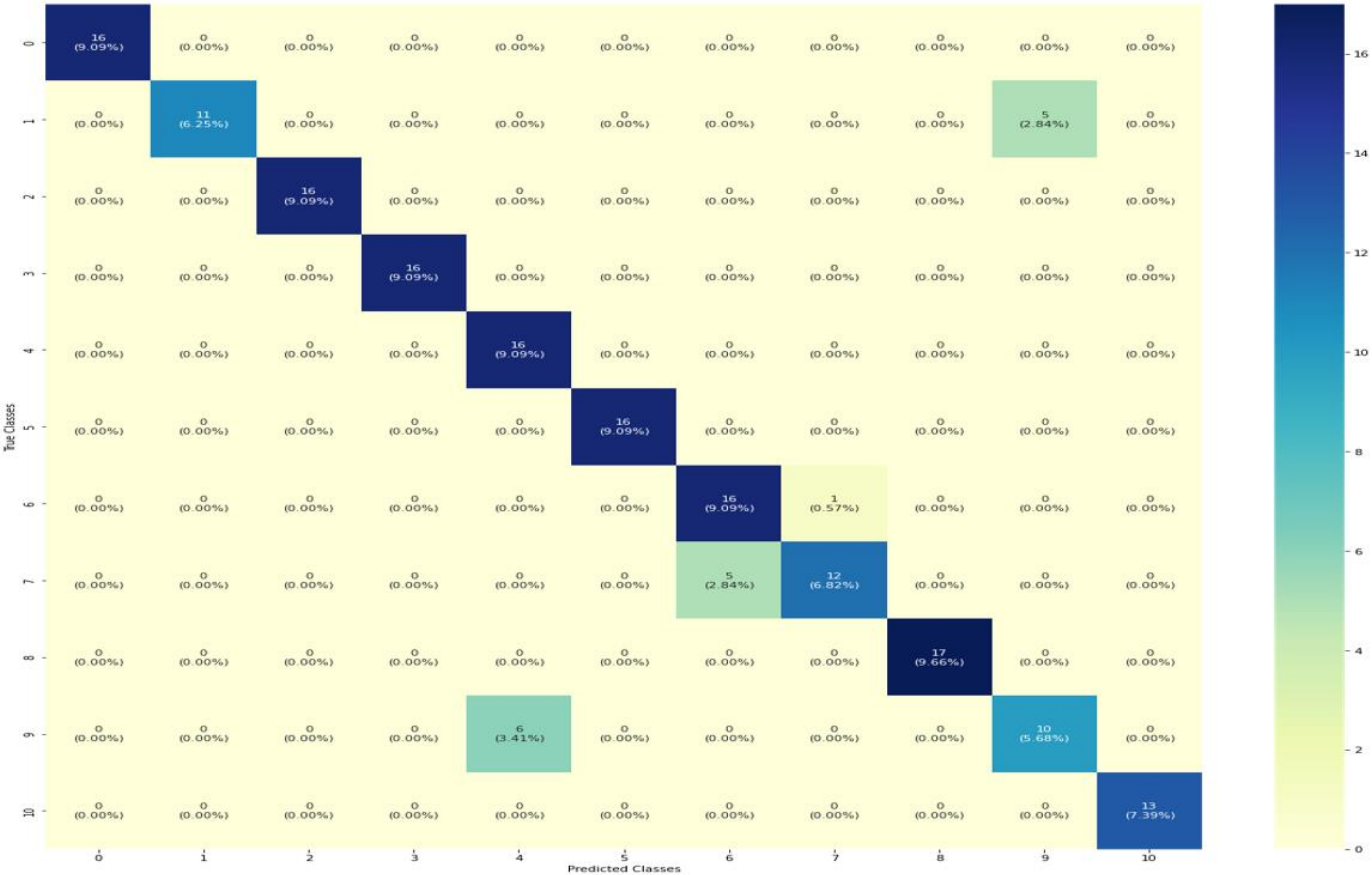

Figure 11. Vitreous group confusion matrix graph

Some results in which our proposed model mislabeled the vitreous and yellow berry groups in the test process are shown in Figure12. Looking at the results, we can say that this error is acceptable due to the close similarities between the images.

Figure 12. Mislabeled Vitreous/Yellow berry group image samples

As in our study, a two-stage classification was not found in the literature. When compared with other studies (Table 5), we can say that our results are in a reliable range, because the image classes used in our study are different and the margin of error may be slightly higher especially in multiple classes. An accuracy value of 98.71% was achieved in the separation into 2 different groups as Vitreous/Yellow berry class. Then, the images separated into vitreous and yellow berry were classified for the 11 wheat varieties mentioned in the study. Thus, it was possible to classify a total of 22 different classes of images and the accuracy value was calculated as 89.5%.

Considering the number of images in the data set, we can say that our study was quite successful.

Table 5. Comparison of techniques used for food classification.

Varieties	Number of classes	Number of images	Classification techniques	Accuracy (%)	References
Wheat	15	15000	CNN	98	[26]
Wheat	2	200	ANN	99.9	[29]
Rice	30	1500	Sparse-representation-based classification (SRC)	89.1	[30]
Pistachio nuts	4	600	CNN	95-98	[31]
Strawberry	4	4211	Swin-MLP-CNN	98	[24]
Wheat Yellow Rust Infection	4	1640	Embedded AI (A pre-trained U2 Net model)	96	[32]
Wheat	2	840	CNN	98.71	Proposed CNN architecture
Wheat	22	2320	CNN	89.5	Proposed CNN architecture

4. CONCLUSIONS

For companies that process or trade wheat, it is of great importance to determine the variety of wheat and its vitreous/yellow berry status. Extraction of wheat images by U2-Net architecture segmentation and preprocessing of images played an important role in increasing success. After, process is carried out with a two-stage classification system. With the CNN model we proposed, we performed the wheat multi-class detection process in two stages. In the first stage, the average accuracy for binary classification was calculated as 98.71%. In the second stage, the average accuracy value for the multiclass results (yellow berry, vitreous) was found to be 88.96% and 90.34%, respectively. This developed classification system has the potential to help experts in both seed producers, farmers and wheat processing factories and contribute to minimizing personal errors. In line with the results, it was seen that first, small, and difficult to distinguish grain groups, and then the use of segmentation and classification problems together were successfully carried out. In future studies, we plan to work on segmentation of the U2-Net model on different datasets with existing hyperparameters, and then on classification with CNN networks.

Declaration of Ethical Standards

The authors declare that the materials and methods used in this study do not require ethical committee permission.

Credit Authorship Contribution Statement

Mustafa Şamil ARGUN: Conceptualization, Methodology, Formal analysis, Writing- Reviewing and Editing. **Fuat TÜRK:** Methodology, Data curation, Writing- Original draft preparation, Writing- Reviewing and Editing. **Zafer CİVELEK:** Visualization, Investigation.

Declaration of Competing Interest

The authors declare that there is no conflict of interest concerning publication of this article.

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Data Availability

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

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