All Sciences Proceedings
http://as-proceeding.com/

2nd International Conference on Scientific and Academic Research
March 14-16, 2023 : Konya, Turkey

ICSAR

A Novel Method for Classification of Butterfly Species Using CNN

Halit Çetiner*

[1]Computer Technology, Vocational School of Technical Sciences, Isparta University of Applied Sciences, Türkiye

*(halitcetiner@isparta.edu.tr) Email of the corresponding author

Abstract – Researchers studying in the field of lepidopterology want to learn about the family life of butterflies and to examine detailed information such as the shape and species of butterflies. It is of great importance to classify butterflies by invasive methods without harming them. In engineering approaches, the development of reliable, fast and cost-effective systems is suitable to offer solutions to vital problems. In this study, automatic species classification of butterflies is provided by data augmentation with a new method based on Convolutional Neural Network (CNN) for automatic examination and classification of butterflies. In the article, a CNN model that provides automatic classification of 832 butterfly images belonging to 10 butterfly species is proposed. Data augmentation of the proposed model was performed between classes with unbalanced data distribution. To evaluate the effect of the data augmentation process on the performance, the classification process was performed without any data augmentation process. As a result of the data augmentation process, the proposed CNN model reached 93.41% validation accuracy. The proposed CNN model, which does not apply any data augmentation process, has reached 91.72% validation accuracy. The proposed CNN model, which is flexible and highly capable, caused 1.69% performance difference. It is seen that the approach that performs close to or superior to similar studies in the literature is successful. The proposed CNN model is important in that it is both a lightweight and faster system than any pre-training transfer method.

Keywords –Butterfly, Data Augmentation, Classification, Convolutional Neural Network, Butterfly Species

I. INTRODUCTION

In the animal kingdom, the Lepidoptera family, which is the most crowded family of insects, is closely related, with a diversity of between 15,000 and 21,000 [1], [2]. The word lepidoptera, which consists of two different words, lepido and petra, is a Greek word [3]. Since butterflies and moths belong to the same family group, they are also very similar to each other. Researchers state that butterflies differ from moths in the filamentous and stick-like structure of their antennae [4]. Butterflies have more vivid colors, shine and wing patterns than moths [4]. Moths, on the other hand, are duller in color than butterflies, with fringe-like or saw-edged antennae [5].

Butterflies do not have enough expert personnel to differentiate their diversity among species. At this point, there is a need for artificial intelligence supported systems that automatically classify the butterfly class by using butterfly features to assist expert personnel. Automatic species identification using a dataset of ecological pictures of butterflies in nature with different morphological features will make an important contribution to the literature. At the same time, the lack of qualified personnel in butterfly classification is another main reason for automatic butterfly classification [6]. Most of the butterfly datasets, which are widely used for educational purposes in the literature, consist of butterflies with pattern images that do not have morphological features in nature [6]. At this point, considering the difficulty of automatically classifying a dataset with the image of natural butterflies, artificial intelligence supported systems are needed.

In butterfly classification, two different methods are seen in the literature, namely classical machine learning and deep learning techniques. When classical machine learning techniques are examined, the studies of Kaya et al., Xie et al., Zhu and Spachos are seen. According to Kaya et al. [1] have classified 92.85% of 140 butterflies with the help of artificial neural networks by extracting different angles, color and texture features with the local binary mode. According to Xie et al. realized a new recognition system for the classification of insects living in agricultural products such as wheat and corn with multiple kernel techniques [7]. Zhu and Spachos classified 18 different insect species belonging to the lepidoptera family using wavelet approaches [8].

When deep learning-based approaches are examined, especially recent studies have been examined. Rajeena et al., ResNet50, Inception V3, MobileNet, Xception, VGG16 and VGG19 seem to perform classification of butterfly species with pre-trained weight values [5]. Although transfer learning approaches and classification approaches, which are pre-trained and have weight values in terms of size, can give very high results, they are non-lightweight methods. They achieved a 94.66% success rate with the Inception V3 method. Sedaemeltekkara et al. classified a dataset consisting of 7148 butterfly species images, 80% of which was training and the rest was testing, using CNN-based methods with an accuracy of 89.73% [9]. The importance of the parameters used, especially the optimization parameter, is drawn attention to the success of CNN-based methods.

Almryad et al. captured 44,659 butterfly images with complex features such as different shooting angles, location and distance [6]. In total, 104 different butterfly species were classified using transfer learning-based methods named VGG16, VGG19 and ResNet50. Achieved performance values of 100 epochs using 900 samples for each butterfly class. It is seen above that approaches for automatic classification of butterflies have been developed with both classical machine learning techniques and deep learning-based methods. These methods are an incentive to develop a system for automatic classification of butterfly species without any expert intervention. At the same time, the basis for the studies to be carried out is the source for the classification or segmentation of moths and other insects that are close to the butterfly family. Transfer-learning-based approaches are generally dominant in deep learning-based studies in the literature. Compared to CNN-based methods, which do not use any pre-trained weights as the number of layers, transfer learning-based methods, which contain many layers, perform feature extraction automatically. CNN-based methods are generally similar to transfer learning-based methods, but the number of layers is smaller. Classification performance measures are similar to learning-based transfer approaches.

The main contributions of the article to the literature are presented below.

- The sensitivity of butterfly species consisting of different image patterns to data augmentation techniques has been observed.
- High-performance results were obtained with a CNN model, which is more lightweight than transfer learning techniques.
- A basis has been established for automatic classification of animal varieties from different families, such as moths and insects.
- Although data augmentation processes do not always give good results, they provided a result compatible with the proposed CNN model within the scope of this article.

In Section 2, which is one of the remaining parts of the article, the data set used in the article and the methods used are presented in detail. In Section 3, the performance results of the automatic classification of butterfly species are plotted. In Section 4, the study is concluded with future studies.

II. MATERIALS AND METHOD

A. *Material*

There are 832 images in total in the butterfly dataset, which consists of 55 to 100 images in each category [10].

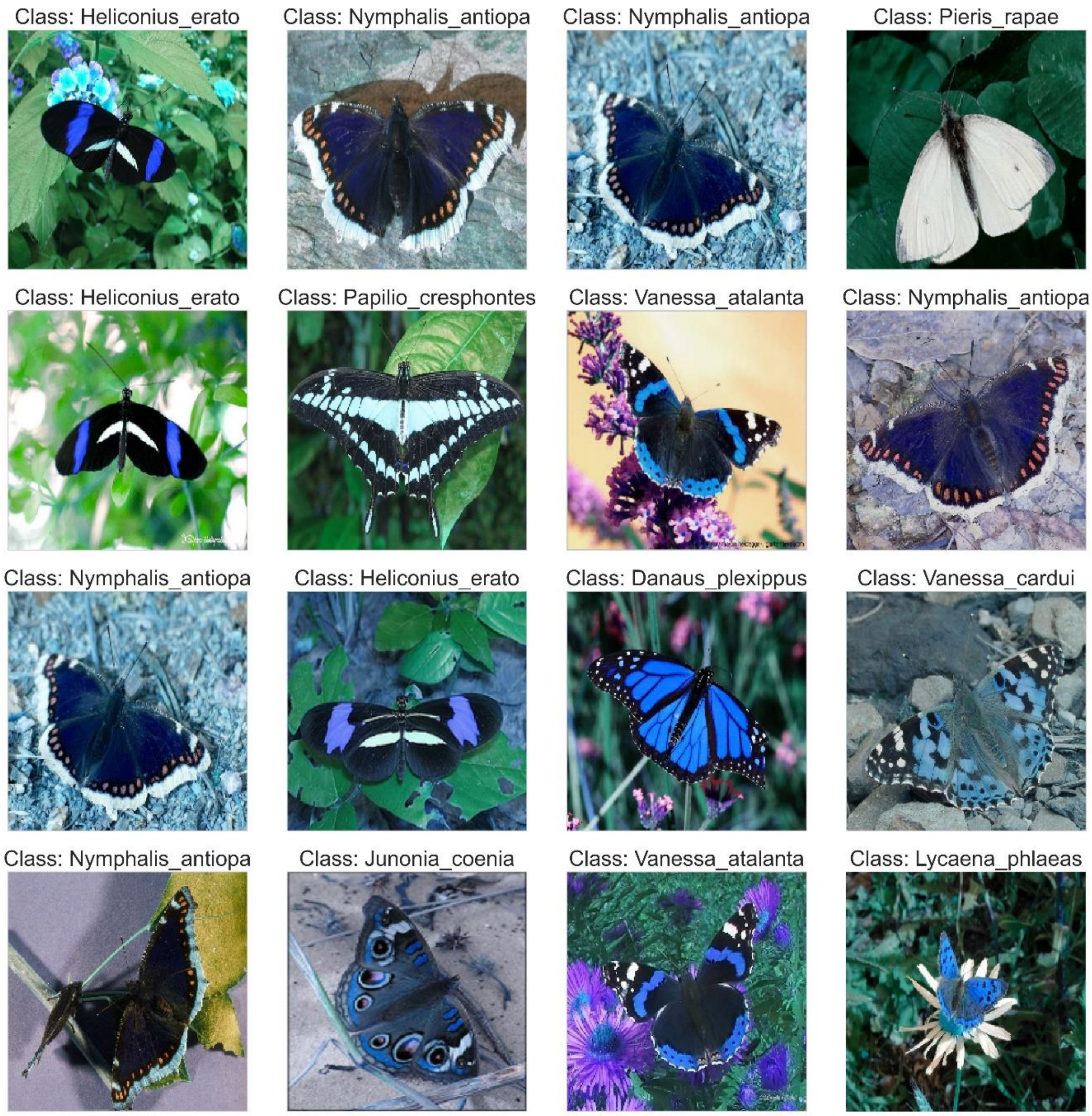

Fig. 1 Some images of butterfly classes in the dataset

In this study, a dataset consisting of 10 different categories of butterfly images called Danaus plexippus, Heliconius charitonius, Heliconius erato, Junonia coenia, Lycaena phlaeas, Nymphalis antiopa, Papilio cresphontes, Pieris rapae, Vanessa atalanta, Vanessa cardui was used. Butterfly images of some classes are presented in the data set used in Fig. 1.

B. *Proposed Model*

In artificial intelligence-based applications, applications based on deep learning are very popular lately [10]. Deep learning-based applications in many different fields from computer vision to natural language processing provide great success [11], [12]. Deep learning approaches, which require more labeled data than classical machine learning techniques, have become very important today.

In this article, a CNN-based butterfly classification model is proposed due to its proficiency and powerful features. Better results were obtained from the data augmented with the proposed model. All original images are provided with data augmentation using image data generation. In this way, different butterfly images were obtained and the existing data set was expanded. Random rotating, zooming, vertical and horizontal flipping techniques were applied in the data augmentation process. In random rotating operation, any degree of rotation between 0 and 360 can be applied. Horizontal and vertical flipping can be performed with Flipping. With the zooming technique, the zooming state of the image is obtained.

The proposed model consists of 16 layers. In the first layer, the image is inputted to have three color channels. This layer is called the input layer. In the second layer, 32 filtered convolution layers with 3x3 window sizes were used. In the third layer, a maximum pooling layer with 3x3 window sizes has been added. The batch normalisation layer was applied in the fourth layer. In the fifth layer, 32 filtered convolution layers with 5x5 window sizes are used. In the sixth layer, a max pooling layer with 3x3 window sizes has been added. In the seventh layer, a convolution layer was applied with 64 filters in 3x3 window sizes. In the eighth layer, a maximum pooling layer with 2x2 window sizes has been added. In the ninth layer, a convolution layer with 128 filters in 3x3 window sizes was applied. In the tenth layer, a maximum pooling layer with 2x2 window sizes has been added. In the eleventh layer, a convolution layer with 128 filters in 3x3 window sizes was applied. In the twelfth layer, a maximum pooling layer with 2x2 window sizes has been added. Added Flatten layer, which converts the resulting features to one dimension. The Flatten layer in the thirteenth layer has vectorized the feature matrix. In the fourteenth layer, 0.7 neuronal dropout was achieved. In this way, a possible model overfitting problem is prevented. In the 15th layer, a dense layer with 100 neurones with ReLU activation function has been added. This layer is also referred to as the fully connected layer. An output layer with softmax activation function with 10 outputs is provided in the sixteenth layer.

III. Results and Discussion

Train accuracy, validation accuracy and train loss, validation loss results with the Proposed model are presented in Fig. 2-6. Two different experimental studies of 50 epochs were conducted. The parameters used in the experimental study using Adam [13] optimization were kept the same. The numerical values of the results presented in Fig. 2-6 are given in Table 1.

Table 1. Performance results of the model with and without using data augmentation

Model	**Train accuracy**	**Train loss**	**Validation accuracy**	**Validation loss**
Without Augment	0.9830	0.2542	0.91702	0.6106
With Augment	0.9954	0.1492	0.9341	0.4385

When Table 1 is examined, a better accuracy and loss values were obtained, even if less than the data set with data augmentation. These results do not mean that data augmentation will have a positive effect on all data sets. Deep learning is generally considered to be effective because it is more effective in a large amount of data.

Fig. 2 shows the train accuracy performance results of the proposed model. There is 0.0124 accuracy difference between both runs.

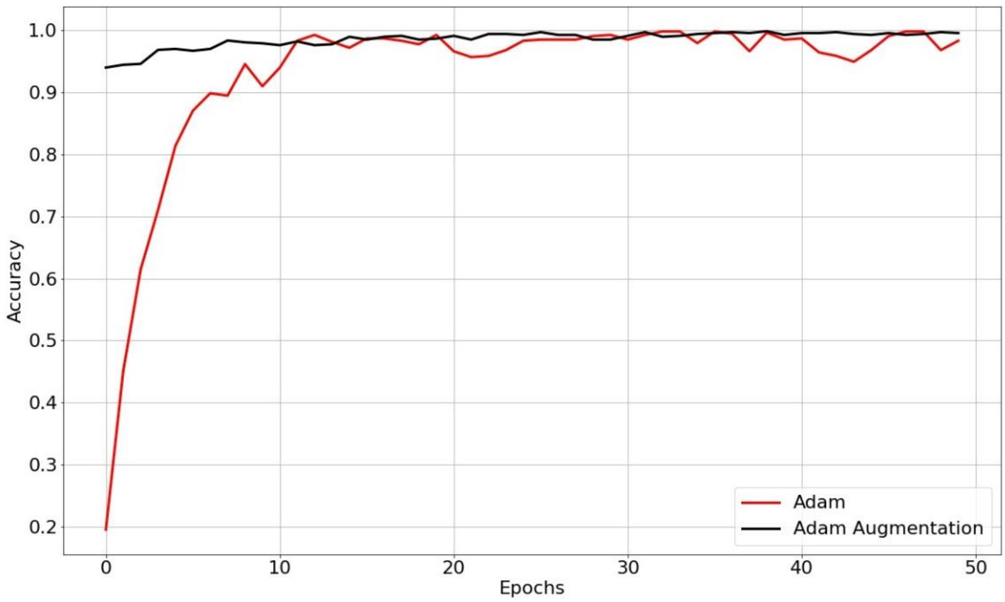

Fig. 2 Train accuracy

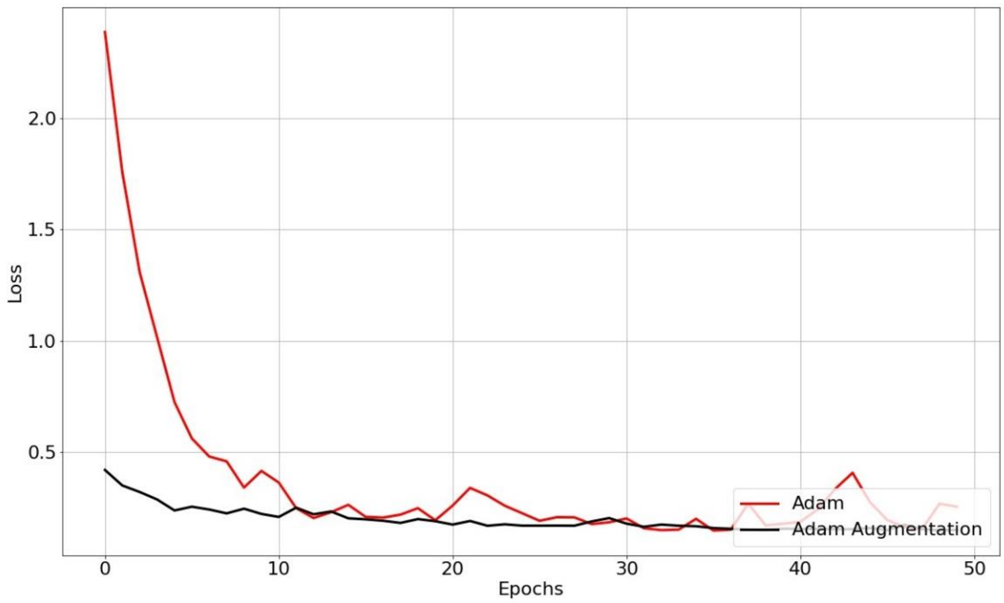

Fig. 3 Train loss

In Fig. 3, less loss values were obtained than the augmented data. The classification process with data augmentation, which has 0.105 less loss value, seems to be more effective.

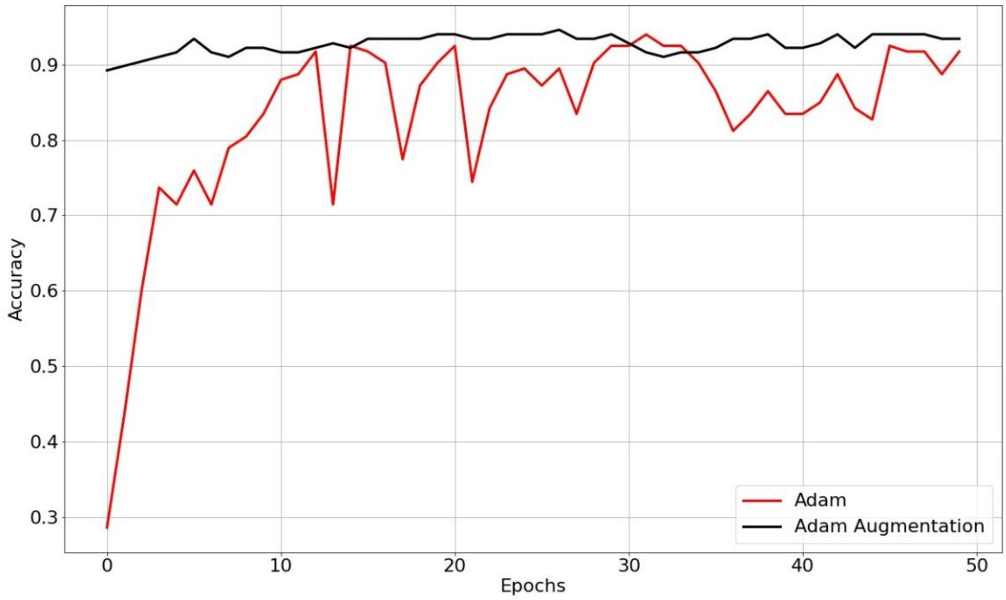

Fig. 4 Validation accuracy

In Fig. 4, the validation accuracy performance results of the proposed model are given. The performance value of the proposed model 0.9341 was reached on the data augmented data. With a difference of 0.017, better validation accuracy was obtained on the data augmented data.

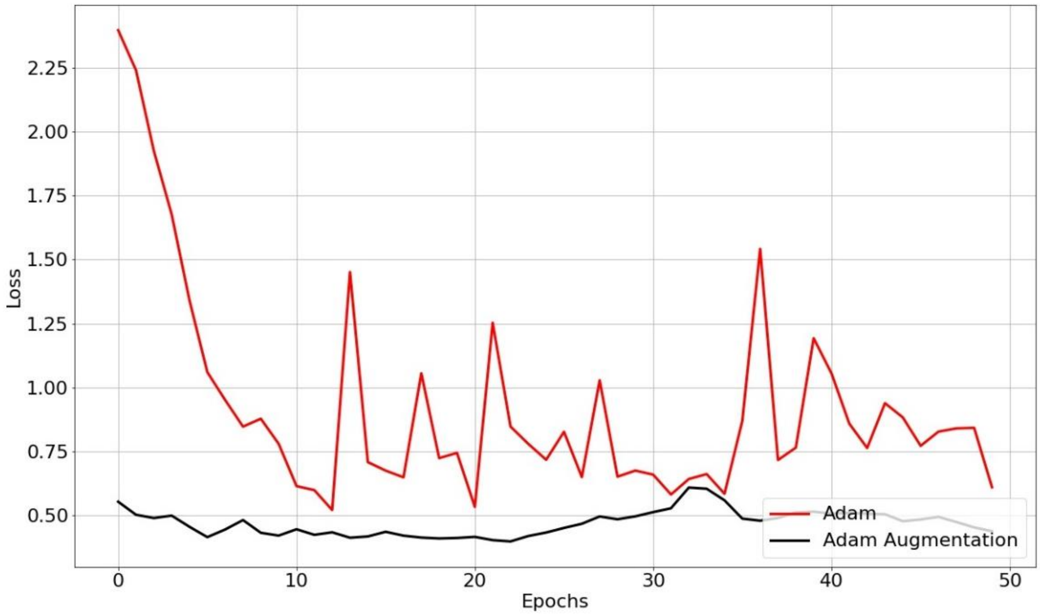

Fig. 5 Validaton loss

In Fig. 5, less loss value was obtained as validation loss value than the enhanced data of the data. The classification process with data augmentation, which has 0.1721 less loss value as the validation loss value, seems to be more effective.

Table 2. Comparison of butterfly classification performance results with similar and different datasets

Index	Model	Train accuracy (%)	Validation accuracy (%)
1	ResNet [6]	84.8	70.2
2	VGG16 [6]	80.4	79.5
3	VGG19 [6]	77.6	77.2
4	ResNet50	-	43.99
5	VGG19	-	92.00
6	VGG16	-	86.66
7	Inception V3	-	94.66
8	Xception	-	87.99
9	MobileNet	-	81.33
10	This study	99.54	93.41

While the proposed model surpasses most of the transfer learning-based methods in Table 2, it is quite close to the highest result. A successful butterfly classification process has been completed with the proposed CNN model.

IV. CONCLUSION

In this study, a tool has been developed to assist personnel in classifying creatures such as butterflies, especially expert entomologists. A method as successful as the studies carried out with transfer learning techniques containing high weight values with high performance sensitivity has been proposed by increasing the data with different data augmentation techniques on the input images of butterflies. Although factors such as the location of butterflies, the shooting angle, and background complexity affect success, these problems are easily overcome with robust layers with different filters and window sizes in CNN-based methods.

REFERENCES

[1] Y. Kaya and L. Kayci, "Application of artificial neural network for automatic detection of butterfly species using color and texture features," *Vis. Comput.*, vol. 30, no. 1, pp. 71–79, 2014, doi: 10.1007/s00371-013-0782-8.

[2] F. Fauzi, A. E. Permanasari, and N. A. Setiawan, "Butterfly Image Classification Using Convolutional Neural Network (CNN)," in *2021 3rd International Conference on Electronics Representation and Algorithm (ICERA)*, 2021, pp. 66–70.

[3] N. N. K. Arzar, N. Sabri, N. F. M. Johari, A. A. Shari, M. R. M. Noordin, and S. Ibrahim, "Butterfly Species Identification Using Convolutional Neural Network (CNN)," in *2019 IEEE International Conference on Automatic Control and Intelligent Systems (I2CACIS)*, 2019, pp. 221–224. doi: 10.1109/I2CACIS.2019.8825031.

[4] N. A. S. A. Zarim and A. B. Ahmad, "Checklist of butterfly fauna at Kuala Lompat, Krau wildlife reserve, Pahang, Malaysia," *J. Wildl. Park.*, vol. 28, pp. 63–72, 2014.

[5] F. Rajeena P. P. *et al.*, "A Novel Method for the Classification of Butterfly Species Using Pre-Trained CNN Models," *Electronics*, vol. 11, no. 13. 2022. doi: 10.3390/electronics11132016.

[6] A. S. Almryad and H. Kutucu, "Automatic identification for field butterflies by convolutional neural networks," *Eng. Sci. Technol. an Int. J.*, vol. 23, no. 1, pp. 189–195, 2020, doi: https://doi.org/10.1016/j.jestch.2020.01.006.

[7] C. Xie *et al.*, "Automatic classification for field crop insects via multiple-task sparse representation and multiple-kernel learning," *Comput. Electron. Agric.*, vol. 119, pp. 123–132, 2015.

[8] L. Zhu and P. Spachos, "Towards image classification with machine learning methodologies for smartphones," *Mach. Learn. Knowl. Extr.*, vol. 1, no. 4, pp. 1039–1057, 2019.

[9] M. Pinzari *et al.*, "Chemically mediated species recognition in two sympatric Grayling butterflies: Hipparchia fagi and Hipparchia hermione (Lepidoptera: Nymphalidae, Satyrinae)," *PLoS One*, vol. 13, no. 6, p. e0199997, 2018.

[10] H. Çetiner, "Citrus disease detection and classification using based on convolution deep neural network," *Microprocess. Microsyst.*, vol. 95, p. 104687, 2022.

[11] H. Çetiner and İ. Çetiner, "Classification of Cataract Disease with a DenseNet201 Based Deep Learning Model," *Journal*, vol. 12, no. 3, pp. 1264–1276, 2022.

[12] H. Çetiner, "Multi-Label Text Analysis with a CNN and LSTM Based Hybrid Deep Learning Model," *J. Eng. Sci. Adiyaman Univ.*, vol. 9, no. 17, pp. 15–16.

[13] D. Kingma and J. Ba, "Adam: A Method for Stochastic Optimization," *Int. Conf. Learn. Represent.*, Dec. 2014.