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Classification of Traffic Signs Using Transfer Learning Methods

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Transfer Öğrenme Yöntemleri Kullanılarak Trafik İşaretlerinin Sınıflandırılması

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Abstract

Transportation refers to a process based on the movement of people or vehicles from one place to another. Sea routes and roads have existed for centuries. They generally play a very important role in people's daily life, trade and industrial activities. Highway, a mode of transportation, is the first preferred mode of transportation worldwide. However, various signs and rules have been set by the authorities to prevent chaos on the highways. Traffic signs are the most important of these rules. In this study, transfer learning models (VGG16, VGG19, Xception and EfficientNet) are used to classify traffic signs using a state-of-art traffic signs dataset (German Traffic Sign Detection Benchmark-GTSDB). Accuracy was used as the classification evaluation criterion. The CNN model designed for the study gave the best result with an accuracy rate of 98% and a model competing with the literature was proposed.

Keywords: *Trafik işareti görüntüleri; görüntü işleme; sınıflandırma; transfer öğrenme*

Öz

Ulaşım, insanların veya araçların bir yerden başka bir yere hareketine dayanan bir süreci ifade eder. Deniz yolları ve karayolları yüzyıllardır var olmuştur. Genellikle insanların günlük yaşamında, ticaretinde ve endüstriyel faaliyetlerinde çok önemli bir rol oynarlar. Bir ulaşım şekli olan karayolu, dünya genelinde ilk tercih edilen ulaşım şeklidir. Ancak karayollarında yaşanan kaosu önlemek için yetkililer tarafından çeşitli işaretler ve kurallar belirlenmiştir. Trafik işaretleri bu kuralların en önemlisidir. Bu çalışmada, transfer öğrenme modelleri (VGG16, VGG19, Xception ve EfficientNet) son teknoloji bir trafik işaretleri veri kümesi (German Traffic Sign Detection Benchmark-GTSDB) kullanılarak trafik işaretlerini sınıflandırmak için kullanılmıştır. Sınıflandırma değerlendirme kriteri olarak doğruluk kullanılmıştır. Çalışma için tasarlanan CNN modeli %98 doğruluk oranı ile en iyi sonucu vermiş ve literatürle yarışan bir model önerilmiştir.

Anahtar Kelimeler: *Traffic sign images; image processing; classification; transfer learning*

1. Introduction

Transportation is a fundamental necessity that enables people to move from one place to another and is an instinctual phenomenon for humanity. Basic transportation routes like sea and road have been in existence for centuries. Factors such as wars between countries, the development of trade, and air transportation have led to the evolution of various platforms in the field of transportation. Especially, road transportation is a preferred mode of transportation for many countries, including Turkey. Various signs and rules have been developed to ensure order in road traffic, and these traffic signs are a significant part of this order. Computer technologies have made groundbreaking advancements in data storage and processing fields. These developments have contributed significantly to the progress of artificial intelligence technologies, particularly. Significant innovations have been made in various artificial intelligence fields such as image processing. Deep learning methods have accelerated image processing processes and enabled the development of products that add value in various fields such as transportation (Mete et al., 2022), healthcare (Orhan & Yavşan, 2023), and more (Barstuğan & Osmanpaşaoğlu, 2023; Yavsan & Ucar, 2015).

In this study, VGG16, VGG19, Xception, and EfficientNet transfer learning methods were employed for the classification of traffic signs related to road transportation in Turkey. Performance metrics such as accuracy, precision, recall, and F1 score of the methods used were examined. According to the evaluated performance criteria, the model with the best results achieved an accuracy rate of 98% with the Xception model. The flowchart of the study is presented in Figure 1.

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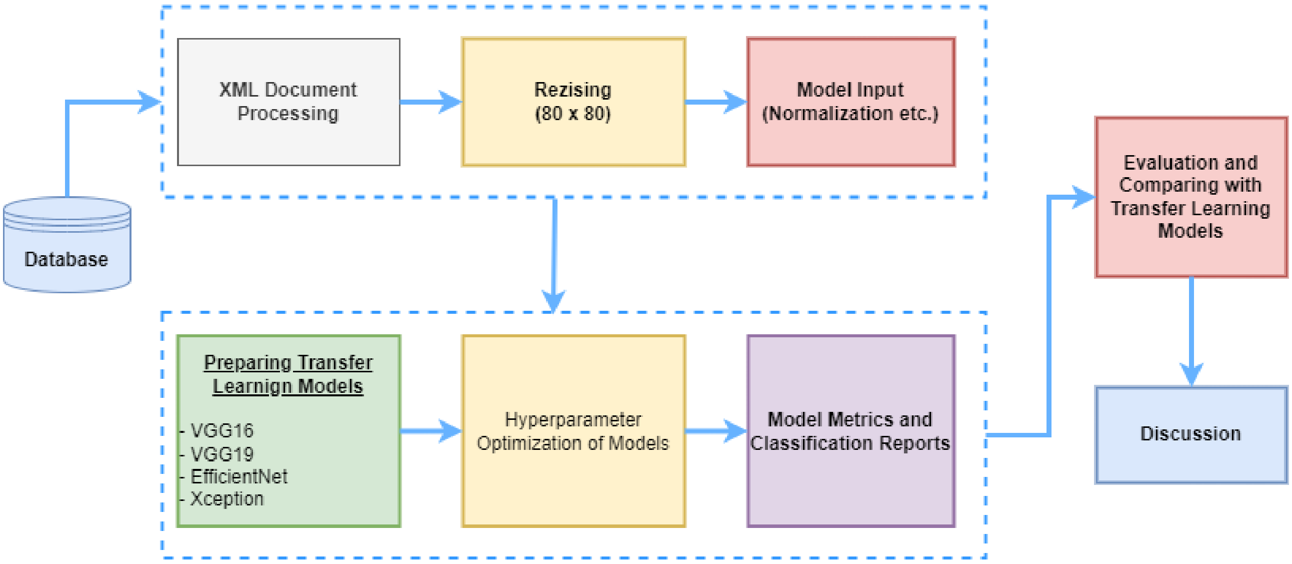

Figure 1. Architecture of the study.

The second section in the remainder of the study covers the literature review; the third section encompasses the data sources and models used in the study; the fourth section includes performance evaluation metrics and the performance results of the models. The evaluation of the results and comparisons with examples from the literature are presented in the fifth.

2. Literature Review

Traffic signs are of great importance in road transportation. With these signs, road transportation continues within the framework of the rules without interruption. In order to prevent human error with the developing artificial intelligence techniques, many researchers have developed systems to recognize these traffic signs with image processing techniques and specially to warn tired drivers. Many published works by researchers show that this topic is frequently studied. For the study, the author has reviewed some important papers in this area to properly select the proposed model and performance metrics and to understand the practical significance of the related work.

In their study, Yıldız and Dizdaroğlu proposed a new method based on image processing for traffic sign detection (Yildiz & Dizdaroglu, 2019). In the feature extraction phase, they improved the performance of their proposed method by considering both color information and geometric shapes of traffic signs. They used RGB color space in their study. Maldonado *et al.* classified traffic signs according to their color and shape using a Linear Support Vector Machine (SVM) (Maldonado-Bascon et al., 2007). They then used SVMs with Gaussian kernels to recognize the content of the signs. Ruta et al. developed an image representation method called Color Distance Transform. All these methods work on the principle of difference maximization. They also emphasized that the Color Distance Transform method is better than the Principal Component Analysis (PCA) and the AdaBoost method and used the K-Nearest Neighbor model as the classification model (Ruta et al., 2010). Before the classification process, Chen et al. divided the traffic signs into 6 different categories according to their colors and shapes. They used Simple Vector Filter for color segmentation and Hough transform and curve fitting for shape analysis. The classification of the signs was performed by classifying the features obtained with Pseudo-Zernike moments with SVM (Chen et al., 2011). In their method, Fleyeh et al. tried to find the most effective parts of the traffic sign images in the classification process using the PCA model and expressed the importance of these parts by calculating weights from the most effective eigenvectors of the signs. They performed the classification process using Euclidean distance (Fleyeh & Davami, 2011). Cireşan et al. achieved 99.46% success in their proposed model using the German Traffic Sign Detection Benchmark (GTSDB) dataset (Cireşan et al., 2012). Sermanet et al. used Folded Neural Networks, a biology-inspired multilevel structure that automatically learns the hierarchy of invariant features on the GTSDB dataset. They achieved 99.17% success by applying this method on gray level images (Sermanet & LeCun, 2011). Çetinkaya and Acarman obtained 91% precision, 94.76% recall, 92.74% recall and 92.74% F-score results in classification results after segmentation with deep learning (Çetinkaya & Acarman, 2020). Yuan et al. obtained 89.65% precision, 87.84% recall, 88.84% recall and 88.73% F score results in their study on GTSDB dataset (Yuan et al., 2015). Ellahyani et al. obtained 90.13% precision, 91.07% recall and 90.60% F-score results in their study on GTSDB dataset (Ellahyani et al., 2016). Torres, et al. obtained 94% precision, 91% recall and 93% F-score results in their study on GTSDB dataset with Fast R-CNN (Torres *et al*., 2019). T. Palandız et al. studied a CNN (Convolutional Neural Networks) model trained with three different deep learning methods, namely ResNet50, MobileNetV2 and NASNetMobile. With the ResNet50 method, they obtained an accuracy of 78.75% on the test data. They obtained 48.12% accuracy for MobileNetV2 and 41.56% accuracy for NASNetMobile (Palandız *et al*., 2021).

Küçük et al. performed 15 different classifications using 14,780 images from the videos obtained to create the Traffic dataset with R-CNN. They used 1000 images for each classification. To create the training dataset, they used a road camera placed on the windshield of a personal vehicle and video camera data from traffic lights and traffic signs on the roads of Selçuklu and Meram districts of Konya province. They trained an artificial neural network model using the data set obtained from the personal vehicle and achieved 90% accuracy in this experimental study. After the traffic sign and lamp recognition system, they developed a lane recognition and curve detection system for an autonomous vehicle platform. With this system, the steering angle of the vehicle was calculated, and the steering of the vehicle was controlled autonomously with a PID controller (Küçük et al., 2021).

Ortataş and Çetin created an individual data set at Gazi University. They resized the dimensions of the positive images that make up the dataset to vary approximately between 95x95 and 110x110. They conducted experiments with machine learning models with different numbers of data sets belonging to a signboard. They obtained accuracy values between 69.23%-90% in the classification study on a total of 10 different classes such as Traffic Lamp, Stop Sign, Parking Sign, No Left Turn Sign, Stop Sign, No Entry Sign, Forward and Right Obligatory Direction Sign, No Parking Sign, Road Closed to Traffic Sign, Forward and Left Obligatory Direction Sign (Ortataş & Çetin, 2023). Hasçelik performed a classification study on a dataset with 12.629 images. Of the images in the dataset, 11.366 images were used for training and 1263 images were used for testing. Recognition rate of 17 signs was realized between 56%-85% (Hasçelik, 2021). In their study on the GTSRB dataset, designed a CNN model using the deep learning library TensorFlow for real-time recognition of 6 different traffic signals. The classification success of the model they designed is 99.94% (Shustanov & Yakimov, 2017). Thanh achieved 96% success on more than 500 test data in the model he designed with MLP after PCA (Thanh, 2014). Bueno et al. classified 9 different traffic signs in a Spanish traffic sign dataset. In combination with a two-layer perceptron network, they achieved 98.72% accuracy on a dataset of 78 images for testing (Vicen-Bueno *et al.,* 2007). Hannan et al. obtained a success rate of 84.4% on a test data set of 300 images with two layers (Hannan, *et.al*., 2014).

3. Material and Methods

This section of the study includes the dataset, the designed CNN model and the transfer learning models.

3.1. Data Source

The dataset used in the study was introduced at the IEEE International Joint Conference on Neural Networks in 2013 (Houben et al., 2013) . The dataset consists of 900 images (600 for training and 300 for testing). Researchers have categorized signs of similar visuals into three categories:

- Prohibitory signs (red, circular)
- danger signs (red, triangular)
- Mandatory signs (blue, circular)

3.2. Data Prepration

The publicly shared dataset is prepared and annotated according to Object Detection algorithms. The images are annotated with an XML file containing folder, file name, path, source, size, partitioned, object tags. In addition, object tags containing the desired attributes such as name (class), bndbox (xmin, ymin, xmax, ymax) are also included.

3.3. EfficientNet

Convolutional Neural Networks (CNN) are a special kind of neural network for processing data and use a grid-like structure (Tan & Le, 2019). Convolutional is a special kind of linear operation. In simpler terms, CNNs are neural networks that use convolution instead of general matrix multiplication in at least one layer (Kabakus & Erdogmus, 2022). The CNN model designed for the study consists of 3 convolution layers and 1 fully connected layer. The first convolution layer consists of 8 different 3x3, 16 different 3x3 filters, Dropout and MaxPooling layers. The second convolution layer consists of 32 different 3x3 filters, Dropout and MaxPooling layers. The third convolution layer consists of two 64 different 3x3 convolution layers and a MaxPooling layer. The fully connected layer consists of Flatten, Dense and Dropout layers. Dropout value is set to 0.2.

3.4. VGG16 and VGG19 Models

VGG16 is one of the most widely used architectures in computer vision and can extract the necessary features from images for classification. The input image size of this model is 224x224xChannel Number as proposed. VGG16 consists of 16 layers, hence the "16" in the name (Khaliki & Başarslan, 2024) These layers consist of successive dense convolutional and pooling layers. It performs image processing using small 3x3 filters. The dense layers are located at the end of the model. VGG19 has a similar deep learning architecture to VGG16. The difference between the two models is that VGG19 has more layers than VGG16. The higher number of deep layers allows to extract more complex features in large datasets and achieve higher accuracy.

3.5. Xception Model

The Xception model, which stands for "Extreme Inception", is based on the Inception model and was designed by François Cholet (Chollet, 2016) . Composed of 71 layers, the Xception model uses separable convolutions that make the convolution process more efficient and computationally more efficient. These transformations perform the convolution process in two stages, first the intra-channel (depthwise) transformation and then the inter-channel (pointwise) transformation. Xception can be used especially effectively in visual tasks such as image classification, object detection and image segmentation. Figure 3 shows the revisions made to the proposed models for the study. The hyperparameters used to train the models are presented in Table 1.

4. Experimental Results

In this section, the performance evaluation metrics of the models used in this study and the performance results of the models are presented.

4.1. Performance Metrics

The confusion matrix in Figure 2 shows the predicted values and the actual values because of the classification performance of the models. The mathematical calculation formulas for the Accuracy (A), Precision (P), Recall (R) and F-score (F) metrics obtained using CM are given in Eq. (1), Eq. (2), Eq. (3), and Eq. (4) respectively.

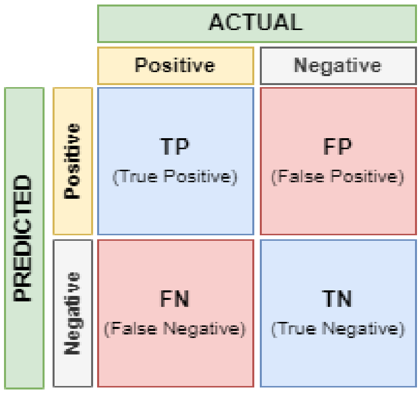

Figure 2. Confusion matrix.

$$A = \frac{TP * TN}{TP + TN + FP + FN} \quad (1)$$

$$P = \frac{TP}{TP + FP} \quad (2)$$

$$R = \frac{TP}{TP + FN} \quad (3)$$

$$F = 2 * \frac{P * R}{P + R} \quad (4)$$

5. Experimental Results

In this section, the experimental results obtained from the data set used in the study are given.
As seen in Table 2, the classification performance results of the transfer learning models used in the study are presented. The Xception model achieved the best result.

The training-test accuracy and loss graphs of VGG16, VGG19, EfficientNet, and Xception are given in Figure 3 through Figure 6. Accuracy and Loss graphs of VGG16, VGG19, Xception and EfficientNet models whose performance results are analyzed in this study are given in Figure 4, Figure 5, Figure 6 and Figure 7 respectively.

Table 1. Hyperparameters used to train the models.

Hyperparameters for Training						
Models	**Epoch**	**Batch Size**	**Optimizer**	**Learning Rate**	**Dropout**	**Loss Function**
VGG16	10	16	Adam	0.001	0.2	Categorical Cross Entropy
VGG19	10	16	Adam	0.001	0.2	Categorical Cross Entropy
Xceptipn	10	16	Adam	0.001	0.2	Categorical Cross Entropy
EfficientNet	10	16	Adam	0.001	0.2	Categorical Cross Entropy

The results of the models created with VGG16, VGG19, Xception and EfficientNet are given in Table 2. The training and test accuracy loss graph matrix of VGG16, VGG19, Xception and EfficieintNet models are given in Figure 4 to Figure 7. As seen in Figure 4, the model is robust. The VGG19 model shown in Figure 5 is an outlier at Epoch 7 in the validation set compared to VGG16 shown in Figure 4.

Figure 6 shows that the Xception method had a more robust training process than the other two transfer learning methods. Figure 7 shows that the EfficientNet model has a good training process compared to VGG16 and VGG19, but one step behind the Xception transfer learning method. The confusion matrix of the Xception model, which gives the best result in the study, is given in Figure 8. The explanations of the label numbers in the confusion matrix shown in Figure 8 are given in Table 3.

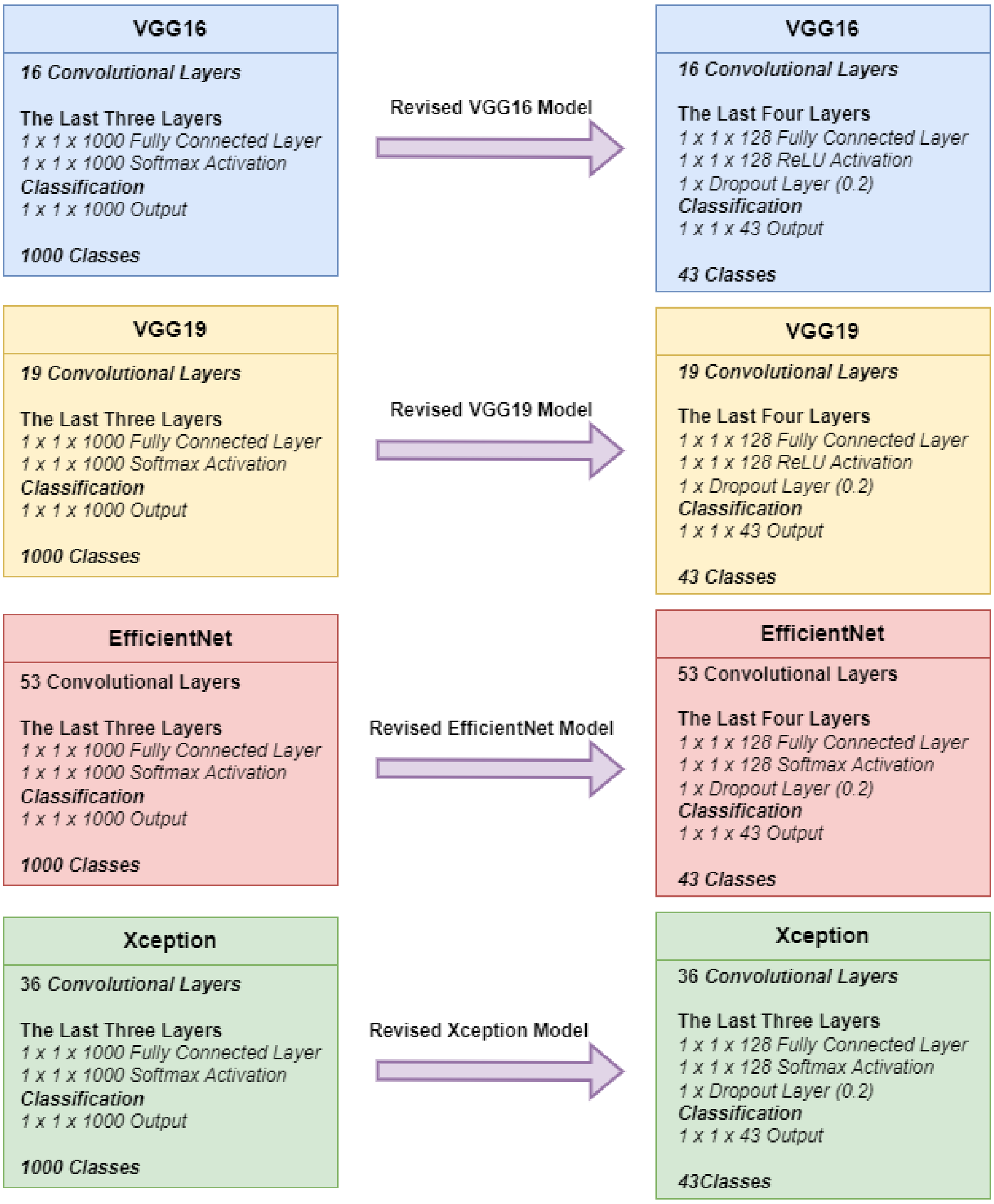

Figure 3. Revised Transfer Learning Models.

Table 2. Results of the models used in the study.

	Metrics			
Methods	**Accuracy**	**Precision**	**Recall**	**F-Score**
VGG16	91	88	88	88
VGG19	92	89	89	89
Xception	**98**	**98**	**98**	**98**
EfficientNet	96	95	95	94

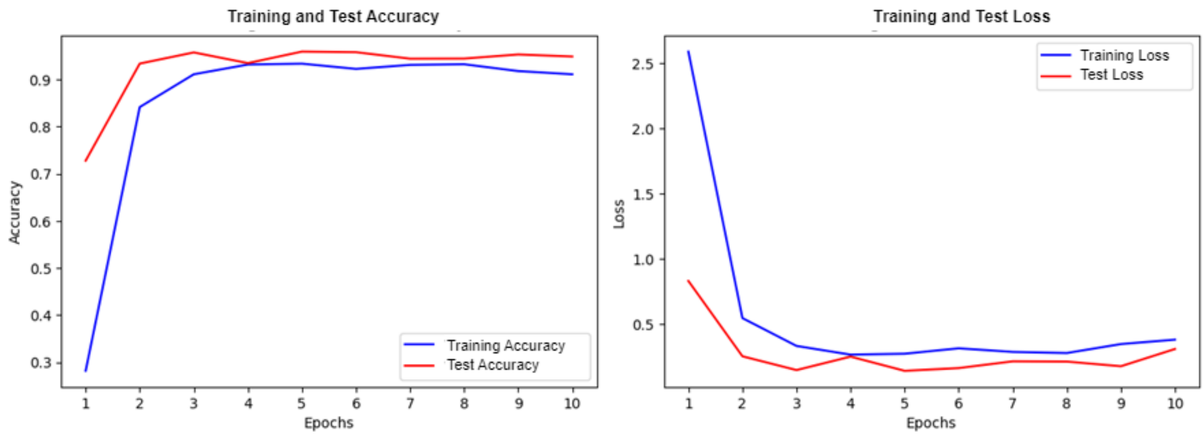

Figure 4. VGG16 training and validation accuracy, loss graphics matrix.

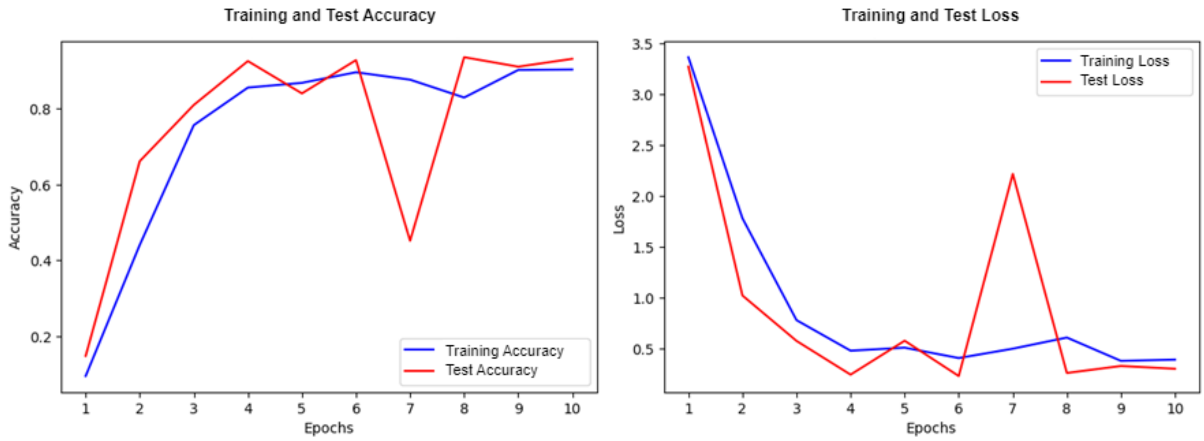

Figure 5. VGG19 Model training and validation accuracy, loss graphics matrix.

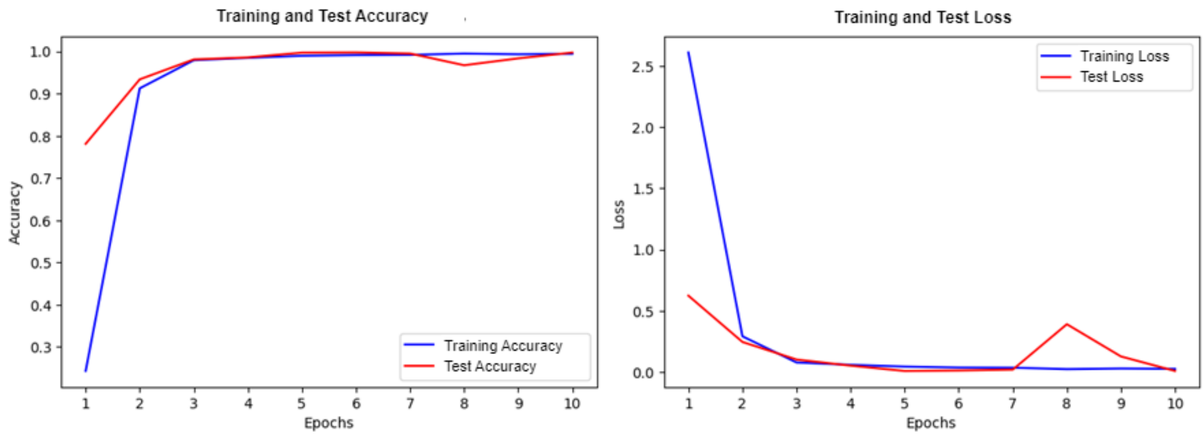

Figure 6. Xception Model training and validation accuracy, loss graphics matrix.

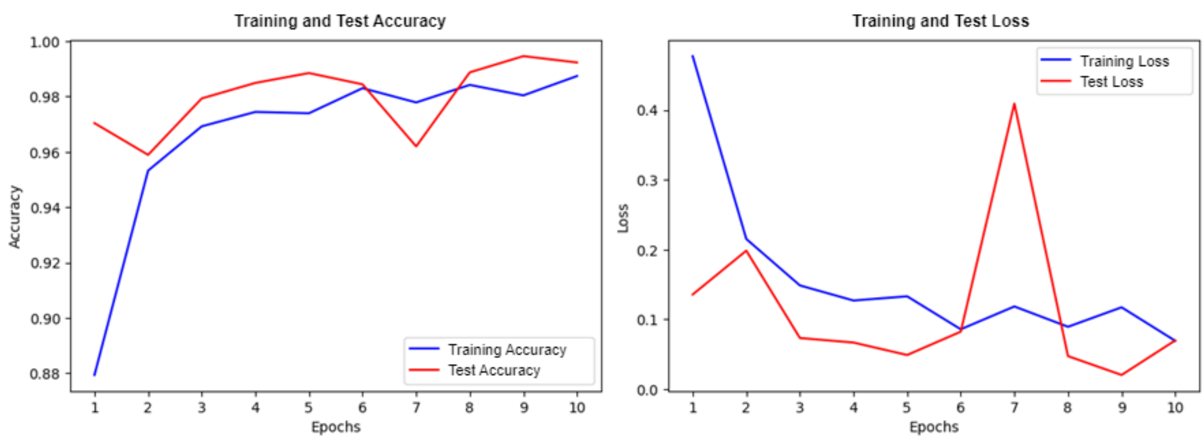

Figure 7. EfficientNet Model training and validation accuracy, loss graphics matrix.

Table 3. Descriptions of the label numbers in the confusion matrix of the Xception model.

Label	Definition	Label	Definition
1	Speed Limit 20	22	Forced Right Turn
2	Speed Limit 30	23	Winding Road
3	Speed Limit 40	24	Kasis
4	Speed Limit 50	25	Slippery Road
5	Speed Limit 60	26	Contraction on the Right
6	Speed Limit 70	27	Work on the Road
7	Speed Limit 80	28	Traffic Sign Warning
8	80 End of Speed Limit	29	Spring Crossing
9	Speed Limit 90	30	School Crossing
10	Speed Limit 100	31	Bicycle Path
11	Speed Limit 120	32	Icy Floor
12	No Overtaking	33	Level Crossing
13	Truck Cannot Overtake	34	Wild Animal
14	Secondary Road Junction	35	End of All Bans
15	Highway	36	Forced Right Turn
16	Give way	37	Forced Left Turn
17	Stop	38	Straight Ahead
18	Truck	39	Go to the Right
19	Dead End	40	Crossroads
20	Danger	41	Go Left
21	The Tame Animal Can Come Out	42	The End of the Overtaking Ban

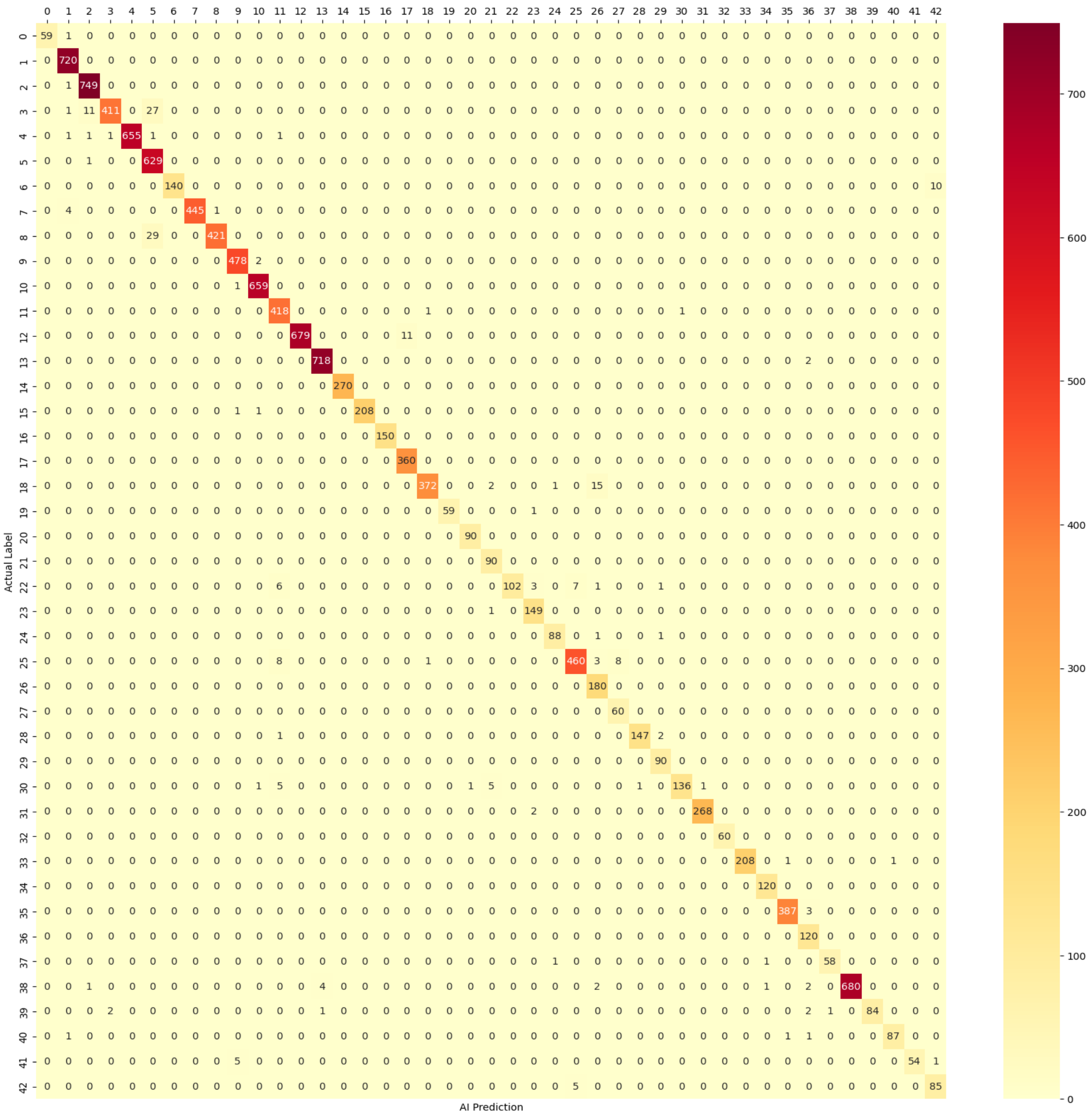

Figure 8. Confusion matrix of Xception model.

Table 4. Previosly study traffic sign similar Datasets.

References	Models	A (%)
Cireşan et al., (2012)	DCNN	99
Sermanet & LeCun, (2011)	CNN	99
Çetinkaya & Acarman., (2020)	Segmentation with deep learning	92
Yuan et al., (2015)	Graph based	88
Ellahyani et al., (2016)	HSI based segmentation	90
Torres et al., (2019)	Faster R-CNN	91
Palandız et al., (2021)	ResNet50	78
Küçük et al., (2021)	R-CNN	90
Ortataş & Çetin, (2023)	CNN	90
Hasçelik, (2021)	R-CNN, Fast-R-CNN Faster-R-CNN	85
Shustanov & Yakimov., (2017)	CNN	99
Yakimov, (2017)		
Thanh, (2014)	MLP	96
Vicen-Bueno, (2007)	MLP	98
Hannan, *et.al.*, (2014)	2 MLP	84
The Present	VGG16	91
	VGG19	92
	Xception	**98**
	EfficientNet	96

6. Results and Discussion

Competitive results have been achieved compared to similar studies in the literature. The results are presented in Table-3 by comparing them with related work in the literature. Working with image processing techniques for traffic signs holds paramount significance in the realm of transportation and, primarily, for human safety. In line with this objective, this study aims to enhance road transportation safety by employing artificial intelligence techniques to detect traffic signs. The results obtained from the transfer learning models used in this study have demonstrated competitive performance when compared to the outcomes of existing studies in the literature, as shown in Table II. As a conclusive outcome of this study, it is strongly recommended that CNN-based transfer learning models be prioritized for detection tasks pertaining to all types of transportation signs, with a particular emphasis on road traffic signs. Specifically, the Xception model, employed in this study, has exhibited a higher accuracy rate compared to the VGG16, VGG19, and EfficientNet models. The application of image processing techniques to traffic signs holds critical importance for transportation safety and, ultimately, human life. This study has contributed to the ongoing research efforts in this domain. In the future, more comprehensive studies encompassing different modes of transportation, such as air travel, are envisioned. The transfer learning methods used in this study are planned to be used in combination with esnemble methods in the future

Declaration of Ethical Standards

The authors declare that they comply with all ethical standards

Credit Authorship Contribution Statement

Author-1: Data analysis, research, writing, interpreting results.
Author -2: Conceptualization, experiments and evaluations, manuscript draft preparation
Author -3: Evaluations of the results, experiments, and evaluations.

Declaration of Competing Interest

The authors have no conflicts of interest to declare regarding the content of this article.

Data Availability

All data generated or analyzed during this study are included in this published paper.

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