Classification of Traffic Signs with Convolutional Neural Network

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Abstract – Rapidly changing and developing technology and related investments are growing rapidly. Despite the rapid development of technology, there are problems that continue as a problem. It is necessary to deal with the problems that are still seen as a problem today by taking advantage of the possibilities and opportunities of technology. Traffic signs should be distinguished by drivers both at night and during the day and should be easily perceived in terms of life safety. At the same time, artificial intelligence supported solutions should be produced in order to reduce vehicle accidents caused by human errors. In order to achieve this, a CNN-based deep learning model suitable for real-time work has been proposed. The running performance of the proposed deep learning model was measured according to the raw input and preprocessed image type. According to the KFold 3 technique, training and test data were separated and the proposed model was trained. As a result of the experimental studies, 99% precision, recall, F1 score, and accuracy measurement metrics were achieved with the CNN model with preprocessed input type. According to the raw input type that has not undergone any preprocessing, success rates of 98%, 97%, 98%, and 98% were achieved in terms of precision, recall, F1 score, and accuracy metrics, respectively.

Keywords –Traffic Sign, Driver Safety, Convolutional Neural Network, Preprocessing, Computer Vision

I. INTRODUCTION

Solid objects that provide information to drivers and other users moving on the road are called traffic signs. [1]. Traffic signs should consist of basic shapes and colors that are simple enough to be perceived by all road users [2]. To achieve this, a contract has even been signed for the standardization of traffic signs and signals [1]. However, it is stated that the desired standardization could not be achieved despite all studies [1]. For this reason, automatic recognition of traffic signs is important. Traffic sign recognition, on the other hand, is a problem consisting of an uneven distribution of signs consisting of too many categories. Traffic sign recognition, which has been researched for decades, has become even more important with the development of computer vision and artificial intelligence technology. There are traffic sign identification systems that direct vehicles with limited data sets. However, these data sets are stated to be insufficient and need to be expanded [3]. Recognition of traffic signs is important for many different reasons, such as driver safety, traffic surveillance, and automatic control of road routes.

The recognition of traffic signs is very important both in terms of the localization of traffic signs and the classification of their type [4], [5]. Traffic signs should be easily perceived in terms of the safety of drivers at night and during the day. It is also essential to create all the necessary technological infrastructure so that it can be easily perceived. Designing the signs with different shapes and types increases the distinctiveness. For this reason, road signs are designed so that drivers can easily perceive and recognize them. Traffic signs are designed with distinctive structures such as symbols, text, shape, and color. However, road signs that fall into the same category as speed limits are similar in appearance. Similar road signs form subsets within themselves. When the figures in the subsets are examined, the proposed classifier has to deal with different problems such as changes in weather lighting, post-storm rotations, and wear.

Traffic signs must be detected automatically by autonomous vehicles or by different vehicles. In this way, it is possible to prevent possible traffic accidents by informing the driver. Powerful properties of deep neural networks are used in this study to help drivers. Deep neural network architectures bring great opportunities in AI-powered solutions. Recognition of traffic signs is not easy because of different difficulties such as dimensional differences, weather conditions, visibility, and lightning strikes. CNN (Convolutional Neural Network) based models have achieved significant performance in different computer vision tasks such as image classification [6]–[8], segmentation [9]–[11], object detection [12] in recent years. Examining the literature, Bahlmann et al. conducted a study to classify traffic signs consisting of 23 classes [13]. Keller et al. achieved 92.4% accuracy with a classifier trained on 2880 traffic sign images [14]. Maldonado et al. have classified 36.000 Spanish traffic signs with 193 sign classes with 95.5% accuracy using the support vector machine algorithm [15]. However, the data set is not public [3]. Although it is a more comprehensive data set than the data set used in this article, it is seen that it is not shared.

There are studies published in recent years as well as the previous studies mentioned above. Megalingam et al. have automatically classified the traffic signs belonging to India with a CNN algorithm based on R-CNN (Region Based Convolutional Neural Network). In this study, in order to reduce the number of traffic accidents in Indian regions, 6480 of 7056 Indian traffic sign samples were classified in 87 categories. Lee and Kim developed a CNN-based detection system that predicts the boundaries and locations of high-resolution traffic signs [14]. Hu et al. tried to recognize car, bicycle, and traffic signs with a learning-based detection system [16]. Temel et al. proposed a model for the recognition of traffic signs in harsh weather conditions, such as rain [17]. However, the accuracy rate of the proposed model was limited to 80%. Kamal et al. proposed a new neural network for the classification of traffic signs by combining the SegNet and UNet algorithms. It has been stated that the proposed model has higher precision and recall values than Faster RCNN Inception ResNet V2 and RFCN (Region Based Fully Convolutional Networks) ResNet 101 algorithms [18]. Rodriguez et al. realized 1426 Mexican traffic signs with modified ResNet50 architecture [19]. The model, in which the RCNN and ResNet50 structures were used together, offered 95.33% precision performance. The model consisting of the combination of YOLO v3 (You Only Look Once) and ResNet50 structures provided a success rate of 90.33%.

This article focuses on the classification of traffic signs based on the data set we use. As a result of the classification studies, the main contributions of the article to the literature are given below.

- A lightweight CNN model is proposed for the classification of traffic signs. F1 score, recall, precision, and accuracy values are presented in order to evaluate the performance results of the proposed model.
- A model as successful as high-dimensional architectures was obtained with a lightweight CNN without using any transfer learning architecture.
- The effect of applying image preprocessing steps to the proposed deep learning architecture has been measured.
- The performance results obtained with and without image preprocessing are presented within the scope of the article.
- As a result of the experimental studies, 99% precision, recall, F1 score, and accuracy measurement metrics were achieved with the CNN model with preprocessed input type.
- According to the raw input type that has not undergone any preprocessing, success rates of 98%, 97%, 98%, and 98% were achieved in terms of precision, recall, F1 score, and accuracy metrics, respectively.

The next steps of the article consist of three sections. In the next section, the publicly available data set used in the article is explained in detail. In the second section after this step, the performance results obtained with and without pretreatment are presented. In the last section, the article is concluded.

II. Materials and Method

In this study, the data set prepared for automatic recognition of traffic signs with machine learning methods was used, close to the performance of drivers on the road. To measure the success performance of the proposed CNN-based model, a widely used dataset was preferred [3].

Fig. 1. Samples of traffic signs in the dataset

The image samples in the data set used are shown in Figure 1. Although speed limits are frequently used in traffic, the warning signs that prevent passengers from having an accident attract attention. A figure consisting of different traffic signs showing movement in the direction of the arrow, slippery ground, pedestrian can pass next to the signs and showing that there is work on the road is presented in Figure 1.

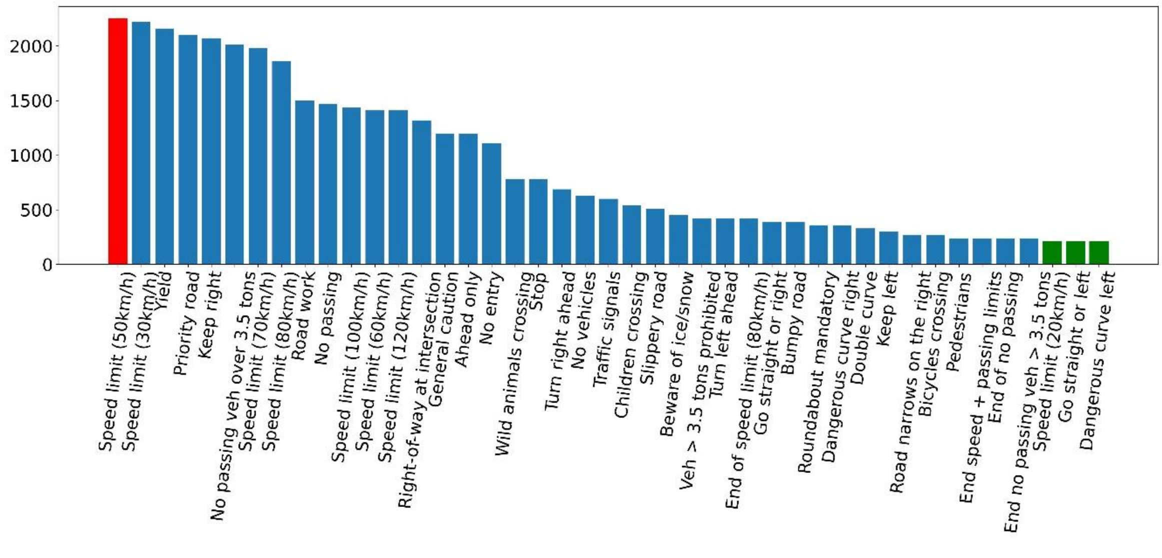


Fig. 2. Traffic signs in the dataset

The parameters of the proposed deep learning model are optimized according to the preferred data set. There are 43 classes in the data set. Free access to the dataset with more than 50,000 images of German road signs. The traffic sign classes in the data set are presented in Figure 2. The class with the most signs is shown in red, while the class with the least number of signs is shown in green. The plate showing the speed limit as 50 km/h contains 2250 images of the plate. The Dangerous curve left traffic sign contains 210 traffic signs. In addition to this traffic sign, the speed limit (20km/h) and the go straight or left traffic signs each have 210 signs. In determining the effect of the proposed CNN model on traffic signs, two separate performance studies were carried out with and without the preprocessing steps, which are frequently used in classical machine learning methods.

A. *Pre-processing Steps*

The preprocessing steps are presented as shown in Figure 3. This image shows the change in the images with the pre-processing step. Thresholding and gray transformed states of four different traffic signs according to RGB, HSV, V channel are shown in Figure 3 as Figure 3a, 3b, 3c and 3d, respectively. Figure 3a shows the original traffic sign image prepared without any transformation. The raw state of the images in the data set is shown. Figure 3b shows the image converted to HSV color channel. When the literature is examined, it is reported that HSV color channels (Hue-Saturation-Brightness) are effective channels for adjustments in saturation and brightness (Sugimoto and Imaizumi 2022). In this study, especially the V channel was threshold. Only the V channel is reported to be more effective than brightness adjustments.

Fig. 3. a) Original, b) HSV, c) V channel post edit, d) Gray format

At the same time, there are studies that reach the ideal brightness value by making modifications only on the V channel while keeping the other color channels constant [20]. For these reasons, it has been converted because it is thought that it is easier to operate in the HSV color space in the brightness adjustment of the image. Figure 3d shows the image converted to gray format. Faster processing is possible with an image converted to gray format instead of three-channel color images. Different experimental studies have been carried out to determine whether preprocessing steps have an effect on the classification success of the CNN method proposed in the article. To evaluate performance comparison results, the F1 score, recall, precision, accuracy measurement metrics, which are widely used in the literature, were calculated in both ways. The results obtained from the measurement are shown with graphics. The results obtained from these processes are presented in detail in the third section.

B. *Proposed Model*

In this study, the KFold technique was applied to avoid large differences between each run of the proposed model. According to the KFold 3 technique, the training and test data were separated and the model was trained. Two different result tables and figures were obtained, the results of the same model on both pre-processed images and the results obtained on unprocessed raw images.

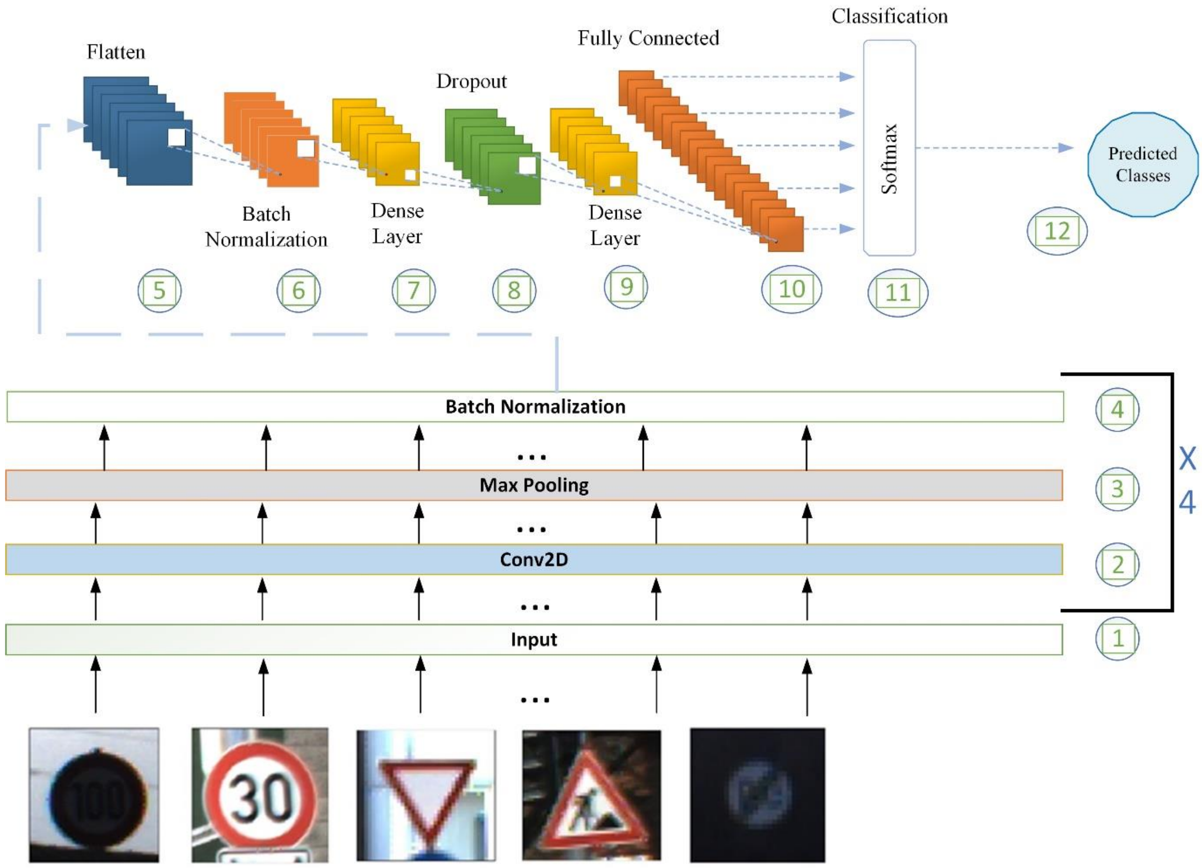


Figure 4. Proposed model

The proposed model is shown in detail in Figure 4. The first layer of the model is where the preprocessed input image and the raw input image change. Afterwards, the structures in the second, third, and fourth layers are repeated four times. In the first iteration, a two-dimensional convolution layer with a 32 3x3 window size ReLU activation function was used. A maximum pooling layer with 2x2 strides was added immediately after. After the specified layers, the batch normalization layer has been added, which normalizes the inputs between the layers. In the second iteration, these processes continued with a two-dimensional convolution layer with 64 3x3 window size ReLU activation function. As in the previous iteration, a maximum pooling layer of 2x2 has been added. In this way, the most effective of the features were selected. In the last step of the second iteration, batch normalization was added, which normalizes the inputs between the layers. In the third iteration, a two-dimensional convolution layer with a 128 3x3 dimensional ReLU activation function has been added. As in the other iteration, a maximum pooling layer of 2x2 has been added. The best features obtained from 128 3x3 two-dimensional convolution layers were selected. In the last iteration, 512 3x3 two-dimensional convolution layers with the ReLU activation function were added. Afterwards, the feature map was clarified again with 512 3x3 convolution layers. The iteration part has been completed with the max-pooling layer and batch normalization layers in the other iteration. After the iteration part of the model, the Flatten layer has been added, which converts the model outputs to a one-dimensional vector. This layer was applied in step five. A batch normalization layer has been added, which normalizes the flattened layer outputs obtained in the sixth step. In the seventh layer, dense layer with 1000 hidden neurons and ReLU activation function has been added. In the eighth step, the dropout layer, which performs 0.9 neuronal dropout, was applied. In the ninth step, as in the seventh step, dense layer with 1000 hidden neurons with ReLU activation function was applied. In the tenth step, the fully connected layer and the attribute maps obtained in the previous layers are connected to the classification layer. In the eleventh step, considering that there are 43 classes in total in the data set, the classification layer with the 43 output softmax activation function was created.

C. *Experimental Results and Discussion*

In order to perform the performance analysis of the method proposed in this article, training and test data are separated using the KFold 3 technique. According to the allocated data, the training and accuracy results are mainly presented according to the KFold options. The results obtained according to different input types are presented separately. The accuracy and loss values obtained for each KFold option are given in Table 1. The evaluation results obtained from the KFold option according to each input type are given in Table 1. When examined in detail, the accuracy results obtained by the model with the preprocessed input type gave a result close to the raw input results. Both types of input can be used effectively in the classification of traffic signs.

Table 1. KFold results

Input type	KFold Number	Accuracy	Loss	Average Accuracy	Average Loss
Pre-processed	1	0.99	0.0089		
Pre-processed	2	1.00	1.5732	0.9993	0.00312
Pre-processed	3	0.99	0.0004		
Raw input	1	0.98	0.0751		
Raw input	2	0.99	0.0052	0.9926	0.02837
Raw input	3	0.99	0.0047		

In Table 2, training performance results are given according to the pre-processed and raw input type. These given values belong to the KFold 1 option of both input types. The training performance results obtained according to the specified KFold option are presented in detail in Table 2. All performance graphics and table information after this step of the article consist of the results obtained according to the KFold 1 option.

Table 2. Training performance results

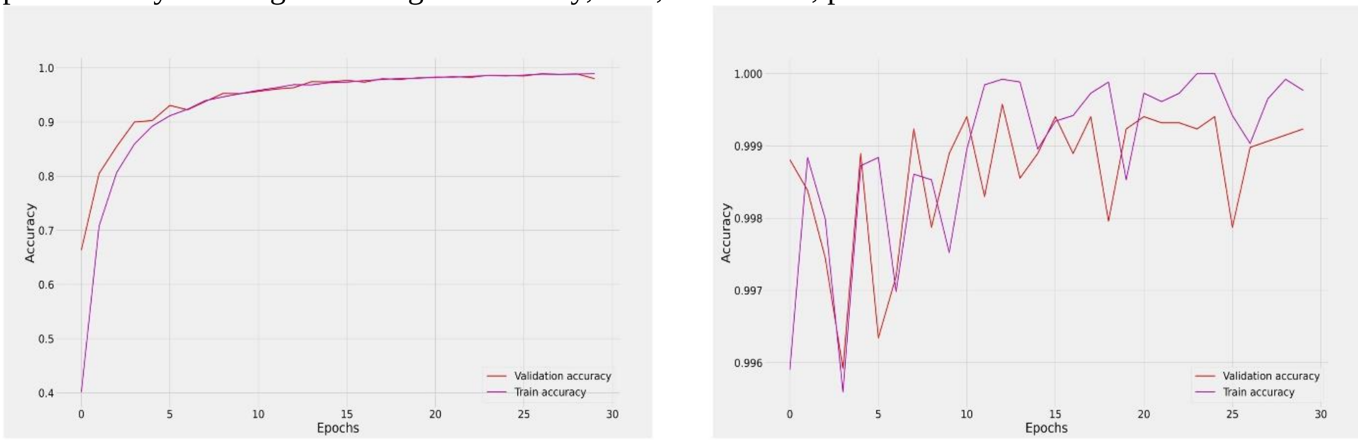
Input type	Precision	Recall	F1 Score	Accuracy
Pre-processed	0.99	0.99	0.99	0.99
Raw input	0.99	0.98	0.98	0.98

In Table 3, the validation performance results obtained according to the input types are given. According to these results, it is seen that both input types give very close results. From this it can be easily said that data sets can be trained without pre-processing in the classification of CNN models.

Table 3. Results of validation performance

Input type	Precision	Recall	F1 Score	Accuracy
Preprocessed	0.99	0.99	0.99	0.99
Raw input	0.98	0.97	0.98	0.98

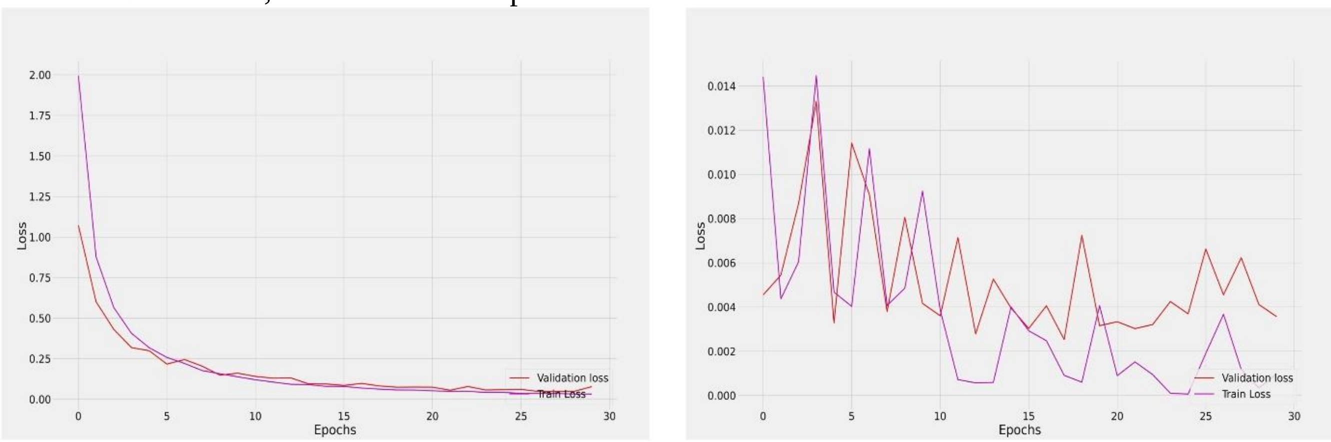
When studies in the literature are examined, it is seen that F1 score, recall, precision, and accuracy metrics are used as performance metrics. The graphical equivalents of the numerical values obtained according to the results of Table 1, Table 2 and Table 3 are drawn in detail after Figure 6. The model outputs obtained according to two different input types in the graphic drawings are presented by drawing according to accuracy, loss, F1 score, precision and recall order.



a) b)

Fig. 5. The accuracy performance results of the proposed model are a) raw input and b) preprocessed

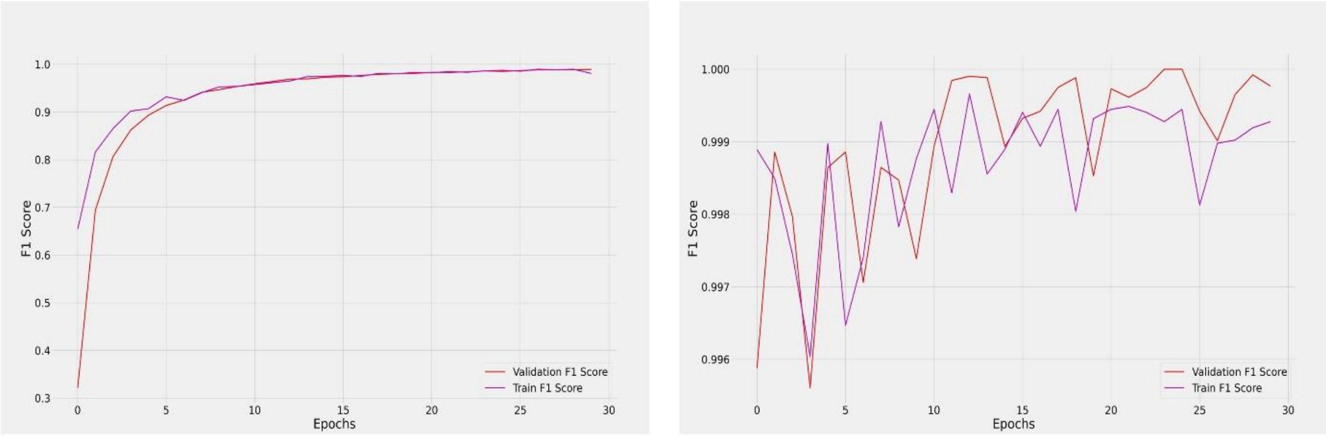
In Figure 5, the training and test accuracy graphs obtained from the training and test data separated according to the KFold 1 technique are presented. When these graphs are examined, the results obtained from the raw input and the results obtained from the pre-processed inputs are close to each other. However, while the raw input results are normal in the graphics output, the pre-processed output results are messy. The messy loss is also seen in the F1 score, precision, and recall charts. In Figure 5a, the raw input reached 98% success rate, while in Figure 5b, the preprocessed input type reached 99% success rate.



a) b)

Fig. 6. The loss performance results of the proposed model are a) raw input, b) preprocessed

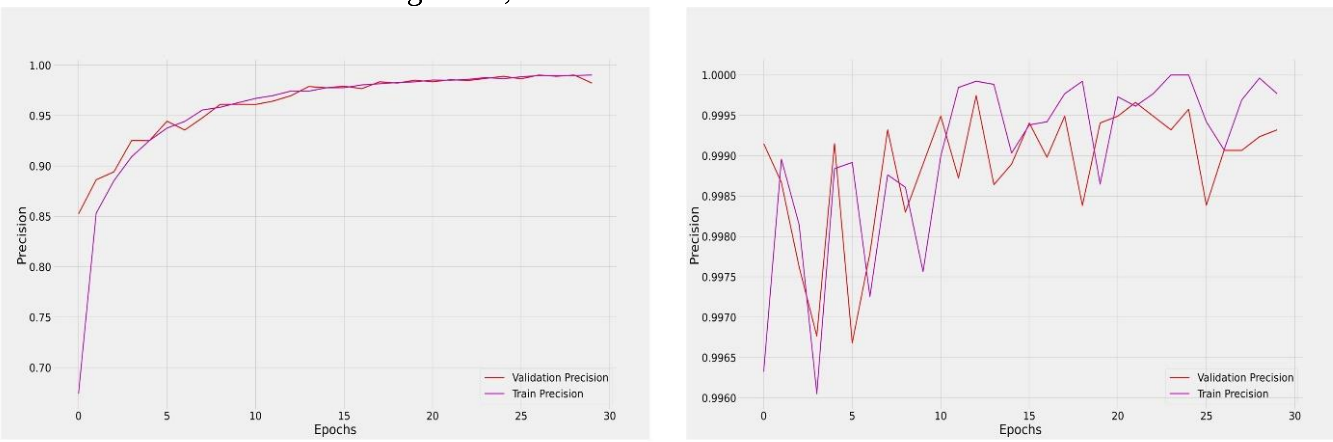
In Figure 6a, the raw input training loss decreased to 0.03182, while the validation loss decreased to 0.07733. In Figure 6b, the validation loss decreased to 0.00356 while the training loss decreased to 0.00097.



a) b)

Fig. 7. F1 score performance results of the proposed model, a) raw input, b) preprocessed

In Figure 7a, the measurement of the F1 score of raw input training and the measurement of the validation F1 score reached 98%. In Figure 7b, the measurement of the validation F1 score and the measurement of the training F1 score reached a 99% success rate. In Figure 8a, the precision measurement of raw input training reached a success rate of 99% and the precision measurement of validation reached 98%. In Figure 8b, validation precision measurement and training precision measurement reached 99% success rate. When F1 score and accuracy measurement metrics are evaluated together, it is seen that performance metrics change in a parallel and harmonious way. As with other charts, charts containing F1 score plots are similar. Figure 8b shows a wavy graph, while Figure 8a shows a flat graph.



a) b)

Fig. 8. Precision performance results of the proposed model, a) raw input, and b) preprocessed

In Figure 9a, the raw input training recall measurement reached a success rate of 98% and the validation precision measurement remained at 97%. In Figure 9b, validation precision measurement and training precision measurement reached 99% success rate.

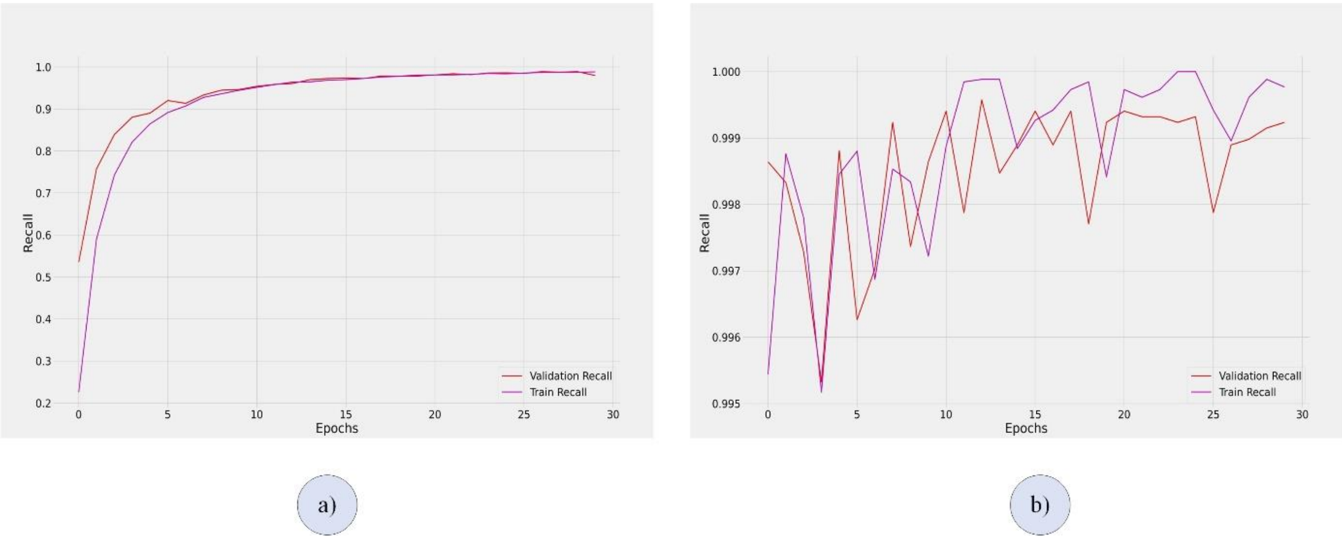


Figure 9. Recall performance results of the proposed model, a) raw input and b) preprocessed

When the results of Figure 9a and 9b are evaluated together, there is a 2% difference between the validation recall performance results of the deep learning model run with two different inputs. In other metrics, a difference of around 1% was detected. When these differences are evaluated together, it can be assumed that both input methods can be used in the automatic classification of traffic signs. However, the model with preprocessed input has been proven to be more successful, albeit slightly, not only with the accuracy value, but also with the F1 score, precision and recall values.

Until this step of the article, the training and validation data were processed. With these data, the proposed model was trained and validated. After this step, the model is ensured to be tested using data that are not used in any training and validation processes. In the test processes, the actual label of the test data and the estimated label were printed as a title on the traffic sign image. As a result of the experimental studies, the proposed model estimation and actual label values are presented comparatively. There are 43 classes in total in the data set. The actual and predicted labels have a class label from 1 to 43. The performance result of the system in line with the specified information is given in Figure 10.

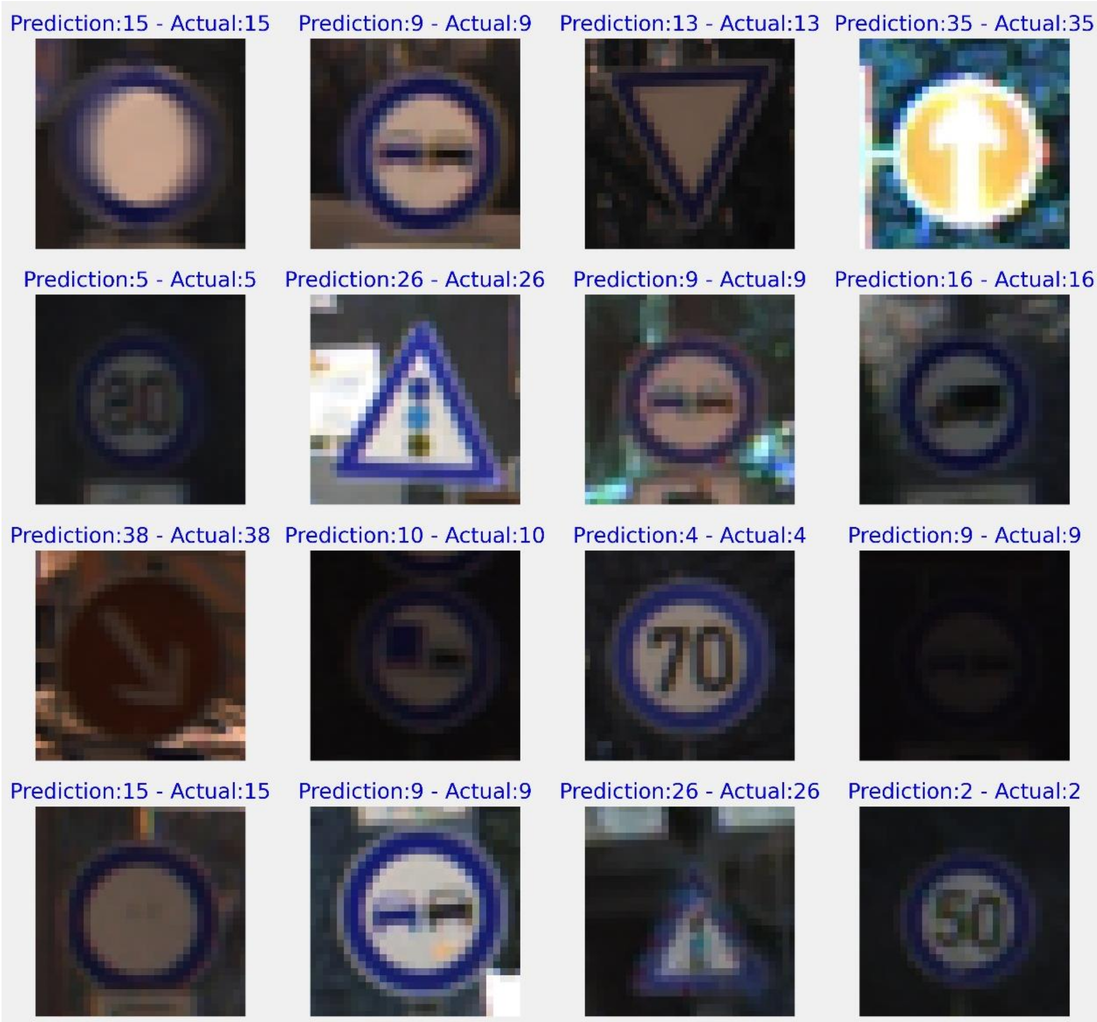


Fig. 10. Test performance results of the proposed model

Traffic sign classification studies are carried out in order to reduce motor vehicle accidents and increase the life safety of drivers. In this article, a CNN model with a learning rate of 0.001 with batch size 64 and multi-layer structures is proposed using Adam optimization method. A 98% to 99% result was obtained from the model tested by preprocessing and on raw traffic sign data. The results obtained are presented in Tables 1, 2 and 3. F1 score, recall, precision and accuracy values also provided similar results. The originality of the proposed model and the examination of the success performance of the proposed model according to the input type have different aspects from the literature.

According to the information obtained from different literatures, Staravoitau states that the success of people in traffic sign classification varies between 98.3% and 98.8% on average [21]. Likewise, Naim and Moumkine, in their study on the classification of traffic signs with a light architecture, declare that the traffic sign classification performance of an average person is 98.81% [22]. It is seen that traffic signs are classified with a 99.15% success rate with a less and lighter CNN model. They reported that they paid attention to filter structures so that the distinctiveness of the features could be high. Mishra and Goyal developed an efficient traffic sign classification model using deep CNN networks [23].

Prasanna et al. classified traffic signs with a CNN-based method with a success rate of 96.8% [24]. It is seen that they use the two-dimensional convolutional layer and the maximum pooling layer in their work. The proposed system in the study worked in gray images rather than in the RGB color channel. According to Xie et al. developed a deep learning model consisting of different stages for the classification of traffic signs [25]. The study is valuable in terms of using the data set used in this study in testing the proposed deep learning models. The model proposed in Xie et al. study was compared with the model results obtained using the pre-trained architecture approaches LeNet5 and AlexNet. It is seen that different results are obtained by applying positive samples and negative samples separately in classification. When applied to positive samples only, LeNet5 and AlexNet achieved success rates of 87.2% and 91.7%, respectively. Afterwards, when the same two models were applied to randomly generated negative samples in the same order, an improvement of 0.3% and 0.7% was observed, respectively. Finally, when applied to the selected negative samples, it is seen that the success rates of LeNet5 and AlexNet models are 87.9% and 92.8%, respectively.

III. CONCLUSION

Classification of unevenly distributed traffic signs with too many categories is an important problem. Computer vision and artificial intelligence techniques and classification of traffic signs have been investigated for decades. Automatic classification of traffic signs with a sufficient data set is very important for drivers, especially autonomous vehicles. It will perform traffic surveillance and automatic control of road routes to prevent accidents for driver safety. In this study, which aims to increase passenger safety in traffic, it is aimed to inform the drivers automatically. An average of 99% accuracy, F1 score, precision and recall performance metrics have been achieved with the study carried out with deep learning, one of the popular subfields of artificial intelligence. These values can also be the guarantee of safe travel. The article study can be expanded with the location detection and recognition functions of traffic signs.

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