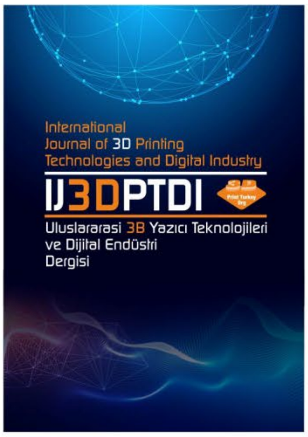


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# CONTROL OF SEAT BELTS OF VEHICLE DRIVERS WHILE DRIVING WITH AN UNMANNED AERIAL VEHICLE WITH ARTIFICIAL INTELLIGENCE

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## ABSTRACT

Today, with the rapid development of technology, the areas of use of artificial intelligence technologies are also rapidly increasing. Artificial intelligence applications are frequently used in many fields such as education, engineering and health. One of the important areas of use of artificial intelligence systems is mechatronic engineering. Artificial intelligence methods are frequently used especially in robotics and unmanned aerial vehicle applications. In the study, an artificial intelligence model developed to detect seat belt use by drivers using unmanned aerial vehicles is introduced. Seat belts play an important role in reducing injuries and deaths in traffic accidents, but current examination methods are time-consuming and limited. In this study, image processing techniques were used to determine whether drivers are wearing seat belts. For this purpose, a dataset consisting of in-car images taken under different driving conditions was created and Gaussian filters were applied to these images to remove noise and interference. Convolutional neural network architecture was used for model training and the results were compared with common models such as ResNet-18 and AlexNet. The model developed as a result of training has an accuracy rate of 94.55%. Test results showed that the developed special convolutional neural network model is superior to other models in terms of accuracy and performance. The study revealed that artificial intelligence and image processing techniques can increase traffic safety by monitoring seat belt use more effectively.

**Keywords:** Image processing, Unmanned Aerial Vehicle, Deep Learning.

## 1. INTRODUCTION

Fatal and injury incidents that occur after traffic accidents are considered one of the most important public health problems in the world [1]. In such accidents, the use of seat belts, which is one of the simplest and most effective precautions, is of great importance. According to research, seat belt use reduces the risk of fatal accidents by 40-65% and the risk of injury accidents by 40-50% [1].

A simple safety measure, the seat belt is one of the most effective methods of saving lives in traffic accidents [3]. Drivers and passengers who are wearing seat belts in a vehicle are protected from serious injuries by remaining stable in the vehicle during an accident and preventing them from being thrown. According to scientific research, seat belts have been shown to significantly reduce head, neck and chest injuries by keeping the body in a safe position during a collision [3]. In addition, with the developing technology, other safety measures in modern vehicles must be worn in order for them to work actively and correctly. For example; airbags perform best when seat belts are worn.

Injuries and deaths resulting from not wearing a seat belt clearly show how serious the consequences of neglecting this simple safety precaution can be. For example, in the United States, approximately 7,000 people die and more than 100,000 people are reported to be injured each year due to not wearing a seat belt [2]. In such accidents, passengers who are not wearing a seat belt are at a very high risk of being thrown from the vehicle, which often leads to fatal consequences. According to a study conducted by the General Directorate of Security Traffic Research Center, it was determined that passengers who are not wearing a seat belt have a 75% lower chance of survival after an accident than those who are.

Seat belt use, which is of such importance, was determined to be an average of 45-65% among drivers as a result of intercity checks and inspections carried out around Ankara in 2000. It was observed that this rate was even lower in urban use [1].

Traditional methods such as police checks used in seat belt inspections do not provide a sufficiently effective deterrent as they are time-consuming and usually carried out in limited areas. Therefore, with the advancement of technology, the use of artificial intelligence and image processing techniques in these checks offers the opportunity to monitor and control seat belt use more effectively and comprehensively [4].

By using artificial intelligence and image processing technology, it provides the opportunity to monitor and control seat belt use more effectively and comprehensively [5]. In the study, a comprehensive original data set including different driving conditions and in-car images taken from various angles was created with the data set we created in order to detect those not wearing seat belts. Drivers and passengers with and without seat belts will be manually labeled in the data set. Convolutional Neural Network (CNN) architecture will be used for model training. CNN is a deep learning algorithm that shows superior performance in image processing tasks and in this study, it will be optimized to detect whether seat belts are worn in in-car images. During the training process, Gaussian filter and normalization processes were applied to reduce noise and interference on the collected images in order to increase the accuracy and overall performance of the model. After the training of the model is completed, different tests will be performed on the test data set to evaluate the accuracy and effectiveness of the model. The test results will be used to determine the extent to which the model correctly detects seat belt use in different conditions and angles. The data will reveal the potential of artificial intelligence-based image processing systems in controlling seat belt use and increasing traffic safety.

The study aims to show how artificial intelligence and image processing technologies offer innovative solutions in the field of traffic safety and how they can contribute to increasing seat belt use. The study, which will be carried out with the data set and artificial intelligence model prepared specifically for the study, will be an important step towards identifying drivers and passengers who do not wear seat belts and thus reducing traffic accidents and related injuries and deaths.

## 2. MATERIAL AND METHODS

### 2.1. Material

In the material section of the study, the data set used in the study, the artificial intelligence algorithms and the performance evaluation metrics used in evaluating the results obtained from the artificial intelligence algorithms are discussed in detail under the following subheadings.

#### 2.1.1. Dataset

In the study, an original dataset was created using unmanned aerial vehicles to determine whether the drivers of moving vehicles have their seat belts fastened. The images in the dataset were taken while the drivers were wearing or not wearing their seat belts. The images in the dataset were recorded in color at 240x240 dimensions. The collected images were subjected to Gaussian filtering and normalization processes in order to reduce noise and interference on them. The dataset, which consists of a total of 1000 images, consists of 600 drivers wearing seat belts and 400 drivers not wearing seat belts. A sample image taken from the dataset prepared specifically for the study is shown in Figure 1.

(a) (b)

**Figure 1.** Example image of a person (a) not wearing a seat belt (b) wearing a seat belt for the dataset

### 2.1.2. Convolutional neural network

CNN is a deep learning method frequently used in image processing and computer vision applications. Studies conducted in 2023 focused on improving the performance of CNNs. For example, the integration of attention mechanisms into CNNs has been proposed to increase the accuracy of deep learning models [6]. In addition, studies have been conducted on reducing the training time and improving the performance of CNNs using transfer learning methods [7]. In the field of biomedical image processing, CNNs have provided high accuracy, especially in COVID-19 diagnosis [8]. In autonomous systems, CNNs have shown reliable performance for autonomous vehicles despite harsh environmental conditions [9]. Finally, studies to increase the scalability of CNNs on large data sets are also attracting attention as of 2023 [10].

### 2.1.3. Resnet 18

ResNet-18 is an architecture among deep neural networks that can learn more complex features by increasing the number of layers. However, residual connections were used to solve the "gradient extinction" problem that occurs with increasing the number of layers [10]. A study conducted in 2023 showed that ResNet-18 provides more efficient and faster results compared to deeper models on various datasets [1 1]. In particular, ResNet-18's ability to run with low latency on devices with limited resources has widespread its use in areas such as autonomous systems and mobile applications [12]. In addition, studies on optimizing ResNet-18 with transfer learning have highlighted the flexible structure of this model that can easily adapt to different areas [13].

### 2.1.4. AlexNet

AlexNet is known as one of the first architectures that revolutionized the field of deep learning and attracted attention especially with its success in the ImageNet competition in 2012. Studies conducted in 2023 show that AlexNet is still frequently preferred in applications with low hardware requirements because it is smaller and faster compared to more modern networks [14]. In one study, it was emphasized that the simple structure of AlexNet is ideal for mobile devices and low-cost systems, and it was stated that it achieved high accuracy results especially in image classification tasks [15]. In addition, studies have been conducted to increase the applicability of AlexNet to more complex data sets with transfer learning techniques [16]. Thus, today, AlexNet still provides an effective solution in many different areas, especially in systems with limited resources [17].

### 2.1.5. Performance evaluation metrics

Performance evaluation metrics are critical in evaluating the success of a model. Accuracy, recall, precision, and F1 score are commonly used metrics, especially in classification problems. Accuracy is the ratio of the examples correctly classified by the model to the total number of examples and is calculated using the mathematical expression given in equation 1 [18].

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

In the equation, TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) represent the classification results [18]. The accuracy metric is useful in cases where the classes in the dataset are balanced; however, it can be misleading in imbalanced datasets.

Recall indicates how many of the true positives were classified correctly and is calculated using the mathematical expression given in equation 2. [19].

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

This metric is especially preferred in cases where under classification is important. High recall indicates that the model performs well without skipping positive classes [19].

Precision measures how many of the model's positive predictions are correct and is calculated using the mathematical expression given in equation 3 [20].

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

Sensitivity is often used, especially in cases where false positive results are costly . High sensitivity indicates that the model is consistent in its positive predictions [20].

F1 Score is the harmonic mean of precision and recall and is used to evaluate the performance in imbalanced classes in a more balanced manner and is calculated using the mathematical expression given in equation 4 [21]

$$F1\ Score = 2\ x\ \frac{Precision\ x\ Recall}{Precision + Recall} \quad (4)$$

F1 score is an ideal solution metric for situations where both precision and recall are important [21].

### 2.2. Method

The workflow process followed in the study is presented in Figure 2. In this study, we used an image classification approach to detect seat belt usage in moving vehicles using three different models: Custom CNN, ResNet-18, and AlexNet. The methodology involved multiple stages, which are detailed below:

**Dataset Preparation:**
The dataset consisted of 1000 images captured using an unmanned aerial vehicle (UAV) under various driving conditions. Each image was manually labeled to indicate whether a seat belt was worn. The images were recorded at a resolution of 240x240 pixels and included diverse lighting and weather scenarios to ensure robustness.

**Data Preprocessing:**
Preprocessing played a critical role in improving model performance. Gaussian filtering was applied to the images to remove noise and interference, which is crucial in reducing false positive and false negative results. This step ensured the images were clear and consistent, facilitating effective feature extraction. Additionally, normalization was performed to scale pixel values between 0 and 1, standardizing the dataset and improving the training convergence of the models.

Custom CNN: A convolutional neural network (CNN) designed specifically for this task. It included multiple convolutional layers, pooling layers, and dense layers optimized for the dataset.
ResNet-18: A deep residual network known for its efficiency in handling complex image processing tasks.
AlexNet: A simpler architecture that demonstrated strong performance in earlier image classification challenges, chosen for comparison.
Training Process:
All models were trained for 100 epochs using the same dataset and hyperparameters. The learning rate was set to 0.0001, and cross-entropy loss was used as the optimization criterion. During training, techniques such as data augmentation and early stopping were employed to enhance generalization and prevent overfitting.

**Performance Evaluation:**
The models were evaluated using metrics such as accuracy, recall, precision, and F1 score. These metrics were calculated based on the confusion matrices generated from the classification results. The training process also involved monitoring loss values to assess the models' learning efficiency over time.

**Implementation Tools:**
The models were implemented using Python and TensorFlow libraries. GPU acceleration was utilized to expedite the training process. The results were visualized using matplotlib to better interpret model performance trends.

By elaborating on these methodological details, we aimed to ensure clarity and reproducibility of the study. The comprehensive workflow allows future researchers to replicate and build upon our findings.

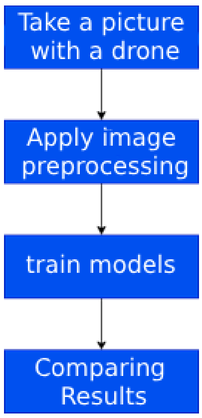

**Figure 2.** Workflow diagram

In the study, a system was developed that aims to detect whether the drivers of the vehicles are wearing seat belts while driving, using images collected using an unmanned aerial vehicle (UAV). In this context, a Convolutional Neural Network (CNN) based model was created and this model was trained with ResNet-18 and

AlexNet architectures in order to make a performance comparison. The dataset used in the study consists of images obtained with the UAV and this dataset was subjected to a series of pre-processing stages before training.

First, a Gaussian filter was applied to remove noise and interference from the images. This process made the images clearer and cleaner, thus contributing to the model producing more reliable results. Removing the noise is a critical step to reduce the possibility of the model giving false positive or false negative results. After the Gaussian filter, the normalization process was applied to the images in the dataset. Normalization shortened the training time of the model by scaling the pixel values in each image within a certain range and also increased the learning ability of the model. This process also helped the model to perform more generally under different lighting and contrast conditions.

A specific set of hyperparameters was used for training the models. Both models were trained for 100 epochs, and the learning rate was set to 0.0001. In this process, appropriate training strategies were adopted to prevent the model from overfitting. During training, both ResNet-18 and AlexNet models were trained with the same dataset and parameters, thus comparing the performances of the two models. During the training process, different metrics were used to monitor accuracy, loss values, and model performance during training.

## 3. RESULTS

In this study, the performance evaluations and obtained results of the CNN-based model developed to detect whether the drivers of moving vehicles are wearing seat belts are presented. In our study, the findings obtained in terms of accuracy, training time and overall performance of the model as a result of the trainings performed using ResNet-18, AlexNet and the CNN model we specially developed were discussed in detail. During the experimental process, the training accuracies of the models and their performances in the test phase were compared and presented, and it was discussed which model gave more effective results in this direction. Model training results are given in Table 1.

**Table 1.** Model Performance Metrics

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1 Score (%) |
|---|---|---|---|---|
| CNN Model | 94.55 | 95 | 93.8 | 94.4 |
| Resnet18 | 89.54 | 90 | 89.1 | 89.55 |
| AlexNet | 88.33 | 88.5 | 88.2 | 88.35 |

The accuracy graph shown in Figure 3 shows the accuracy values obtained by the models during the training process for 50 epochs. The graph was created to compare the accuracy performances of three different models (custom CNN model, ResNet-18 and AlexNet). As can be seen from the figure and the graph, the initial accuracy levels of the models were quite low, and all three models exhibited similar performance during the first 5 epochs. In this phase, the accuracy rates of all models changed around 10-15%.

As the number of epochs increases, especially after the 15th epoch, a significant increase in the accuracy rates was observed in all three models. It is seen that the specially developed CNN model reached a higher accuracy rate than the other two models as of the 20th epoch and this superiority continued throughout the training process. ResNet-18 and AlexNet models showed similar performance, but it was determined that the AlexNet model sometimes had lower accuracy rates than ResNet-18. After the 35th epoch, both models reached a stable point in terms of accuracy and settled at approximately 85% levels.

On the other hand, the special CNN model continued to increase the accuracy rate until the last epoch and reached approximately 95%. This shows that the model is more successful in seat belt detection than the other two models. It is thought that the deep learning model developed specifically for the study, which consistently obtained higher accuracy values throughout the training process, may have been positively affected by preprocessing steps such as denoising and normalization. The results obtained reveal that the CNN model developed specifically for the study provides a more effective solution to seat belt classification problems.

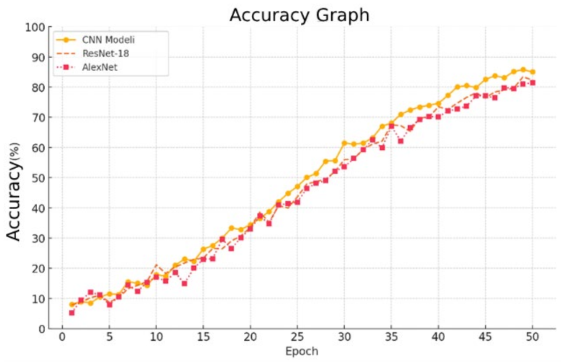


**Figure 3.** Accuracy graph

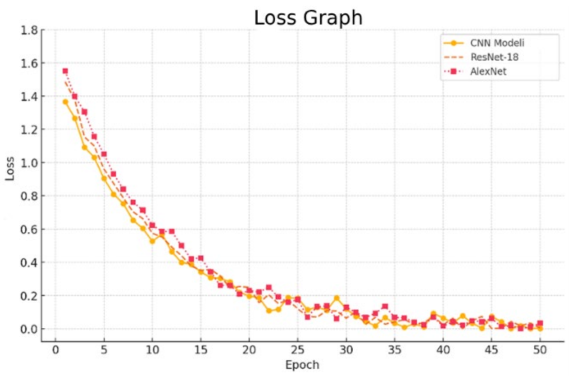


**Figure 4.** Loss graph

The loss graph given in Figure 4 shows the CNN model, ResNet-18 and AlexNet deep learning models used in the study, and the loss values they encountered during the training process. The loss value represents a metric used to measure the accuracy of the results predicted by the model. Therefore, a lower loss value means that the model performs better.

When the graph is examined, it is observed that all three models start with very high loss values at the beginning of the training process. In the beginning, especially during the first few epochs, the loss values are at the level of 1.6. However, as the number of epochs increases, a rapid decrease is observed in the loss values of all three models. This decrease shows that the models start to learn the dataset better and their prediction performance improves.

The loss value of the special CNN model started to be lower than the other two models starting from the 10th epoch. This shows that the model has a faster learning capacity and is better suited to the dataset. ResNet-18 and AlexNet models showed approximately similar loss values, but it was observed that the AlexNet model had slightly higher loss values than ResNet-18 at certain points. Starting from the 20th epoch, the rate of decrease in the loss values of all three models slowed down and after the 30th epoch, the loss values decreased below 0.2 and continued to be stable. Especially as of the 35th epoch, the loss value of the CNN model developed specifically for the study decreased below 0.1 and achieved the lowest loss value during the training period. ResNet-18 and AlexNet models completed the process with loss values at the level of 0.2. In general, the success of the special CNN model in the loss graph shows that the model has a better generalization ability on the dataset and makes fewer errors. ResNet-18 and AlexNet models exhibited similar performances, but they completed the training with slightly higher loss values compared to the CNN model developed specifically for the study. This suggests that the CNN model developed specifically for the study may be suitable for classifying images of seat belt fastening/not fastening.

The performance of the models developed and compared in this study—Custom CNN, ResNet-18, and AlexNet—was assessed using confusion matrices Table 2. These matrices summarize the classification results, providing insights into each model's ability to correctly identify seat belt usage.

**Table 2.** Model Confusion Matrices

| | Custom CNN | ResNet-18 | AlexNet |
|---|---|---|---|
| TP | 938 | 890 | 882 |
| FP | 46 | 89 | 101 |
| FN | 7 | 15 | 15 |
| TN | 7 | 4 | 1 |

The confusion matrices highlight that the Custom CNN model outperforms the other two models in terms of both sensitivity (true positive rate) and specificity. The Custom CNN achieves a significantly higher number of true positives (938) while maintaining a lower false positive (46) and false negative (7) count compared to ResNet-18 and AlexNet. In contrast, AlexNet, while having a slightly lower number of true positives (882), exhibits the highest number of false positives (101) and a minimal count of true negatives (1), indicating challenges in distinguishing negative instances. The ResNet-18 model performs moderately, with true positives and false positives falling between those of Custom CNN and AlexNet. However, its higher false negative count (15) compared to the Custom CNN suggests potential room for improvement in recall. These findings underscore the superiority of the Custom CNN model for the classification task, reflecting its robustness and reliability in detecting seat belt usage under varying conditions.

In the new studies to be carried out, the use of advanced and up-to-date models and performance comparison in real-time applications will be made. In addition, the visuals in the data set will be diversified and the performance in different weather conditions will be improved.

## ETHICAL APPROVALS

The study was carried out by the Scientific Research and Publication Ethics Committee of Isparta University of Applied Sciences with the decision of the ethics committee numbered 202/01.

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