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Classification of Eye Images by Personal Details With Transfer Learning Algorithms

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Abstract

Machine learning methods are used for purposes such as learning and estimating a feature or parameter sought from a dataset by training the dataset to solve a particular problem. The transfer learning approach, aimed at transferring the ability of people to continue learning from their past knowledge and experiences to computer systems, is the transfer of the learning obtained in the solution of a particular problem so that it can be used in solving a new problem. Transferring the learning obtained in transfer learning provides some advantages over traditional machine learning methods, and these advantages are effective in the preference of transfer learning. In this study, a total of 1980 eye contour images of 96 different people were collected in order to solve the problem of recognizing people from their eye images. These collected data were classified in terms of person, age and gender. In the classification made for eye recognition, feature extraction was performed with 32 different transfer learning algorithms in the Python program and classified using the RandomForest algorithm for person estimation. According to the results of the research, 30 different classification algorithms were used, with the ResNet50 algorithm being the most successful, and the data were also classified in terms of age and gender. Thus, the highest success rates of 83.52%, 96.41% and 77.56% were obtained in person, age and gender classification, respectively. The study shows that people can be identified only by eye images obtained from a smartphone without using any special equipment, and even the characteristics of people such as age and gender can be determined. In addition, it has been concluded that eye images can be used in a more efficient and practical biometric recognition system than iris recognition.

Keywords

Eye image; Eye recognition; Transfer learning; Classification.

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1 Introduction

Biometrics is a science that measures the physical, chemical and behavioural characteristics of living things and focuses on identifying people in particular (Jain et al., 2007). Biometrics is frequently used in computer science to identify people from their physical and characteristic features. Biometric features generally consist of physical characteristics and behavioural characteristics of individuals arising from their anatomy. Fingerprint, facial structure, hand geometry and vascular structure of the hand, ear shape, DNA, iris and retina are the physical biometric characteristics of humans. Features such as signature and handwriting are examples of behavioural biometrics. Although voice is classified as a physical feature, it can be considered both a physical and behavioural biometric feature, as it can vary depending on the disease state or can be altered by individuals. Biometric recognition systems are systems that identify people by comparing their previously recorded biometric features with the person's current situation or behaviour through scanning and analysis (Şan, 2013). In order for biometric recognition systems to work correctly and reliably, there should be no errors in measuring and recording the biometric characteristics of individuals. In order to ensure this, processes should be recorded by making measurements with multiple repetitions (Şan, 2013).

Generally, biometric recognition systems are easy to use and manage, and this ease provides efficiency to system suppliers and users. On the other hand, there may be situations where biometric recognition systems are not suitable for every user. Identification of users with damage or disability in organs such as the face, eyes or fingers or use of these systems by disabled individuals may pose a problem. In order for a biometric recognition system to be used efficiently, all users must be identifiable by the system and be able to use the system. In addition, the initial investment costs of biometric recognition systems can be high for institutions and organizations. It is inevitable that the costs of ownership will be high, especially in systems where more than one verification method is used and integrated with complex software systems (Hadid et al., 2015). In the field of biometric systems, researchers are increasingly focusing on studies that improve the performance and usability of these systems, and the number of studies in this field is growing. Artificial intelligence, which is one of the areas to which countries attach the most importance in investments (Talan, 2021), emerges as a new way for researchers to develop biometric systems.

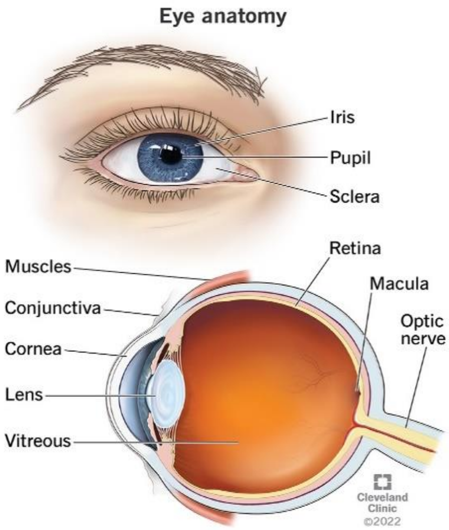

Figure 1. *Anatomical structure of the eye. Source: (ClevelandClinic, 2022).*

The eye is an organ found in an orbital socket made up of bone or cartilage in all vertebrates. In most living things, eyes are made up of fat, ligaments and musculature, and they have a certain range of motion. The eye, which needs protection as the only organ of living things that is generally open to the external environment, is also supported by the skull and eyelid (Franz-Odendaal & Vickaryous, 2006). The anatomical structure of the human eye is shown in Figure 1.

When you look at the human face, it can be said that the eyes are among the places that attract the most attention. The eye and its surroundings have different shapes and movements in expressing different emotions of people. In this way, the eye and its surroundings allow people to get an idea about others' cognitive processes, emotions and thoughts. This allows the use of the eye and its surroundings in automatic classification studies (Jaimes et al., 2001). In applications related to eye recognition, there are stages such as iris identification, determination of the inner and outer borders of the pupil and sclera, determination of the lower and upper borders of the eyelid, and detection of the eyelashes and cornea.

Iris recognition, or iris scanning, involves taking a high-contrast infrared photograph of a person's iris at close range, creating the iris pattern and converting this pattern into binary data. The purpose of iris recognition is to extract the mathematical model of this pattern of the iris, which has a unique and complex pattern, and to use it in the recognition and authentication of people by biometric systems. It is stated that iris recognition systems are both faster and safer than fingerprint systems since it is easier for people to change, hide or distort their fingerprints than to interfere with their own iris (Daugman & Cybernetics, 2007). However, there are some disadvantages to scanning the iris. In iris recognition, the scanning accuracy decreases due to the reflection of light in the use of normal cameras. For this, cameras with infrared light features should be used. In addition, a closeness of 15-20 cm to the camera is required for scanning. This proximity for registration and verification can cause discomfort to users. In this study, first of all, a new dataset was obtained from people's eye images. Classification of eye images was made with a model developed using artificial intelligence techniques on the created dataset. Thus, the identification of the individuals was carried out by classifying the eye images.

Machine learning is the adaptation of computer systems to a learning style based on data, akin to features of human beings in a new learning process by using their existing knowledge and continuing learning. Thanks to the data processing capacity of computer systems and this technology, machine learning methods are very useful in solving problems that people have difficulty dealing with in daily life or even cannot solve.

Face recognition, which is a branch of computer vision, is based on the measurement of the organs of the human face, such as the eyes, nose and mouth, and the mathematical modelling of their distance from each other. Facial recognition systems have become a biometric diagnosis system that is frequently used in public and private sectors for identity verification and personal identification. However, epidemics such as the coronavirus, which has affected the whole world in recent years and made the use of masks obligatory, have greatly reduced the success of face recognition systems due to masks. Because important areas of the face such as the mouth, nose and chin cannot be identified due to the use of masks, it has become difficult to detect people with face recognition systems. In addition, the aging of the human face, deformation, small image size, poor image quality, and the inability to identify the face due to different face angles are other important problems of these systems. Face recognition algorithms want the face to be clearly visible. However, it is shown that with the method used here, a high-accuracy recognition of a face from parts that can only be seen around the eyes can be achieved. The eyes are smaller organs and it is very difficult to change the eyes in terms of biometric recognition or to make any intervention to the eye. Based on these reasons, this study aimed to obtain biometric data from eye images. In other words, we aimed to determine the biometric differences in eye images with transfer learning algorithms and to classify people according to their eye images. Transfer learning algorithms are trained on more images compared to other machine learning algorithms. The success at the end of the training was proven by comparison with other methods using the same images. Therefore, this method is far ahead of other methods. For this reason, many transfer learning algorithms used in different images were tested in this study. Tests were carried out with the most commonly used methods in the literature. Thus, instead of using a single method, the results of many comparative methods are shown. The default parameters of the methods in the study were used. In this way, care was taken to make the comparisons simple and understandable. The importance of the study is to show that economically efficient biometric systems can be developed using cameras for data collection and biometric recognition, as iris and retina recognition systems, which are eye-based recognition systems, require devices with high costs and low availability. For these systems, it is not possible to obtain data with hardware without infrared light. However, in this study, eye images were obtained using a smartphone camera. Eye images were classified using problem-specific machine learning methods on the dataset consisting of obtained images. Thus, it is possible to say that even a personal smartphone can be adapted to a biometric eye recognition system.

In summary, the main contributions of this study are:

- Collecting eye images and creating a data set from these images and bringing this data set to the literature;
- presenting that people, their age and gender can be identified from eye images; and
- showing that eye images obtained only with smartphones can be used in biometric recognition, without the need for infrared light.

This section continues with a literature review. The rest of this article is organized as follows. Chapter 2 explains the methodology of the study, with subheadings of data collection, data analysis, success measures, and transfer learning. Chapter 3 describes the findings of the research. Finally, Chapter 4 presents the results of the study and the discussion and concludes.

1.1 Literature review

Cerme and Karakaya (2015) investigated the effect of the three-dimensional structure of the iris on iris recognition using different eye models. As a result, it has been observed that the distance between the iris increases as the angle between the front and non-angle iris images increases. Zhang et al. (2011) proposed a new iris recognition method for robust iris feature matching. Experimental results in two iris image databases show that this method is better than state-of-the-art iris recognition methods. The results obtained reached 0.21% EER in the DB1 dataset and 0.59 EER in the Lamp dataset. A performance analysis of the iris recognition system is presented according to the gender and health status of the users. As a result of the study, it was observed by the researchers that the diabetic effects on the performance of the iris recognition system were more intense in men than in female users (Azimi et al., 2019).

Wang et al. (2020) proposed a high-throughput deep learning-based iris segmentation method called IrisParseNet. To train and evaluate the proposed approach, the researchers manually tagged three representative and challenging iris databases. These databases were "CASIA.v4-distance", "UBIRIS.v2" and "MICHE-I". Bakshi et al. (2015) proposed a new model to increase the search accuracy of the iris recognition system. The inhomogeneous K-d tree structure used in the proposed model stores and maps the iris code. The proposed model was tested on IITD and CASIA datasets. In these datasets, 99.34% and 98.5% accuracy were obtained, respectively. A deep learning-based method called DeepIrisNet for iris display is presented by Gangwar and Joshi (2016). The presented approach includes several approaches taken from recent successful CNNs and deep learning architecture. Researchers used two different datasets "ND-iris-0405" and "ND-CrossSensor-Iris-2013" for validation. Dong et al. (2009) developed an adaptive iris matching method in order to increase the efficiency of iris recognition systems. With the experimental study, 95.73% accuracy was obtained in the CASIA 1.0 dataset.

Devi (2017) demonstrated an automated approach for iris segmentation and iris recognition with a focus on twins. The researchers stated that technically it is necessary to localize and segment the iris, followed by iris normalization and discriminating features. Sharkas (2016) developed a new approach for an iris recognition system using both eyes. In the study, images of the right and left eyes of three people in the third version of the CASIA iris database were used. Tan and Kumar (2014) presented the development of a new anti-spoofing approach that takes advantage of statistical grey level dependencies in both localized and global eye regions surrounding the iris. Vatsa et al. (2010) used colour iris images characterized by three spectral channels (red, green and blue) and a quality-based fusion scheme was proposed to improve the recognition accuracy. In the study, a 99% accuracy rate was obtained by using the WVU multispectral iris database. Zhang et al. (2010) proposed a hierarchical fusion scheme for low-quality images in uncontrolled situations. Jalilian et al. (2020) investigated the effect of different angles of view on CNN-based non-angle iris segmentation and their recognition performance and presented an enhancement scheme to compensate for some segmentation distortions caused by non-angle distortions.

Sun et al. (2014) proposed a new texture pattern representation method called the Hierarchical Visual Code Book (HVC) to encode the texture bases of iris images as a general framework for iris image classification based on texture analysis. Frigerio et al. (2012) proposed a new method to correct non-angle iris images. Gale and Salankar (2016) used Haar transform, PCA, Block sum algorithm to extract features in certain parts of the iris in order to improve the performance of an iris recognition system. Dillak and Bintiri (2016) proposed a method for obtaining accuracy based on Elman Recurrent Neural Network / Levenberg-Marquardt algorithm. Popplewell et al. (2014) presented a multispectral iris recognition scheme using Circular Hough Transform (CHT) and a modified Local Binary Pattern (mLBP) feature extraction technique. Ng et al. (2010) proposed an iris recognition system using a basic and rapid Haar wavelet decomposition method to analyse the pattern of the human iris. This system has been tested with the CASIA iris database and achieved an accurate recognition rate of 98.45%. Danlami et al. (2020) suggested the use of Legendre wavelet filters with the most commonly used filters. The researchers tested these filters on three different datasets.

It is understood from the above-mentioned that the studies within the scope of the eye organ for biometric recognition are mostly focused on iris recognition. This situation draws attention only to the iris region of the eye in eye recognition researchers. Studies targeting the iris take into account some limitations, such as the use of infrared cameras and obtaining iris images from a certain distance. In order to overcome these limitations and offer a different way of eye recognition, it has been an important research question whether the eye itself can be used to identify people. With the study carried out based on this interest, it can be seen as an important contribution of the study to expand eye recognition from being a subject that is only focused on the iris to the eye itself.

2 Research methods

2.1 Dataset

During the data collection phase of the research, first of all, some brief information was given to the participants about the study, and how the data would be used and what to do. Photographs of the eye area were collected from participants consisting of a total of 96 different people aged between 3 and 64. It was clearly stated that there would be no situations that would define them during the photo shoot. Then, at least ten images of the right eye area of each person were taken. In addition, at least ten photographs of the left eye area were taken. Along with these photographs, no data other than the age and gender of the persons were recorded. Below are images of two people of different genders.

A total of 1980 images were obtained from the participants, as in the figure above. More than ten images were obtained from some people. For this reason, there is a difference in the number of photos of people. Care was taken to use different angles and lights so that each photograph does not form the same frame. Thus, photographs that were not all the same were collected. In order to prevent photographs being confused, a naming rule was developed to express the person, age, gender and the number of the photograph taken. An underscore ("_") character is inserted between each expression. Each expression used in the naming convention is given below in order:

- **Person ID:** It is a unique code value for each person photographed. This value ranges from 1 to 100.
- **Age:** The age is written directly as a number to express how old the person is. This value varies between 3 and 64.
- **Gender ID:** The value of 1 is expressed if the person photographed is male, and the value of 0 if it is a woman.
- **Photo ID:** Due to the fact that more than one photo was taken for each person, each photo was numbered sequentially from 1 to 10.

The dataset used in the study was shared in a dataset repository called Zenodo. It can be downloaded for public use from https://doi.org/10.5281/zenodo.6979283. Thus, it will be possible to conduct new studies with the use of these data.

Figure 2. *Sample eye contour images.*

2.2 Data analysis

All data were analysed with Python 3.x program. First of all, simple statistical analyses were made. As a result of these analyses, it was checked whether the data were stacked on any age or gender. In the analysis of these data, which do not have any problematic distribution, a computer with a Windows operating system, 40GB RAM and Intel(R) Core(TM) i5-1035G1 CPU, 3.70GHz processor was used. Transfer learning algorithms in the keras library, which was also written for Python, were used to extract the attributes of each image. The features of each image were extracted with 32 different algorithms. Thus, we aimed to find the best feature extraction algorithm. In the method used here, only the image size is given as a parameter. The lowest resolution accepted by each algorithm was used as the image size. Thus, the success of the recognition process has been demonstrated even in the worst images. Apart from this, no other parameters were used and when no parameters were used, the default values of the algorithms were used automatically. The use of parameters becomes usable after great experience in machine learning. The use of parameters is not preferred in order to enable a normal user to operate it easily. After this process, the data were classified according to person, age and gender with 30 different classification algorithms. The classification algorithms used are listed below:

- discriminant_analysis
    - LinearDiscriminantAnalysis
    - QuadraticDiscriminantAnalysis
- ensemble
    - AdaBoost

  - Bagging
  - extraTrees
  - GradientBoosting
  - HistGradientBoostingClassifier
  - randomForest
  - Voting
- linear_model
  - LogisticRegression
  - LogisticRegressionCV
  - PassiveAggressiveClassifier
  - Perceptron
  - RidgeClassifier
  - RidgeClassifierCV
  - SGDClassifier
- naiveBayes
  - bernoulliNB
  - CategoricalNB
  - complementNB
  - gaussianNB
  - multinomialNB
- neighbors
  - KNN
  - NearestCentroid
  - RadiusNeighborsClassifier

- neural_network
  - MultiLayerPerceptron
- svm
  - LinearSVC
  - NuSVC
  - SVM
  - DecisionTree
  - ExtraTreeClassifier

2.3 Success measures

There are a number of analysis methods to measure how successful the machine learning algorithms prove to be in the prediction made on a dataset. Among these analysis methods, the ones that are frequently used in classification problems are the correct classification rate and complexity matrix methods. The ratio obtained by dividing the data that should be labelled in the correct class by the number of the whole sample from the findings obtained by running the classification methods is the correct classification rate.

$$Correct\ classification\ cate = \frac{Number\ of\ correctly\ classified\ samples}{Total\ number\ of\ samples} \tag{1}$$

The complexity matrix, which is another frequently used success criterion, is used to analyse the success in classification in more detail. This method is also called the error matrix. Detailed information about the error matrix is shown in Table 1.

Table 1. Error (confusion) matrix.

		Predict value	
		Class 1	Class 2
Real value	Class 1	True Positive (TP)	False Negative (FN)
	Class 2	False Positive (FP)	True Negative (TN)

The meanings of the terms TP, FN, FP and TN shown in Table 2.1 are explained below.

- **True Positive (TP):** This value is the number of samples that actually belong to Class 1 and are found to be in Class 1 as a result of predictions, that is, correctly predicted.
- **True Negative (TN):** This statement covers the same situation as saying false to false. That is, the value of 0 is estimated as 0.
- **False Positive (FN):** This is the case where the predictive value is 1 while the true value is 0, that is, those that are incorrectly predicted. In other words, they are predictions that mean right to wrong.
- **False Negative (FN):** Predictions that mean right or wrong.

Here, in summary, the estimates under TP and TN are correct estimates, while FN and FP are incorrect estimates. Using the data in the error matrix, many success metrics can be calculated. The main purpose is to increase the number of TPs and TNs, that is, correct predictions in the prediction made.

2.4 Transfer learning

Transfer learning is a research topic in machine learning that focuses on recording the knowledge obtained in solving a problem and then using it to solve a different problem. Transferring the learning obtained in transfer learning provides some advantages over traditional machine learning methods, and these advantages are effective in the preference of transfer learning. The advantages of transfer learning compared to traditional machine learning approaches can be expressed as efficiency in terms of time and hardware resources and higher performance with fewer data (Çelik, 2020).

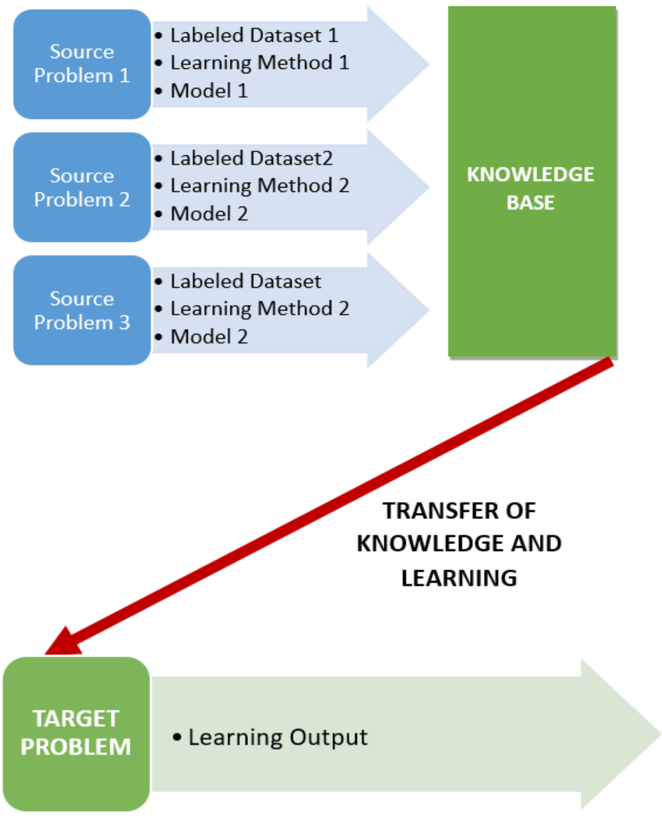

Figure 3. Transfer learning model structure.

In order to use transfer learning, it is necessary to mention the existence of at least two problems, one of which is the target problem, which is expressed as the main problem to be solved. The source problem(s) on which learning is based in solving the target problem constitute(s) the other problem type. It is the source where there are more datasets than the target problem; this dataset is trained with a specific machine learning algorithm, a model is presented and learning is transferred as a contribution to the solution of the target problem. The general structure of the transfer learning approach is shown in Figure 3. When Figure 3 is examined, it can be explained that the knowledge base, which consists of the models obtained by working with the machine learning methods of the source problems, is used by transferring the knowledge and learning experience to the targeted problem.

The convolutional neural network (CNN), which forms the basis of deep learning and transfer learning algorithms, is an approach based on an animal vision system, in which filtering is used to make the features of the image evident. With the filtering process, the functions that are used to determine the features of the image are identified. The use of these filters in different sizes and values facilitates the emergence of non-specific features (Doğan & Türkoğlu, 2019). In this study, libraries on the Python platform were used for transfer learning. These algorithm methods are briefly mentioned in the following sub-headings.

- **AlexNet:** In the AlexNet algorithm, the size of the input image data is reduced by filters applied in five different convolution layers. In the last three layers, the features from the previous layers are combined into a one-dimensional vector in order to make predictions. This layer is the full link (feature) layer (Bayram, 2020).
- **VGG:** The visual geometry grouping (VGG) algorithm, which proved its success by reducing the error rate in image classification to 7.3% in the ILSVRC-14 competition, was designed in 6 different architectures up to 19 convolution layers. Unlike the deep learning algorithms before it, 2x2 and 3x3 filters are used in VGG (Doğan & Türkoğlu, 2019; Simonyan & Zisserman, 2014). The VGG algorithm is named according to the number of layers used. For example, if a 16-layer structure is used, this algorithm is expressed as VGG16, if a 19-layer architecture is used, this algorithm is called VGG19.
- **ResNet:** ResNet, developed by Microsoft, was the algorithm with the deepest architecture developed until 2015 with 152 layers. While the error rate in human vision is between 5% and 10%, ResNet, which succeeded in classifying images with an error rate of 3.57%, came first in the ImageNET ILSVRC competition in 2015 due to this success (Özkan & Ülker, 2017; Wu et al., 2018).
- **DenseNet:** In this architecture, the information flow density between the network layers is at the maximum level. Because in DenseNet architecture, each layer transmits the feature maps that it creates to the next layer, thanks to the input from the previous layers. The biggest advantage of the use of this algorithm is that it ensures the reusability of the features obtained by ensuring that the features produced in each layer reach the next layers. DenseNet algorithms can be used in different versions such as DenseNet121, DenseNet169, DenseNet201 depending on the number of layers used (Ergün & Kılıç; Huang et al., 2017).
- **EfficientNet:** This model can be thought of as a group convolutional neural network model. It showed an accuracy performance of close to 85% in the classification problem in the ImageNet competition. EfficientNet algorithms consist of a total of eight model groups named B0 to B7. As the model numbers increase, the number of parameters to be calculated by the relevant model does not increase; on the contrary, the accuracy reached by the model increases significantly. This model aims to increase efficiency by scaling parameters such as resolution, width and depth (Uçar, 2021).
- **Inception-V3:** This architecture, which was trained and developed by Google, is based on the principle of simultaneous filtering and pooling and is based on the Inception network structure

and can consist of up to 42 layers in total. In the Inception-V3 algorithm, filters of different sizes and numbers are combined into a new filter and an initial model is presented. Thanks to such a design, it is among the most successful algorithms in image classification, as the number of parameters and computational complexity are reduced (Uçar, 2021).

- **MobileNet:** This algorithm is designed for mobile and embedded platforms; it is smaller in size and has higher performance than popular models. Because MobileNet consists of separable convolutions for different depths, it can process transactions much faster. Due to its architectural feature, MobileNet has been preferred in terms of usability in mobile and embedded platforms, which are limited in terms of power and hardware, since the calculation complexity can be minimized by reducing the transaction volume and the number of parameters (Gökalp & Aydin, 2021; Howard et al., 2017).
- **Xception:** With the further development of the Inception architecture by Google, the Xception model has emerged. This model is designed with a deeper and wider architecture than the others. The model consists of three streams: inlet, middle and outlet streams. After the data pass through the inlet stream, they pass through the middle stream, which repeats eight times to the outlet stream. In the Xception model, normalization operations are applied in all convolution layers (Akgözlüoğlu, 2021).
- **NasNet:** NasNet is a model developed by the Google Brain team. An important advantage of NasNet is that the model size is small and it gives good results with little complexity. NasNet is not a fixed structure, but consists of cell structures that can change dynamically. These cells, in which convolutional processes take place, are of two types: normal cells and reduction cells. A reduction cell differs from a normal cell in that it reduces the size of the output it receives (Balga, 2020).

3 Results

3.1 Statistical findings

The gender data of the image files were subjected to a simple statistical analysis and the situation given in the table below emerged.

Table 2. *Distribution of genders in dataset.*

Gender	Number of persons	Percent
Male	940	47.48%
Female	1040	52.52%
Total	1980	100%

Even though the number of female subjects was slightly higher among the data, a similar number of samples were obtained. When the age situation in the dataset is examined, it will be seen that there are a number of samples ranging from 3 to 64 years old. The sample distribution of these ages is given visually in the graphic below. Examining this graph, it can be observed that while fewer samples were obtained under the age of 20 and above the age of 40, more samples were obtained between the ages of 20-40. The numbers here refer to the number of images obtained from people, not to the people. A total of 20 images were obtained: 10 images of the right and left eyes of each subject. Therefore, the minimum values in the chart start from 20 and are in multiples of 20.

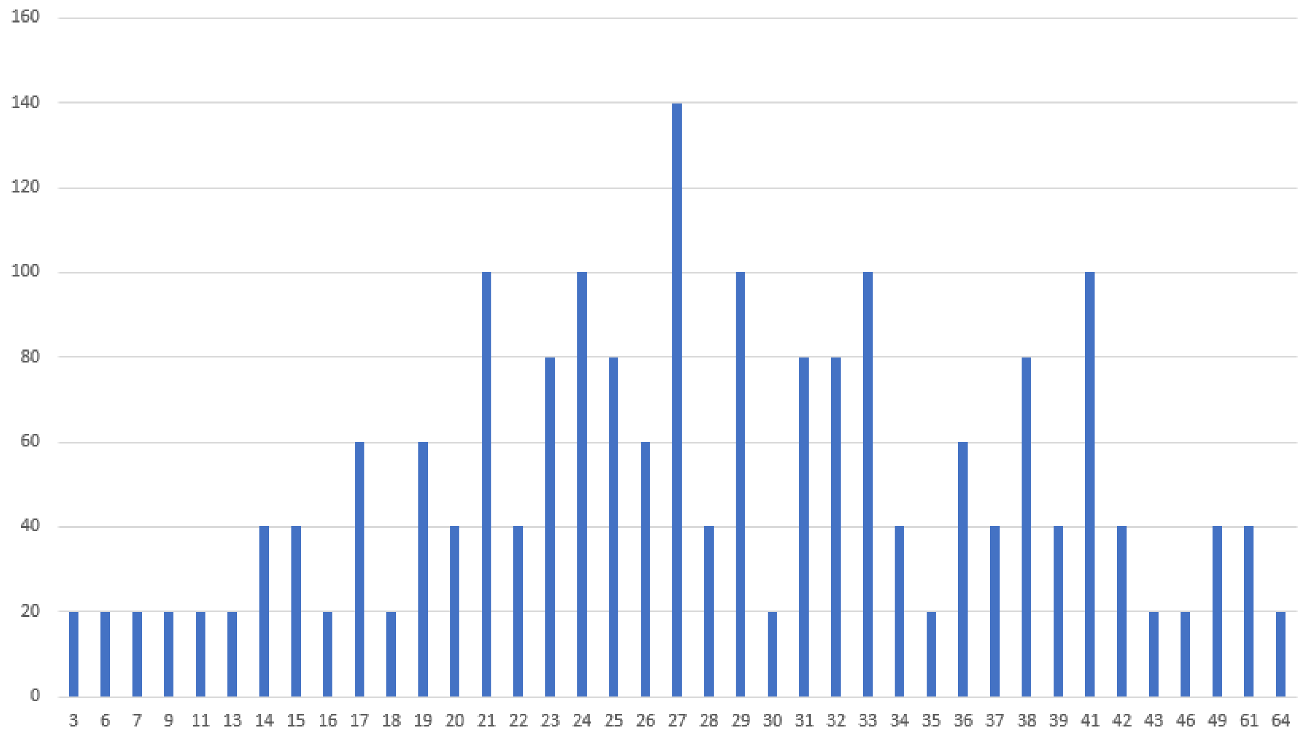

Figure 4. *Graph showing how many images are of each age.*

3.2 Person classification findings

Images were obtained from 96 different people. Thirty-two different transfer learning algorithms were used to extract the features of these images. In order to determine which of each feature extraction algorithm performs better first, the method named RandomForest was chosen from the classification algorithms and all the features were classified with this method. The obtained accuracy rates and method names are given in the table below in order of accuracy rates from smallest to largest. Here, the separation of data into training and testing is 30% test and 70% training. Here, the 10-fold cross-validation method was not preferred as it would repeat the process ten times and prolong the processing time. The purpose here is only to determine the best feature extraction method.

Table 3. *Accuracy rates of different transfer learning algorithms.*

ID	Transfer learning feature extraction algorithm	Accuracy
1	InceptionResNetV2	0.304714
2	NASNetMobile	0.382155
3	InceptionV3	0.424242
4	NASNetLarge	0.436027
5	ResNet50V2	0.468013
6	DenseNet121	0.478114
7	MobileNet	0.508418
8	MobileNetV2	0.513468
9	Xception	0.521886
10	EfficientNetV2S	0.56229
11	AlexNet	0.572391
12	EfficientNetV2B2	0.582492
13	EfficientNetV2B0	0.585859
14	EfficientNetV2B1	0.604377

ID	Transfer learning feature extraction algorithm	Accuracy
15	EfficientNetV2M	0.609428
16	DenseNet201	0.617845
17	EfficientNetV2B3	0.627946
18	VGG16	0.62963
19	EfficientNetB2	0.631313
20	EfficientNetB0	0.631313
21	EfficientNetV2L	0.631313
22	EfficientNetB3	0.639731
23	VGG19	0.639731
24	EfficientNetB6	0.648148
25	EfficientNetB5	0.649832
26	EfficientNetB1	0.651515
27	DenseNet169	0.656566
28	EfficientNetB4	0.658249
29	EfficientNetB7	0.681818
30	ResNet101	0.708754
31	ResNet152	0.712121
32	ResNet50	0.723906

For the data here, the ResNet50 algorithm was found to be the most successful feature extraction method. Now, these attributes can be used for different classification algorithms. For this, 27 different classification algorithms were used, and the results given in the table below were obtained. These results are shown with the grouped version of each method. The fact that the RandomForest method produces different results compared to the above table is due to the fact that the codes produce results with different parameters in each run. Here, the separation of data into training and testing is 30% test and 70% training. Here, the 10-fold cross-validation method was not preferred as it would repeat the process ten times and prolong the processing time. The aim here is only to determine the best classification method. When this table is examined, LinearSVC method achieved the highest result with a success rate of 0.83. Although many of the other methods produced results close to these values, the LinearSVC method will be preferred and continued.

Table 4. *Results obtained with different classification methods of ResNet50 Attributes.*

Group	Classification method	Accuracy	F-measure	Recall	Precision
discriminant_analysis	LinearDiscriminantAnalysis	0.8081	0.7785	0.7919	0.7900
discriminant_analysis	QuadraticDiscriminantAnalysis	0.0606	0.0641	0.0734	0.0762
ensemble	ExtraTreesClassifier	0.7298	0.6841	0.7187	0.6973
ensemble	RandomForestClassifier	0.7121	0.6664	0.7015	0.6931
ensemble	VotingClassifier	0.7096	0.6724	0.6972	0.7126
ensemble	HistGradientBoostingClassifier	0.6869	0.6675	0.7105	0.6726
ensemble	BaggingClassifier	0.5152	0.4840	0.5219	0.5326
ensemble	GradientBoostingClassifier	0.3561	0.3775	0.3659	0.4862
ensemble	AdaBoostClassifier	0.0253	0.0146	0.0342	0.0174
linear_model	LogisticRegressionCV	0.8359	0.8283	0.8493	0.8360
linear_model	RidgeClassifier	0.8283	0.8033	0.8192	0.8178
linear_model	RidgeClassifierCV	0.8283	0.8033	0.8192	0.8178
linear_model	LogisticRegression	0.8232	0.8213	0.8344	0.8376

Group	Classification method	Accuracy	F-measure	Recall	Precision
linear_model	PassiveAggressiveClassifier	0.8081	0.7785	0.8065	0.7871
linear_model	SGDClassifier	0.7828	0.7606	0.7924	0.7831
linear_model	Perceptron	0.7601	0.7324	0.7733	0.7457
naive_bayes	BernoulliNB	0.6869	0.6697	0.6962	0.6954
naive_bayes	MultinomialNB	0.6793	0.6412	0.6547	0.6738
naive_bayes	ComplementNB	0.4621	0.4351	0.4664	0.5344
naive_bayes	GaussianNB	0.2753	0.2843	0.2890	0.4317
neighbors	KNeighborsClassifier	0.6717	0.6543	0.6730	0.7169
neighbors	NearestCentroid	0.6237	0.5871	0.5958	0.6329
neural_network	MLPClassifier	0.8030	0.7828	0.8052	0.7987
svm	LinearSVC	0.8384	0.8337	0.8493	0.8377
svm	SVC	0.6515	0.6358	0.6777	0.6786
tree	ExtraTreeClassifier	0.2348	0.2063	0.2242	0.2156
tree	DecisionTreeClassifier	0.0480	0.0340	0.0469	0.0332

In the operations so far, the data were divided into 30% test and 70% training, and we aimed to find the best feature extraction algorithm and the best classification method. ResNet50 was found to be the best feature extraction algorithm and LinearSVC method was found to be the best classification algorithm. Here, the results of the use of the 10-fold cross-validation method, which is widely preferred in the literature and uses all data as both training and testing, were elicited in the fragmentation of data into training and testing. For this reason, the results in this method were obtained as given in the table below.

Table 5. *Ten-fold cross validation results.*

Success criterion	Percent
Accuracy	0.8352
Recall	0.8421
Precision	0.8378
F-measure	0.8268

Since the confusion matrix of data belonging to 96 people is too large, the values are not shown here because they cannot be read. When the results obtained are examined, it is seen that the 10-fold cross-validation results produce very close results with 30%-70% divergence.

3.3 Gender classification findings

Thirty-two different feature extraction methods were used on the images around the eyes. This time, we tried to classify these data not according to the person but according to the gender. All of them were tested with the RandomForest classification method, with the thought that a different feature extraction algorithm could be more successful in determining gender compared to the previous one. The results given in the table below were obtained.

Table 6. *Accuracy rates of different transfer learning algorithms.*

ID	Transfer learning feature extraction algorithm	Accuracy
1	ResNet152	0.915824916
2	EfficientNetB6	0.902356902
3	ResNet101	0.902356902

ID	Transfer learning feature extraction algorithm	Accuracy
4	DenseNet201	0.897306397
5	EfficientNetB7	0.895622896
6	ResNet50	0.892255892
7	EfficientNetV2B1	0.892255892
8	EfficientNetB5	0.888888889
9	DenseNet169	0.885521886
10	EfficientNetV2M	0.885521886
11	EfficientNetB4	0.882154882
12	EfficientNetB3	0.882154882
13	EfficientNetB2	0.878787879
14	EfficientNetB0	0.878787879
15	VGG19	0.878787879
16	VGG16	0.878787879
17	EfficientNetV2L	0.875420875
18	EfficientNetV2B0	0.868686869
19	EfficientNetV2B3	0.865319865
20	Xception	0.838383838
21	EfficientNetV2B2	0.838383838
22	AlexNet	0.833333333
23	InceptionV3	0.823232323
24	MobileNet	0.814814815
25	ResNet50V2	0.814814815
26	MobileNetV2	0.813131313
27	NASNetMobile	0.730639731
28	InceptionResNetV2	0.718855219
29	EfficientNetB1	0.898989899
30	EfficientNetV2S	0.877104377
31	NASNetLarge	0.82996633
32	DenseNet121	0.82996633

Since the best feature extraction algorithm was found, we tried to find the most successful classification algorithm. For this purpose, these features were tested with 28 different classification methods and the results are given in the table below. The classification method named MLPClassifier achieved 96.46% successful classification. Another name for this most successful method is artificial neural networks. There are some other methods that produce results close to these values.

Table 7. *Results obtained with different classification methods of ResNet152 attributes.*

Group	Classification method	Accuracy	F-measure	Recall	Precision
discriminant_analysis	LinearDiscriminantAnalysis	0.8359	0.8356	0.8366	0.8355
discriminant_analysis	QuadraticDiscriminantAnalysis	0.6869	0.6795	0.6986	0.7280
ensemble	HistGradientBoostingClassifier	0.9571	0.9570	0.9577	0.9566
ensemble	GradientBoostingClassifier	0.9419	0.9416	0.9412	0.9422
ensemble	ExtraTreesClassifier	0.9268	0.9262	0.9248	0.9290
ensemble	AdaBoostClassifier	0.9242	0.9241	0.9252	0.9238
ensemble	VotingClassifier	0.9217	0.9210	0.9194	0.9247

Group	Classification method	Accuracy	F-measure	Recall	Precision
ensemble	RandomForestClassifier	0.9091	0.9086	0.9081	0.9093
ensemble	BaggingClassifier	0.8712	0.8703	0.8694	0.8722
linear_model	PassiveAggressiveClassifier	0.9444	0.9444	0.9461	0.9444
linear_model	LogisticRegression	0.9419	0.9419	0.9437	0.9421
linear_model	Perceptron	0.9419	0.9418	0.9431	0.9416
linear_model	LogisticRegressionCV	0.9394	0.9394	0.9413	0.9397
linear_model	SGDClassifier	0.9394	0.9390	0.9382	0.9403
linear_model	RidgeClassifier	0.9192	0.9191	0.9201	0.9188
linear_model	RidgeClassifierCV	0.9192	0.9191	0.9201	0.9188
naive_bayes	BernoulliNB	0.7551	0.7509	0.7500	0.7591
naive_bayes	ComplementNB	0.7247	0.7233	0.7230	0.7238
naive_bayes	MultinomialNB	0.7222	0.7206	0.7203	0.7213
naive_bayes	GaussianNB	0.6540	0.6451	0.6661	0.6932
neighbors	KNeighborsClassifier	0.9444	0.9442	0.9442	0.9442
neighbors	NearestCentroid	0.7020	0.6976	0.6972	0.7032
neural_network	MLPClassifier	0.9646	0.9646	0.9657	0.9642
svm	NuSVC	0.9394	0.9390	0.9382	0.9403
svm	LinearSVC	0.9369	0.9368	0.9392	0.9379
svm	SVC	0.9268	0.9261	0.9245	0.9298
tree	DecisionTreeClassifier	0.7348	0.7338	0.7337	0.7339
tree	ExtraTreeClassifier	0.7197	0.7184	0.7182	0.7187

So far, both in the classification of all features with RandomForest and in the testing of ResNet152 features with different classification methods, the data were separated into 30% test and 70% training. Since we wondered whether the results would change when the 10-fold cross-validation method was used, this time, the data were tested by separating them in this way. The results are given in the table below.

Table 8. *Ten-fold cross validation results.*

Success criterion	Percent
Accuracy	0.964123468184382
Recall	0.9641793993632571
Precision	0.9646035623101692
F-measure	0.9639744806181051

The confusion matrix of the results obtained is given in the figure below. Examining the matrix, it will be seen that only 71 of the 1980 samples were misclassified.

Figure 5. *Gender result confusion matrix.*

3.4 Age classification findings

Image data belong to subjects of different ages. These ages are 39 different species and range from 3 to 64. Although there are so many different types, we wondered whether the age of people can be estimated by looking around the eyes. First of all, ages were classified by RandomForest method with different feature extraction algorithms. The results obtained for the situation where 70% were randomly selected as training data and the remaining 30% were test data are given in the table below. Age tags, just like person tags, produced the best results with the ResNet50 feature extraction algorithm. Although other algorithms produced close values, the ResNet50 algorithm will be preferred in this study.

Table 9. *Accuracy rates of different transfer learning algorithms*.

ID	Transfer learning feature extraction algorithm	Accuracy
1	InceptionResNetV2	0.338384
2	NASNetMobile	0.373737
3	InceptionV3	0.427609
4	MobileNetV2	0.434343

ID	Transfer learning feature extraction algorithm	Accuracy
5	ResNet50V2	0.43771
6	DenseNet121	0.441077
7	NASNetLarge	0.454545
8	Xception	0.496633
9	MobileNet	0.521886
10	AlexNet	0.538721
11	EfficientNetV2B2	0.575758
12	EfficientNetV2S	0.584175
13	EfficientNetV2B0	0.599327
14	EfficientNetV2M	0.614478
15	EfficientNetB2	0.621212
16	EfficientNetB0	0.624579
17	EfficientNetV2B1	0.62963
18	EfficientNetV2B3	0.632997
19	DenseNet169	0.638047
20	DenseNet201	0.639731
21	VGG16	0.641414
22	EfficientNetV2L	0.644781
23	EfficientNetB3	0.649832
24	EfficientNetB5	0.651515
25	EfficientNetB1	0.651515
26	EfficientNetB6	0.666667
27	ResNet101	0.666667
28	VGG19	0.666667
29	EfficientNetB4	0.675084
30	EfficientNetB7	0.685185
31	ResNet152	0.70202
32	ResNet50	0.715488

The feature extraction algorithm named ResNet50 was the algorithm that produced the most successful results for the images here. Now, with this algorithm, the most successful classification algorithm can be tested. For this, 27 different classification methods were used, and the results are as in the table below.

Table 10. *Results obtained with different classification methods of ResNet152 attributes.*

Group	Classification method	Accuracy	F-measure	Recall	Precision
discriminant_analysis	LinearDiscriminantAnalysis	0.7753	0.8061	0.8064	0.8265
discriminant_analysis	QuadraticDiscriminantAnalysis	0.0985	0.0997	0.1025	0.1490
ensemble	VotingClassifier	0.7677	0.8067	0.7994	0.8283
ensemble	ExtraTreesClassifier	0.7500	0.7717	0.7522	0.8466
ensemble	HistGradientBoostingClassifier	0.7475	0.7512	0.7611	0.7693
ensemble	RandomForestClassifier	0.7323	0.7748	0.7542	0.8490
ensemble	GradientBoostingClassifier	0.5682	0.5663	0.5486	0.6805
ensemble	BaggingClassifier	0.5455	0.5741	0.5734	0.6393
ensemble	AdaBoostClassifier	0.0985	0.0388	0.0769	0.0334
linear_model	RidgeClassifier	0.8712	0.8982	0.8940	0.9172

Group	Classification method	Accuracy	F-measure	Recall	Precision
linear_model	RidgeClassifierCV	0.8712	0.8982	0.8940	0.9172
linear_model	LogisticRegressionCV	0.8636	0.8956	0.8984	0.9056
linear_model	PassiveAggressiveClassifier	0.8561	0.8911	0.8935	0.9056
linear_model	LogisticRegression	0.8131	0.8345	0.8395	0.8494
linear_model	SGDClassifier	0.8106	0.8439	0.8495	0.8866
linear_model	Perceptron	0.7222	0.7708	0.7765	0.8282
naive_bayes	BernoulliNB	0.5480	0.6366	0.6221	0.7134
naive_bayes	MultinomialNB	0.5328	0.6275	0.6392	0.6749
naive_bayes	GaussianNB	0.4848	0.4789	0.4630	0.5884
naive_bayes	ComplementNB	0.3687	0.3617	0.3779	0.5298
neighbors	KNeighborsClassifier	0.7525	0.7717	0.7831	0.7948
neighbors	NearestCentroid	0.4495	0.5377	0.5898	0.5524
neural_network	MLPClassifier	0.8384	0.8628	0.8593	0.8856
svm	LinearSVC	0.8763	0.9102	0.9099	0.9203
svm	SVC	0.6389	0.6524	0.6387	0.7621
tree	ExtraTreeClassifier	0.2525	0.2467	0.2532	0.2649
tree	DecisionTreeClassifier	0.1465	0.0882	0.1092	0.0900

As in the previous person recognition, the most successful classification algorithm was LinearSVC with 87.63%. In the analyses made so far, the data were randomly divided into 70% for training and 30% for testing. Since they were tested with many methods, this method was preferred to produce fast results. However, if the data are parsed with the 10-fold cross-validation method, all of the data are used for both testing and training. For this reason, tests were carried out after parsing these data with 10-fold cross validation and the results are presented in the table below.

Table 11. *Ten-fold cross validation results.*

Success criterion	Percent
Accuracy	0.7756165718094652
Recall	0.8275885225885226
Precision	0.8425287196081509
F-measure	0.8160964372282458

There were no very great differences in person recognition results between testing data with 10-fold cross-validation and testing with the 30%-70% separation. However, there is large variation here. Among the reasons for this situation is the random selection of data in training and test decomposition. This randomness can sometimes keep well-predicted data in the test group and produce more successful results. With 10-fold cross-validation, all data were used as both training and testing, eliminating this randomness. Thus, while there was an accuracy rate of 87.63%, an accuracy rate of 77.56% was obtained. Here, too, since the difference of 39 is the age value, the values in the mixed matrix cannot be read, so they are not shown.

4 Discussion and conclusion

The study aimed to classify the age, gender and person from images around people's eyes. For this purpose, eye images obtained from 96 different people were used. In this study, first of all, files consisting of eye images were arranged. 32 different attribute files were obtained with 32 different transfer algorithms for person ID attributes. 32 different attribute files of the person ID were classified with the random forest algorithm and the attribute file with the highest success rate was found. The feature file with the highest success rate was classified with 30 different classification algorithms and thus the classification algorithm with the highest success rate was found. In this way, the most successful feature and the most successful classification algorithm were combined and the most successful classification rate was obtained. The aforementioned procedures were repeated for both age and gender. The method used here was only tested with images in the generated dataset. In order to overcome this limitation in the study, it is important to use more and more different images. In addition, the eye contour images were obtained with close shots. In order to overcome this limitation, it would be good to compare with farther shots. The algorithm that showed the greatest success in feature extraction in the dataset was the ResNet50 algorithm. In the continuation of the study, classification algorithms were run using the extracted features. At this stage, where 27 different classification algorithms were used, LinearSVC method was the best performing algorithm by offering the highest success rate in classifying people. ResNet152 algorithm showed the highest accuracy rate in determining the features for gender classification as male and female from images around the eyes. The highest accuracy rate was achieved with the MLPClassifier method (artificial neural networks) when the eye images were classified for gender using the features determined by the ResNet152 algorithm. For age labels, as in-person classification, the ResNet50 algorithm in the feature extraction stage and the LinearSVC algorithm in age classification were the algorithms that provided the best results.

The study shows that eye images can be used as a source in a biometric recognition system to identify people, their gender and age status. In the classification studies conducted for this purpose, the highest success rates were obtained in age, person and gender classification, respectively. These success rates were calculated as 96.41%, 83.52% and 77.56%, respectively. It can be said that such a high performance in age is due to the structural changes occurring in the eye area in parallel with ageing in humans. Again, due to advancing age, it is possible to observe changes in the vascular and nerve structures of the eye that will reflect on the eye image, so age has been seen as a meaningful identification method that can be obtained from the image. While the probability of correctly predicting the gender of a person from the eye image alone is 50%, the performance obtained with the transfer learning approach shows that eye images can be used as an accurate tool in gender recognition. The fact that the people whose eye images were obtained in the study were generally under the age of 20-40 can be seen as a limitation of the research. However, it is an undeniable fact that age differences can be detected as a feature in the images. The fact that the numbers of men and women in the study are close to each other is an important condition for the high rate of correct classification of gender, because the accumulation of the number of data in a certain quality may be misleading about the performance of the classification.

To emphasize what kind of a gap the study has filled and what kind of innovations it offers, based on its relations with its counterparts in the literature, it is seen that there are studies on iris recognition or eye regions recognition. Person recognition studies from eye-only images are generally performed using the iris recognition method. Çanak (2017) classified wrinkles around the eyes in his thesis. The researcher studied the images of the right and left eyes and foreheads of volunteers consisting of five women and five men. He achieved a maximum accuracy of 63% in classifying wrinkles. The success rates in the study are much higher than the study of Çanak. In addition, the number of records in the dataset used in this research is considerably higher than the dataset used by Çanak. Bayraktar (2018) analysed the chaotic structure of the iris by using UBIRIS, a ready-made dataset consisting of 100 people in his study. In this study, instead of using a ready-made dataset, a dataset consisting of 1980 eye images collected from volunteers was made available to other researchers, contributing to the literature. Öz (2021) created a dataset from 1660 images in his study, which aimed to classify the eye as the sclera, iris, eye and background from eye photographs using deep neural networks. In this study, no examination was made in terms of recognizing people since the eye was classified according to its parts. Bircan (2021) performed iris recognition using the data in the Casia iris database in his study. In this study, unlike Bircan's study, a ready-made dataset was not used, our own dataset was created, and classification was made based on the eye's own image instead of iris recognition, which is more commonly studied in the literature.

There are various disadvantages arising from the hardware or biometric features used in almost all of the systems used in biometric recognition. In terms of security, fingerprint recognition systems can be deceived by imitating people's fingerprints through patterns. The same can be said for iris recognition systems. It is possible that the system will be overcome by printing an iris pattern on lenses and placing these lenses on the high-resolution iris image (Hidimoğlu, 2010). Wearing glasses or not looking at a fixed reader can also be seen as a disadvantage of retinal scanning systems (Şan, 2013). Again, damage, deformation and injuries that may occur in the hands, face and fingers may cause failure of recognition systems in which these organs are used. Such disadvantages directly affect the performance, reliability and therefore usability of biometric recognition systems.

The main contributions of the study are collecting human eye images and bringing the data set obtained from these images to the literature. With this data set, it is possible to detect people from eye images and to show that features such as age and gender can be identified. Moreover, this study explains that people can be identified with high accuracy only from eye images obtained from a certain distance with a smartphone camera, without using any special equipment or techniques. This study shows a way to develop biometric recognition systems, which typically require complex and expensive equipment, with simpler equipment, where eye images can be obtained only with the help of a high-resolution camera, at more affordable costs. Thus, a positive contribution has been made to reach more users of the developed cheaper systems and to the widespread use of biometric recognition systems for security and verification purposes in the society. In addition, a different perspective was presented to researchers, experts and government administrators with the study, which was carried out so that public authorities could develop new, easy and efficient systems for recognizing people, thanks to the databases to be created even using eye images for internal and external security.

In future studies, classification studies can be performed using eye images obtained from more participants. In addition, studies can be carried out on sick and healthy people in order to detect people with chronic diseases such as diabetes, hypertension or other diseases from eye images. Since images of the eye and its surroundings can be easily obtained with any camera, experimental studies for research areas where eye recognition can be used in both health and informatics fields contribute to researchers and the literature.

Additional Information and Declarations

Conflict of Interests: The authors declare no conflict of interest.

Author Contributions: C.A.: Conceptualization, Methodology, Software. Y.M.H.R.: Data curation, Writing – Original draft preparation, Visualization, Investigation. E.A.: Supervision, Software, Validation, Writing – Reviewing and Editing.

Institutional Review Board Statement: Ethical review and approval were waived for this study due to the use of a fully anonymized (according to the applicable Turkish laws) and publicly available dataset. Obtaining the dataset of eye photos cannot cause physical or mental strain on the participants.

Data Availability: The data supporting this study's findings are available in Zenodo at https://doi.org/10.5281/zenodo.6979283.

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