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An Application on Identification With The Face Recognition System

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Abstract: Measures taken in areas such as tracking personnel, patients, students, and criminals, protecting mobile devices, and combating fraud have evolved with technological developments in artificial intelligence. Today, face recognition systems are used as one of the fast and precise solutions determined for this need since the identification of the person and identity in these problems requires instantaneous and high accuracy. These systems are generally created by comparing the features in the face images taken from the picture, historical or live video with the features in the real image of the person previously taken. Face recognition systems can be integrated into many applications, as a person and identity verification may be required in almost every sector. In this study, a face recognition system was developed in order to verify the driver using public transportation in the transportation sector. In order to prevent any accident and violation caused by unauthorized driving, it has become necessary to add a personnel recognition and identity verification module to the system. For this requirement, after the driver has verified his biometric data, it was decided that the verification should be repeated instantaneously throughout the ride and at certain intervals so that the driver does not give the ride to another driver. By avoiding the methods such as a fingerprint reader and an iris verification that will distract the driver and risk the driving, a facial recognition system has been created to provide control with video images taken while driving through cameras that are currently on the vehicles and see the driver. In order to check the accuracy of the relevant system, a separate database was created for each driver, which contains images taken from videos during driving at different times. Based on a pre-trained deep learning network with pictures represents the driver, the system was tested by using test images in a database using TensorFlow and OpenCV libraries. In summary, the developed face recognition module is designed to improve the driving safety of authorized and approved personnel on the intelligent transportation system, reduce accidents caused by unauthorized users and ensure driver control.

Keywords: Face Recognition Systems; Deep Learning; Identification; Intelligent Transportation Systems

Yüz Tanıma Sistemi ile Kimlik Tespiti Üzerine Bir Uygulama

Özet: Personel, hasta, öğrenci ve suçlu takibi, mobil cihazların korunması, dolandırıcılıkla mücadele gibi alanlarda alınan önlemler yapay zekadaki teknolojik gelişmelerle birlikte evrilmiştir. Bu problemlerde kişi ve kimliğin tespiti anlık ve yüksek doğruluk gerektirdiğinden, günümüzde yüz tanıma sistemleri bu ihtiyaca yönelik belirlenen hızlı ve kesin çözümlerden biri olarak kullanılmaktadır. Bu sistemler genellikle geçmiş veya canlı videodan alınan yüz görüntülerindeki özelliklerin, kişinin daha önce çekilmiş gerçek görüntüsündeki özelliklerle karşılaştırılmasıyla oluşturulmaktadır. Yüz tanıma sistemleri hemen hemen her sektörde kişi ve kimlik doğrulaması gerektiren birçok uygulamaya entegre edilebilmektedir. Bu çalışmada, ulaşım sektöründe toplu taşıma kullanan sürücüyü doğrulamak için yüz tanıma sistemi geliştirilmiştir. Yetkisiz araç kullanmanın yol açacağı kaza ve ihlallerin önüne geçebilmek için personel tanıma ve kimlik doğrulama modülünün sisteme eklenmesi zorunlu hale gelmiştir. Bu gereksinim için, sürücü biyometrik verilerini doğruladıktan sonra, sürüşü başka bir sürücüye devretmemesi için doğrulamanın yolculuk boyunca anlık ve belirli aralıklarla tekrarlanması gerektiğine karar verilmiştir. Sürücünün dikkatini dağıtacak ve sürüşü riske atacak parmak izi okuyucu ve iris doğrulaması gibi yöntemlerden kaçınılarak, halihazırda araçlarda bulunan ve sürücüyü gören kameralar aracılığıyla sürüş sırasında çekilen video görüntüleri ile kontrolün sağlanması için yüz tanıma sistemi oluşturulmuştur. İlgili sistemin doğruluğunu kontrol etmek amacıyla her sürücü için farklı zamanlarda sürüş sırasındaki videolardan alınan görüntülerin yer aldığı ayrı bir veri tabanı oluşturulmuştur. Sürücüyü temsil eden resimlerle önceden eğitilmiş bir derin öğrenme ağına dayanan sistem, TensorFlow ve OpenCV kütüphaneleri kullanılarak oluşturulan bir veritabanında test görüntüleri test edilmiştir. Özetle, akıllı ulaşım sistemi üzerinde yetkili ve onaylı personelin sürüş güvenliğini artırmak, yetkisiz kullanıcıların neden olduğu kazaları azaltmak ve sürücü kontrolünü sağlamak için geliştirilen yüz tanıma modülü tasarlanmıştır.

Anahtar Kelimeler: Yüz Tanıma Sistemleri; Derin Öğrenme; Kimlik Tespiti; Akıllı Ulaştırma Sistemleri

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1. Introduction

A biometric system is an automatic verification system for making certain of (or be conscious of) having seen before the mind and physical qualities of a living person based on physiological quality of like a fingerprint, face shapes, voice, iris image, DNA controls or some aspects of behavior like handwriting or push button on keyboard designs [1], [2]. When these biometric authentication systems are used in identity comparison, physiological methods such as fingerprint readers, face recognition systems, and DNA related controls are more stable than behavioral detection methods such as keystrokes, voice, and handwriting. Because the physiological characteristics of the person are generally not deteriorated, changed, and remain stable, except for major serious injuries. Despite the aging factor, even if the model can be improved over time, other behavioral characteristics may fluctuate instantaneously due to stress, fatigue, or illness, and the detection result may be deviated [3]. A physiological biometric verification system is a widely used subject in the field of computer vision for identification and identification. With the spread of fraud, there has been a need for biometric verification in almost every sector. Face recognition system is one of the frequently used verification systems to meet this need.

In this study, a facial recognition system has been developed for biometric verification in order to determine whether the driver using the public transportation vehicle is authorized to drive the vehicle. This need has arisen from the fact that it is not possible to understand whether the driver who uses the vehicle is authorized and that the driving safety gaps caused by the unauthorized user are attributed to the administrators. In the current system, drivers start their journey by operating the vehicles with their personnel cards. However, the authorized driver may violate the rules by giving his personal card to an unauthorized driver and risk driving. When the drivers who are not authorized to drive have an accident, it has become a necessity for the managers to identify the unauthorized drivers, as both the accident cost and the penalty for the unauthorized drivers are reflected the municipalities. For this reason, it has been understood that personnel cards are insufficient for driver authorization and a biometric recognition system should be used together with personnel cards.

In the first part of the study, the face recognition system and the deep learning approach used for this system are mentioned. In the second part, the applied face recognition system is introduced and the results of the study are mentioned.

2. Related Work

Before the use of deep learning networks, at the beginning of face recognition studies, Woody Bledsoe simply classified facial images by using grid lines [4]. In this project, the project was called a human-machine project because the features were extracted manually from human pictures and then used for face recognition by the computer [5]. Then, with a big leap in the recognition system, the study of identifying the face space with eigenfaces, which are the eigenvectors of the cluster of faces, has been brought to the literature [6]. This eigenfaces technique has been developed and applied in many studies [7], [8]. Subsequently, a number of studies were published on methods such as SIFT [9], [10], [11] LBP [12], [13], LEM [14] and HOG [15], [16] increase face recognition performance. In addition to these methods, methods such as linear discriminant analysis [17], independent component analysis [18], linear regression [19], and principal component analysis [20], [21] were also used for face identification.

Many successful studies on deep convolutional neural network (DCNN) modeling, which are frequently used in modern face recognition applications, have been brought to the literature [22], [23], [24.] In recent years, models that work with different approaches using the DCNN infrastructure are popularly used. For example, the VGG-Face approach was used to estimate the ages of people with face pictures. [25], [26]. Another study used the FaceNet approach to directly optimize embedding without using any intermediate bottleneck layers [27]. The OpenFace approach was proposed and introduced with different applications for the turning point of the face, the posture of the head, the unit of activity of the face, and eye-gaze predictions [28], [29]. DeepFace, one of the frequently used approaches, was proposed by Facebook AI Research [30]. ArcFace, which is introduced with its feature of having a clear geometric interpretation because it fits exactly to the geodetic distance in the hypersphere, is another common approach using DCNN [31].

3. Face Recognition System

Face recognition system is frequently used for purposes such as fraud detection, missing person detection, student, children, patient and criminal tracking, passport control, access control for a specific building or a room, and protection of personal electronic devices. This type of control mechanism should be met with fast and highly accurate solutions, as they can be verified from past videos or pictures, and more importantly, they may also need to be made from instant videos. For example, if the verification is not done quickly, long queues occur in ticket validation, which makes the customer tired. If electronic devices opened with biometric verification are accessed late, long waiting times occur at the doors opened with access control and similar problems arise. If the accuracy rates are low in verification, criminals may not be detected, devices belonging to someone else may fall into the hands of users who do not have access, users without pass permission may pass through private gates, and the user with an invalid ticket in ticket validation may pass. Or, on the contrary, since the ticket of the user whose ticket is valid cannot be verified and he cannot use his right of access. The owner of the mobile device cannot access his own device. The passport holder does not match his own passport. For these reasons, Deep Convolutional Neural Network (DCNN) is used in the literature to result in fast and high accuracy of face identification systems.

DCNNs first provide normalization of the pose in the image containing the face and then map the facial appearance according to the distances between certain features by extracting certain features of the face [31]. While a large data set is available, the ability of this large-scale pattern recognition system to be end-to-end optimized to develop characteristics that strengthen the identification signal, while being resistant to exposure, lighting, and expression variations in the image, is a powerful feature of the DCNN [32]. For the face recognition system, there are generally two basic stages, face verification and face recognition, and three sub-stages for each of them, face detection, feature extraction, and classification, respectively. A DCNN detects if there is a face in the image given to it and tags the face. It can extract the high-level features of the face. It yields superior performance measurement results even with a relatively simple classification architecture with multilayer perceptron networks [33].

3.1. Face Recognition Using DeepFace and ArcFace

DeepFace provides a face recognition method based on similarity measurement by adding richer identity information to the features learned by the DCNN. With this method, the face appearance is captured with high accuracy by making 3-dimensional alignment very quickly. When alignment is complete, the position of each face region is fixed at the pixel level. Hence, it is possible to learn from raw RGB pixel values without the need to apply multiple convolution layers as is done in many other networks[33], [34], [35]. This method uses a data set of 4 million samples covering 4000 unique identities. It uses a Siamese network architecture in which the same CNN is applied to pairs of faces to label the compared faces using some metrics such as cosine similarity, euclidean distance, and L2 form to distinguish identifiers. With this architecture, the distance between compatible face pairs is minimized and the distance between incompatible pairs is maximized [23]. In summary, with the DeepFace approach, an effective deep neural network (DNN) architecture and learning method has been developed using very large labeled face datasets to obtain a face representation that is well generalized to other data sets. However, an effective face alignment system based on open 3D modeling of faces and a significant improvement in the comparison of labeled faces has been made [30].

In the ArcFace method, the angular margin penalty is added, which is equal to the geodetic distance margin penalty in the normalized hypersphere, so that L1 normalization is used to simultaneously adjust the inconsistency and intra-class compactness of the loss function soft-max loss. This is done by distributing the learned embedding features on a radius hypersphere. The deviation amount is fixed at 0 when adding the margin penalty. The cosine transform is applied to the angle between the i-th property and the weight of that property. Then, the individual weight is fixed by L2 normalization. Therefore, the embedded features are corrected with L2 and scaled again [31]. The steps of the ArcFace approach are presented in Fig. 1.

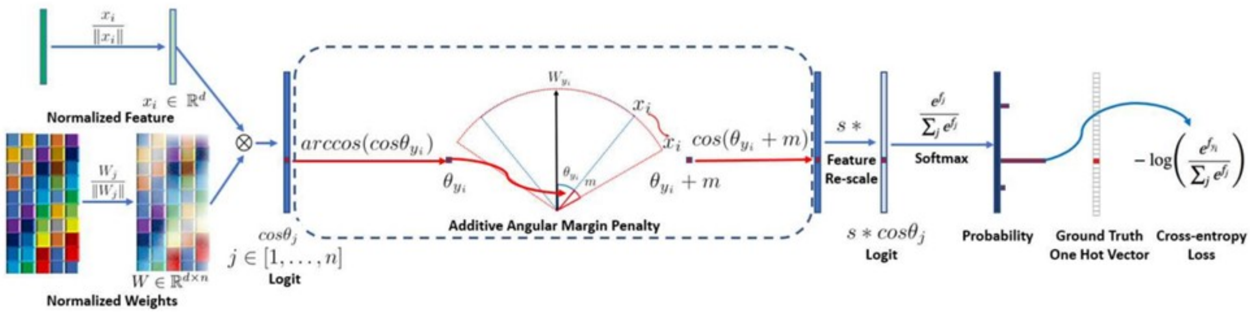

Fig. 1. ArcFace Approach Steps

The steps implemented in Fig. 1 can be summarized as follows.

- DCNN is trained using the ArcFace loss function.
- Cos θj (logit) transformation is applied.
- Arccos is calculated well.
- The angle between the Xi property and its weight is taken.
- Angular margin penalty is added to.
- cos (yi + m) is calculated.
- All logits are multiplied by the feature scale s.
- Logits contribute to the loss of cross-entropy by passing through the softmax function.

4. Case Study: Driver Identification

In this application, since the card-based authorization is not sufficient in a public transportation system where the drivers are authorized with their personal personnel cards, the deep learning face recognition system has been worked on. In the card-based system, it has been observed that the authorized driver can violate the rules by handing over his personal card to an unauthorized driver, thus putting the driving at risk and accidents caused by the unauthorized user. For this reason, it is necessary to add personnel recognition and identity verification modules to the system in addition to authorization with personnel cards. For this requirement, after the driver has verified his biometric data, the verification must be repeated instantaneously at specific intervals throughout the trip, so as not to transfer the vehicle to another driver.

The reason why face recognition was preferred in the study is to prevent other biometric verifiers such as fingerprint reader and retina recognition from risking driving by distracting the driver, and the fact that the voice recognition verifier has lower rates of verification with other noises that may occur in the vehicle and due to traffic. In order to check the accuracy of the applied system, the system was checked offline before authorization control in the live system. For the control, two different data sets consisting of test and original faces were created and these two data sets were compared using DeepFace and ArcFace approaches. Cosine similarity is used as the distance metric used when comparing faces. This distance criterion is a method of measuring the similarity between vectors by computing the cosine angle between two vectors in a multi-dimensional space. Based on pre-trained deep learning networks with visuals representing drivers, the system was tested with test visuals in databases using TensorFlow and OpenCV libraries.

4.1. Data Set

Application data were obtained from Kentkart, a company working on smart transportation systems, which is a pioneer in the public transportation sector. A vehicle that the company works with has been taken into consideration for testing and a separate test data set was created for each driver authorized to drive this vehicle at different times, with images at the time of driving. In other words, for this data set, pictures were taken from the video images recorded while driving through cameras that saw the driver in public transportation vehicles, without detecting the driver (in order not to risk the driving). In order to verify the driver, the pictures with the labels on the personal personnel cards of the drivers are used.

A total of 50 drivers were handled for the test. In order to avoid bias in the performance measurement results, wrong pictures are added as the number of the drivers' own pictures in the test data set of each driver. In the last case, a total of 578 pictures were tested, half of which consisted of correct and half incorrect images.

4.2. Result and Analysis

In order to measure the success of the face recognition application, the confusion matrix was first created and performance measurements were made on this matrix. In a two-class classification problem, there are 4 basic elements of the complexity matrix; True Positive (TP), False Negative (FN), False Positive (FP), and True Negative (TN). The rows of the matrix show the actual state, and the columns the estimated states. Table 1 represents confusion matrix design.

		Predicted	
		Positive	Negative
Actual	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

Table 1. Confusion Matrix

The confusion matrix elements are explained as follows:

- TP: The number of correctly predicted data when the reference value is correct.
- FN: The number of incorrectly predicted data when the reference value is correct.
- FP: The number of correctly predicted data when the reference value is incorrect.
- TN: The number of incorrectly predicted data when the reference value is incorrect.

The confusion matrix obtained as a result of the study is as follows in Table 2.

		Predicted	
		Positive	Negative
Actual	Positive	225	64
	Negative	8	281

Table 2. Confusion Matrix Result

According to the results of Table 2, 225 of the 578 pictures in total belong to the right drivers and were correctly estimated as a result of the application. It was determined that the pictures of 281 different drivers belonged to the wrong drivers. 64 pictures were wrongly guessed when they belonged to the right drivers, and 8 pictures were correctly estimated when belonging to the wrong drivers.

Accuracy, recall, precision, and F1 score metrics were used to measure the success of the face recognition system. Metric formulations have results between 0 and 1, and the higher the results, the higher the successful performance of the algorithm from the angle tested.

Accuracy: This ratio simply shows how accurate the algorithm is. It gives the ratio of the number of correctly classified users in the test dataset to the number of all users. That is, it shows the percentage of correctly tagged drivers among all drivers. The calculation formulation of the accuracy criterion is shown in (1).

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

When the accuracy result of the study was calculated, it was seen that 87.5% accuracy was obtained as in (2). This means that around 87 out of every 100 pictures can be labeled correctly.

$$ACC = \frac{225+281}{225+281+8+64} = 0.875 \tag{2}$$

Recall (Sensitivity): It is the value obtained by dividing the number of correctly estimated positive samples by the number of positive samples in the entire data set. That is, it gives the ratio showing how much of the data truly classified as positive were correctly classified. It gives the sensitivity of the measurement. The calculation formulation for the recall criterion is shown in (3).

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

When the formulation in (3) is applied to the confusion matrix results, the result of 77.8% is obtained as in (4). In this case, the model constructed is successful in capturing 77.8% of positive classes.

$$Recall = \frac{225}{225+64} = 0.778 \quad (4)$$

Precision: It is the value obtained by dividing the number of correctly labeled positive data by the number of positive samples in the entire data set. That is, it shows how much of the data classified as positive is truly positive. In other words, it gives the positive predictive value of the model. The precision formula is presented in (5).

$$Precision = \frac{TP}{TP+FP} \quad (5)$$

Considering (5), the precision result obtained 96.5% in (6). In this case, the ability of the applied model to avoid mislabeling can be interpreted as 96.5%.

$$Precision = \frac{225}{225+8} = 0.965 \quad (6)$$

F1 Score: This criterion is a combination of the recall and precision metrics that are inversely related to each other. The F1 score provides a balance between these two metrics. So this criterion takes into account both false positives and false negatives. It is calculated as in (7) by taking the harmonic average of the sensitivity and precision classes.

$$F1 = \frac{2TP}{2TP+FP+FN} \quad (7)$$

When the model is evaluated in terms of F1 score, the success of the model was determined as 86.2% as seen in (8).

$$F1 = \frac{2*225}{2*225+8+64} = 0,862 \quad (8)$$

5. Conclusion

In this study, a face recognition application was carried out by comparing the real face pictures of the drivers and the random face pictures taken while driving in order to check whether the drivers driving the public transportation vehicle are authorized to drive or not. In the developed method, drivers were inspected with pre-trained networks using DCNNs, which is a frequently used artificial intelligence method. The application code is written in Python language using DeepFace and ArcFace packages.

As a result of the application, a total of 506 of the 578 images used were correctly identified and thus 87.5% correct labeling result was achieved. In practice, since the main purpose is to detect the unauthorized driver, it is more important to minimize the cases where unauthorized drivers are mislabeled as if they were authorized. For this reason, when focusing on the rate of false positives, obtaining a precision value of 96.5% is a satisfactory result for the application.

The main challenge of the identification life cycle is that changes in the appearance of people over time can affect the recognition/authorization performance. In order to overcome this difficulty, it was decided to periodically update the training dataset and repeat the tests. In addition, in order for the identity check to be carried out reliably, the detected face must be compared effectively with the data in the electronic identity and possible violations must be detected with a periodic inspection along the vehicle route. Increasing the frequency of this check so as not to miss the wrong driver between two checks is a challenge to work with. In order for the detection phase not to take too long, it is necessary to reach the correct parameters and avoid the use of unnecessary variables. In future studies, an intelligent system will be implemented instead of an experimental study for this purpose. Also in future studies, it is planned to impose a driving ban on drivers who are found to be unauthorized while running the application on the live system. Considering this situation, it was seen that a balanced minimization should be applied between false negatives and false positives. For this reason, images will be taken by adding a 3D camera and/or infrared sensor to the vehicles to reduce false labeling situations in future studies. It is also planned to compare the results by creating an ensemble output by integrating the artificial intelligence algorithm operated with other successful recognition algorithms such as VGG-Face and FaceNet.

With this study, since a system that will prevent and control the use of public transportation vehicles belonging to public or private institutions by unauthorized drivers will be implemented, security, financial, legal, and efficiency problems that may arise in public transportation systems will be prevented. In addition, the modular structure of the developed platform will provide a viable solution not only for driver identification in the public transportation sector but also for authentication needs in the automotive, defense industry, manufacturing sector, and other sub-sectors. Therefore, this study provides identification recommendations that are applicable to various sectors.

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