Journal of Computer Science
https://dergipark.org.tr/en/pub/bbd

ISSN,e-ISSN: 2548-1304
Volume:IDAP-2023, pp:7-18, 2023
https://doi.org/10.53070/bbd.1361811
Research Paper

Enhancing Image Classification Performance through Discrete Cosine Transformation on Augmented Facial Images using GANs

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Received:Sep.7, 2023 Accepted:Sep.7,2023 Published:Oct.18,2023

Abstract— The continuous advancements in technology are profoundly influencing various domains, including the realm of artificial intelligence. Within this field, the development and training of facial recognition systems have emerged as one of the most prominent research areas. Nowadays, facial recognition systems are rapidly replacing traditional security methods. In order to develop a good face recognition system, the training process must be provided with sufficient data. Recently, the number of open-source data that can help improve the accuracy of face recognition systems is limited. Generative Adversarial Networks (GANs) are a type of machine learning algorithm comprising two interconnected neural networks that engage in a competitive relationship. It is widely used in work domains such as image creation, image manipulation, super-resolution, text visualization, photorealistic images, speech production, and face aging. In the study, the lack of data for training face recognition systems was first solved with synthetic face images obtained with GANs. In the subsequent stage of the investigation, the aim was to enhance the image classification procedure through the application of the discrete cosine transform to the images. This approach aimed to fortify facial recognition systems against the presence of authentic-looking fabricated faces within virtual environments. In the study, it was found that the classification of faces could be improved by 30% compared to the normal classification model. The primary objective of this research endeavor is to make a significant contribution towards the development of highly accurate facial recognition systems.

Keywords : *Generative Adversarial Network, Deep Learning, Discrete Cosine Transform, Image Classification.*

1. Introduction

With the development of technology, there have been significant developments in Deep Learning in recent years (Wu, et.al., 2017). The method that includes artificial neural networks and similar machine learning methods that consist of one or more hidden layers is called Deep Learning. Deep learning aims to extract novel information from existing data by employing one or more artificial neural networks (Bengio, et.al., 2007; Francois, et.al., 2018). Deep learning techniques are used in many fields today. One of these areas is image generation in the computer environment (Wu, et.al., 2017). The model, which can generate images in a computer environment using deep learning, was developed by Goodfellow in 2014 (Goodfellow, et.al. 2014). This model is known as GAN (Generative Adversarial Network) (Çelik and Talu, 2020). With the development of GANs, computers can produce realistic facial images that can easily fool humans (Liu, et.al., 2020). As technology continues to advance at a rapid pace, there has been a notable surge in the volume of data being generated on a daily basis. This huge amount of data, combined with the increased power and speed of the computer processors used due to technological development, has contributed to the creation and rapid development of advanced face recognition systems. Since the 1970s, facial recognition systems have been one of the topics that continue to enjoy great popularity today. The primary objective of face recognition systems is to perceive and identify faces in images, mirroring the functionality of the human visual system. Through the development of such systems, it becomes feasible to establish a more dependable and secure environment.

The main function of facial recognition systems is to establish or verify the identity of a person based on facial images. It should be noted that the accuracy rate of facial recognition systems has increased significantly since their introduction. The fact that facial recognition systems require only that the user be in the camera's field of view is an indication of why they are more useful and preferred over other traditional security methods. Facial recognition systems find extensive applications across diverse domains, encompassing areas such as security, healthcare, education, and entertainment.

Numerous studies have been conducted in the field of face recognition methods. (Wang, et al.,2022) focus their research on detecting facial images that are generated or synthesized using GAN models. (Cho, et al., 2009) propose a hardware architecture specifically designed for a face recognition system that utilizes the AdaBoost algorithm and incorporates Haar features. (Ayo, et al., 2022) present an automatic face recognition algorithm (YOLO) that accurately identifies human faces through geometric analysis while disregarding non-human face objects. (Verma, et. al.,2022) propose a method in their study that achieves superior results compared to existing algorithms in recognizing facial images captured from various angles. (Liao, et. al., 2022) comprehensively detail the technology of video facial recognition in health information systems, covering aspects such as video image acquisition, image preprocessing, face recognition, and face detection. In their research, (Ullah, et. al., 2022) strive to develop a real-time framework based on machine learning and deep learning techniques to recognize and identify human faces in CCTV images. (Obaida, et. al., 2022) present a method for recognizing and tracking the faces of witnesses in court, where the Viola-Jones method is employed for face extraction followed by specific transformations for image cropping. Witness and non-witness images are classified using convolutional neural networks (CNN). (Funda and İsmail, 2022) have developed a Deep Learning-based application that performs emotion recognition using the KDEF and PICS datasets, leveraging convolutional neural networks (CNN) as part of their approach. (Tahir, et. al., 2022) introduce a novel algorithm for a group of elements within the unit image, along with techniques for face recognition that involve storing image information in dedicated folders and emphasizing the background. (Archana et. al., 2022) have developed a web-based tool designed to identify faces in real-time environments, such as online classes.

In recent years, developments in the field of computer vision have been rapid. The result of these developments are image recognition, object recognition, image classification, etc. It has popularised many subjects (Liu, et.al., 2019). Image classification process: it is a process that compares the pixels that compose the image according to the features set by the user with the other pixels on each image, and collects the pixels with high similarity degree in the same classes (Campbell, 2011). The primary objective of image classification is to categorize images based on their shared spectral characteristics. (Gao, 2009).

Numerous studies have been conducted in the field of face recognition using classification methods on images. (Zehra and Burhan,2013) utilized classification techniques to determine the membership of face images to specific individuals. (Do, et. al., 2018) proposed a deep convolutional neural network in their research to recognize faces in forensic images. (Nesrin and Derya, 2018) developed a face recognition application employing support vector machines. (Ersin and Çetin, 2020) conducted a study on sex determination using appearance-based facial recognition methods. (Yaman, et al., 2017) focused on gender recognition from facial images using Deep Learning approaches in their investigations. (Adhinata, and Junaidi, 2022) explored gender classification in videos using the FaceNet algorithm and supervised machine learning techniques. (Tao and Pan, 2022) performed face recognition based on scale invariant feature transformation and fuzzy reasoning in their study.

In the study, a Generative adversarial network based solution was first proposed as a data augmentation method to overcome the lack of data used in training face recognition systems. In the next step of the study, a new fake face detection model is proposed, which is important in face recognition systems in terms of security in the virtual environment, using the existing dataset and the augmented data obtained.

Chronologically, the researcher's principal scientific contributions can be outlined as follows:

- Conducting a systematic exploration of Convolutional Neural Network (CNN) architectures for differentiating between authentic and forged faces in face recognition systems.

- Developing and leveraging Generative Adversarial Networks (GANs) to generate synthetic face images specifically designed for training face recognition systems.

- Proposing the augmentation of existing datasets through the inclusion of synthetic face images as a means to improve classification performance. This approach involves increasing the dataset size by incorporating synthetic faces.

- Employing the discrete cosine transform on images as a technique to enhance classification accuracy, specifically in the context of image recognition tasks.

2. Background

2.1. Data Lack and Data Augmentation:

A good face recognition system is possible with well-prepared test and training datasets. Modern face recognition systems are trained with datasets containing large amounts of images. Using excess data in training the created systems increases the performance of the model and also prevents the model from being memorized. One of the biggest problems researchers face is the lack of datasets consisting of freely available facial images for training the face recognition systems developed today. To address this issue, a viable solution is to augment the training data by expanding its quantity. Data augmentation encompasses techniques that involve altering the existing data or generating new synthetic data to create an augmented training set (Shorten and Khoshgoftaar, 2019). The data generated by an artificial intelligence algorithm developed on the computer is called synthetic data. In generating synthetic data, the artificial intelligence model developed first is trained using all the properties of the real data and the relationships between the data. Then, the trained artificial intelligence algorithm generates new data related to that data using the properties of the original real data. In other words, artificial intelligence algorithms generate synthetic twins by imitating real data. The representative illustration of synthetic data generation using artificial intelligence model is shown in Figure 1.

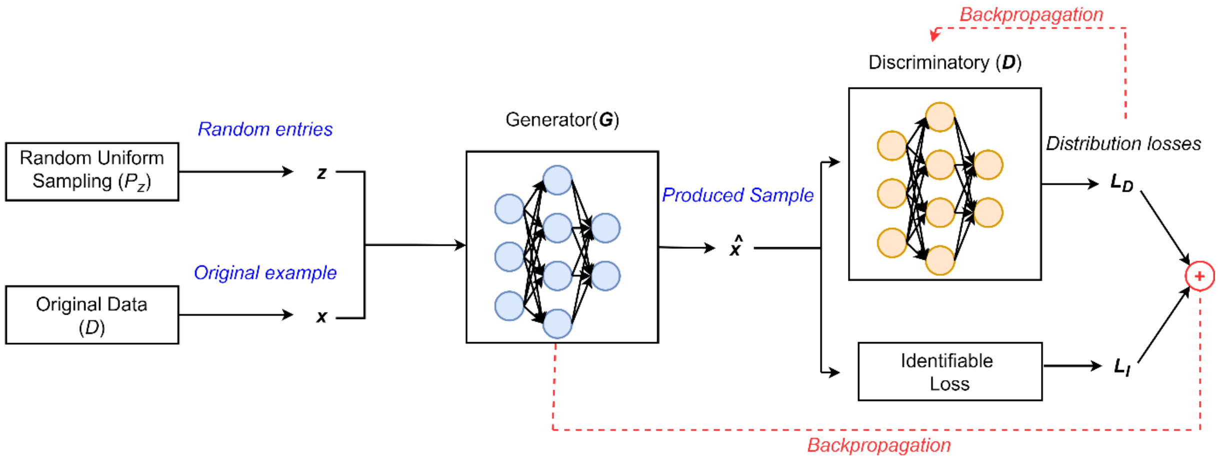

Figure 1. Synthetic data generation scenario

2.2. Generative Adversarial Network (GAN):

Working principle of generative models: it learns the unique features of the dataset given to that model and generates new data that approximate the data it is working with, using the learned features. Prominent examples of generative models include Variational Autoencoders, Naive Bayes, Deep Belief Networks, and Generative Adversarial Networks (GANs) (Alimovski, 2019). Among these, GANs have gained significant attention as a neural network architecture that enables the generation of data. In recent years, GANs have emerged as one of the most popular subfields within Deep Learning, capable of generating diverse types of images ranging from fuzzy figures to remarkably realistic facial images. GANs are used for image synthesis, sound synthesis, field matching, etc. They have been successfully used in many other applications. The most popular application for GANs is to create images that have never existed before. GANs learn about the world (objects, animals, etc.) and create new versions of these images that never existed before. GANs consist of two essential components: the generator (G) and the discriminator (D). The generator (G) is responsible for producing synthetic images, while the discriminator (D) assesses the generated images and provides feedback on their similarity to the training images. The generator aims to generate images that are indistinguishable from the real images, while the discriminator strives to accurately differentiate between real and generated images. This dynamic interplay between the generator and discriminator promotes the iterative improvement of the generator's ability to produce high-quality and realistic synthetic images. When training the network, both the producer and discriminator learn together and start from scratch (Goodfellow, et.al., 2014). The output of the generator network is directly fed into the discriminator network, creating a competitive reasoning mechanism that facilitates the training of both networks. Through this adversarial process, the generator and discriminator networks engage in a dynamic interplay where the generator learns to produce increasingly realistic images to deceive the discriminator, while the discriminator learns to improve its discrimination ability to accurately differentiate between real and generated images. This automatic and iterative training process enables the networks to learn and improve their respective capabilities in a mutually competitive manner. The nets perform their contention operations by computing a score in terms of cross entropy, as shown in (Equation 1) (Bird, et.al., 2022).

$$E_x\left[\log\left(D(x|y)\right)\right] + E_z[\log(1 - D(G(Z))] \tag{1}$$

The equation (1) can be divided into two parts: the first part, E_x [log(D(x | y))], represents the evaluation of real images, while the second part, E_z [log ⟦(1-D(G(Z))⟧], characterizes the assessment of fake images. Here, EX and EZ represent the expected values for real and fake data, respectively. In the equation, X denotes the current input from the dataset, while Z represents a random noise input given to the generator. The function D(x) denotes the probability that a given data point is genuine, and it is inverted to detect fake images. In the second part of the equation, D(x) is replaced by G(z), reflecting the fact that the generator outputs G when the discriminator receives the random input vector Z. In Equation 1, the objective of the generator is to maximize the equation, while the goal of the discriminator is to minimize it. This adversarial objective drives the generator to generate more realistic images to deceive the discriminator, while the discriminator aims to accurately distinguish between real and generated images. Figure 2 provides an illustrative example scenario of a GAN.

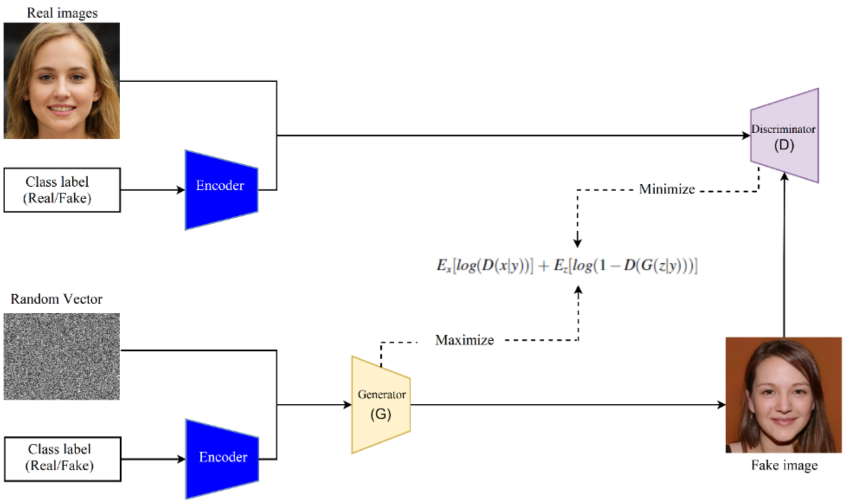

Figure 2. Scenario of image generation with GANs

2.3. Data Augmentation by GAN:

In the first phase of the study, synthetic facial images were generated using GANs to address the lack of data. An open source dataset consisting of images with real and fake faces was used for the synthetic face images. The dataset used was created by the Computer Science Department of Yonsei University, Computational Intelligence and Photography Laboratory. The dataset contains high quality face images created by experts and processed using Photoshop. The dataset consists of 2041 images, 960 fake face images and 1081 real face images. Fake face images in the dataset: eyes, nose, mouth, etc. A face is a combination of different faces divided into image segments. Moreover, fake face images are divided into 3 categories: light, medium and heavy. The images in the dataset have a resolution of 600x600 pixels (P.Lab .Dataset, 2019). Some of the images that make up the dataset are shown in Figure 3.

Figure 3. Real and Fake face images (P.Lab .Dataset, 2019)

In the study, images were resized to shorten the training process for the data augmentation model. After resizing, the images in the dataset were reduced to a resolution of 64x64 pixels. The dataset utilized in the study comprises a total of 2041 images, with 960 images representing fake faces and 1081 images representing real faces. All of these images were included and utilized in the research investigation. In the next step of the study, the hyper-parameters of the model were determined. Color images were preferred for training the model. Since it would be time-consuming, memory-consuming, and learning-consuming to process all the data in the model's dataset simultaneously in the system, the dataset is divided into batches. Consequently, the mini-batch size for the model was determined as 8, indicating that 8 images were processed simultaneously in each training iteration. Moving forward, the subsequent phase of the study involves constructing and specifying the specific architecture of the generator and discriminator networks employed in the model. The details of the generator network's parameters can be found in Table 1, which provides comprehensive information regarding its configuration and settings.

Tablo 1. Parameters of the Generator model.

Layer (Type)	Output Type	Parameter #
dense (Dense)	(None, 8192)	2105344
batch_normalization	(None, 8192)	32768
leaky_re_lu (LeakyReLU)	(None, 8192)	0
reshape (Reshape)	(None, 8, 8, 128)	0
conv2d_transpose	(None, 16, 16, 256)	524544
batch_normalization_1	(None, 16, 16, 256)	1024
leaky_re_lu_1 (LeakyReLU)	(None, 16, 16, 256)	0
conv2d_transpose_1	(None, 32, 32, 256)	1048832
batch_normalization_2	(None, 32, 32, 256)	1024
leaky_re_lu_2 (LeakyReLU)	(None, 32, 32, 256)	0
conv2d_transpose_2	(None, 64, 64, 256)	1048832
batch_normalization_3	(None, 64, 64, 256)	1024
leaky_re_lu_3 (LeakyReLU)	(None, 64, 64, 256)	0
conv2d_transpose_3	(None, 64, 64, 256)	1048832
batch_normalization_4	(None, 64, 64, 256)	1024
leaky_re_lu_4 (LeakyReLU)	(None, 64, 64, 256)	0
conv2d_transpose_4	(None, 64, 64, 256)	1048832
batch_normalization_5	(None, 64, 64, 256)	1024
leaky_re_lu_5 (LeakyReLU)	(None, 64, 64, 256)	0
conv2d (Conv2D)	(None, 64, 64, 3)	19200
Total parameters: 6,882,304 **Trainable parameters:** 6,863,360 **Non- trainable parameters:** 18,944		

The characteristics and parameters of the discriminator network utilized in the model are outlined in Table 2. This table presents a comprehensive overview of the specific settings and configurations employed within the discriminator network for the study.

The training of the GAN model, developed for the study, was conducted over a span of 20 epochs, representing a predefined number of training rounds. The progress and evolution of the losses (errors) for both the generator and discriminator networks throughout the training process are graphically depicted in Figure 4. This plot provides a visual representation of the fluctuation and convergence of the respective network's losses as the model is being trained.

The image comparing the images obtained from the model after 20 epochs with the images generated in the second epoch is shown in Figure 5. Examining the image, it is clear that the artificial face images generated in the second epoch contain too much noise. At the end of the 20th epoch, it can be seen that the images contain more realistic facial images compared to the first days of training.

Tablo 2. Parameters of the Discriminator model.

Layer (Type)	Output Type	Parameter #
conv2d_1 (Conv2D)	(None, 64, 64, 256)	19456
batch_normalization_6	(None, 64, 64, 256)	1024
leaky_re_lu_6	(None, 64, 64, 256)	0
conv2d_2 (Conv2D)	(None, 32, 32, 256)	1638656
batch_normalization_7	(None, 32, 32, 256)	1024
leaky_re_lu_7 (LeakyReLU)	(None, 32, 32, 256)	0
conv2d_3 (Conv2D)	(None, 16, 16, 256)	1638656
batch_normalization_8	(None, 16, 16, 256)	1024
leaky_re_lu_8 (LeakyReLU)	(None, 16, 16, 256)	0
conv2d_4 (Conv2D)	(None, 8, 8, 256)	590080
batch_normalization_9	(None, 8, 8, 256)	1024
leaky_re_lu_9 (LeakyReLU)	(None, 8, 8, 256)	0
conv2d_5 (Conv2D)	(None, 4, 4, 128)	819328
batch_normalization_10	(None, 4, 4, 128)	512
leaky_re_lu_10 (LeakyReLU)	(None, 4, 4, 128)	0
flatten (Flatten)	(None, 2048)	0
dropout (Dropout)	(None, 2048)	0
dense_1 (Dense)	(None, 1)	2049
Total parameters: 4,712,833 **Trainable parameters:** 4,710,529 **Non- trainable parameters:** 2,304		

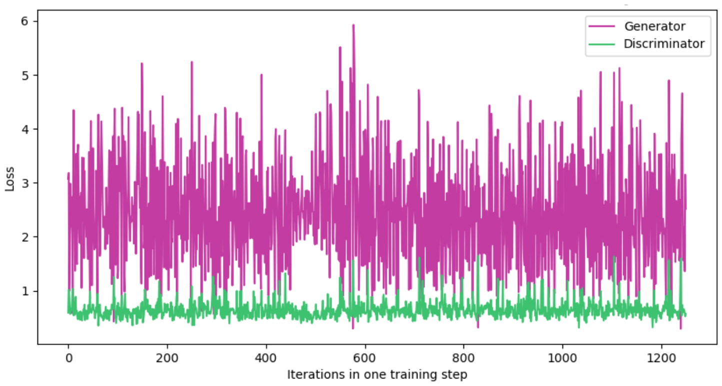

Figure 4. Observed losses (errors) in the generator and discriminator networks of the model GAN during training.

Figure 5. Synthetic face samples were generated by the developed model in the first and last epoch.

3. Method

In the background of the study, synthetic facial images were created using GANs to compensate for the lack of images in the dataset. The summary of the following parts and the general structure of the study are shown in Figure 6.

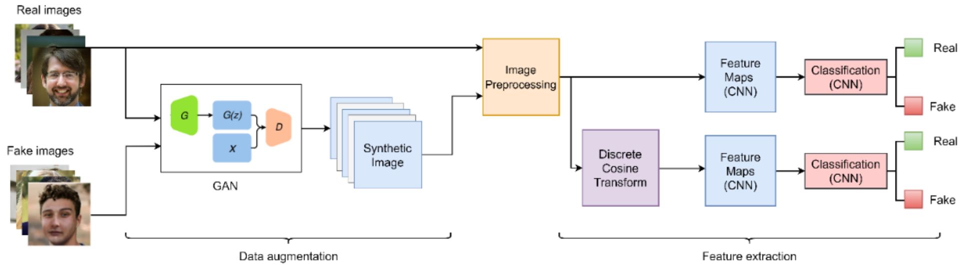

Figure 6. Flowchart of the proposed method

3.1. Deep Learning:

Deep Learning is a machine learning approach that is capable of making predictions or generating outcomes suitable for datasets comprising multiple layers. Its fundamental objective is to extract novel information from processed data using artificial neural networks. Among the various techniques employed in Deep Learning, the Convolutional Neural Networks (CNN) architecture stands out as the most widely used method (Gu, et.al., 2018). Designed to mimic the functioning of the human brain's visual cortex, CNNs excel at recognizing patterns and features in images and performing classification tasks by aggregating them (Min, et.al., 2017). The CNN architecture encompasses several key components, including convolutional layers, non-linear layers, pooling layers, normalization layers, and fully connected layers (Hanbay, 2020).

3.2. VGG-19:

VGG-19 is a deep neural network that employs 24 layers, making it a highly complex architecture. It comprises 16 convolutional layers, 5 pooling layers, and 3 fully connected layers (Toğaçar, et.al., 2020). This network has been pre-trained on an extensive dataset consisting of over a million images from the ImageNet database. The input images for VGG-19 are typically resized to 224 x 224 pixels. Notably, the architecture of VGG-19 encompasses approximately 138 million parameters, which contribute to its powerful representation learning capabilities (Huang, et.al., 2018). To reduce the number of parameters, VGG-19 utilizes 3x3 pixel filters in the convolutional layers. Figure 7 provides a visual representation of the VGG-19 architecture.

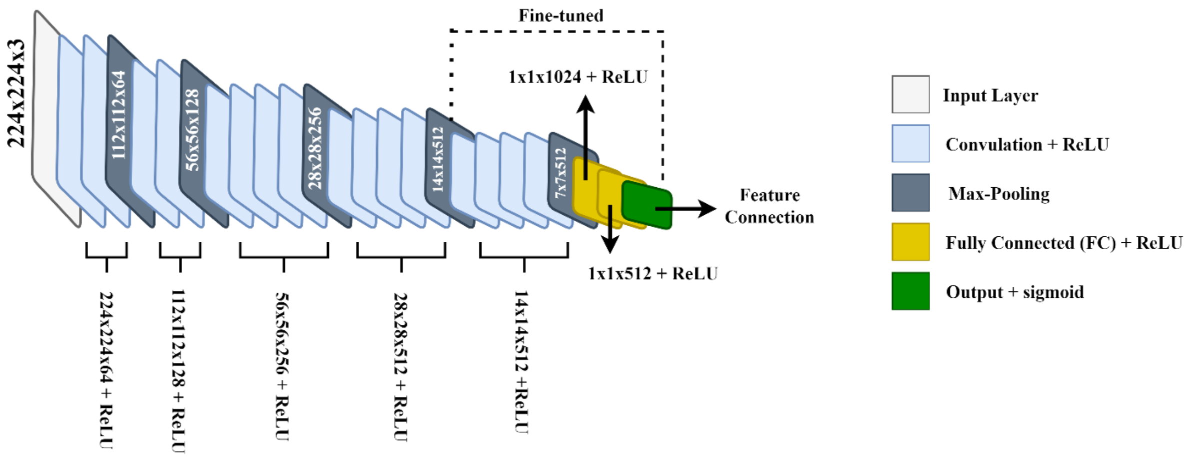

Figure 7. VGG-19 architecture (Mostafiz, et.al., 2020)

3.3. Discrete Cosine Transform:

The discrete cosine transform (DCT) is the representation of a signal as a cosine function when transformed to the frequency plane (Atalar, 2008). An image of size NxN; Equation 2 shown below is used to calculate the DCT coefficient in u,v row, and column.

$$F(u,v) = \frac{2}{N} C(u)C(v) \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x,y) \cos\frac{(2x+1)u\pi}{2N} \cos\frac{(2y+1)v\pi}{2N} \tag{2}$$

The cosine coefficients obtained after the calculation belong to the real part of the signal. In the Fourier transform and some other transformation methods, the signal is expressed by its real and imaginary parts. For this reason, the memory requirement increases due to the increase in the amount of information. The use of DCT reduces the memory requirement (Atalar, 2008).

3.4. Proposed Approach:

In this step of the study, the number of images was increased by adding the images obtained by GANs using the images in the dataset, in addition to the dataset of fake and real face images obtained from the Computational Intelligence and Photography Laboratory of Yonsei University, Department of Computer Science. Classification operations were then performed on these images. The general structure of the study is shown in Figure 8. In the study, using the VGG-19 classification model, the accuracy of the normal state of the images and the discrete cosine transform used in the classification was compared. In this step of the study, the resizing of the images was performed. The purpose of this process is to speed up the classification process and prevent it from consuming too much space in the computer memory. Resizing involves resizing the images to a fixed, predetermined size. When setting the image size, care should be taken not to reduce the image more than necessary. When images are resized excessively, it becomes challenging to extract the essential information required for accurate classification. In accordance with this information, the images of the dataset were resized to 224 x 224 pixels before the classification processes. In the next step, the normal and discrete cosine transform states of the images of the dataset were separately given as input data to the VGG-19 classification model and an attempt was made to determine their effects on the classification.

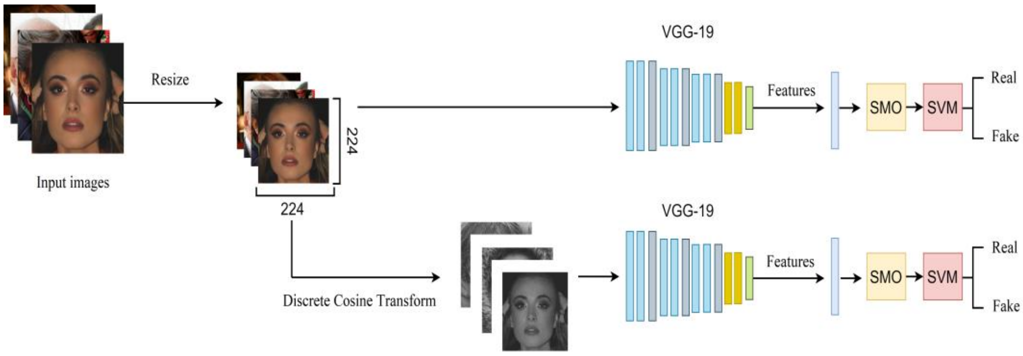

Figure 8. The overall concept of the proposed approach

4. Expermental Results and Research Findings

In the study, a complexity matrix was employed to assess the performance of the classification methods utilized. The complexity matrix included the following terms: TP (True Positive), FP (False Positive), TN (True Negative), and FN (False Negative). These terms were instrumental in calculating various evaluation metrics such as precision, sensitivity, accuracy, and F1 score for the model. Equations 3, 4, 5, and 6 were utilized to perform the necessary mathematical computations for deriving these metrics.

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

$$Sensitivity = \frac{TP}{TP + FN} \tag{4}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

$$F1 - Score = \frac{2TP}{TP + FP + FN} \tag{6}$$

A total of 2041 images, including fake and real faces, were selected in the study, and about 13% of these images were used for classification. Of the 270 images used in the study, 100 were used for testing, 140 for training, and 30 for validation. In the study, the classification process consists of two stages. In the first stage of the study, the classification of fake and real face images was performed using the VGG-19 classification architecture. In the first stage, no image processing technique was applied to the images in the dataset. The images were only converted to a resolution of 224 x 224 pixels, which is the input size of the classification model. The resized images are classified. In the second phase of the experiment, in addition to resizing for the classification model, the Discrete Cosine Transform was applied to each image. The newly obtained images were classified. The analysis results of the classification methods are shown in Table 3. According to the analysis results, the VGG-19 architecture achieved the best classification success with the Discrete Cosine Transform of the images. Considering the obtained general classification success, the accuracy is 40% for normal images and 70% for Discrete Cosine Transform images, respectively.

Tablo 3. Parameters of the Discriminator model.

Method	**Sensitivity %**	**Precision %**	**F1-Score %**	**Accuracy %**
Normal	46.67	41.18	43.75	40
DCT	73.33	68.75	70.97	**70**

According to the methods used in the study for the VGG-19 classification model, the success rates for accuracy versus testing and loss rates versus training, etc., are shown in Figure 9.

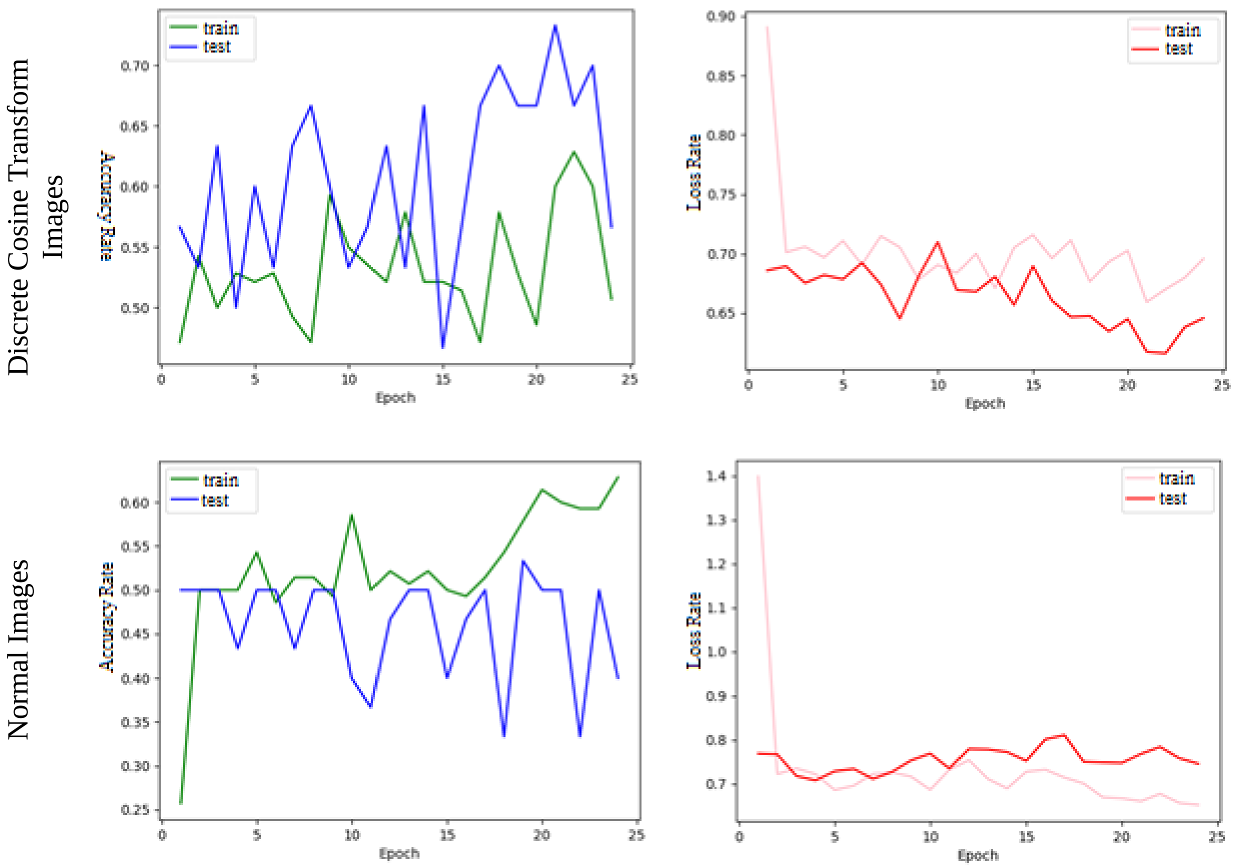

Figure 9. Plots of the accuracy and loss rates of the VGG classification model depending on the method used

The results obtained according to the classification methods are shown in Figure 10 as complex matrices of the methods.

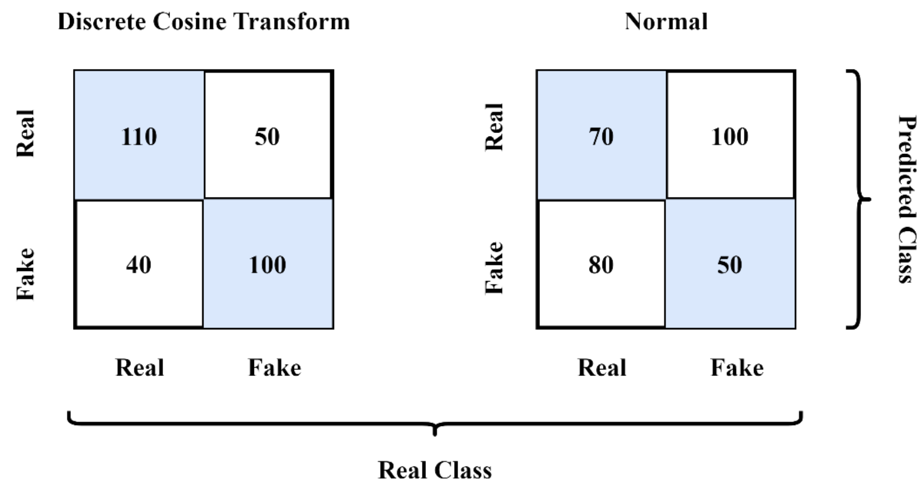

Figure 10. Methods of complexity matrices

5. Discussion

In the research, two different classification methods were implemented on a dataset comprising genuine and synthetic face images, and their results were compared. The comparative analysis revealed that the discrete cosine transform yielded the highest classification accuracy. Table 4 presents details regarding the dataset employed in the study and provides information on related studies that utilized a similar dataset, along with their respective outcomes.

Tablo 4. Comparison of studies performed with similar data sets.

Article	Architecture/Method	Accuracy (%)
Mittal, et.al., (2020)	IQIEA-FS	58,3
McCloskey and Albright, (2018)	SVM/ AN-Pipeline Feature	70
Recommended Method	**VGG-19/ DCT**	**70**

6. Results

Nowadays, with the development of technology, the development of face recognition systems is accelerating. In order for the newly developed face recognition systems to keep up with this speed, the training processes must be carried out in a healthy manner. One of the most important factors for the success rate of face recognition systems is the number of images that make up the data sets. A good face recognition system can be trained using datasets with a large number of images. However, the number of open source datasets that contain the required number of images for training face recognition systems is very small. The first phase of the study attempted to create synthetic face images using Generative adversarial network as an alternative to data multiplication methods to overcome this shortcoming. In the following parts of the study, the negative effects of generating high-resolution and highly realistic fake face images in virtual environments on face recognition systems are highlighted. At the beginning of these negative results are fraud and deception in virtual environments, tampering, manipulation of images, etc. To solve this forgery problem, this study proposes a method to determine whether a face is a real face or a fake face. It shows that applying discrete cosine rotation to the images with the proposed method has a significant effect on detecting the separation of realand fake face. In the study, the VGG-19 classification architecture and the Discrete Cosine Transform achieved an accuracy rate of 70%.

In future studies, the accuracy rate will be improved by changes to the images in the dataset and the architecture used.

Kaynaklar

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