[Baghdad Science Journal](https://bsj.researchcommons.org/home)

Volume 22 | Issue 2 Article 29

2025

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How to Cite this Article

AL-Muttairi, Hasan Sabah K.; Kurnaz, Sefer; and Aljuboori, Abbas Fadhil (2025) "Enhancing Cold Cases Forensic Identification with DCGAN-based Personal Image Reconstruction," *Baghdad Science Journal*: Vol. 22: Iss. 2, Article 29.
DOI: https://doi.org/10.21123/bsj.2024.10896

BAGHDAD SCIENCE JOURNAL 2025;22(2):730–739

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RESEARCH ARTICLE

Enhancing Cold Cases Forensic Identification with DCGAN-based Personal Image Reconstruction

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ABSTRACT

With the improvement of artificial intelligence and deep learning techniques, especially deep convolutional generative adversarial network (DCGAN), there has been a significant development in personal identity and generating images through facial reconstruction systems. This study focuses on proposing a model of personal image reconstruction from forensic sketches using DCGAN. The model comprises two networks: a generator to convert sketch images into real images and a feature network to determine the similarity of the generated images to real ones. Forensic sketches provided by relevant authorities are used as inputs to the proposed model. These sketches include details and information on the perpetrators or missing persons obtained from witnesses or the missing person parents. Prominent facial features extracted from the reconstructed images aid in the process of personal image reconstruction. The proposed model shows good results, achieving up to 99% accuracy in the generated images. The error ratio is reported to be as low as 0.92% based on the evaluation using the CUHKFaces dataset. This study presents a new approach to reconstructing human face images from forensic sketches using DCGAN.

Keywords: DCGAN, Deep learning, Forensic image reconstructing, pix2pix translation, Sketch-to-image

Introduction

The normal human has many distinguished features that can be relied on for personal image reconstruction and the face is one of those features. In law enforcement or criminal investigations, solving cold cases is a unique set of challenges that often require innovative approaches and methods. The cold cases are unsolved criminal investigations that have remind open for a significant period often years or decades. Because of the nature of the reopening of unsolved cases or the lack of sufficient visual evidence, particularly in cases involving the identification of suspected or missing persons or unidentified remains. which in turn depends heavily on the human face. Recent developments in deep learning, in particular the deep convolutional generative adversarial network (DCGAN), provide promising ways to address these challenges. However, current methodologies for facial reconstruction and identification are constrained, including ambiguity and inefficiency. This study aims to bridge this gap by proposing a facial image reconstruction system that leverages DCGAN to transform forensic sketches into realistic images, making it easier to identify missing or wanted persons. Specifically, the research seeks to enhance the accuracy and efficiency of facial reconstruction methods while ensuring accessibility and affordability for forensic analysis tools. The convergence between deep learning techniques and forensic science has paved a new methodology that bodes well for the disclosure of those outstanding issues that have passed years.[1] These methods, which have gained considerable attention in recent years, include the completion of the

Received 8 February 2024; revised 21 May 2024; accepted 23 May 2024.
Available online 28 February 2025

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https://doi.org/10.21123/bsj.2024.10896

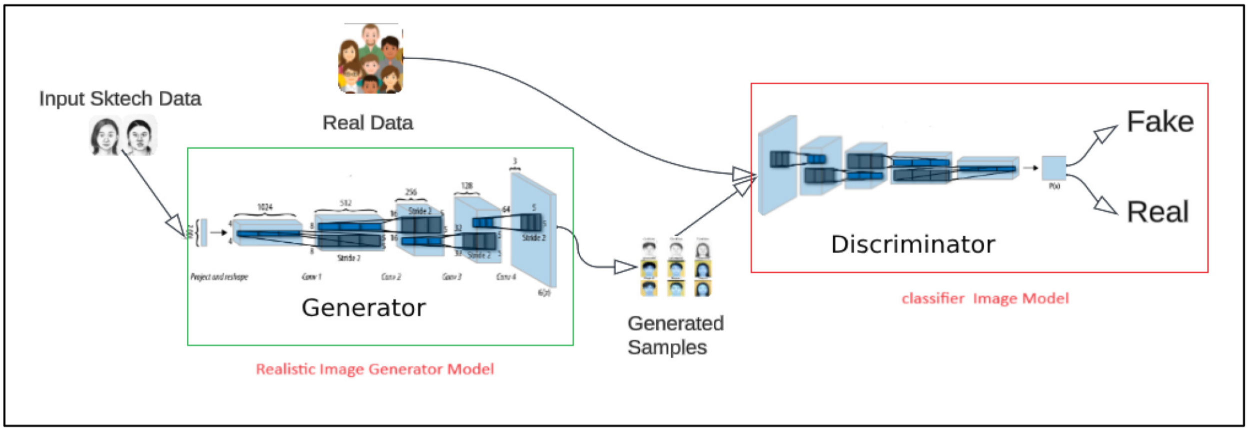

Fig. 1. Image reconstruction system for DCGAN.

latest technology, specifically the use of the deep convolutional generative adversarial network (DCGAN) network to activate cold cases that have contributed to opening up new possibilities for investigators.[2] The power of artificial intelligence to recreate human faces with remarkable accuracy opens up new opportunities in forensic science. The stand at the crossroads of technology and justice, the application of multi-agency databases provides hope for those looking for answers on these cases. DCGAN[3] is a kind of deep learning algorithm that uses two neural networks, generator, and discriminator, to generate realistic images.[4] These institutions operate on the basis of the principle of hostile training, with a network of generators and a discriminator network performing a continuous for improvement, the generator network producing images similar to training data,[5] while the discriminator network evaluates the created images and provides feedback to the network. This process will pass until the generator network produces indistinguishable images of training data. The generator seeks to generate realistic faces, while the discriminator learns to distinguish between real and generated images.[6] Based on a person's identity, decisions are made in two ways: either to protect society from those wanted for justice or to detect and return missing persons to their families. This paper aims to design a facial image reconstruction system that can be easily integrated into forensic analysis tools and at low-cost prices by developing a process for analyzing sketches and converting them into realistic representations which will facilitate the identification of missing or wanted persons of relevant institutions. The generating model is modified based on the basic face image and this generative modelling can be used to predict how the face appears when there is a gap in the image. In this paper, DCGAN is used to generate a human face image generation based on the sketch images entered into it as input. Images drawn by the relevant authorities that take details of the perpetrator or the missing person from witnesses or close persons of the missing person are inserted into the DCGAN algorithm, which in turn produces images that are more real and similar to the requested person, Fig. 1 shows the DCGAN algorithm in reconstructing personal images. In this paper aim to design a facial recognition system that can be easily integrated into forensic analysis tools and at low-cost prices. In addition, develop a process for analyzing drawings or sketches and converting them into realistic representations that will facilitate the identification of missing or wanted persons of relevant institutions. Where the generating model is modified: Based on the basic face image, generative modeling can be used to predict how the face appears when there is a gap in the image. In this paper DCGAN is used to generate a human image generation image based on the sketch's images entered into DCGAN algorithm. Images drawn by the relevant authorities that take details of the perpetrator or the missing person from witnesses or close persons of the missing person are inserted into the DCGAN algorithm, which in turn produces images that are more real and similar to the requested person.

Main contribution

1. Design a facial image reconstruction system utilizing DCGAN for converting forensic sketches into realistic representations.
2. Modification of the generating model based on the basic face image, enabling generative modeling to predict facial appearance in cases of missing information.

3. Integration of the proposed system into forensic analysis tools at low-cost prices, facilitating the identification of missing or wanted persons by relevant institutions.
4. Demonstration of the efficacy of DCGAN in generating human images based on inputs sketch images, enhancing the accuracy and efficiency of facial reconstruction methods.

Related works

Li Zecheng et al.[7] It is suggested to use the GAN and DCGAN networks to generate cartoons illustrations that represent anime pictures. In addition to PyTourh technology, the researchers employed the DCGAN network. ReLu was employed in the generator, and the LeakyReLu activator was used in the functionality across all layers. The dataset for the learning process consisted of 50,000 images, and the results were obtained through a series of experiments conducted in covenants ranging from 600 to 18,400 covenants, where the images displayed prominent animated characters. Researchers have made suggestions for future algorithm improvements.

Yin et al.[8] It is proposed to improve the deep convolution neural network (DCGAN) to address the problems of model instability and poor quality during the training process by adding patch normalization for both generator and discriminator. The researcher replaced the ReLU activation guest with SeLU to give the image more details as well as insert ResNet50 blocks to improve the accuracy of the images. More than 1,692 images of different people's faces were collected as a data set for the proposed algorithm test. The researcher compared the original DCGAN algorithm with the improved algorithm and provided results at the 98.9% accuracy and recall rate based on the confusion matrix, and because the improved network offers the most stable remaining network structure ResNet50 depth, the value of the generator loss is more stable and fluctuates in very few cases, and the value of the loss eventually stabilized at around 0.15. The researcher evaluated image performance by Sum of Modulus of Gray Difference (SMD), Frichet Inception Distance score (FID) and structural similarity (SSIM). In addition to future work, the researcher recommends applying these algorithms to the most challenging data enhancement scenarios to verify the generalization capability of the model from multiple perspectives.

Jadli et al.[9] used DCGAN to build a visual document classification model and produce images of scanned documents. CNNs use of documents is classified and the researchers aim is to assess whether the fake images formed via the proposed model contain sufficient features and variations to effectively increase the training dataset. The researcher used concrete factual data such as bank cheques, receipts, handwritten invoices, electronic invoices, as well as photographs of those documents from different angles, certain lighting and others. The researcher came up with the production of counterfeit documents similar to the true documents well, and the researcher said that combining the two approaches brought the production accuracy of improving models to 89%. He also recommended that this approach be used in practice in the absence of labelled document classification data.

Liu W et al.[10] proposed a new hyperparameter value that may be employed in Adams technique while performing data processing in DCGAN to get decent results when the number of epochs is limited. Furthermore, researchers employed 200,000 photos of famous people faces as a CelebA the data set, which was full of variety and diverse emotions. Researchers feel that extending the number of training times is neither necessary or significant since they have found a balance between the expense of time and the benefit of training after only four epochs. In addition to locating improved hyperparameters for the optimization technique. In order to avoid sequence collapsing and the gradual loss of the network gradients that the researchers will finally concentrate on the framework's effectiveness in training for a small amount of data and distribute it across various sorts of tasks.

Canan et al.[11] suggested employing DCGAN, which consists of two boundaries networks that interfere with each other and where the network of generators applies the transposed layer of convolution when it attempts to generate the fake picture, as well as Batch Normalization, which uses simultaneously learning considering all of the layers on the network that are learning do not have to wait for their preceding layer to learn. This enables for faster training. ReLu and Tanh were also employed as activation functions by the researchers. The last layer is Sigmoid, which evaluates the real picture to the fake picture as a beginning class as well as in the middle of the picture. 10,000 mixed images, a combination of men's and women's photos, were taken from CelebA. The study's findings demonstrated that the phony images clarity significantly changed as the amount of data increased.

Ammar et al.[12] It proposes a technique which combines image data generation methods and basic processors with a support vector machine, or SVM, for facial recognition, where the sap support is produced by a deep convolutional generative adversarial network (DCGAN) to produce samples with realistic

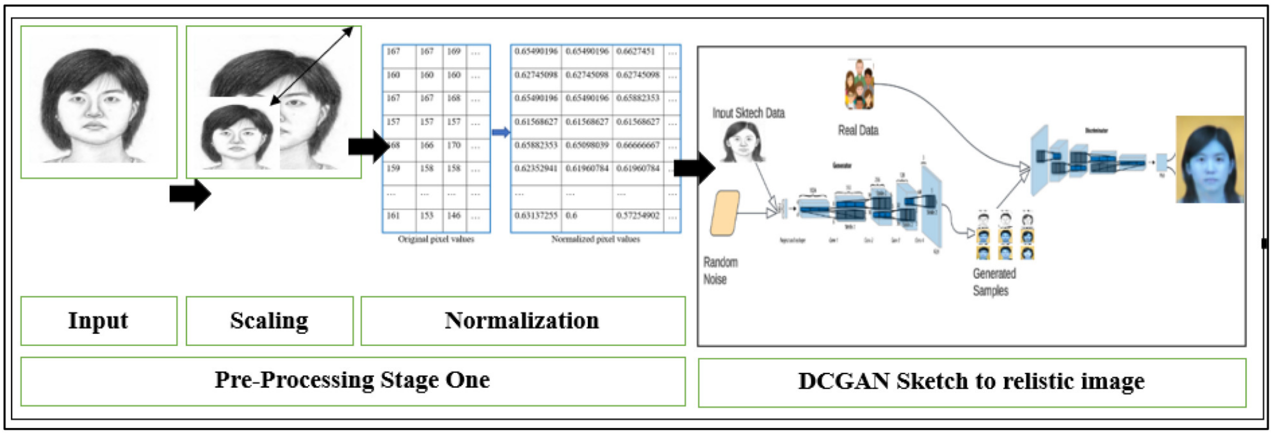

Fig. 2. The procedure of proposed system.

characteristics which are indistinguishable from those found in the original datasets. SVM was employed above embedding for classification where researchers utilized FaceNet as a model for recognizing fachu. In addition to the LFW and VGG photo databases, as well as the Chokepoint video database. To solve the problem of uncommon picture data, the researcher used a mix of DCGAN and simple image editing. In order he made the decision to supplement the original facial data with synthetic images. The methodology consisted of four steps: (1) applying MTCNN to identify faces; (2) using the MTCNN output as input from DCGAN to produce synthetic images; (3) applying fundamental manipulation to DCGAN-created images; and (4) adding images to the original data. where the accuracy ratios on the LFW and VGGFace2 datasets were 94.5% and 92.2%, respectively, for the researcher. The study outlined how DCGANs may be enhanced to provide more realistic and diverse face samples, which could increase the accuracy of the findings. These adjustments could be made to factors like batch size, progress, and learning rate. To enhance the quality of the pictures produced, future research may employ Wasserstein loss with a graded penalty, Table 1 shows the related works summary.

The proposed system

The proposed system presents a Person face image reconstruction System based on facial sketches forensics analysis using deep convolutional generative adversarial neural networks (DCGAN). It is built by model representing the model-specific function stage performed respectively: the realistic person face image generator model, all preceded by the pre-processing stage. Each model has several steps that perform different functions, these are features extraction (to extract prominent features of the input image), and the realistic person image generator, person image reconstructing steps built on these characteristics. The process begins with the pre-processing stage, where the input sketches are subject to initial preparation. This may include tasks such as noise reduction, image resizing and normalization to ensure consistency and improve input quality for later stages. After pre-processing, the feature extraction stage extracts prominent features from the input sketches. These features serve as the basis for creating realistic images. Through technologies such as convolutional neural networks, key facial features are identified and coded to inform the subsequent image reconstruction process. Each stage performs a special task and uses a few layers to accomplish this special goal. The Fig. 2 is the main procedure of the proposed system stages the model is the realistic person face image generator model to come up with a representation and matching scheme for realistic faces. With the recent success of GAN-based architectures, it can generate high-resolution and natural-looking output. The first model is designed on a pre-trained DCGAN algorithm structure that's trained and tested on a dataset named CUHKFace dataset, this dataset is used for research purposes and is open-source with images of people's sketches.[13] DCGAN has two constituent parts are generators and discriminators that must be trained against one another with the least amount of preparation. The generator consists of batch normalization layers, striped wrap layers, and LeakyRelu as the activation function. A picture of 3 × 64 × 64 can be utilized as an input. A 3 × 64 × 64 RGB picture will be the end generated.[14] Either an entry from a generator or a "real" sample of a dataset was used by the feature. Inputs are categorized as either real or generating by the discriminator. The feature employs an intersecting probability loss function for training, which is dependent on the quantity of inputs that are properly categorized as generators and as real.

Phase one pre-processing

Data or inputs must be processed in a specific form so that they can be used in model training. In order to make input images acceptable for training, all necessary preparations are completed at this stage. By changing size or expanding and normalizing, the data becomes clean, well-organized and appropriate. This step also allows the system to spread so that any input image can be used. Because undesirable results may emerge from inputs that have not been cleaned or processed before.

Scaling and flipping input data

An important concept in improving data processing is the dimension of image measurement. The term "dimension" refers to the quantity of features or input variables in the dataset, while "volume samples" refer to the procedure of making the quantity of input features into a fixed range.[13] It is suitable for deep learning identification model and offers built-in generic images as well. The image scale may be seen as an image measurement that involves reconstructing the image by editing the overall pixels count in photo samples from pixel to pixel.[15] For better results when measuring an image, an image measurement technique is used, which estimates values not available in lost locations by achieving known data (values discovered in surrounding pixels) in the image. One image from the CUHKFace range has been expanded to dimensions (256 × 256 pixels).

Normalization

The process of converting the data sets column to the same scale is known as normalization. Normalization ensures that all features, regardless of their initial size or number of units, affect the model in the same way, improving the performance of machine learning models and reliability.[16] Pixel values for images consist of accurate correct numbers (0 and 255) indicating how severe each person is. Normalization technology adjusts the intensity range of pixel values and is often checked to ensure that each pixel value falls between 0 and 1.[17] Min-Max Scaling, which concentrates data around the average with standard unit deviation, and Min-Max Scaling, which converts

167	167	169	…
160	160	160	…
167	167	168	…
157	157	157	…
168	166	170	…
159	158	158	…
…	…	…	…
161	153	146	…

Original pixel values

0.65490196	0.65490196	0.6627451	…
0.62745098	0.62745098	0.62745098	…
0.65490196	0.65490196	0.65882353	…
0.61568627	0.61568627	0.61568627	…
0.65882353	0.65098039	0.66666667	…
0.62352941	0.61960784	0.61960784	…
…	…	…	…
0.63137255	0.6	0.57254902	…

Normalized pixel values

Fig. 3. The normalization pixel value.

data into a common range within a specified range, are common approaches to normalization and Fig. 3 illustrates an example of normalization.

Sketch to realistic image phase

In this stage, deep convolutional generative adversarial networks (DCGAN) that have been trained on the CUHKFace dataset are included in the generative adversarial network model. To ensure that effectively lead to realistic recognition at the final step, the trained model's primary goal is to convert the painted picture of individuals into a realistic and bright image for use in person identification. To predict the potential distribution of actual pictures (samples), this was accomplished by adjusting the optimally trained model. A high degree of accuracy is achieved by drawing a parallel between the produced and original pictures. After comparing the images, the discriminator calculates the probability that a certain picture originated from actual data instead of being provided by the generator themselves. The purpose at this stage is to translate the image into the image (pix2pix),[18] which entails creating a new synthesized version of that image with a specified alteration and Fig. 4 shows some samples from the proposed model. This approach allows images to be converted from one type of shape to another while keeping certain visual features such as style, color, or texture. The GAN model offers automated image-to-image translation for model development without related samples.[19] Unsupervised models are trained using set of images of the target and source ranges that are not connected in any way. The suggested model makes use of a DCGAN structure that allows Two discriminator models and two generator models will be trained continuously.[20]

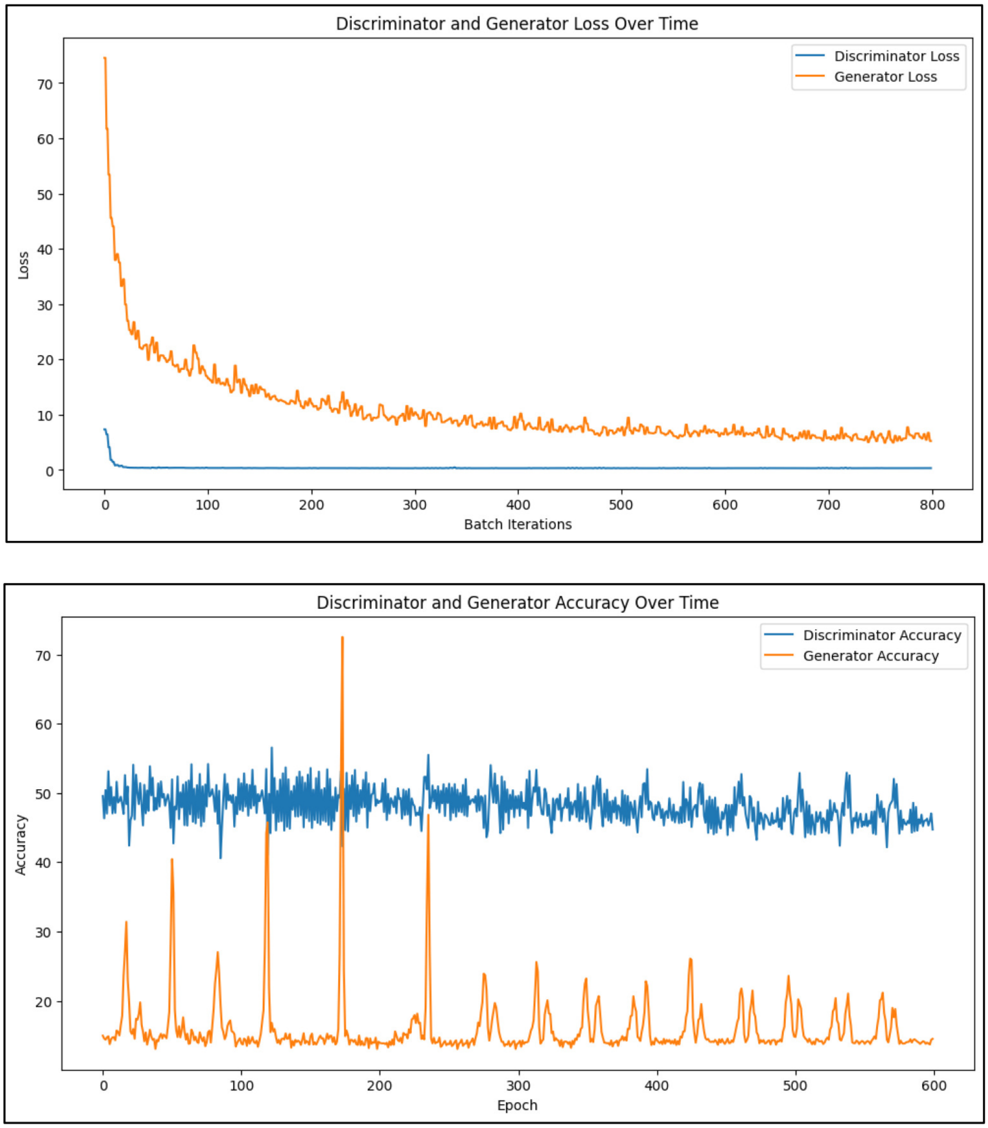

Fig. 4. Loss function and accuracy of the suggested system.

Results and discussion

The performance of the proposed model is assessed by measurement: measurement of accuracy and measurement of loss. An easy way to comprehended the proposed model's adaptive behaviour on a given dataset is to evaluate training and verification data set for each epoch and images results. Part (a) of Fig. 4 shows the loss in the model and part (b) shows the accuracy of suggested system model. Model efficiency and image quality take the effectiveness of the DCGAN algorithm is reflected in the reconstruction of personal images by its ability to transform sketches into vibrant realistic images. The Fig. 5 shows a selection of samples generated through the proposed system algorithm. It should be noted that deep learning models often show variation in their output when provided with the same inputs due to their random nature. Thus, evaluating the quality of the created images requires good analysis.

Based on the results, the DCGAN algorithm's efficiency in reconstructing personal face images is demonstrated by the transformation of sketches into vibrant realistic images. Different definitions can be given, and as a result, they have different general features. The model evaluation produces distinct results when the same model is trained using K fold Cross Validation on different information, according to the standard skills evaluation approach (model change control). The resulting images quality is evaluated using a nearest neighbour method. Many of the original images of people have been selected and a few of the

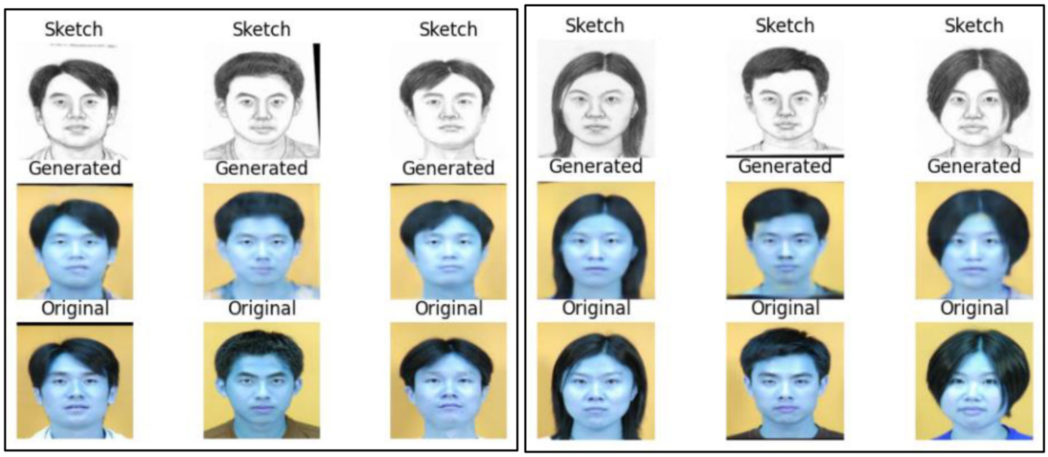

Fig. 5. Samples of proposed system sketch to realistic image model.

similar images are found. The most equivalent images are selected using the traditional distance between the pixel data. With all of the images in the folder, the customary spacing between each produced image is verified. This score indicates that, regardless of its low value, the created image is more similar to the original. Evaluating the Stochastic models skill, or model stability control, is the second phase. Results from various models trained on the same dataset. The average skill of the estimated medium model, also referred to as the average, is determined by repeating the evaluation method of the non-random model many times.

Measurement of the model

This technique of deep learning gives different predictions whenever the model is installed on the similar data and can be said to be indiscriminate. The system measured through the k-fold cross-authentication technique to estimate the skills of the system, where k-fold was calculated and as shown in Table 2 that gave mixed the results when the similar model is trained on data. echo the experience of examining a non-randomized model several times and then calculate the average skill for the expected medium-sized model, commonly referred to as the mean. Accuracy and recall results were F1-score from the system shows in Table 1. the proposed model to predict the identity of the requested person or if it is not present in the dataset. The model is applied with the proposed deep neural network structure with a specific dataset.

For every value of K, the dataset will be split into Tr (80%) + Va (10%) = 90% and Te = 10% in the suggested method, with test performance being recorded based on the approved resolution of the meter employed. In order to show results, the mean efficiency is finally determined. The results of the study are detailed in Table 2 and the application of the 10-Fold's curriculum vitae.

Table 1. Assessment metric value.

Accuracy	Classification Error	Recall	Precision	F1-Score
0.9908	0.0092	0.8909	1.0000	0.9908

Table 2. 10-folds for person identification.

No of Folds	Accuracy in each Fold
1	97.9%
2	98.8%
3	98.8%
4	99.0%
5	98.8%
6	98.8%
7	98.8%
8	98.8%
9	99.05%
10	99.05%

Limitation of the proposed system

There may be several factors in the limitations of the proposed study that can be summarized at several points:

1. Dataset Dependency: The performance of the DCGAN model depends heavily on the quality of the dataset used for training.
2. Hyperparameter Sensitivity: DCGAN networks require particular tuning of hyperparameters, such as learning rate, batch size. Insufficient tuning or suboptimal selections for parameters can lead to ineffective performance.
3. Complexity and Resources: Training deep neural networks such as DCGAN networks can be

computationally intensive and time-consuming, requiring significant computational resources, including high-performance GPUs. This may limit access to the proposed method for researchers with limited computational resources. However, there are several ways that can be invested to get results such as using google colab.

4. Evaluation metrics: The selection of evaluation metrics to evaluate the performance of the DCGAN model may affect the interpretation of results. Accurate selection and justification of evaluation metrics are necessary to ensure meaningful and reliable assessments of the model's performance.
5. Ethical considerations: The use of facial reconstruction techniques in forensic investigations raises ethical considerations, including privacy concerns and potential biases in created images. Guidelines and ethical safeguards must be carefully considered and adhered to in the dissemination of such techniques.

Conclusion

The use of DCGAN to convert forensic pix2pix indicates a significant leap in forensic technology, providing a new and powerful tool for law enforcement agencies to activate cold case investigations. It best recommended technique to achieving best accuracy and giving improved outputs than other standard methods in terms of loss functions and accuracy. Where important features can be extracted while ignoring weak features using ReLU activation function that is integrated with the Deep Convolutional Neural Network Layer (CNN), and the DCGAN application has demonstrated remarkable capabilities in creating highly realistic facial images from forensic sketches, which may provide investigators with more accurate data for suspects or persons of interest. The successful application of DCGAN in forensic transformation from drawing to face paves the way for future research and development, including efforts to improve the accuracy and reliability of created images, as well as to explore multimedia approaches to identifying people. In addition, the theoretical implications of this research contribute to the growing knowledge about the application of generative adversarial networks (GANs) in forensic science. The practical advantages of using DCGAN in pix2pix for forensic medicine are several, including the ability to create highly realistic face images from forensic sketches, which can help investigators identify suspects or persons of interest. However, this research is not without its limits. The accuracy and reliability of the created images can still be improved, and there is a need to further explore multimedia approaches to identify people. Therefore propose the following areas for future research:

- Explore the potential of DCGAN in other forensic applications, such as fingerprint or fingerprint analysis.
- Explore new technologies to improve the accuracy and reliability of created facial images, such as integrating additional features or using the most advanced GAN structures.

Authors' declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours.
- No animal studies are present in the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee at University of altinbas.

Authors' contribution statement

In this study, H. S. K.: contributed to making the design and test the suggested system, and literature review, contributed to forming the idea, and the analysis of results; S. K. and A. F. A. contributed to checking the spelling and checking in terms of content.

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تعزيز التعرف على الحالات الباردة بالطب الشرعي من خلال إعادة بناء الصورة الشخصية المستندة إلى DCGAN

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الخلاصة

مع تحسن الذكاء الاصطناعي وتقنيات التعلم العميق، وخاصة شبكة الخصومة التوليدية التلافيفية العميقة (DCGAN)، كان هناك تطور كبير في التعرف على الهوية الشخصية وتوليد الصور من خلال أنظمة إعادة بناء الوجه. تركز هذه الدراسة على اقتراح نموذج لإعادة بناء الصورة الشخصية من رسومات الطب الشرعي باستخدام DCGAN. يتكون النموذج من شبكتين: شبكة مولد لتحويل الصور الرسومية إلى صور حقيقية وشبكة مميز لتحديد تشابه الصور التي تم إنشاؤها مع الصور الاصلية. وتستخدم رسومات الطب الشرعي التي تقدمها السلطات المختصة كمدخلات للنموذج المقترح. وتشمل هذه الرسومات تفاصيل ومعلومات عن الجناة أو الأشخاص المفقودين الذين تم الحصول عليهم من الشهود أو من الوالدين المفقودين. تساعد ملامح الوجه البارزة المستخرجة من الصور المعاد بناؤها في عملية إعادة بناء الصورة الشخصية. ويُظهر النموذج المقترح نتائج جيدة، حيث حقق دقة تصل إلى 99% في الصور التي تم إنشاؤها. تم الإبلاغ عن نسبة الخطأ لتصل إلى 0.92% بناءً على التقييم باستخدام مجموعة بيانات CUHKFaces. تقدم هذه الدراسة نهجًا جديدًا لإعادة بناء صور الوجه البشري من رسومات الطب الشرعي باستخدام DCGAN.

الكلمات المفتاحية: شبكة العدائية التلافيفية العميقة (DCGAN)، التعلم العميق، إعادة بناء الصور الجنائية، ترجمة الصورة الى صورة، رسم الى صورة.