

Deepfake Transition using GAN Model Architecture

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Abstract: Deep fake videos are videos where the features and expressions of a person are replaced with the features and expressions of another person. Videos can be converted or manipulated using powerful Deep Learning techniques. This technology may be used in wrong way or maliciously as a means of spreading misinformation of any activity, manipulation, and persuasion. Currently there are not many solutions to identify products of Deep fake technology, although there is significant research being conducted to tackle or handle with this problem. Generative Adversarial Network (GAN) is the one often researched deep learning technology. These networks preferred to develop or generate the non-existing patterns or creations. In this work, we're working on the development of first order motion model for image animation using Dense motion network. Using key point detectors as a baseline, we train a GAN and extract the facial landmarks from the driving video and building the embedding model to create the synthesized video using the dedicated module to prepare the Deep fakes. At the end, we show's a model to get the efficacy of a group of GAN generators using dense motion networks. Our results generate the augmented animation video using the sequel driving combination of driving video with source image. This project can be used in many areas like multiplying the dataset counts with minimum number source, CG platforms where gaming industry animation industry using to create real-time backgrounds characters, Cloth translations, 3D object generation, etc.

Keywords: Generative Adversarial Network (GAN), Deep Learning, Dense motion networks, 3D object generation, etc

I. INTRODUCTION

Facial expression is one of the most powerful, natural and universal signals for human beings to convey their emotional states and intentions. Numerous studies have been conducted on automatic facial expression analysis because of its practical importance in sociable robots, medical treatment, driver fatigue surveillance, and many other human-computer interaction systems. In the field of computer vision and machine learning, various facial expression recognition (FER) systems have been explored to encode expression information from facial representations

FER systems can be divided into two main categories according to the feature representations: static image FER and dynamic sequence FER. In static-based methods, the feature representation is encoded with only spatial information from the current single image, whereas dynamic based methods [15], [16], [17] consider the temporal relation among contiguous frames in the input facial expression sequence. Based on these two vision-based methods, other modalities, such as audio and physiological channels, have also been used in multimodal systems [18] to assist in the recognition of expression.

Facial Expression Database:

Having sufficient labeled training data that include as many variations of the populations and environments as possible is important for the design of a deep expression recognition system. In this section, we discuss publicly available databases that contain basic expressions and that are widely used in our reviewed papers for deep learning algorithm evaluation. We also introduce newly released databases that contain a large number of affective images collected from the real world to benefit the training of deep neural networks



Fig. 1 Facial Expressions

Exhaustive surveys on automatic expression analysis have been published in recent years [7], [8], [28], [29]. These surveys have established a set of standard algorithmic pipelines for FER. However, they focus on traditional methods, and deep learning has rarely been reviewed. Very recently, deep learning for human affect recognition was surveyed in [30], which reviewed the development of deep affect recognition from 2010 to 2017 and focused on the fusion of audiovisual and physiological sensors.

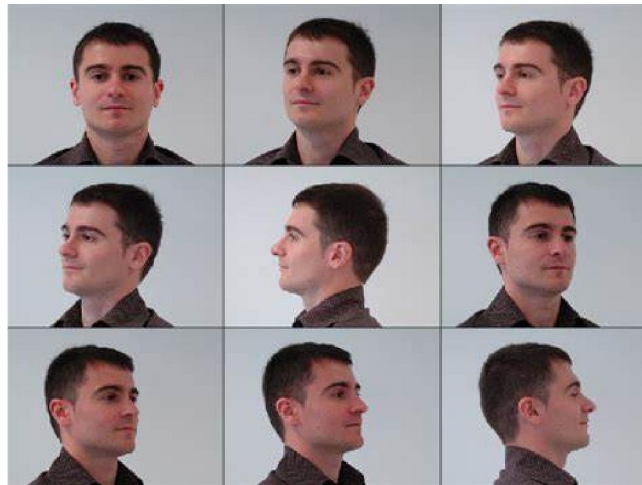


Fig. 2 Deep Fake Expression Recognition

II. PROPOSED METHODOLOGY

The most successful rule for Deep Fake is the GAN, it combines two neural networks that may generate realistic visuals. This machine learning approach can learn from a large number of sources of pictures & afterwards combining these pictures to create a picture that appears authentic to human eyes. The architecture that is Fig-1 shows the various steps to ensure deep fake pictures and gives accurate results. The procedure is divided into four stages, as shown below.:

Step-1: CelebA& MNIST dataset: Downloads the data set from the kaggle repository.

Step-2: It uploads the following Dataset for process it includes all the pictures for restoration and rescalling.

Step-3: After that, the dataset is then divided into two sections: training and testing.

Step-4: GAN Model Created: The training dataset is applied, as a DCGAN intake and the weight optimizer is tweaked to determine if the photos are real or phony.

Data Collection

The datasets we used were MNIST and CelebA Dataset. The MNIST dataset (Modified National Institute of Standards and Technology) is a set of data from the National Institute of Standards and Technology. It's made up of 60000 tiny

square gray scale images of handwritten single numerals ranging from 0 to 9 in a 28 X 28 grid. CelebA stands for CelebFaces Attributes Collection, containing approximately 200K photos, a large-scale facial characteristics dataset.

Process Model

Machine learning technologies are used to suggest the system. To begin, we use the CelebA Dataset, which contains all photographs with resolutions of 4x4, 8x8, and 16x16 pixels to speed up the training process and produce a realistic model test result.

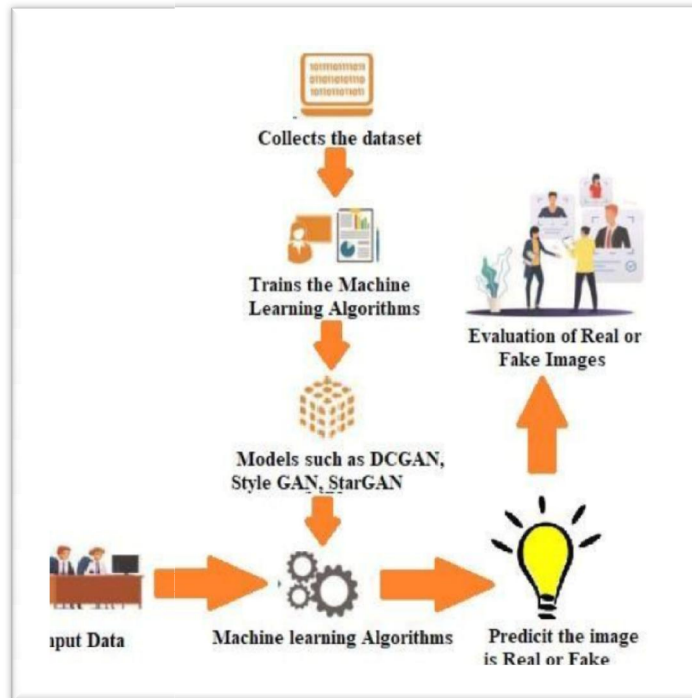


Fig. 3 Architecture Diagram

III. SYSTEM DESIGN

Introduction

The system design for a Deepfake Transition Using GAN Model Architecture project encompasses a comprehensive approach to generating realistic and convincing deepfake transitions while addressing technical challenges and ethical considerations. At the core of the system lies the architecture of Generative Adversarial Networks (GANs), which are designed to produce synthetic content that closely mimics real-world data. Variants such as DCGAN, StyleGAN, or conditional GANs (cGANs) are considered based on the specific requirements of the project, allowing for conditional generation tasks or specialized features such as identity preservation and emotion recognition if needed. These architectures form the backbone of the deepfake transition system, enabling the generation of seamless transitions between faces in videos with high fidelity.

The training phase of the system involves preparing the dataset, which includes tasks such as data collection, preprocessing, and formatting for training. During model training, advanced techniques such as adversarial training, gradient penalty, and regularization are employed to stabilize training and improve convergence. Hyperparameter tuning is conducted iteratively to optimize model performance, ensuring that the generated deepfake transitions exhibit realistic facial expressions, movements, and identities. Additionally, the evaluation phase involves both quantitative metrics and qualitative assessments to measure the quality, realism, and ethical implications of the generated content. Human evaluations play a crucial role in assessing perceptual fidelity, emotion recognition, and identity preservation, providing valuable insights into the effectiveness of the deepfake transition system.

Deployment of the deepfake transition system requires the development of a user-friendly interface or application that facilitates the generation of deepfake transitions. Compatibility with various input formats (images, videos) and output resolutions is ensured to cater to diverse user preferences and requirements. Integration with existing platforms or workflows may be necessary, and security measures such as encryption, authentication, and content moderation are implemented to prevent misuse of the technology. Moreover, ethical considerations are paramount throughout the system design process, with mechanisms in place to obtain consent from individuals whose faces are used in the deepfake transitions. Transparency regarding the use of deepfake technology and user education initiatives are essential to promote responsible usage and mitigate potential risks associated with privacy, security, and misinformation.

Monitoring and maintenance of the deepfake transition system involve ongoing performance monitoring, model updates based on new data and feedback, and periodic security audits to identify and address potential vulnerabilities or misuse. By following this system design approach, developers can create a robust and responsible deepfake transition system using GAN model architecture, ensuring that it meets both technical requirements and ethical standards while providing users with a reliable and engaging experience.

Architectural Design

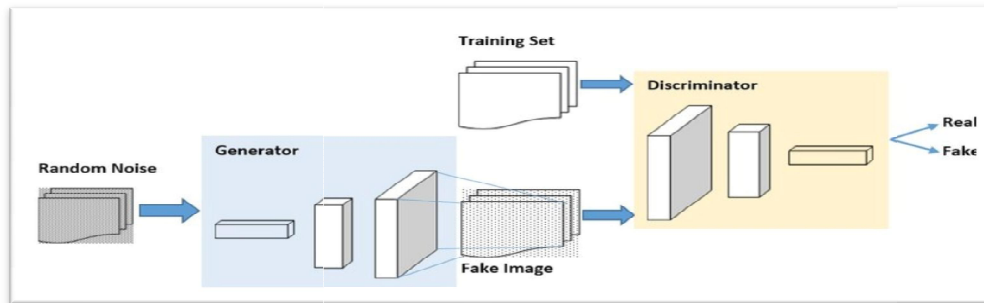


Fig. 4 Architecture Design

Design is a meaningful engineering representation of something that is to be built. It is the most crucial phase in the developments of a system. Software design is a process through which the requirements are translated into a representation of software. Design is a place where design is fostered in software Engineering. Based on the user requirements and the detailed analysis of the existing system, the new system must be designed.

Development Flow

1. Collecting the driving videos source image datasets.
2. Setting up the image animation part to display the comparisons.
3. Creating the generator model.
4. Creating key point detector model.
5. Performing image animation.
6. Testing real-time image animation using Deep GAN.

IV. RESULTS

In this project we are making an application of creating fake face transitions for which we are giving source image and driving video as input as shown in input image. Our results showed that our application was able to produce realistic and convincing face transitions with high quality. The GAN architecture used in our application allowed for the generation of highly detailed and natural looking images.

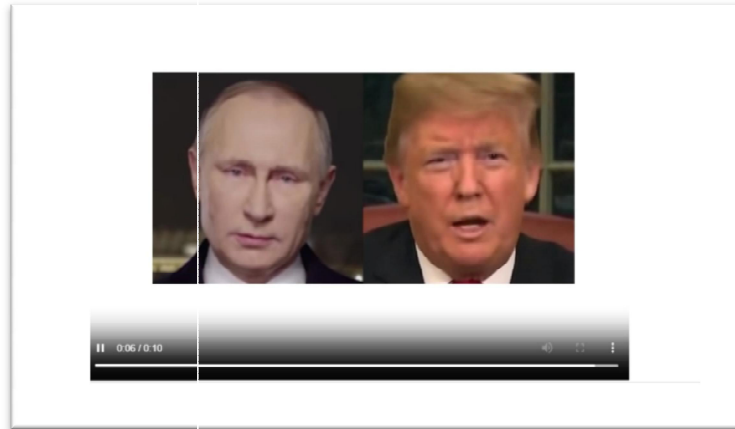


Fig. 5 Input

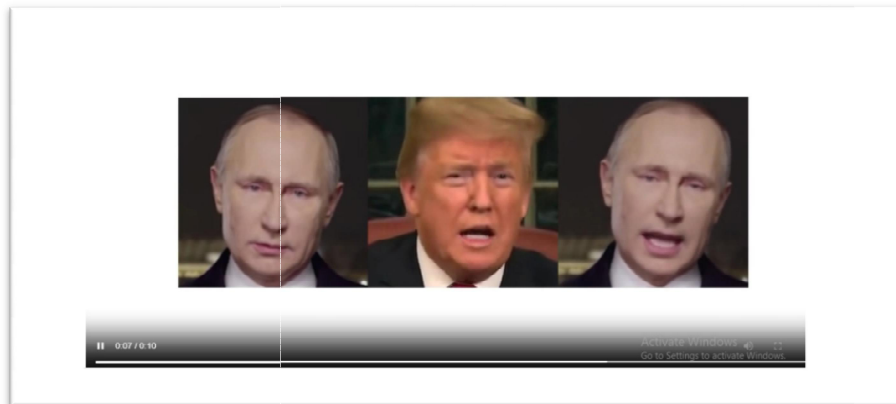


Fig. 6 Output

Furthermore, our study revealed that the quality of the generated face transitions was highly dependent on the quality of the input images. Images with high resolution and quality produced better results compared to lower quality images. One limitation of our study is that GAN model was trained using a limited dataset, and may not be applicable to all types of face transitions. Additionally, the ethical implications of deepfake technology must be considered, as it has the potential to be used for malicious purposes such as spreading misinformation or creating fake news.

V. CONCLUSION

It has always been challenging to detect deepfake content, as they are generated at a different level of abstraction. It has always been treated as a binary classification problem, as real or deepfake class labels. So, CNN is a prominent solution to detect deepfake images. Motivated by this, we have proposed a CNN-based architecture to detect deepfake images in this paper. The proposed architecture offers 97.2% accuracy considering images from 5 different data sources for deepfake images and 2 different data sources for real images.

Even though there is a huge difference between the resolutions of these images, the proposed architecture provides a well-balanced performance over all data sources. The work can be further extended to classify video deepfake content. This model can be used for video deepfake detection, where each video frame is extracted, the face is detected, cropped, and then fed to the model to identify deepfake manipulations. This can be easily done by creating a pipeline to process this video data. Thus, the proposed CNN-based model performs well and has quite a balanced performance over the given dataset with all the data augmentation techniques applied. Furthermore, it shows good generalizability and performance over unseen reserved test sets.

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