
DeepFaceLab: A simple, flexible and extensible face swapping framework

Ivan Perov

Freelancer

1epersonium@gmail.com

Daiheng Gao

Freelancer

samuel.gao023@gmail.com

Nikolay Chervoniy

Freelancer

n.chervonij@gmail.com

Kunlin Liu

USTC

1kl16949@mail.ustc.edu.cn

Sugasa Marangonda

Freelancer

thedeepfakechannel@gmail.com

Chris Umé

VFX Chris Ume

info@vfxchrisume.com

Mr. dpfks

Freelancer

dpfks@protonmail.com

Carl Shift Facenheim

Ctrl Shift Face

ctrl.shift.email@protonmail.com

Luis RP

Freelancer

luisguans@hotmail.com

Jian Jiang

008 Tech

jiangjian@008tech.com

Sheng Zhang

Freelancer

cndeepfakes@gmail.com

Pingyu Wu

Freelancer

wpydcr@hotmail.com

Bo zhou

Multicoreware Inc.

bo@multicorewareinc.com

Weiming Zhang

USTC

zhangwm@ustc.edu.cn

Abstract

DeepFaceLab is an open-source deepfake system created by **iperov** for face swapping with more than 3,000 forks and 14,000 stars in Github: it provides an imperative and easy-to-use pipeline for people to use with no comprehensive understanding of deep learning framework or with model implementation required, while remains a flexible and loose coupling structure for people who need to strengthen their own pipeline with other features without writing complicated boilerplate code.

In this paper, we detail the principles that drive the implementation of DeepFaceLab and introduce the pipeline of it, through which every aspect of the pipeline can be modified painlessly by users to achieve their customization purpose, and it's noteworthy that DeepFaceLab could achieve results with high fidelity and indeed indiscernible by mainstream forgery detection approaches. We demonstrate the advantage of our system through comparing our approach with current prevailing systems.¹

¹For more information, please visit: <https://github.com/iperov/DeepFaceLab/>. (Kunlin Liu is the corresponding author.)



Figure 1: Face swapping by DeepFaceLab. Left: Source face. Middle: Destination face for replacement. Our results appear in the left, demonstrating that DeepFaceLab could handle occlusion, bad illumination and side face. For more information, please visit: <https://github.com/iperov/DeepFaceLab/>

1 Introduction

Since deep learning has empowered the realm of computer vision in recent years, the manipulation of digital image, especially manipulation of human portraits image, has improved rapidly and achieved photorealistic result in most cases. Face swapping, is an eye-catching task in generating fake content by transferring a source face to the destination while maintaining the facial movements and expression deformations of the source.

The key motivation behind face manipulation techniques is Generative Adversarial Networks (GANs) [8]. More and more faces synthesized by StyleGAN [14], StyleGAN2 [15] are becoming more and more realistic and completely indistinguishable to human vision system.

Numerous spoof videos synthesized by GAN-based face swapping methods are published in youtube and other video websites. Commercial mobile application such as ZAO² and FaceApp³ which allow general netizens to create fake images and videos effortlessly greatly boost the spreading of these swapping techniques, called **deepfakes**. MrDeepFakes, the most famous forum for people who talk about the cutting-edge progress in deepfakes technology itself either the set of skills for produce delicate face swapping videos, further accelerates the promotion of deepfakes-made videos in the Internet.

These content generation and modification technologies may affect the quality of public discourse and the safeguarding of human rights especially given that deepfakes may be used maliciously as a source of misinformation, manipulation, harassment, and persuasion. Identifying manipulated media is a technically demanding and rapidly evolving challenge that requires collaborations across the entire tech industry and beyond.

Researches on media anti-forgery detection is being invigorated and dedicating growing efforts to forgery face detection. DFDC⁴ is a typical example, which is a million-dollar challenge launched by Facebook and Microsoft in 2019.

However, passive defense is never a good idea for detection of deepfakes. In our perspective, for both academia and the general public, it is better to know what deepfake is and how it could make a photorealistic video with source person changed to target person, rather than merely defend against it passively, as the old saying goes: "The best defence is a good offense". Making general netizens realizing the exsistence of deepfakes and strengthening their identification ability for spoof medias published in social network is much more important than agonizing the fact whether spoof media is true or not.

To the best of our knowledge, Synthesising Obama [26], FSGAN [20] and FaceShifter [17] are the most representative works of synthesizing facial-manipulated video. The problem of these works and other related works is that the authors of them do not fully open-source their code or release only

²<https://apps.apple.com/cn/app/id1465199127>

³<https://apps.apple.com/gb/app/faceapp-ai-face-editor/id1180884341>

⁴<https://deepfakedetectionchallenge.ai/>

part of the code, whereas the reproduction of these paper by the open-source communities is almost hard to produce a convincing result as demonstrated in the paper. "The devil in the details" is a motto that we all acknowledge in training generative models. Since the trend of face swapping algorithms have become increasingly complicated with more and more perplex processing procedures inserted, it seems like an unrealistic goal to completely fulfill a fantastic face swapping algorithm according merely based on papers.

Furthermore, these algorithms or systems need difficult human hand-picked operations or specified condition more or less, which raises the threshold for beginners who want to dig deeper. For example, Synthesizing Obama [26] needs a high quality 3D model of Obama and a canonical manually drawn mask, which means when you change to a video clip or reselect the source person you want change, you need to customize a new 3D model and draw a canonical mask for synthesizing texture. Obviously, it is heavy to carry out such plan.

As a whole pipeline of generating fake digital content, besides face swapping, more components are required to fill the whole framework: such as face detector module, face recognition module, face alignment module, face parsing module, face blending module etc. The current works with incomplete pipeline is somehow hindering the progress in this area and increasing the cost of learning for many novices.

To address these points, DeepFakes [4] has introduced a complete production pipeline in replacing a source person's face to the target person's along with the same facial expression such as eye movement, facial muscle movement. However, the results produced by DeepFakes are poor somehow, so are the results with Nirkin's automatic face swapping [21].

This paper introduces DeepFaceLab, an easy-to-use, open-source system with clean-state design of pipeline, which can achieve photorealistic face swapping result without painful tuning. DeepFaceLab has turned out to be very popular with the public. For instance, many artists create DeepFaceLab-based videos and publish it into their youtube channels, among whom, five most popular of them with average subscriptions of over 200,000 and the sum over hits of these in DeepFaceLab made videos over 100 million.

The contribution of DeepFaceLab can be summarize as below:

- A state-of-the-art framework consists of maturity pipeline is proposed, which aims in achieving photorealistic face swapping results.
- DeepFaceLab open-sources the code in 2018 and always keep up to the progress in the computer vision area, making a positive contribution for defending deepfakes both actively and passively, which has drawn broad attention in the open-source community and VFX areas.
- Some high-efficiency components and tools are introduced in DeepFaceLab hence users may want more flexibility in the DeepFaceLab workflow meanwhile find the problems in time.

2 Characteristics of DeepFaceLab

DeepFaceLab's success stems from weaving previous ideas into a design that balances speed and ease of use as well as the booming of computer vision in face recognition, alignment, reconstruction, segmentation etc. There are four main characteristics behind our implementation:

Leras Now DeepFaceLab provides a new high-level deep learning framework built on pure TensorFlow [1], which aims to bail out the unnecessary restrictions and extra overheads brought by some commonly-used high-level frameworks such as Keras [3] and plaidML [29]. **iperov** named it as **Leras**: the abbreviation for Lighter Keras. The main advantages of Leras are:

- **Simple and flexible model construction** Leras alleviate the burden of researchers and practitioners by providing Pythonic style to do model work, similar to PyTorch (i.e. defining layers, composing neural models, writing optimizers), but in graph mode (no eager execution).
- **Performance focused implementation** With the utilize of Leras instead of Keras, the training time is reduced by about 10 20% in average.

- **Fine-granularity tensor management** The motivation for switching to pure Tensorflow is that Keras and plaidML are not flexible enough. In addition, they are largely outdated and do not give full control over how tensors are processed.

Put users first DeepFaceLab strives to make the usage of its pipeline, including data loader and processing, model training and post-processing, as easy and productive as possible. Unlike other face swapping systems, DeepFaceLab provides a complete command line tools with every aspect of the pipeline could be executed in the way that users choose. Notably, the complexity inherent as well as many hand-picked features for fine-grained control such as the canonical face landmark for face alignment, should be handled internally and hidden behind DeepFaceLab. That is to say, people could achieve the smooth and photorealistic face swapping results without the need of hand-picked features if they follow the settings of the workflow, but only with the need of two folders: the source (`src`) and the destination (`dst`) without the need to pair the same facial expression between `src` and `dst`. To some extent, DeepFaceLab could function like a point-and-shoot camera.

Furthermore, according to many practical feedbacks from DeepFaceLab users, a highly flexible and customized face converter is needed since there are a lot of complexity need to be handle: floodlights, rain, separated by glass, face injuries and many other cases. Hence, interactive mode has been applied in the conversion phase, which relieved the workload for deepfake producers since interactive preview can assist them in observing the effects of all changes they make when changing various options and enabling/disabling various features.

Engineering support To drain the full potential of CPU and GPU, some pragmatic measures were added to improve the performance: multi-gpu support, half-precision training, usage of pinned CUDA memory to improve throughput, use of multiple threads to accelerate graphics operations and data processing.

Extensibility and Scalability To strengthen the flexibility of DeepFaceLab workflow and attract the interest of research community, users are free to replace any component of DeepFaceLab that does not meet the needs or performance requirements of their project for most of DeepFaceLab's modules are designed to be interchangeable. For instance, people could provide a new face detector in order to achieve high performance in detecting face with extreme angles or far area. A general case is that many masters of DeepFaceLab tend to customize their network structure and training paradigm, e.g. progressive training paradigm of PGGAN [13] combined with special loss design of LSGAN [19] or WGAN-GP [9].

3 Pipeline

In DeepFaceLab (DFL for short), we abstract the pipeline into three main components: Extraction, Training and Conversion. Those three parts are presented sequentially. Besides, a noteworthy thing is that DFL falls in a typical one-to-one face swapping paradigm, which means there are only two data folders: `src` and `dst`, the abbreviation for source and destination, are used in the following narrative. Furthermore, Unlike prior work, we can generate high resolution images and generalise to variant input resolutions.

3.1 Extraction

Extraction is the first phase in DFL, which contains many algorithms and processing parts, i.e. face detection, face alignment, and face segmentation. After the procedure of Extraction, user will get the aligned faces with precise mask and facial landmarks from your input data folder, `src` is used here for illustration in this part. Plus, as DFL provides many face type (i.e. `half face`, `full face`, `whole face`), which represents the face coverage area of Extraction. Unless stated otherwise, `full face` is taken by default.

Face Detection The first step in Extraction is to find the target face in the given folders: `src` and `dst`. DFL use S3FD [34] as its default face detector. Obviously, you can choose any other face detection algorithm to replace S3FD for your specified target, i.e RetinaFace [5], MTCNN [33].

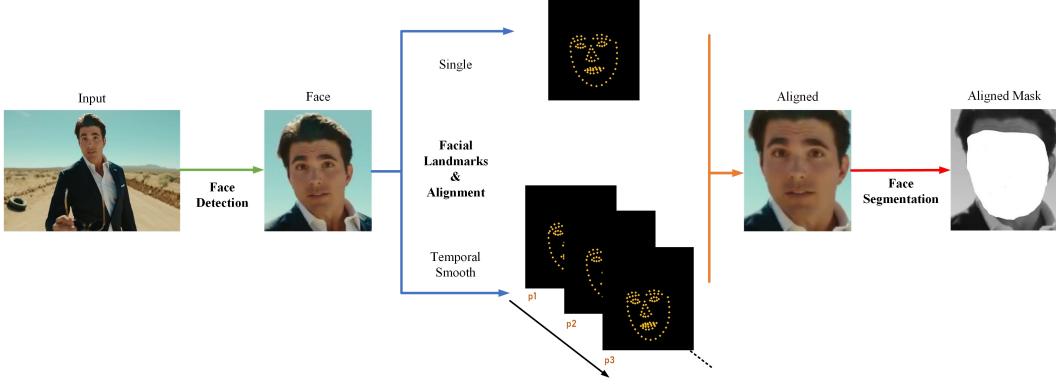


Figure 2: Overview of Extraction in DeepFaceLab (DFL).

Face Alignment The second step is face alignment, after numerous experiments and failures, we need to find a facial landmarks algorithm which could maintain stable over time, which is of essential importance in producing a successful successive footage shot and film.

DFL provides two canonical type of facial landmark extraction algorithm to solve this: (a) heatmap-based facial landmark algorithm 2DFAN [2] (for faces with normal posture) and (b) PRNet [6] with 3D face priori information (for face with large Euler angle (yaw, pitch, roll), e.g. A face with large yaw angle, means one side of the face is out of sight). After facial landmarks was retrieved, we provide an optional function with configurable timestep to smooth facial landmarks of consecutive frames in a single shot.

Then we adopt a classical point pattern mapping and transformation method proposed by Umeyama [28] to calculate a similarity transformation matrix used for face alignment.

As Umeyama [28] method needs standard facial landmark templates in calculating similarity transformation matrix, DFL provides three canonical aligned facial landmark templates: front view and side views (left and right). The noteworthy thing is DFL could automatically determine the Euler angle according to the obtained facial landmarks, which can help Face Alignment in choosing the right facial landmark template without any manual intervention

Face Segmentation After face alignment, a data folder with face of standard front/side-view aligned `src` is attained. We employ a fine-grained Face Segmentation network (TernausNet [10]) on top of aligned `src`, through which, a face with either hair, fingers or glasses could be segmented exactly. It is optionally but usefully, which designed to remove irregular occlusions to keep network in the Training process robust to hands, glasses and any other objects which may cover the face somehow.

However, since some state-of-the-art face segmentation model fails to generate fine-grained mask in some particular shots, the XSeg model was introduced in DFL. XSeg now allow everyone train their own model for the segmentation of a specific faceset (`aligned src` or `aligned dst`) through few-shot learning paradigm. For instance, if a faceset of around 2000 pictures, it is enough to mark the most representative 50-100 samples manually. XSeg then trains to achieve the desired segmentation quality on top of those manually labeled pairs and generalize to the whole faceset.

To be clear, XSeg(optional) is only necessary for those cases when `whole_face` type is being used or it is necessary to remove obstructions from the mask on the `full_face` type. The sketch of XSeg is list in 4.

As the above workflow executed sequentially, we got everything DFL needs in the next stage (Training): cropped faces with its correspond coordinates in its original images, facial landmarks, aligned faces and pixel-wise segmentation masks from `src` (Since the extraction procedure of `dst` is the same with `src`, hence there is no need to elaborate that in detail).

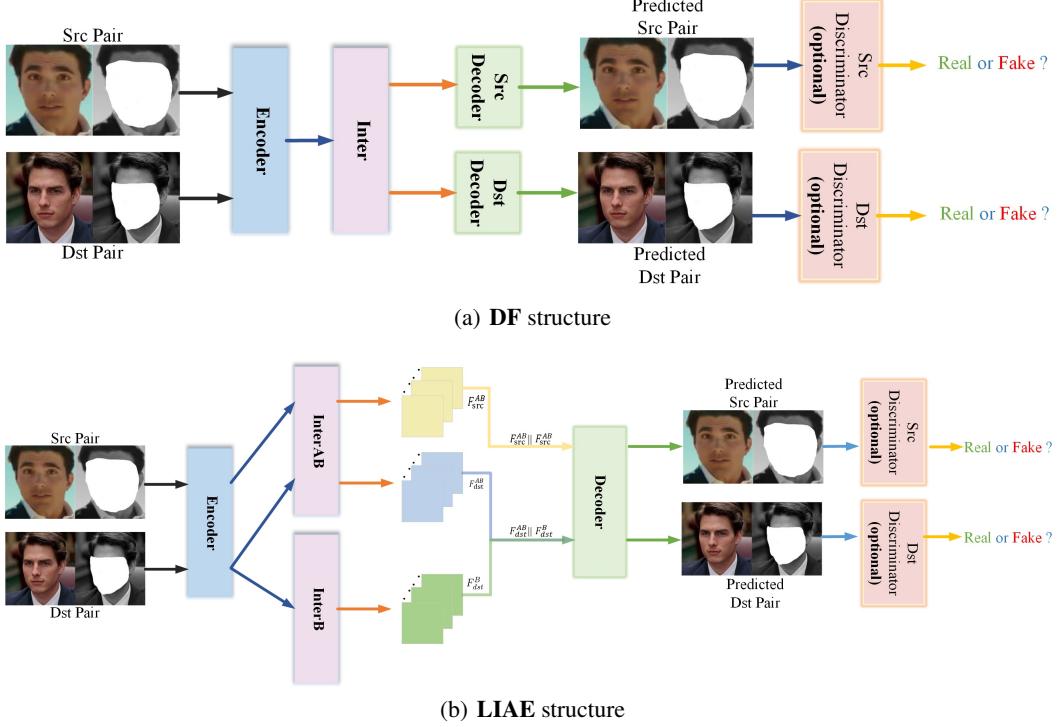


Figure 3: Overview of Training in DeepFaceLab (DFL). structure **DF** and **LIAE** are both provided here for illustration, $\circ \parallel \circ$ represents the concatenation of latent vectors.

3.2 Training

Training is the most vital role in achieving photorealistic face swapping results of DeepFaceLab.

With no request of facial expressions of aligned `src` and aligned `dst` being strictly matched, we are aiming at designing an easy and efficient algorithm paradigm to solve this unpaired problem along with maintaining high fidelity and perceptual quality of the generated face. As shown in Figure 3(a), **DF** consists of an Encoder as well as Inter with shared weights between `src` and `dst`, an another Decoder which belongs to `src` and `dst` separately. The generalization of `src` and `dst` is achieved through the shared Encoder and Inter, that solves the aforementioned unpaired problem easily.

The Latent codes of `src` and `dst` are F_{src} and F_{dst} , both extracted by Inter.

As depicted in Figure 3(b), **LIAE** is a more complex structure with a shared-weight Encoder, Decoder and two independent Inter models. Another difference compared to the **DF** is that InterAB is used to generate both latent code of `src` and `dst` while InterB only output the latent code of `dst`. Here, F_{src}^{AB} denotes the latent code of `src` produced by InterAB and we generalize this representation to F_{src}^{AB}, F_{dst}^B .

After getting all the latent codes from InterAB and InterB, **LIAE** then concatenate these feature maps through channel: $F_{src}^{AB} \parallel F_{src}^{AB}$ was obtained for a new latent code representation of `src` and $F_{dst}^{AB} \parallel F_{dst}^B$ for `dst` as the same way.

Then $F_{src}^{AB} \parallel F_{src}^{AB}$ and $F_{dst}^{AB} \parallel F_{dst}^B$ are put into the Decoder and hence we got the predicted `src` (`dst`) alongside with their masks. The motivation of concatenating F_{dst}^B with F_{dst}^{AB} is to shift the direction of latent code in direction of the class (`src` or `dst`) we need, through which InterAB obtained a compact and well-aligned representation of `src` and `dst` in the latent space.

Except for the structure of the model, some useful tricks are effective for improving the quality of the generated face. Inspired by PRNet [7] and meanwhile driven by the need to make full use of face mask and landmark, a weighted sum mask loss in general SSIM [30] can be added to make each part of the face carry different weights under the AE training architecture, for example, we add more weights

to the eye area than the cheek, which aims to make the network concentrate on generating a face with vivid eyes.

As for losses, DFL uses a mixed loss (DSSIM (structural dissimilarity) [18] + MSE) by default. The reason for this combination is to get benefits from both: DSSIM generalizes human faces faster meanwhile MSE provides better clarity. This combination loss serves to find a compromise between generalization and clarity.

Instead of writing too much boilerplate code, we reduce the burden of user to design their own training paradigm or the network structure, specifically, users could add extra intermediate model to mix up the latent representation of src and dst (i.e., **LIAE**), or when users choose to train with GAN paradigm, self-customized discriminator (i.e. multi-scale Discriminator [12] or RealnessGAN Discriminator [31]) are allowed to put after the decoder to alleviate the semantic gap of generating face, particularly with limited dataset volume of src and dst .

In the case of **src2dst** (Figure 4), we use a fancy true face model *TrueFace* for the generated face of better likeness to the dst in the Conversion phase. For **LIAE**, it aims to make the distribution of $F_{\text{src}}^{\text{AB}}$ approaches to $F_{\text{dst}}^{\text{AB}}$. And for **DF**, destination then turns to be F_{src} and F_{dst} .

Also, unlike fixed resolution limitations of deepfakes and other face swapping frameworks, we can generate high resolution images and generalise to variant output resolutions through adjust the settings of model definition in Training part, which is rather easy by means of DFL’s clean and distinct interface.

Obviously, both **LIAE** and **DF** are support the above feature and those features are designed to be pluggable, further improving the flexibility of the DFL framework. For more details about the design of **DF** and **LIAE**, please refer to Appendix.

3.3 Conversion

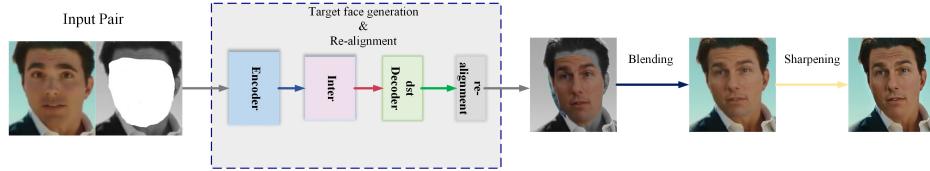


Figure 4: Take **src2dst** and **DF** structure as an example to illustrate Conversion phase of DFL.

Finally, we come to Conversion phase, as depicted in Figure 4, users can swap face of src to dst and vice versa.

In the case of **src2dst**, the first step of the proposed face swapping scheme in Conversion is to transform the generated face I_t^r alongside with its mask M_t from dst Decoder to the original position of the target image I_t in src due to the reversibility of Umeyama [28].

The following piece is about **blending**, with the ambition for the re-aligned reenacted face I_t^r seamlessly fit with the target image I_t along the outer contour of M_t . For the sake of remaining consistent complexion, DFL provides five more color transfer algorithms (i.e. reinhard color transfer: **RCT** [24], iterative distribution transfer: **IDT** [23] and etc.) to make I_t^r more adaptable to the target image I_t . On top of it, the result of blending can be obtained by combining two images: I_t^r and I_t .

$$I_{\text{output}} = M_t \odot I_t^r + (1 - M_t) \odot I_t \quad (1)$$

Any blending must account for, especially at the junctions between I_t^r with delimited region and I_t , different skin tones, face shapes and illumination conditions. Here we define our Poisson blending [22] optimization as

$$P(I_t; I_t^r; M_t) = \begin{cases} \|\nabla I_t(i, j) - \nabla I_t^r(i, j)\|_2^2, & \forall M_t(i, j) = 0 \\ \min \|\nabla f(i, j) - \nabla I_t^r(i, j)\|_2^2, & \forall M_t(i, j) = 1 \end{cases} \quad (2)$$

It is easy to see from Equation 2 that we only need to minimize the facial part with $\forall M_t(i, j) = 1$ since $\|\nabla I_t(i, j) - \nabla I_t^r(i, j)\|_2^2$ is a constant term.

Then we come to the last regular step of both DFL pipeline and Conversion workflow: **sharpening**. A pre-trained face super resolution neural network (denote as FaceEnhancer) was added to sharpen the blended face. Since it is noted that the generated faces in almost current state-of-the-art face swapping works, more or less, are smoothed and lack of minor details (i.e. moles, wrinkles).

If all goes well, we will get a view of HD fake image (put generated face seamlessly onto the designated part of target face and meanwhile adjust the skin tone of the generated face to the target face, then fit it back in the original picture according to its coordinates recorded in phase Extraction), which is hard to distinguish between the true and the false even with the help of frequency domain analysis.

4 Productivity tools in DeepFaceLab

In a general way, DFL serves as a productivity tool in the workflow of making videos when there are faces with a lot of face swapping conditions. Therefore, the demand for authenticity of synthesized fake image is far above ordinary consumer-level product, i.e, high resolution, complex occlusion and bad illumination.

In order to address the issues above, we provide some effective tools in achieving HD fake image of super high fidelity and reality.

In Fig 5, there are two commonly-used tools in the Extraction phase of DFL. Fig 5(a) is a manual face detection and facial landmarks extraction tool which is designed for face with extreme Euler angle where commonly-used face detectors and facial landmark extractors fail.

Besides, when video jitters exist in synthesized video, this tool could help user refine/smooth the facial landmarks of target face through taking reference of adjacent frames.

Similarly, Fig 5(b) is the XSeg manual face segmentation editor for fine-grained control of the facial mask scope designed to avoid the interference of occlusions like hands, hair and etc.

During Training, we provide detailed previews for researchers to test their new ideas without writing any extra code, the loss movements are indicated in the yellow and blue lines in Fig 6, which represent the loss history of `src2src` and `dst2dst`, providing valuable information for people to debug whether their unique model architecture is good or not .

5 Evaluation

In this section we compare the performance of DeepFaceLab with several other commonly-used face swapping frameworks and two state-of-the-art works, and find that DFL has competitive performance among them.

5.1 Noise and error analysis

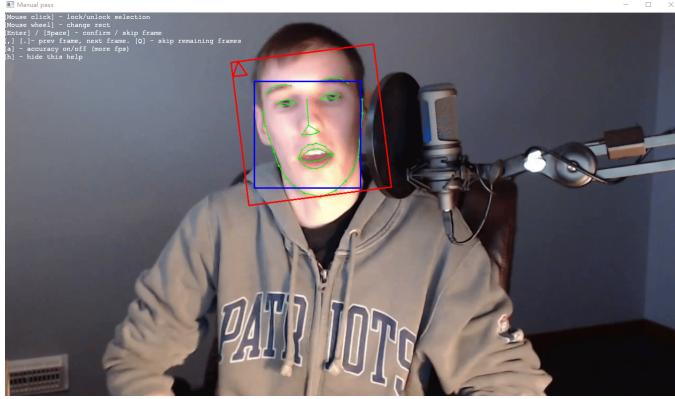
Since most existing face swapping algorithms share the common step of blending a reenacted face into an existing background image, the problem of image discrepancies and discontinuities across the blending boundaries then arises inevitably.

The problem here is that this kind of discrepancies will be amplified in high-resolution images. We illustrate noise analysis⁵ and error level analysis in Figure 7.

5.2 Qualitative results

Fig 8(a) offers face swapping results of representative open-source projects (DeepFakes [4], Nirkin et al. [21] and Face2Face [27]) taken from FaceForensics++ dataset [25]. Examples of different expression, face shapes, and illuminations are selected in our experiment. It's clear from observing the video clips from FaceForensics++ that they are not only trained inadequately but chosen from models

⁵<https://29a.ch/photo-forensics/#noise-analysis>



(a) Manual face detection and facial landmarks extraction



(b) XSeg: Face segementation on the base of few-short learning

Figure 5: Two handy tools in Extraction phase of DeepFaceLab.

with low-resolution. To be fair in our comparison, **Quick96** mode is taken: a lightweight model that **DF** structure underneath, which outputs the I_{output} of 96×96 resolutions (without *GAN* and *TrueFace*). The average training time is restrict within 3 hours. We use Adam [24] ($lr=0.00005$, $\beta_1 = 0.5$, $\beta_2 = 0.999$) to optimize our model. All of our networks were trained on a single NVIDIA GeForce 1080Ti GPU and an Intel Core i7-870 CPU.

5.3 Quantitative results

FaceForensics++ still under use during quantitative experiments. In practice, the naturalness and realness of the results of face swapping method is hard to describe with some specified quantitative indexes. However, pose and expression indeed embody valuable insights of the face swapping result. Besides, SSIM is used to compare the structure similarity as well as perceptual loss [11] is adopted to compare high level differences, like content and style discrepancies, between target subject and the swapped subject.

To measure the accuracy of pose, we calculate the Euclidean distance between the Euler angles (extracted through FSA-Net [32]) of I_t and I_{output} . Besides, the accuracy of the face expression is measured through the Euclidean distance between the 2D landmarks (2DFAN [2]). We use the default face verification method of DLIB [16] for the comparison of identities.

To be statistically significant, we compute the mean and variance of those measurements on the 100 frames (uniform sampling over time) of the first 500 videos in FaceForensics++, averaging them

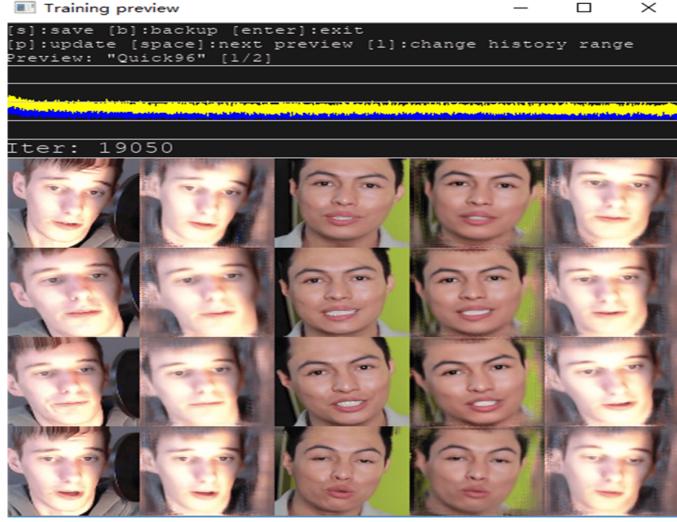


Figure 6: Preview of Training phase of DeepFaceLab, column one and two are source face and its corresponding output of **src** decoder, column three and four are target face and its corresponding output of **dst** decoder, the last column represents a **src2dst** paradigm: target face input, generated face of **src** decoder output.

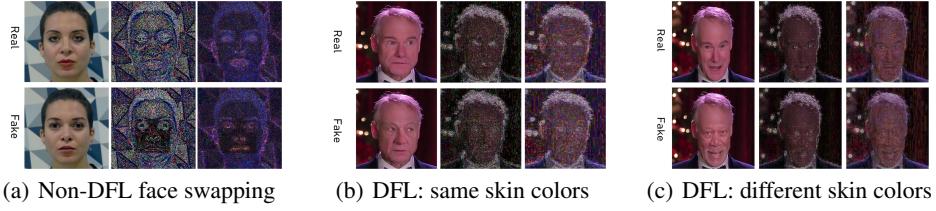


Figure 7: Noise analysis (middle column) and error level analysis (right column) of real images and fake images, it's clear that a rectangular part with uneven noise distribution manifested in Non-DFL face swapping method whereas these rectangular patterns are hard to be found in DFL's results.

across the videos. Here, DeepFakes [4] and Nirkin et al. [21] are chosen as the baselines to compare. It should be noted that all the videos produced by DeepFaceLab were follow by the same settings with 5.2.

Table 1: Quantitative face swapping results on FaceForensics++ [25] face images.

Method	SSIM \uparrow	perceptual loss \downarrow	verification \downarrow	landmarks \downarrow	pose \downarrow
DeepFakes	0.71 ± 0.07	0.41 ± 0.05	0.69 ± 0.04	1.15 ± 1.10	4.75 ± 1.73
Nirkin et al.	0.65 ± 0.08	0.50 ± 0.08	0.66 ± 0.05	0.35 ± 0.18	6.01 ± 3.21
DeepFaceLab	0.73 ± 0.07	0.39 ± 0.04	0.61 ± 0.04	0.73 ± 0.36	1.12 ± 1.07

From the indicators listed in Table 1, DeepFaceLab is more adept at retaining pose and expression than baselines. Besides, with the empowerment of super-resolution in Conversion, DFL often produces I_{output} with vivide eyes and sharp teeth, but this phenomenon couldn't be reflected clearly in the SSIM-like score for they only take small part of the whole face.

5.4 Ablation study

To compare the visual effects of different model choices, GAN settings and etc, we perform serveral ablation tests. The ablation study are conducted on top of three key parts: network structure, training paradigm and latent space constraint.

Aside from **DF** as well as **LIAE**, we enhance **DF** as well as **LIAE** to **DFHD** and **LIAEHD** through adding more feature extraction layers, residual blocks compared to the original version, which serves to enriched the model structures for comparison. The qualitative results of different model structures can be seen in Figure 9 and the qualitative results of different training paradigm are depicted in Figure 10.

Quantitative ablation results are reported in Table 2, the experiment settings of the training are almost the same with 5.2 except for the structure of model.

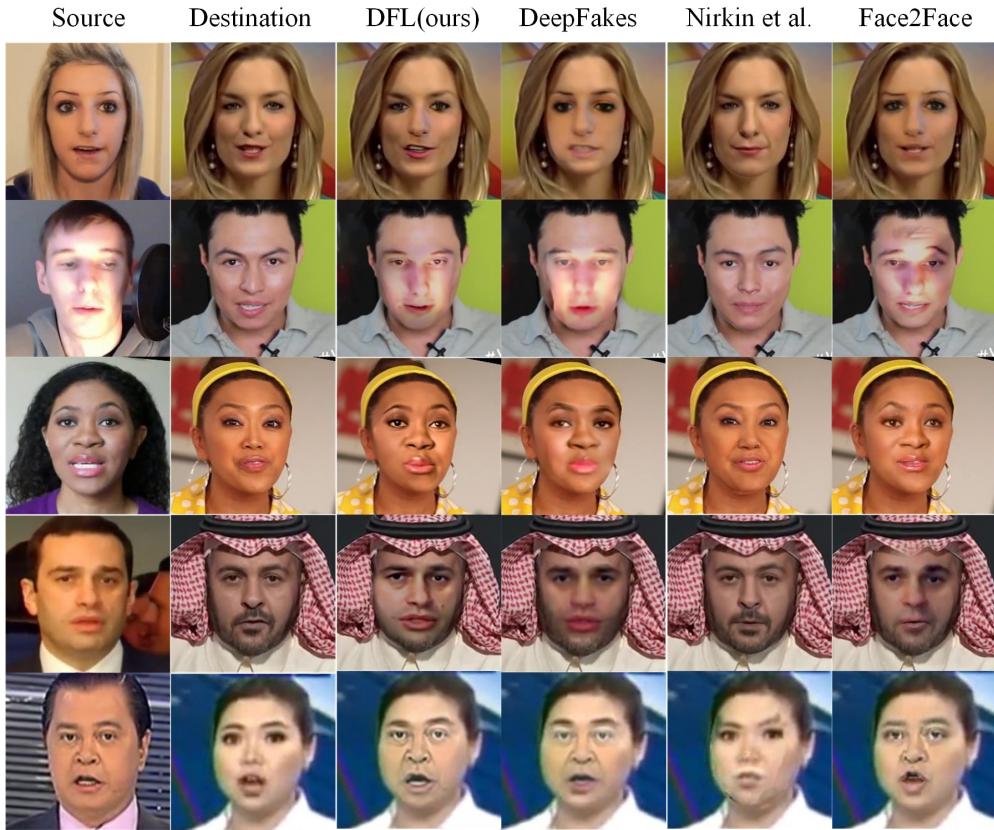
Verification results from Table 2 shows that source identities are preserved across networks with the same structure. With more shortcut connections has been add to the model (i.e. **DF** to **DFHD**, **LIAE** to **LIAEHD**), scores of landmarks and pose decrease without *GAN*. Meanwhile the generated results could have a better chance to get rid of the influence of source face. In addition, we found that *TrueFace* is effectively relieves the instability of *GAN*, through which, a more photo-realistic result without much degradation then achieved. Besides, SSIM progressively increase with network with more shortcut connections, *TrueFace* and *GAN* also do good to it in varying degrees.

Table 2: Quantitative ablation results on FaceForensics++ [25] face images.

Method	SSIM \uparrow	verification \downarrow	landmarks \downarrow	pose \downarrow
DF	0.73 ± 0.07	0.61 ± 0.04	0.73 ± 0.36	1.12 ± 1.07
DFHD	0.75 ± 0.09	0.61 ± 0.04	0.71 ± 0.37	1.06 ± 0.97
DFHD (<i>GAN</i>)	0.72 ± 0.11	0.61 ± 0.04	0.79 ± 0.40	1.33 ± 1.21
DFHD (<i>GAN</i> + <i>TrueFace</i>)	0.77 ± 0.06	0.61 ± 0.04	0.70 ± 0.35	0.99 ± 1.02
LIAE	0.76 ± 0.06	0.58 ± 0.03	0.66 ± 0.32	0.91 ± 0.86
LIAEHD	0.78 ± 0.06	0.58 ± 0.03	0.65 ± 0.32	0.90 ± 0.88
LIAEHD (<i>GAN</i>)	0.79 ± 0.05	0.58 ± 0.03	0.69 ± 0.34	1.00 ± 0.97
LIAEHD (<i>GAN</i> + <i>TrueFace</i>)	0.80 ± 0.04	0.58 ± 0.03	0.65 ± 0.33	0.83 ± 0.81

6 Conclusions

The rapid evolving DeepFaceLab has become a popular face swapping tool in the deep learning practitioner community through freeing people from laborious, complicated data processing, trivial detailed work in training and conversion part. While continuing to keep tight with the latest trends and advances in computer vision, in the future we plan to keep improving the speed and scalability of DeepFaceLab. Inspired by some distinguished researchers of this area: "Suppressing the publication of such methods would not stop their development, but rather make them only available to a limited number of experts and potentially blindside policy makers if it goes without any limits". As a leading, widely recognized and open-source face swapping tool, we found we are responsible to publish DeepFaceLab to the academia community formally.



(a) Compare DFL with representative open-source face swapping projects.



(b) Compare DFL with the latest state-of-art works.

Figure 8: Qualitative face swapping results on FaceForensics++ [35] face images.

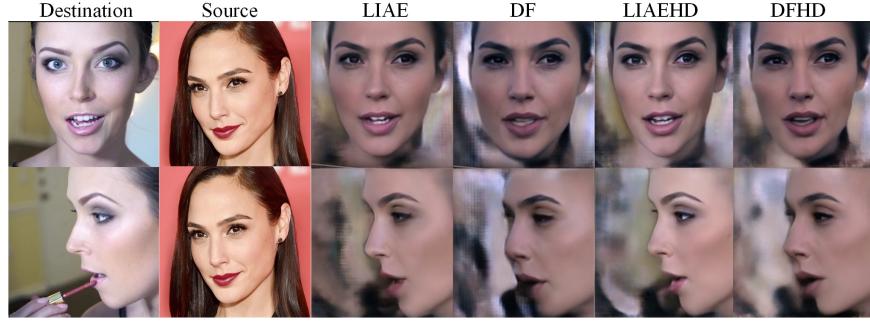


Figure 9: Ablation experiments of different model structures (with *GAN* and *TrueFace*). (Here, we provide training previews instead of the converted faces, which aims to do a fair comparision in model architectures of DFL meanwhile avoid the impact of post-preprocessing from Conversion.)



Figure 10: Ablation experiments of different training paradigm: non GAN-based and GAN-based (The image on the left is the original face, a reconstruction image produced by model that trained without GAN listed to its right, far right is produced by model that trained with GAN). It can be seen clearly that GAN enforce the model become more sensible in capturing the sharp details, i.e, wrinkles and moles. Meanwhile significantly reduce the vagueness compared to the model without the empower of GAN.

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7 Appendix: Dissecting the detailed structure of DF.

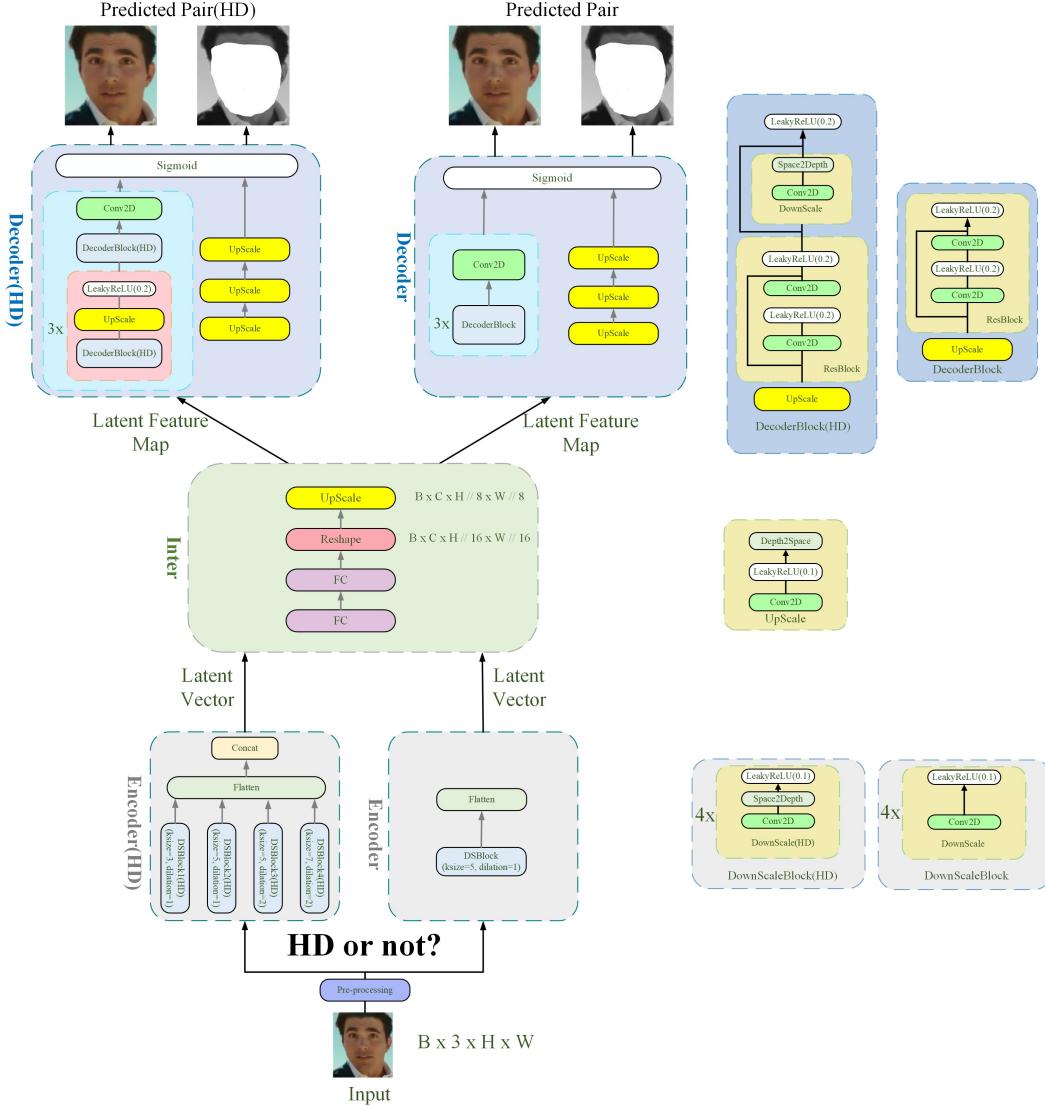


Figure 11: A detailed overview of **DF** in DeepFaceLab. Modules (Encoder, Inter and Decoder) of **DF** are completely same with **LIAE**, which means both InterAB and InterB of **LIAE** owns the same structure and settings.

The layout as well as every specified submodule of the **DF** are depicted in Fig 11. According to the result, it's fairly easy to see the difference between the original **DF** and enhanced edition **DFHD** lies in that **DFHD** have more feature extraction layers and of varied stacking orders. Three typical traits of the structure are:

- We use pixelshuffle (depth2space) to do upsampling instead of transposed convolution neither bilinear sampling followed by convolution, which aims to eliminate the artifact and checkboard effects.
- Identity shortcut connection, which derived from Resnet, are frequently used in composing the module of Decoder. This is because model with more shortcut connections always have many independent effective paths at the same time, which makes the model with ensemble-like behaviour.

- We normalize the images between 0 and 1 other than -1 to 1. Then Sigmoid as the last layer of the Decoder output rather than Tanh.