

RESEARCH REVIEW 2022

**Carnegie  
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# A Machine Learning Pipeline for Deepfake Detection

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Shannon Gallagher  
Dominic Ross  
Jeffrey Mellon  
Catherine Bernaciak

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# Deepfakes Detection Team



**Shannon Gallagher**

Data Scientist



**Dominic Ross**

Multi-Media Design and  
Communications Lead



**Jeffrey Mellon**

Machine Learning Research Scientist



**Catherine Bernaciak**

Senior Machine Learning Research  
Scientist

# Deepfakes Are “Believable Media Generated by Deep Neural Networks” [Mirsky and Lee 2020]

## Detecting Deepfakes



Shannon and Dominic discuss what deepfakes are and how their team is building artificial intelligence and machine learning technology to distinguish real from fake. They share well-known examples of deepfakes and discuss what makes them distinguishable as fake.

## A Dive into Deepfakes



Shannon and Dominic discuss deepfakes, their exponential growth in recent years, their increasing technical sophistication, and the problems they pose for individuals and organizations. They also discuss the SEI’s research in this area.

## Making and Detecting Deepfakes



Catherine and Dominic describe the technology underlying the creation and detection of deepfakes and assessment of current and future threat levels.

[Mirsky and Lee 2020]

Mirsky, Y. & Lee, W. The Creation and Detection of Deepfakes: A Survey. 2020

<https://arxiv.org/abs/2004.11138>

# Deepfakes Are Dangerous



**Conceptual Example of a Faceswap Deepfake**  
The target's face is placed on the source's face.

## Potential Dangers

- Impersonation of political figures and celebrities (e.g., mayor of Kyiv)
- Defamation of citizens
- Mis-, dis-, and mal- information

>700k hours of video are uploaded to the web every day!

**We need fast and reliable detectors.**

# Numerous Deepfake Detection Methods Already Exist

Google Scholar

Articles

Any time  
Since 2022  
Since 2021  
Since 2018  
Custom range...

Sort by relevance  
Sort by date

Any type  
Review articles

README.md

## DeepFake Detection (DFDC) Solution by @selimsef

**Challenge details:**

[Kaggle Challenge Page](#)

**Fake detection articles**

- [The Deepfake Detection Challenge \(DFDC\) Preview Dataset](#)
- [Deep Fake Image Detection Based on Pairwise Learning](#)
- [DeeperForensics-1.0: A Large-Scale Dataset for Real-World Face Forgery Detection](#)
- [DeepFakes and Beyond: A Survey of Face Manipulation and Fake Detection](#)
- [Real or Fake? Spoofing State-Of-The-Art Face Synthesis Detection Systems](#)
- [CNN-generated images are surprisingly easy to spot... for now](#)
- [FakeSpotter: A Simple yet Robust Baseline for Spotting AI-Synthesized Fake Faces](#)
- [FakeLocator: Robust Localization of GAN-Based Face Manipulations via Semantic Segmentation Networks with Bells and Whistles](#)
- [Media Forensics and DeepFakes: an overview](#)
- [Face X-ray for More General Face Forgery Detection](#)

**Solution description**

In general solution is based on frame-by-frame classification approach. Other complex things did not work so well on public leaderboard.

**Face-Detector**

MTCNN detector is chosen due to kernel time limits. It would be better to use S3FD detector as more precise and robust, but opensource Pytorch implementations don't have a license.

Languages

- Python 94.7%
- Shell 4.0%
- Dockerfile 1.0%

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f.com

Google Scholar Image: Google and the Google logo are trademarks of Google LLC.

The DFDC screenshot is used with permission from Selim Seferbekov according to the [MDFDC\\_DeepFake\\_Detection\\_Challenge\\_MIT\\_license](#).

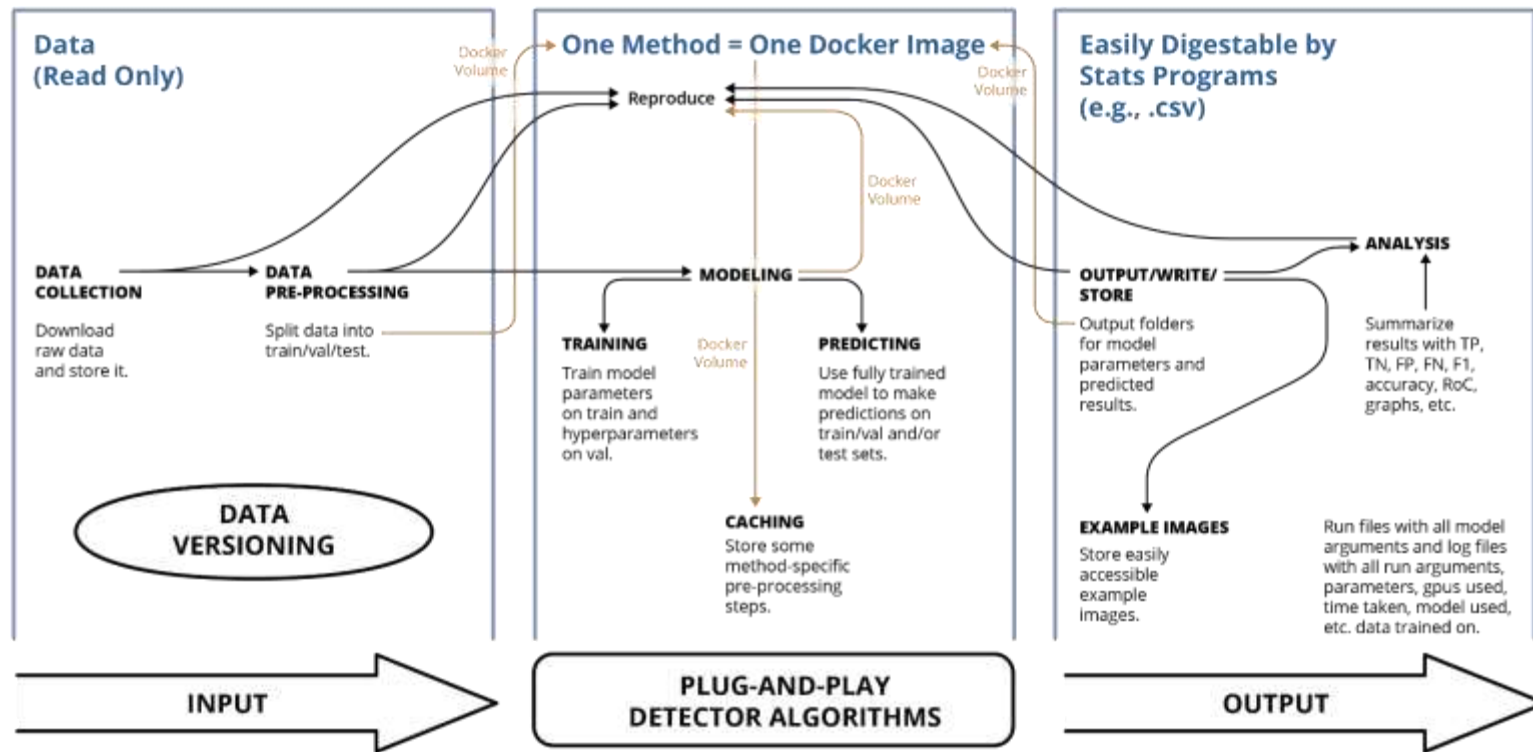
# But Reproducing Results Is...**Difficult**

- Data and formats
- Sparsely documented code
- Changes to packages like opencv2, pillow, and others
- Changes to backends like PyTorch and TensorFlow
- Hardware

The best methods come with a docker run script, but even that can be difficult.

**Takeaway:** It is difficult to compare methods side by side (e.g., **benchmarks**).

# Our Deepfake Detection Pipeline (DDP) Creates Benchmarks



DDP is reproducible, portable, and modular.

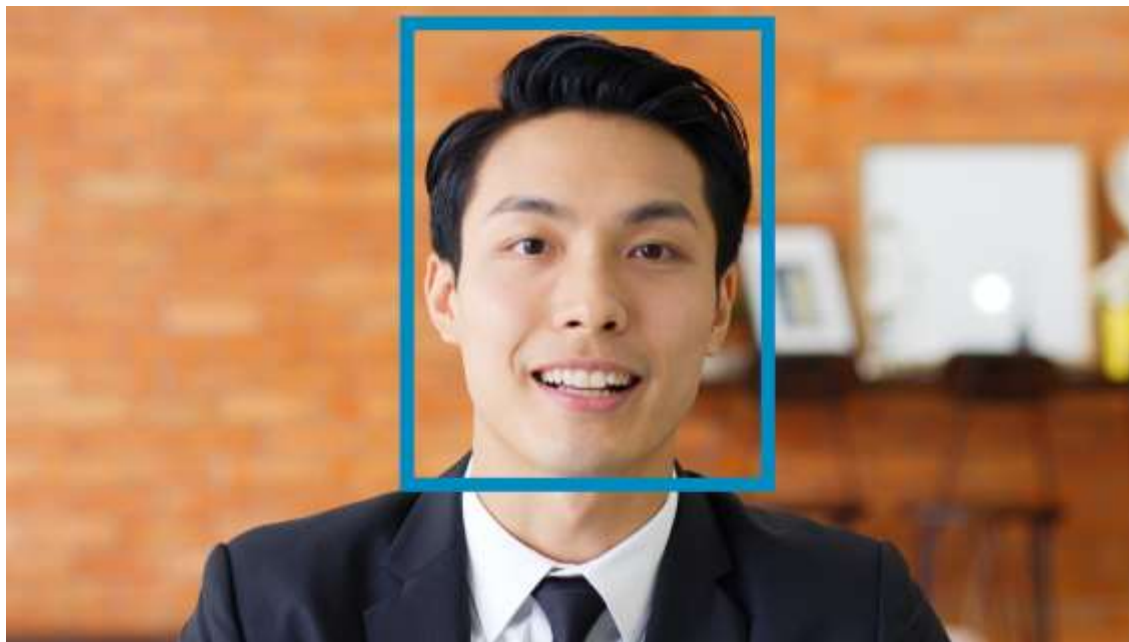
DDP's backend is SEI's Juneberry.

# Several Publicly Available Data Resources

Source	Format	Amount	Label(s)	License?
<a href="#">DeepFake Detection Challenge (DFDC)</a>	.mp4	100k+ Videos	Real/Fake	Yes
<a href="#">Celeb-DF</a>	.mp4	5600+ Videos	Real/Fake	Yes
<a href="#">StyleGAN3</a>	.png	Generate Your Own Portraits	Fake	Yes
<a href="#">Flickr-Faces-HQ</a>	.png and .json	70k Portraits	Real	Yes

# We've Noticed a General Trend in Detection Methods

## 1. Find the face.



# We've Noticed a General Trend in Detection Methods

1. Find face the face.
2. Extract facial landmark(s) and normalize them.



# Extraction, Masking, and Standardizing in DDP

- Hairline
- Edges of eyes
- Corners of mouth
- Chin
- Eyebrows
- Nose
- Boundaries

AVG(REAL) - AVG(FAKE)



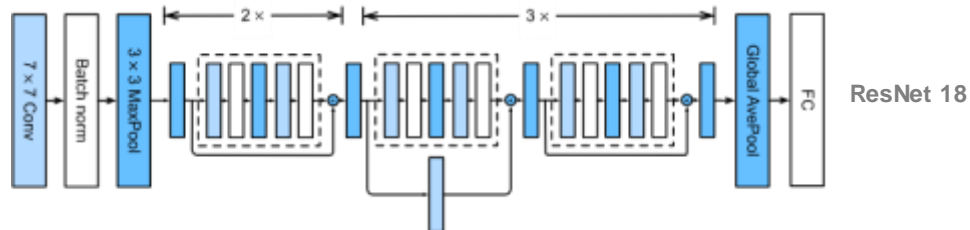
# We've Noticed a General Trend in Detection Methods

1. Find the face.
2. Extract facial landmark(s) and normalize them.
3. Apply masking and/or add noise.



# We've Noticed a General Trend in Detection Methods

1. Find the face.
2. Extract facial landmark(s) and normalize them.
3. Apply masking and/or add noise.
4. Send to a pre-trained image detector.



The ResNet 18 chart is reused with permission from Zachary C. Lipton, co-author of *Dive into Deep Learning*.

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# Pre-Trained Models Available to DDP

[AlexNet](#)

[MNASNet](#)

[SqueezeNet](#)

[ConvNeXt](#)

[MobileNet V2](#)

[SwinTransformer](#)

[DenseNet](#)

[MobileNet V3](#)

[VGG](#)

[EfficientNet](#)

[RegNet](#)

[VisionTransformer](#)

[EfficientNetV2](#)

[ResNet](#)

[Wide ResNet](#)

[GoogLeNet](#)

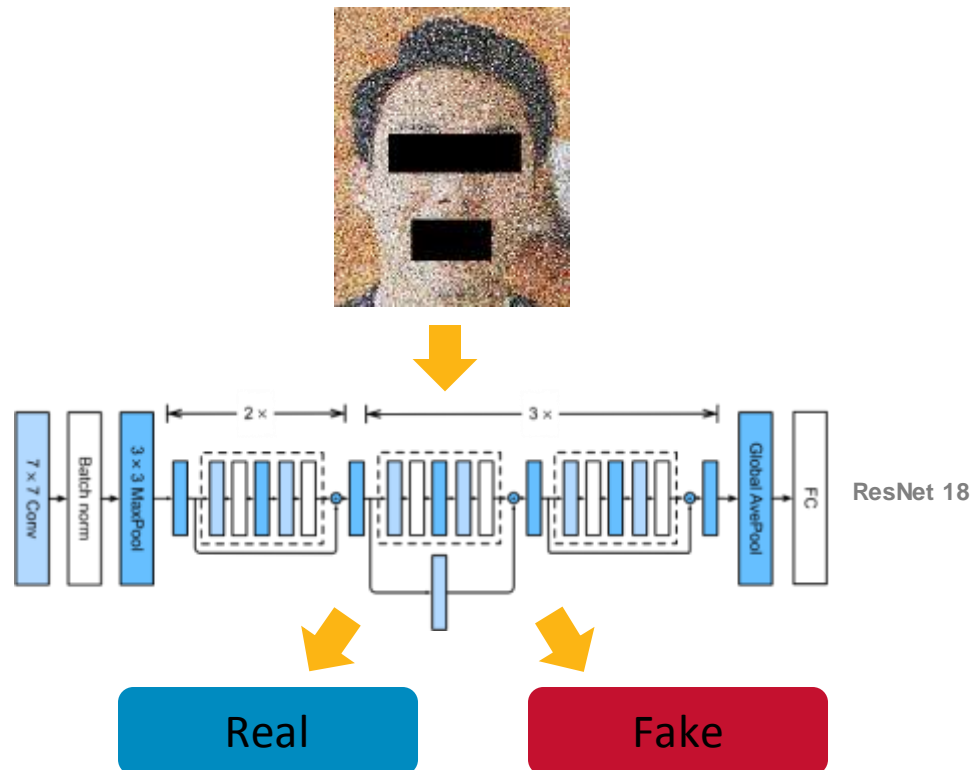
[ResNeXt](#)

[Inception V3](#)

[ShuffleNet V2](#)

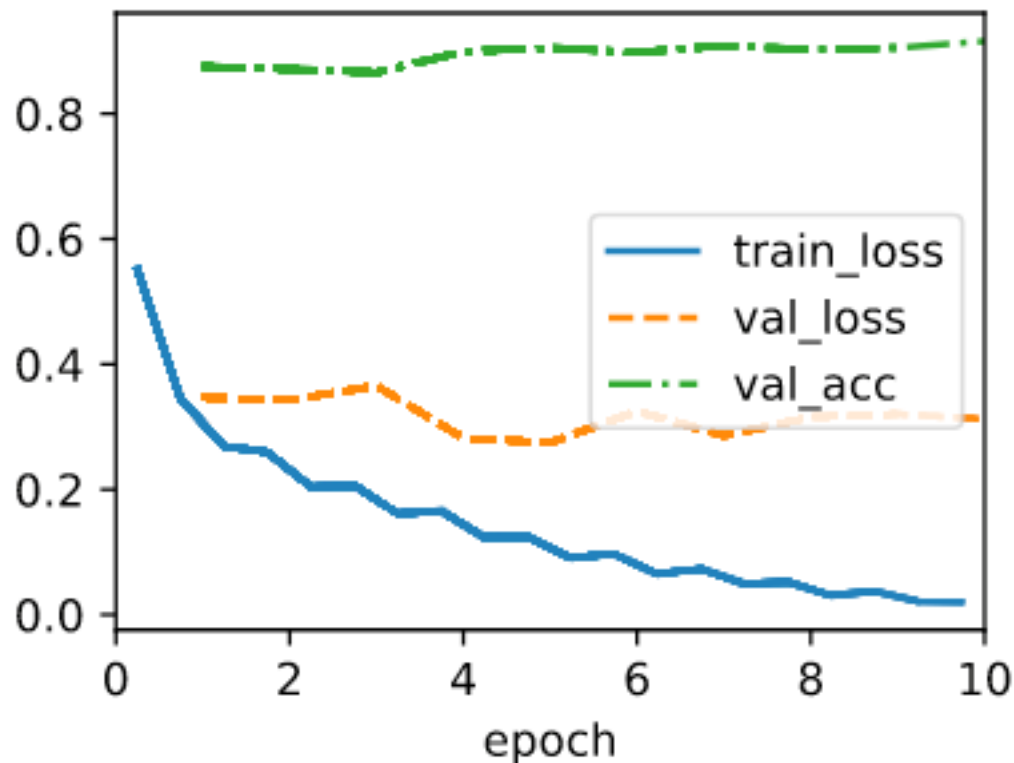
# We've Noticed a General Trend in Detection Methods

1. Find the face.
2. Extract facial landmark(s) and normalize them.
3. Apply masking and/or add noise.
4. Send to a pre-trained image detector.
5. Fine-tune it.



# We've Noticed a General Trend in Detection Methods

1. Find the face.
2. Extract facial landmark(s) and normalize them.
3. Apply masking and/or add noise.
4. Send to a pre-trained image detector.
5. Fine-tune it.
6. Evaluate it.



This chart is reused with permission from Zachary C. Lipton, co-author of *Dive into Deep Learning*.

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# Preliminary Results with DDP

## Accuracy (%) of Fine-Tuned ResNet

		Tested on				
		Celeb DF v1	Stylegan2	Stylegan3-t	Stylegan3-r	DFDC Pt. 0
Trained on	Data Set					
	Celeb DF v1	99.1	44.2	44.2	44.0	51.2
	Stylegan2	24.1	98.7	52.9	48.4	57.4
	Stylegan3-t	16.7	69.7	96.7	84.0	7.0
	Stylegan3-r	16.9	68.0	89.0	97.2	7.0
	DFDC Pt. 0	68.1	57.4	57.5	57.5	88.7

# Next Steps

- Model robustness
- Video-specific detectors
- Improved detectors via ensemble models

# Summary

- Deepfake detection methods need better benchmarks
  - Accuracy, cost, time
- We are doing that via **DDP and Juneberry**:
  - Data collection
  - Data transformation
  - Modeling
  - Evaluation
- Preliminary results confirm that generalizability is a problem.
  - We expect to **improve models** with ensemble detectors via DDP.