

# The Art in the Algorithm

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# Evaluating the Dataset

# Celeb-DF v2



Images sourced from: https://www.cs.albany.edu/~lsw/celeb-deepfakeforensics.html

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# Celeb-DF v2



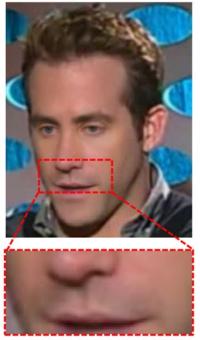
- 590 videos of 59 celebrities collected from YouTube
- 5639 DeepFakes generated
- Gender
  - 56.8% Male
  - 43.2% Female
- Ethnicity
  - 88.1% Caucasian
  - 5.1%Asian
  - 6.8% Black & Brown
- Age Distribution:
  - 65.6% 40 and older
  - 34.4% under 40

Images sourced from: https://www.cs.albany.edu/~lsw/celeb-deepfakeforensics.html

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# Celeb-DF v2

 $256 \times 256$ 



- Recognized the need for higher quality source material
- Used custom algorithm
- Encoding 256 bit
- Decoding 256 bit
- Color correction applied at training
- Kalman smoothing algorithm to reduce temporal flicker
- Facial landmark masking
- Smoothness mask to blend overlay

Images sourced from: https://www.cs.albany.edu/~lsw/celeb-deepfakeforensics.html

# Celeb-DF v2 – Compression

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id23_0000.mg4	15 s 967 ms			Variable	e				1 063 k	:b/s		Lavf58.3.1	00			30.000 FPS		
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	17 s 800 ms			Variable	e				1 578 k	:b/s		Lavf58.3.1	.00			30.000 FPS		
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## The Art in the Algorithm Evaluating the Dataset Where do you want to go?

# Selecting a target subject



Public figures historically are easier targets. Conferencing, social media and tube sites can make us all targets.

The more available footage the better

# Curating found content



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## Evaluating the Dataset Art is born of observation

# **Details Matter**



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# When Source and destination do not match



Images sourced from Celeb-DF Dataset

# Better body shape but...



Image sourced from Celeb-DF Dataset

# How can we improve a dataset?

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# Replicate the target for success



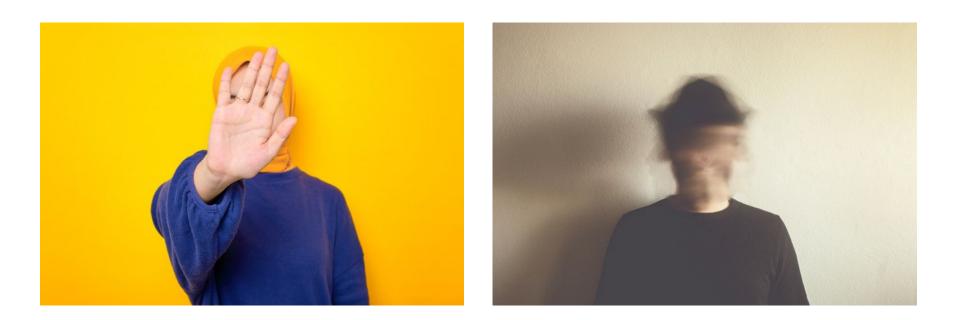
Image sourced from VFXChris Ume YouTube Channel - Deepfake breakdown of Tom Cruise

# Angles and Expressions



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# **Curating Source Files**



## The Art in the Algorithm How can we improve the dataset?

# What would Hollywood do?

# Example 1: The Basics



**Original** id41\_0009, Natalie Portman



**Synthesis** id41\_id42\_0009, Eva Mendes

# Organizing the Project



# Masking & Feathering



V1: Tracking

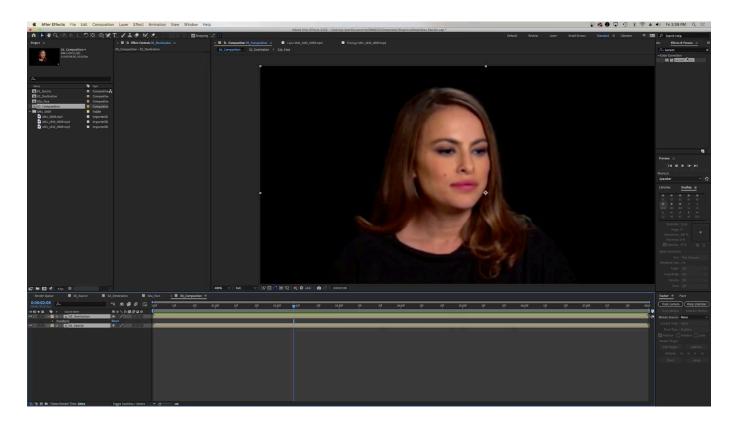


V2: Rudimentary Mask





# **Color Correction**



# Results



**Synthesis** id41\_id42\_0009, Eva Mendes



**Synthesis (corrected)** id41\_id42\_0009, Eva Mendes

# **Detail Transfer**

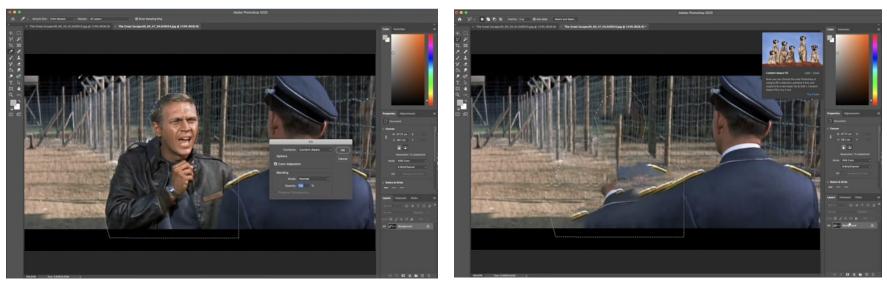


**Original** id28\_0002, Jude Law



Synthesis id28\_id22\_0002, Mark Wahlberg

# **Background Replacement**



Photoshop → After Effects Workflow Content Aware Fill Clone Stamp Tool

Images sourced from Steve Ramsden (YouTube)

# Example 2: Level Up

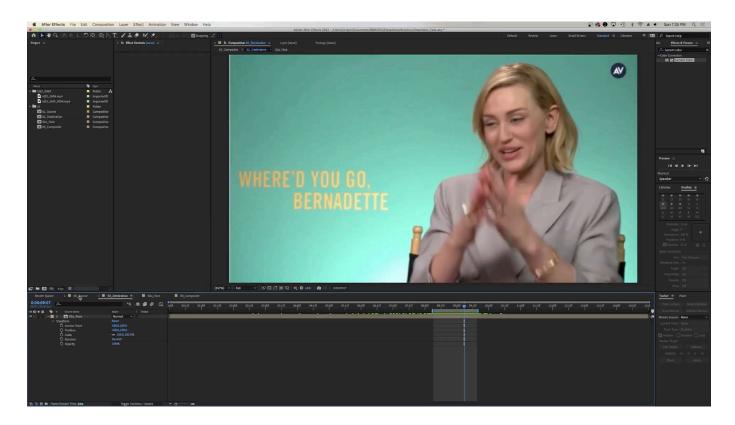


**Original** id52\_0009, Cate Blanchett **Synthesis** id52\_id49\_0004, Miley Cyrus AV

# Breaking a Deepfake



# **Setup Considerations**



# Masking & Feathering



# **Color Correction**



# Results



**Synthesis** id52\_id49\_0004, Miley Cyrus



Synthesis (corrected) id52\_id49\_0004, Miley Cyrus

# Fast-forward the evolution

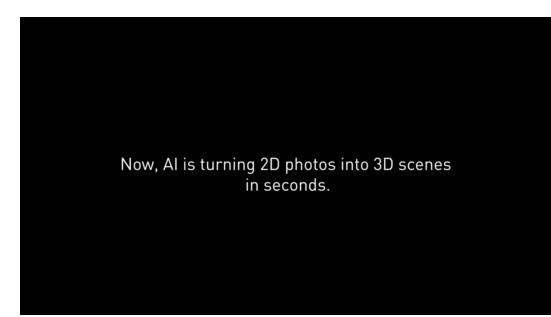
# What happens when encoder/decoder is increased x4



Image sourced from PAGI Studios YouTube Channel

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# Puppet mastery enhanced with NERF



Video sourced from NVIDIA Developer YouTube

#### Cross Identity Audio-driven Results





Audio Source

Audio Driven Results

#### Image sourced from AD-NeRF: Guo Yudong YouTube



Image sourced from Disney Research YouTube

# What are Metahumans

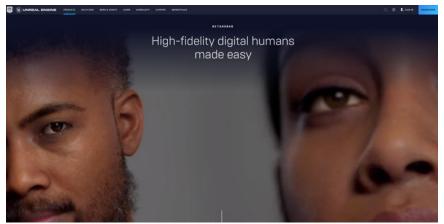
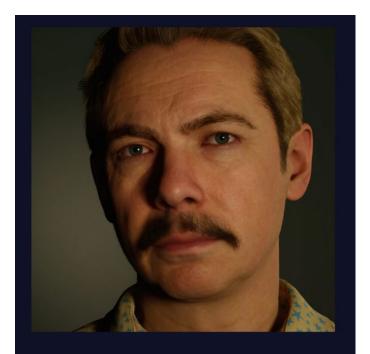


Photo sourced from Unreal

- Data comes from real life scans
- Rigged for animation with live performance capture.
- Tutorials readily available



### Physically plausible

Photo sourced from Unreal

# Mesh to Metahuman

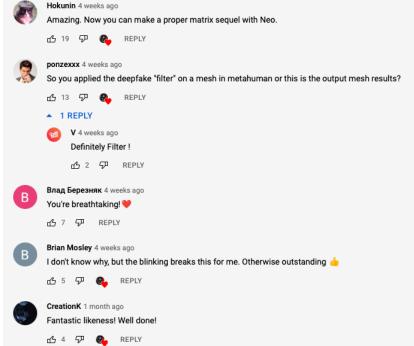


Photo sourced from Unreal

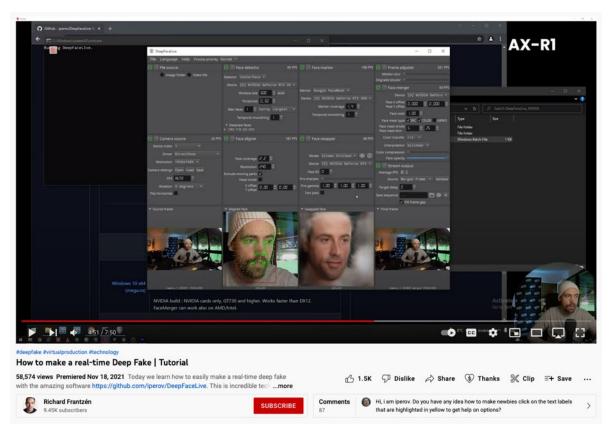
- Photo/Lidar Smartphone App
- 30+ images can create a model
- Neutral Expression
- Mouth Closed
- Even bright lighting
- Model does not have to be water-tight.
- Set Body parameters
- Metahuman Mesh can be created in as little as 10 minutes.

# Metahumans Deepfakes

# Created by NotFace Studio BMETAHUMAN CUSTOM MESH (?) ¢ 07 >

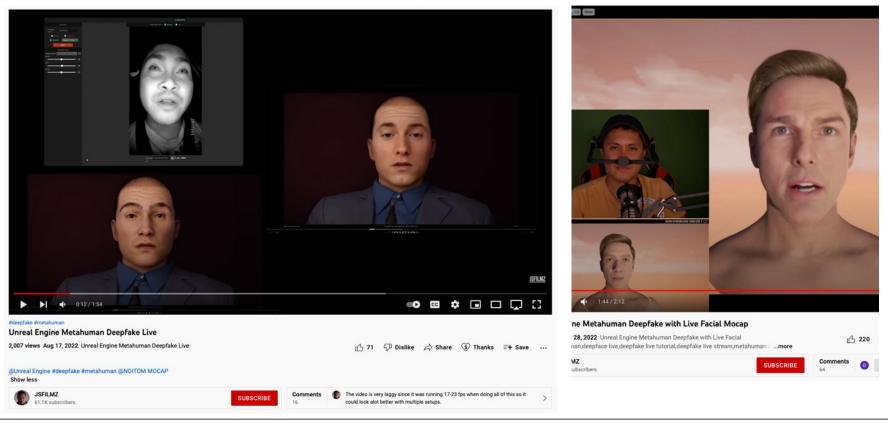


# DeepFaceLab Live



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# DeepFaceLab Live + Unreal Engine 5



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# Live Deepfakes are successful manipulating leaders



Photo sourced from Senatskanzlei Berlin Twitter feed

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