Spot the Difference: Real vs. StyleGAN-generated Faces

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Motivation

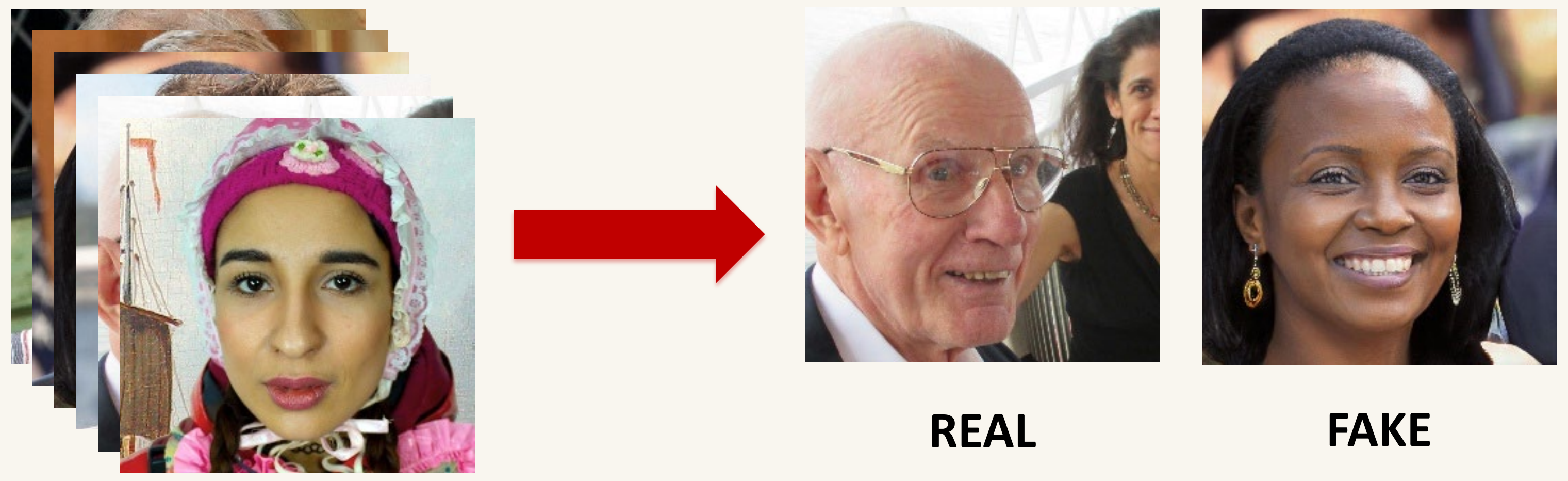
- Generative Adversarial Networks have created fake faces that have been used for misinformation campaigns, espionage, and other harmful uses.
- They have become so accurate that it can be difficult to determine if a face is real or GAN-generated.
- A convolutional neural network (CNN) can be used to help detect GAN-generated faces, which may be helpful to prevent widespread misinformation.

Problem

GAN-generated images are difficult to visually identify

Goal

Build a GAN-generated face detector that has >90% accuracy on labeling StyleGAN images

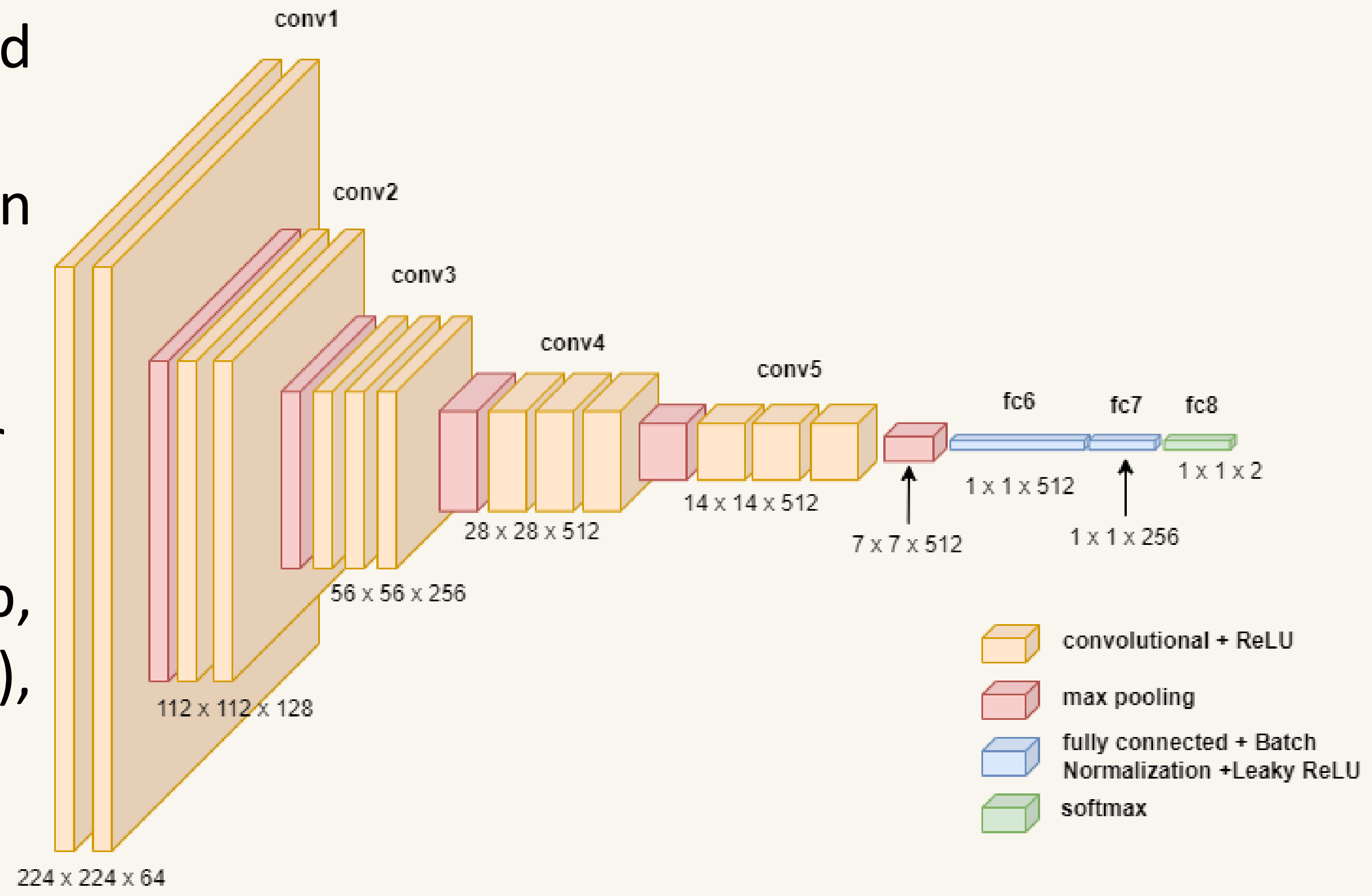


Design Process

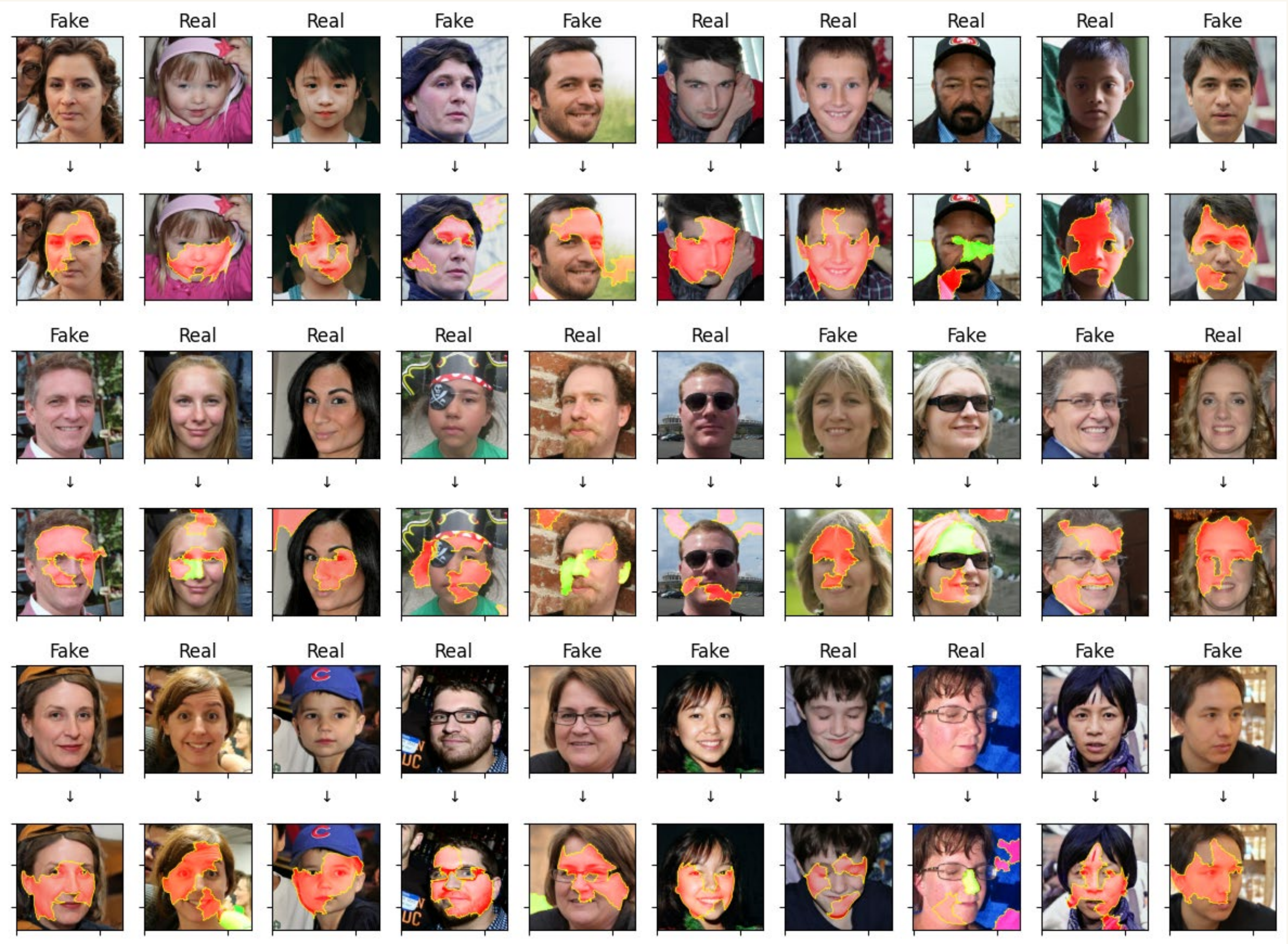
Variable	Initial Attempt	Initial Accuracy	Final Attempt	Final Accuracy
Batch Normalization	0 Layers	84.95%	2 Layers	87.20%
Dropout Layers	1 Layer of 0.5	90.45%	0 Layers	91.60%
Number of Dense Layers	3 Layers	82.75%	2 Layers	86.40%
Leaky ReLU alpha value	0.1	90.45%	0.5	91.00%
Number of Neurons	26 (24+2)	87.45%	770 (512+256+2)	91.90%
Augment. (Bright., Cont.)	0.1, 0.1	91.40%	(0.3,0.2)	93.40%
Trainable vgg16	Trainable	55.34%	Untrainable	92.92%

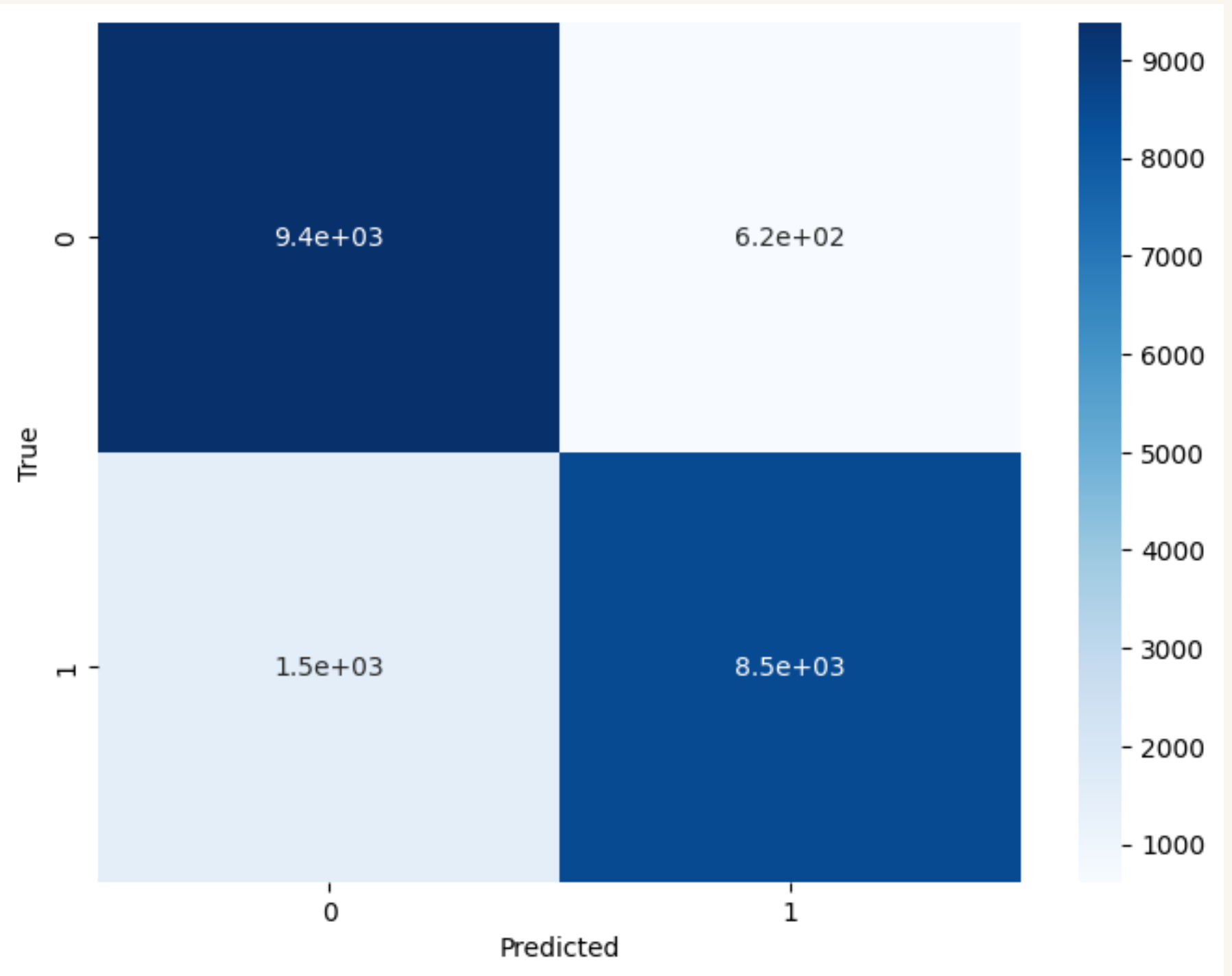
Proposed Solution

- Proposed solution is based off the pretrained vgg16 model
- Specialized feature classifier that has been fine-tuned for face detection
- Optimal modifications:
  - Batch normalization after each dense layer
  - Leaky ReLU activation function with α=0.5
  - Augment block with random horizontal flip, zoom (0.1), rotation (0.1), brightness (0.3), and contrast (0.2)
  - Adam optimizer with learning rate 0.001



LIME Visualization & Confusion Matrix

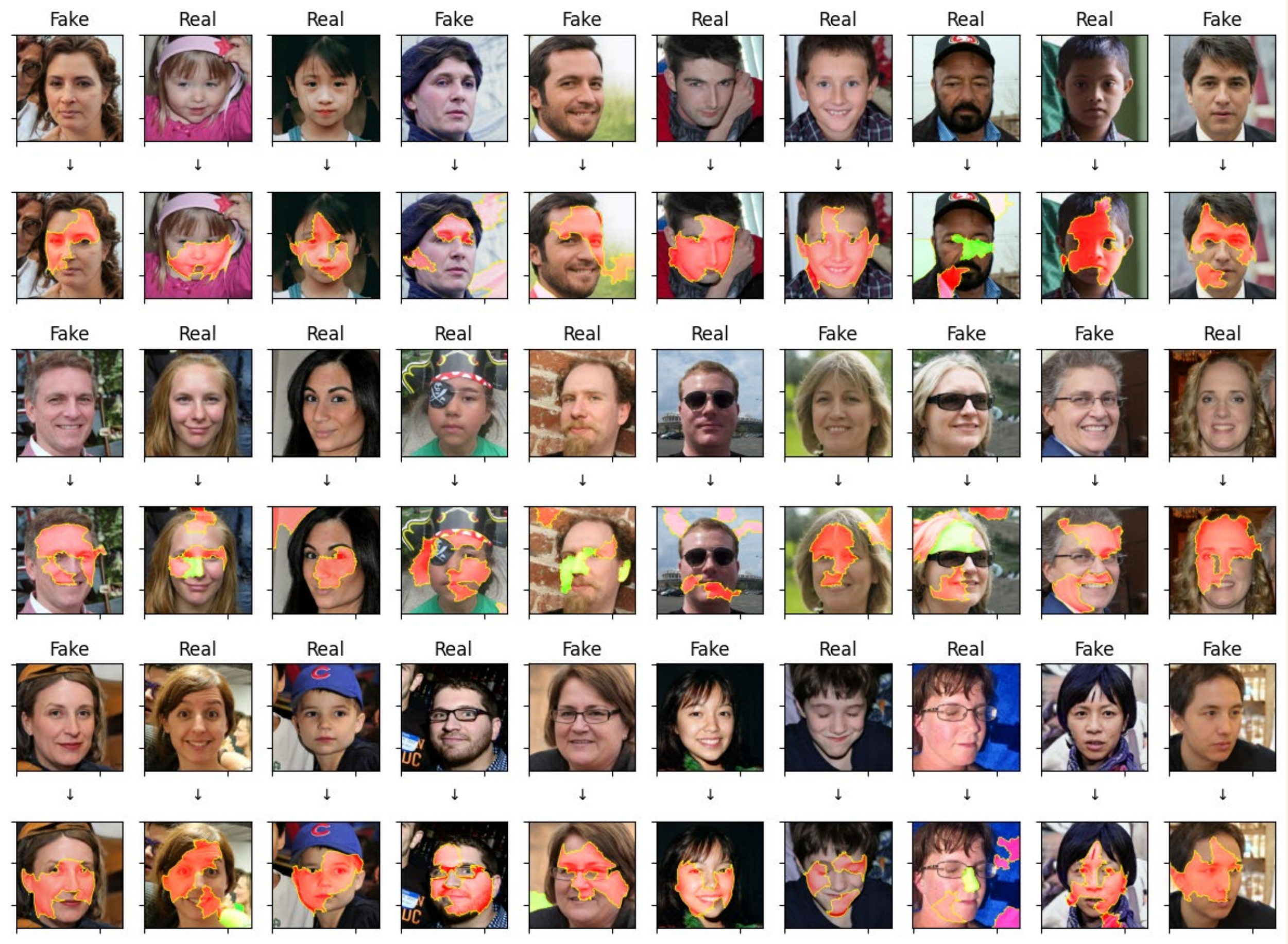




Results Summary & Saliency Maps

Maximum Validation Accuracy:	93.00%
Minimum Validation Loss:	0.1736
Maximum Training Accuracy:	90.61%
Minimum Training Loss:	0.2238

Overall, the project was a success. A 93% validation accuracy was achieved, which exceeded the 90% goal. Further research may focus on improving accuracy and investigating robustness against common adversarial attacks.



References

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