Perplexing Image Recognition Systems Using Mutation Generative Adversarial Networks

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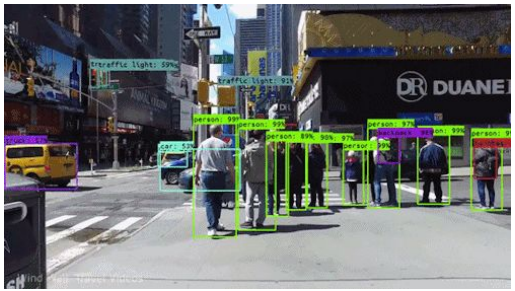
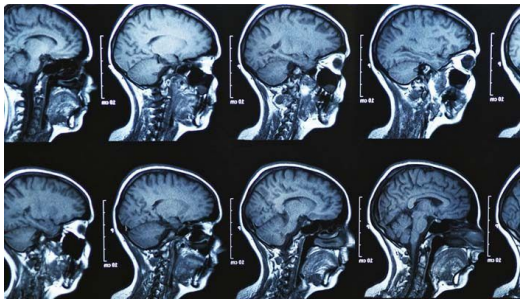
Background

- AI is becoming a pervasive and disruptive force
- Safety-critical applications rely on deep learning for image classification



Self-driving Cars

Facial-recognition ATMs



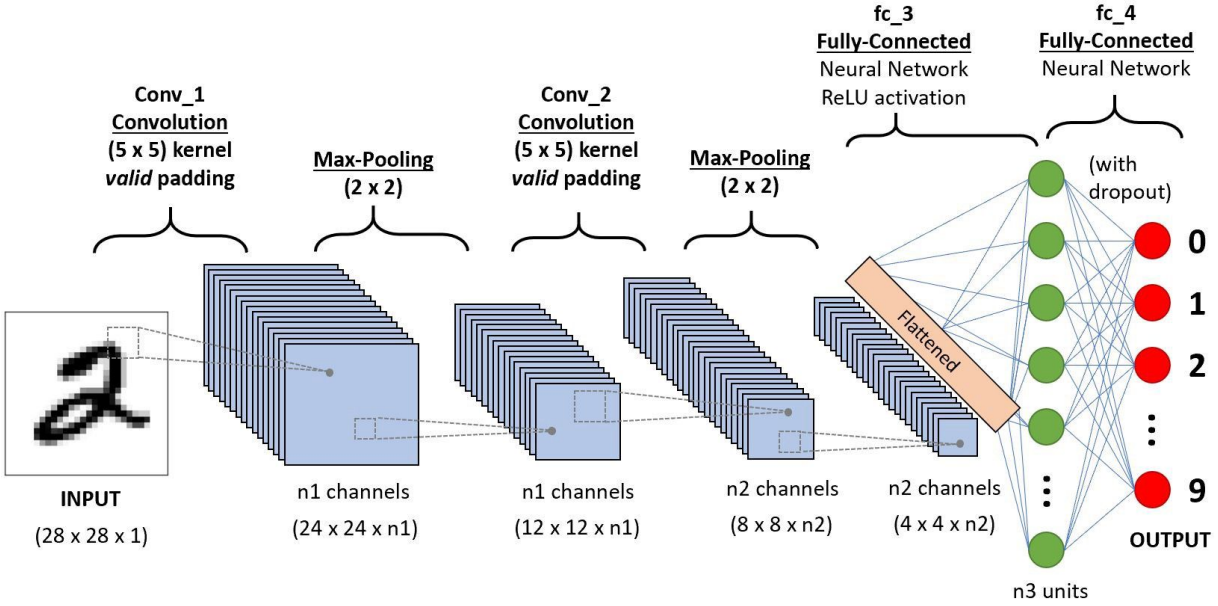
Medical Imaging Systems

What if an AI is hacked? What if an AI goes rogue?

April 2019: Keen Security Lab researchers trick a Tesla Model S in Autopilot mode to swerve towards oncoming traffic

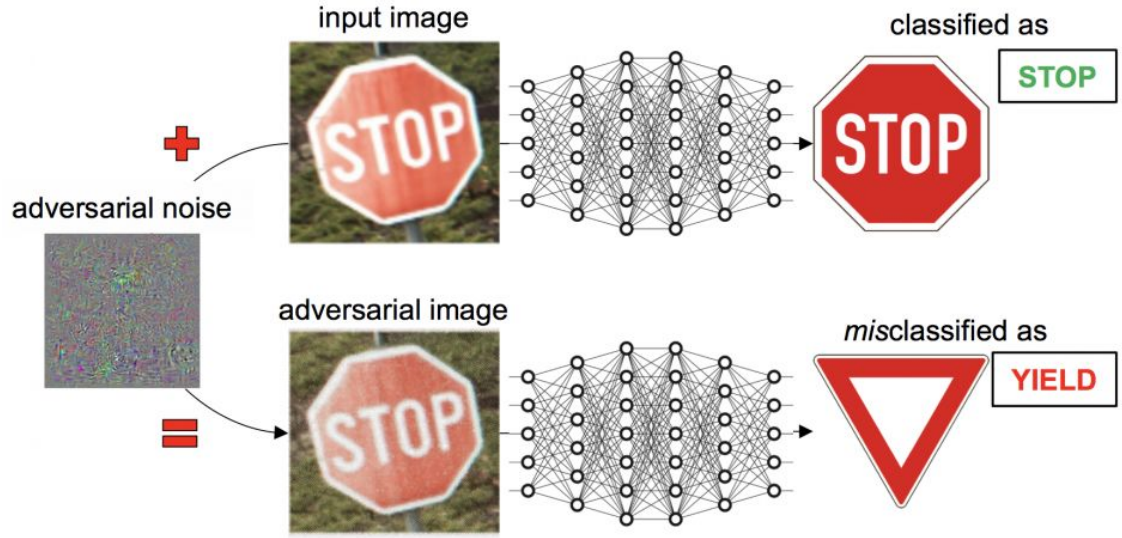
Image Recognition Systems

Convolutional Neural Networks (CNNs)[*LeCun, 1998*]



Adversarial Machine Learning[*Szegedy, 2014*]

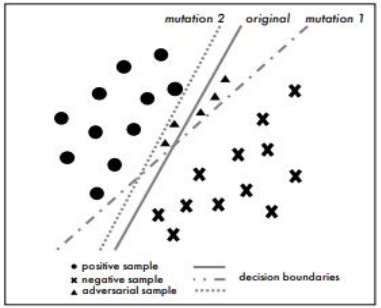
Fooling machine learning models using “adversarial samples” or intentionally perturbed inputs



Model Mutation Testing[*Wang, 2018*]

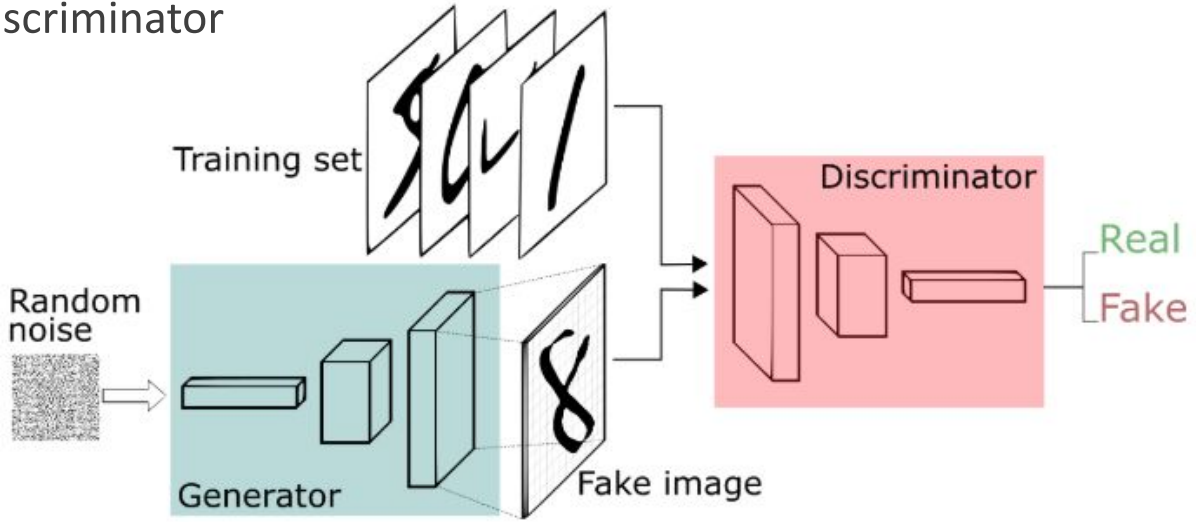
- Detect adversarial samples through the generation of mutant CNNs obtained by applying mutation operators[*Ma, 2018*]
- Label Change Rate (LCR)
  Measures how sensitive an input sample is to mutations imposed on the target model (should be larger for adversarial samples)

Mutation Operator	Level	Description
Gaussian Fuzzing (GF)	Weight	Fuzz weight by Gaussian Distribution
Weight Shuffling (WS)	Neuron	Shuffle selected weights
Neuron Effect Block. (NEB)	Neuron	Block a neuron effect on following layers
Neuron Activation Inverse (NAI)	Neuron	Invert the activation status of a neuron
Neuron Switch (NS)	Neuron	Switch two neurons of the same layer
Layer Deactivation (LD)	Layer	Deactivate the effects of a layer
Layer Addition (LA_m)	Layer	Add a layer in neuron network
Act. Fun. Remov. (AFR_m)	Layer	Remove activation functions



Generative Adversarial Networks (GANs)[*Goodfellow, 2014*]

- Machine learning model used for image generation
- Two-party architecture
  - Generator
  - Discriminator



- State-of-the-Art Defense Mechanisms
  - Detect adversarial samples by taking advantage of their sensitivity to random mutations imposed on the target model
- **Gap:** Current adversarial sample generation methods yield samples that are easily detected, giving a false sense of security!
  - Mutation Generative Adversarial Network (MGAN)
  - Possible to generate more robust adversarial samples i.e. malicious inputs will be misclassified as safe
- **Statement of Purpose:** Improve the security of safety-critical image recognition systems by exposing this vulnerability

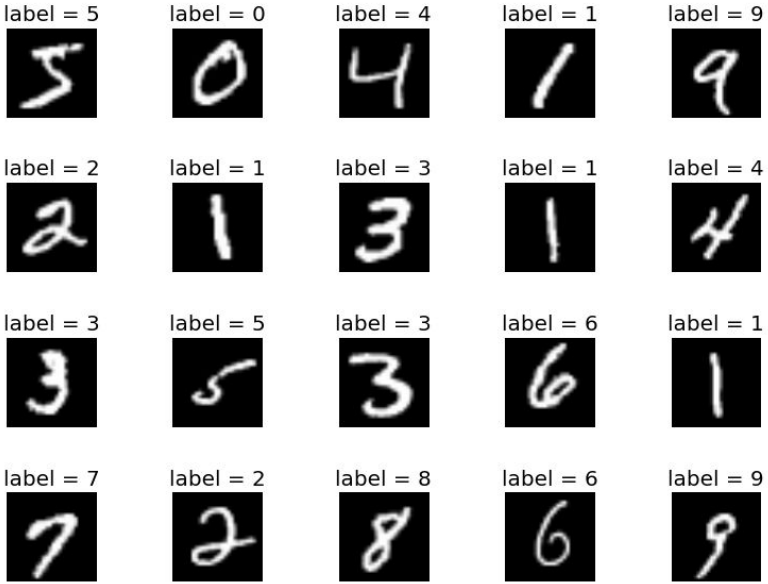
Hypothesis

By wiring mutants as a third component in the original two-party architecture of GANs, we can guide the generation of mutation-consistent yet effective adversarial samples

Data

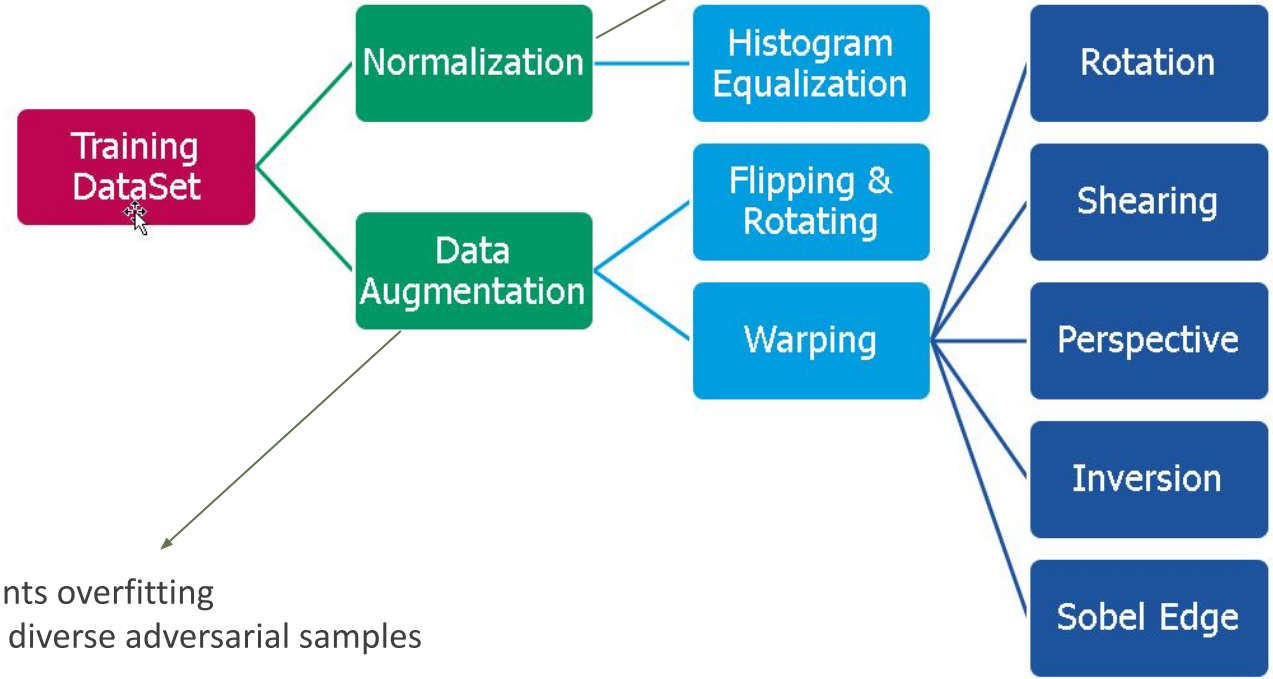
MNIST Dataset[*LeCun*]

- Handwritten digits from 0-9
- Training set of 60,000 samples
- Test set of 10,000 samples



Data Preprocessing

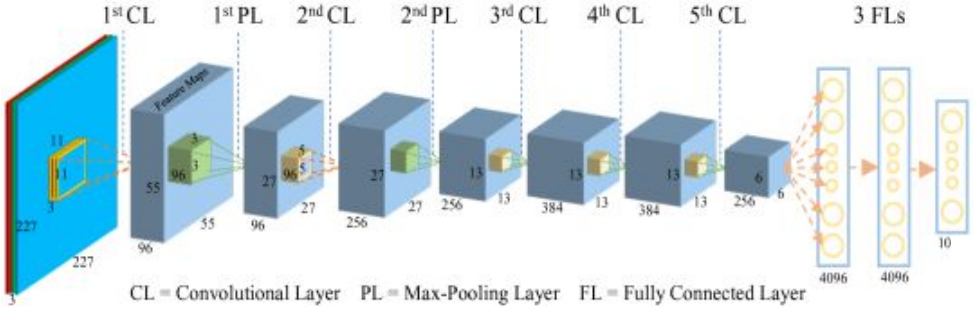
Insensitive to magnitude
Faster convergence



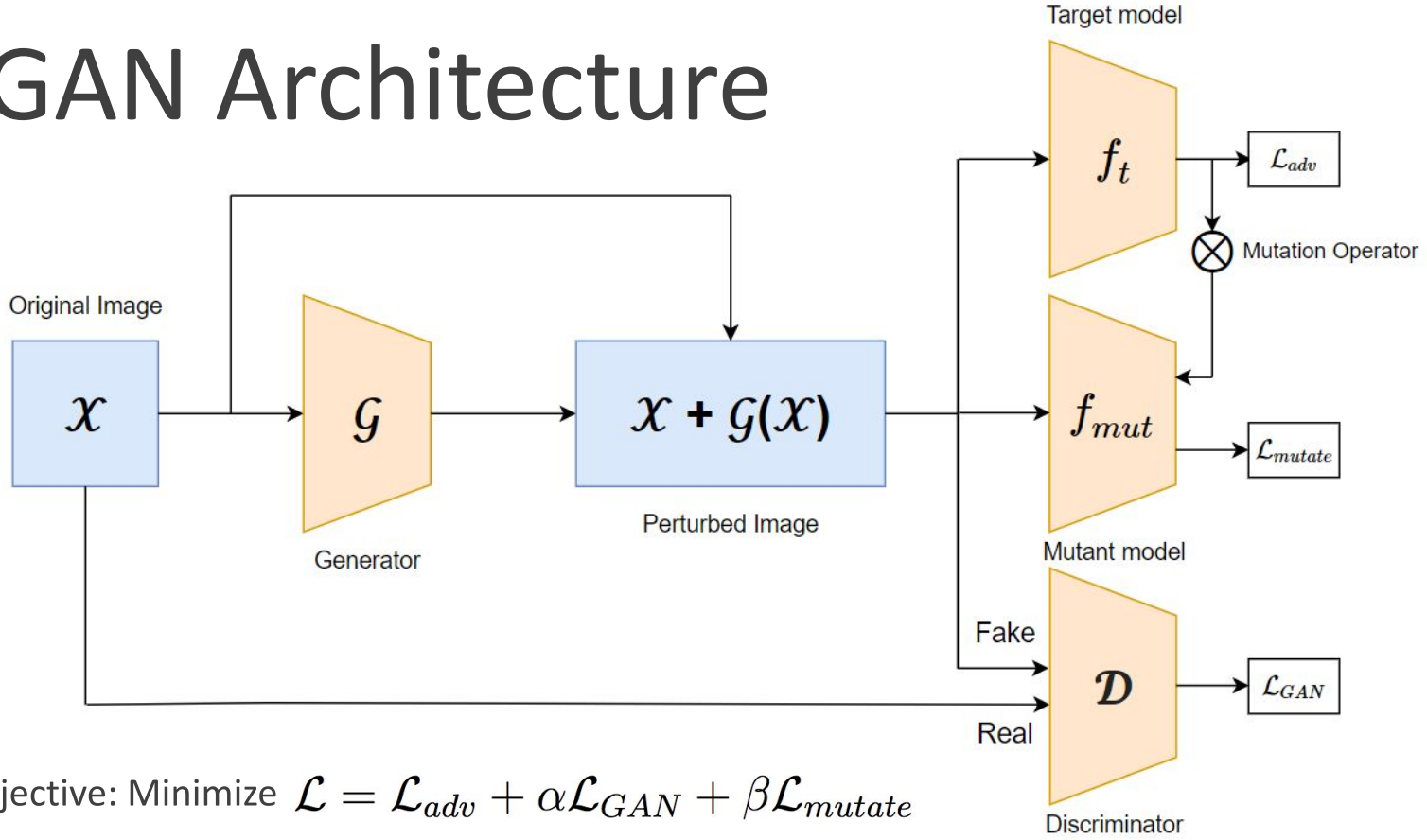
Prevents overfitting
More diverse adversarial samples

Training the Target Model

- Implemented using PyTorch, a Python-based machine learning library
- Trained on PC with RTX 2080-Ti and Intel i-9 9900k
- 99.1% accuracy on testing set



MGAN Architecture



Final objective: Minimize $\mathcal{L} = \mathcal{L}_{adv} + \alpha\mathcal{L}_{GAN} + \beta\mathcal{L}_{mutate}$

Evaluation Criteria

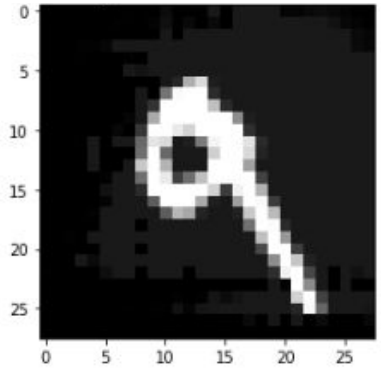
- Compared the results of MGAN and AdvGAN (state-of-the-art)[*Xiao, 2018*]
- Measured:
  - **Accuracy**: the misclassification rate of the adversarial samples
  - **Label Change Rate**: percentage of adversarial samples that are classified differently by the target model after a mutation is applied

Comparable

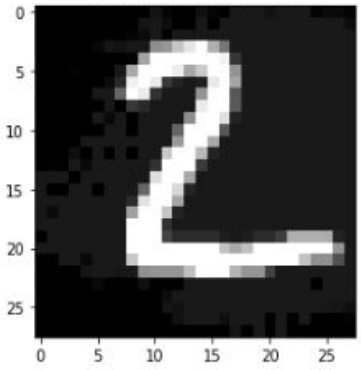
Indistinguishable
Much better than AdvGAN

Mutation Operator	MGAN Accuracy	AdvGAN Accuracy	MGAN LCR	AdvGAN LCR	Normal LCR
WS	96.83%	98.96%	12.21%	24.56%	11.52%
NAI	93.41%		44.83%	77.70%	41.50%
NS	98.21%		7.38%	18.39%	6.57%
GF	97.23%		16.21%	30.28%	15.67%

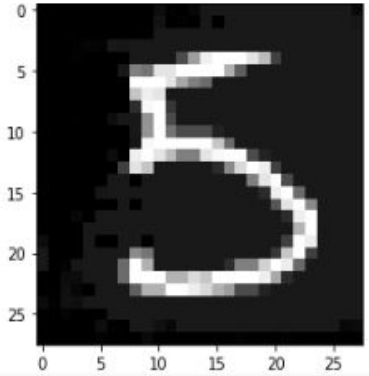
classified as a 3



classified as a 0



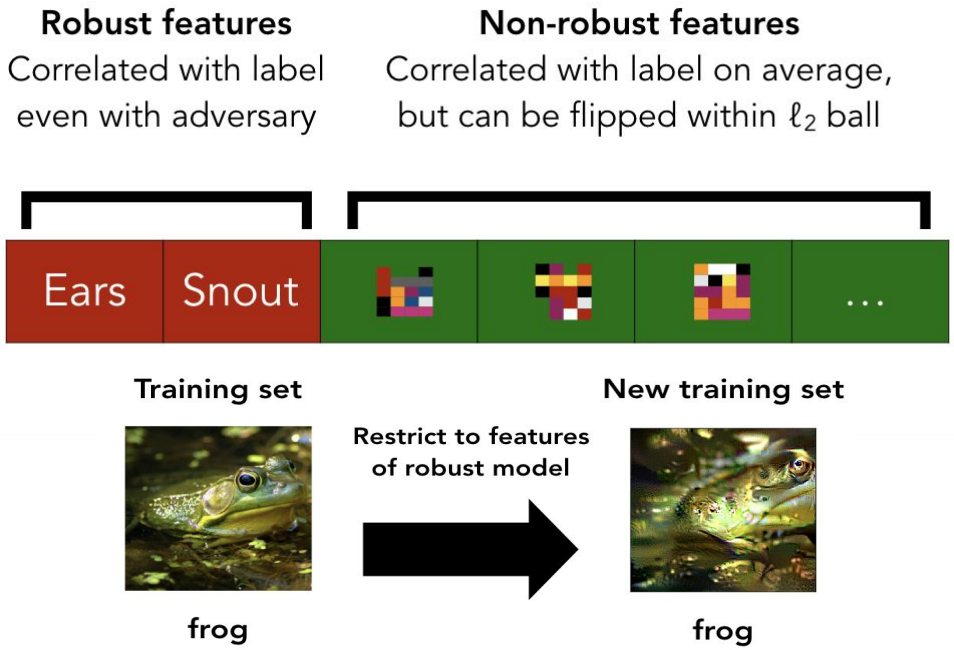
classified as a 6



Conclusion

- Hypothesis supported!
  - MGAN was able to produce effective and mutation-consistent adversarial samples that were undetectable by model mutation testing
- Adversarial samples pose a real threat to AI security
- Does this mean that we should stop deploying AI?
  - No!

Future Steps



Acknowledgements

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Thank you!

Questions?

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Background

Review of Literature

- Image Recognition Systems
- Adversarial Machine Learning
- Model Mutation Testing
- Generative Adversarial Networks

Problem & Hypothesis

- AI Security Risk
- Hypothesis

Methods & Materials

- Data
- Data Preprocessing
- Training the Target Model
- MGAN Architecture

Conclusion

Future Steps