QUANTITATIVE RELIABILITY AND RESILIENCE ASSESSMENT OF A MACHINE LEARNING ALGORITHM

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MOTIVATION

- Machine learning (ML) applications face dynamically changing and actively hostile conditions that lead to system failures and degraded performance
- Systems incorporating ML must be reliable and resilient, especially in safety-critical domains
- Many studies propose techniques to improve the robustness of ML algorithms, but few consider quantitative techniques to assess the reliability and resilience of ML models under likely stresses and attack scenarios.

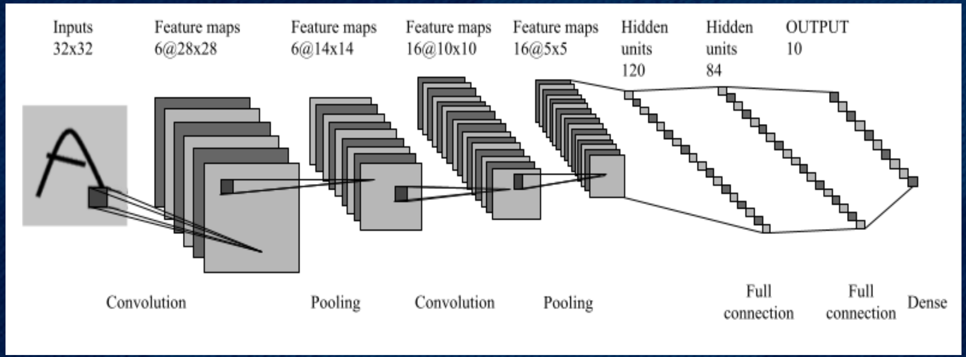
CONTRIBUTION

- Demonstrate how to collect relevant data during training and testing of machine learning models suitable to apply
  - Software reliability models without covariates
  - Software reliability models with covariates
  - Resilience models
- Enable quantitative assessment of ML reliability and resilience during testing and field operations monitoring to ensure systems operate dependably under critical conditions.

MACHINE LEARNING TECHNIQUES

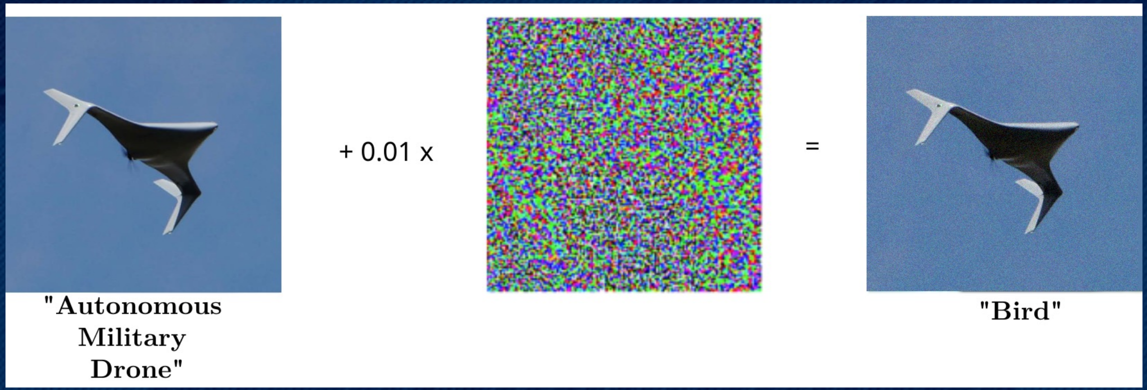
Convolutional Neural Networks

- Image classification
- Object recognition



Generative Adversarial Attacks

- Fast Gradient Sign Method (FGSM)
- Projected Gradient Descent (PGD)



Defense Measure

- Adaptive Adversarial Training

$$\min_{\theta}[\max_{\delta\in\Delta}[\mathcal{L}(x+\delta, y, \theta)]]$$

RELIABILITY AND RESILIENCE MODELING

RELIABILITY

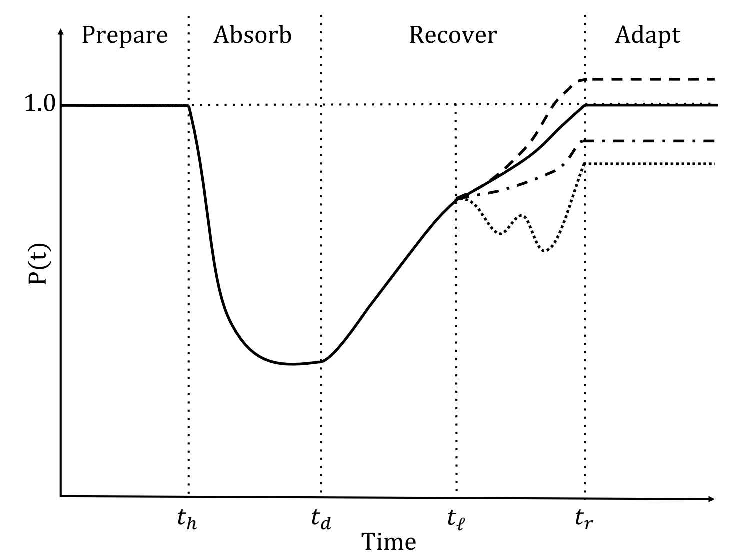
Non-homogeneous Poisson Process Software Reliability Growth Models (NHPP SRGM) estimate the number of defects remaining at any given time and the rate at which defects will be detected and removed.

- Models without covariates
  - Goel-Okumoto (GO)
  - Weibull (Wei)
  - Delayed S-shaped (DSS)
- Models with covariates
  - Geometric (GM)
  - Discrete Weibull of order two (DW2)
  - Type III discrete Weibull (DW3)
  - "S" distribution (S)
  - Truncated logistic (TL)
  - Increasing Failure Rate Salvia and Bollinger (IFR SB)
  - Increasing Failure Rate Generalized Salvia and Bollinger (IFRGSB)

RESILIENCE

A discrete resilience curve incorporating covariates is described as

$$P(i) = P(i-1) + \Delta P(i)$$



- Regression Models
  - Multiple Linear Regression (MLR)
  - Multiple Linear Regression with Interaction (MLRI)
  - Polynomial Regression (PR)

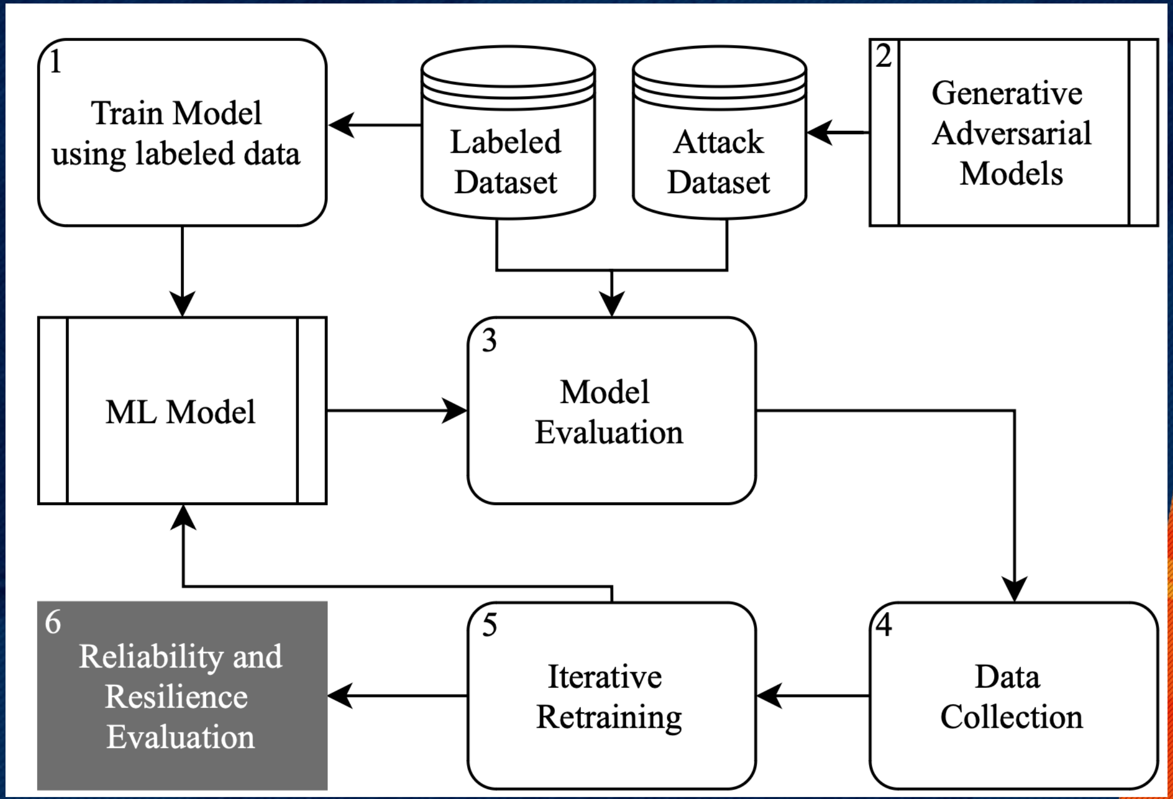
DATA COLLECTION

Factors collected before and after Step 5.

Before		After	
Factor Name	**Acr.**	**Factor Name**	**Acr.**
Failure Time	FT	Alpha	α
Failure Count	FC	Memory	M
Epsilon	ε	Training Accuracy	TrA
FGSM percentage	FGSM%	Training Loss	TrL
PGD percentage	PGD%	Validation Accuracy	VA
Test Accuracy	TeA	Validation Loss	VL
Test Loss	TeL		
F1-Score	F1		

Epsilon ranges considered:

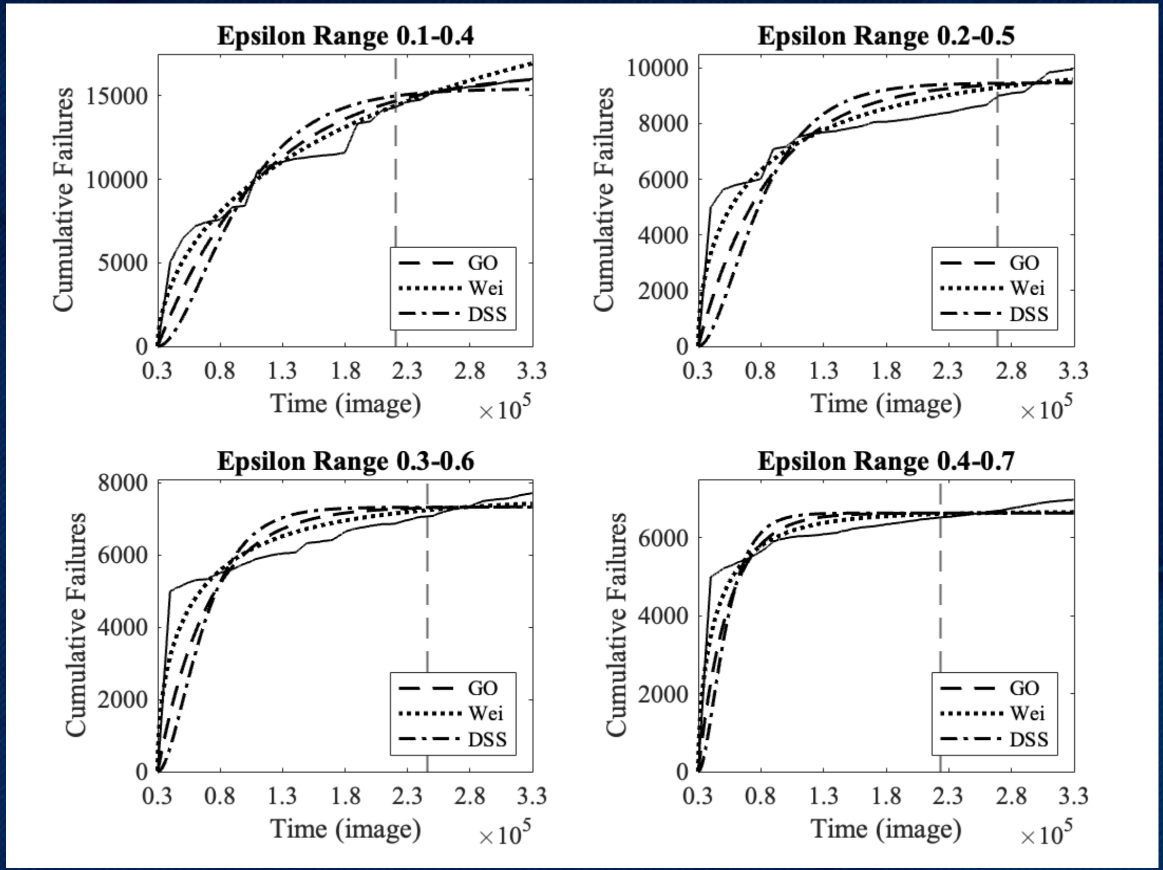
- 0.1-0.4
- 0.2-0.5
- 0.3-0.6
- 0.4-0.7



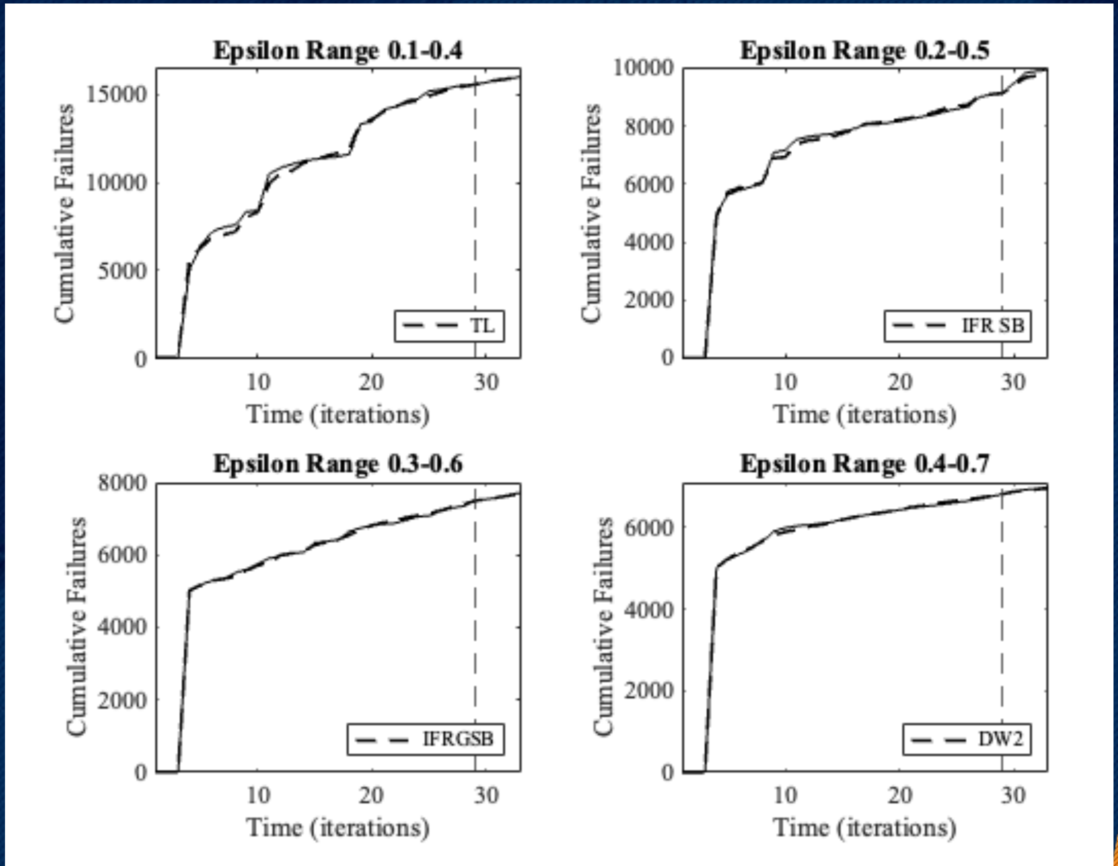
Process for ML data collection to assess reliability and resilience

- ML Model: CNN
- Generative Adversarial Models: FGSM and PGD
- Data set: CIFAR-10

RESULTS ANALYSIS – RELIABILITY



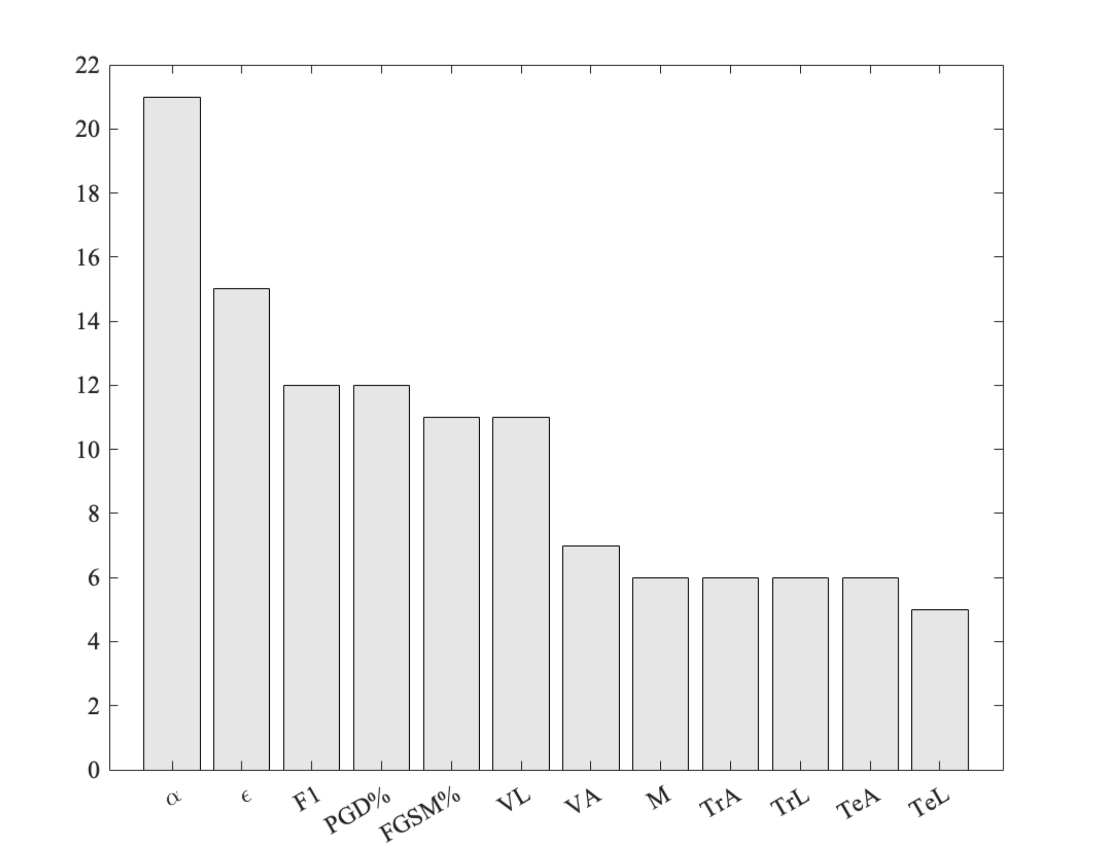
Best-fitting models without covariates



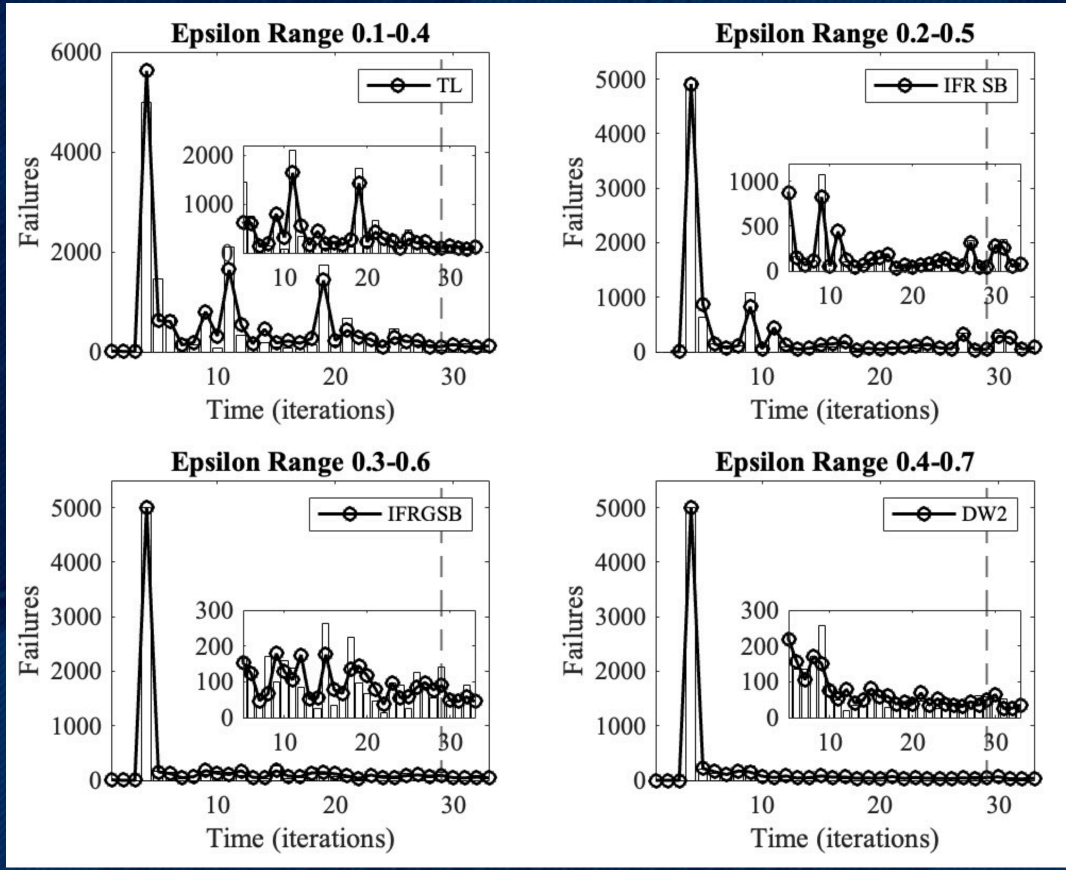
Best-fitting models with covariates

NHPP SRGMs incorporating covariates tracked and predicted more accurately than models without covariates.

RESULTS ANALYSIS – RELIABILITY



Frequency of covariate inclusion in the NHPP SRGM with covariates



Number of failures in each interval of failure count data sets and zoomed-in view of iterations 4 to 33 as well as predictions made by models of best fit with covariates

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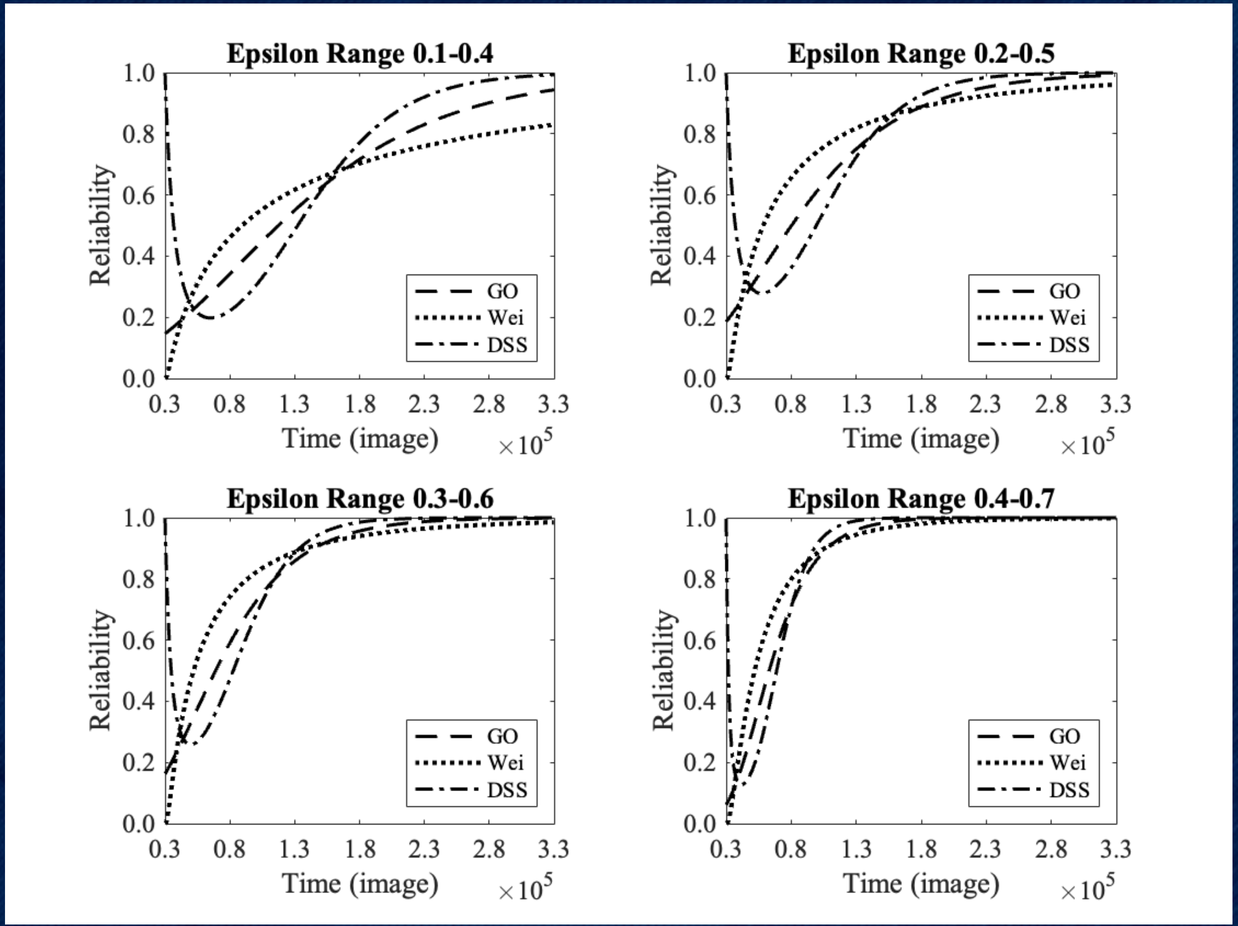
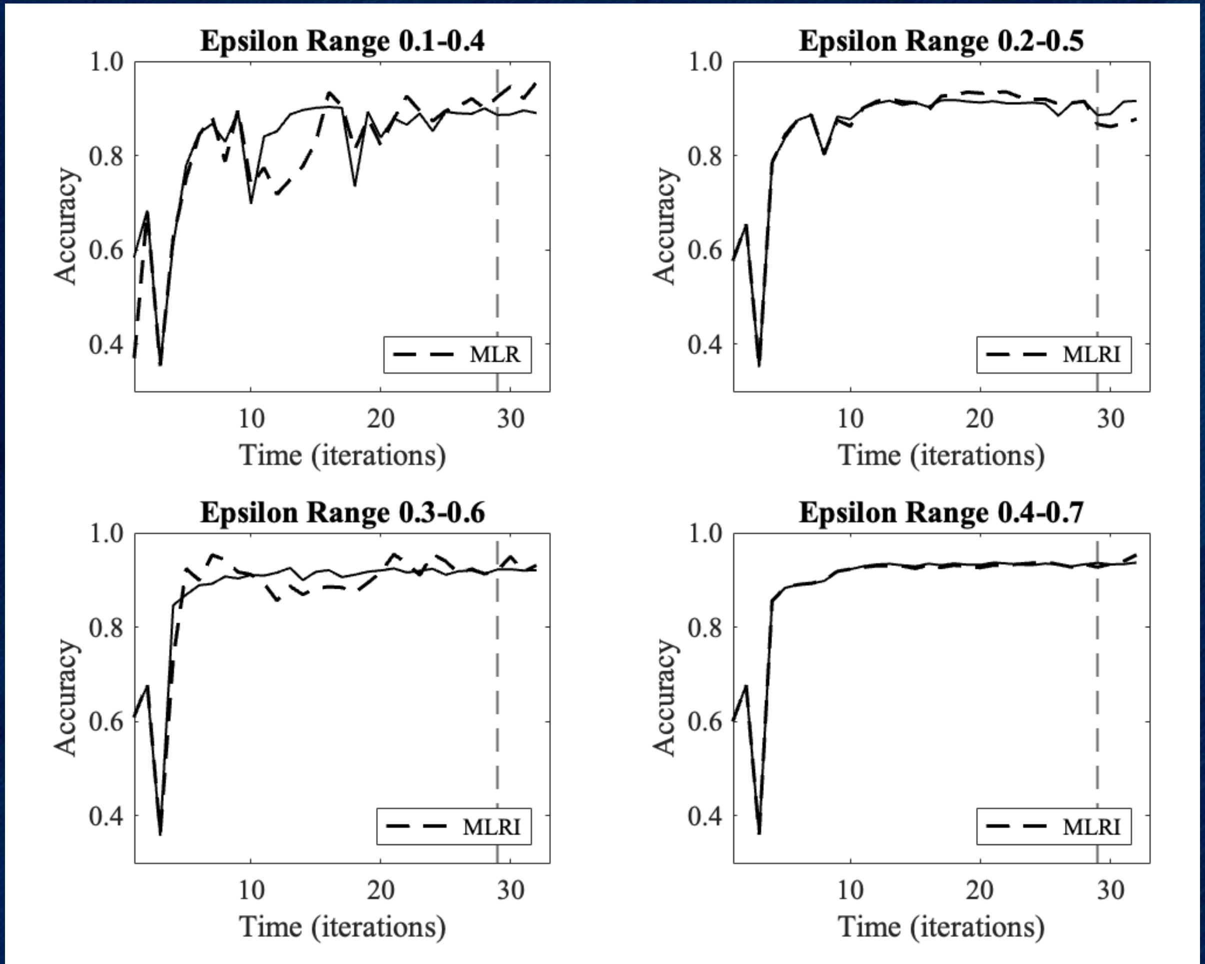
RESULTS ANALYSIS – RELIABILITY



Reliability growth curves of NHPP SRGM models without covariates

Reliability is higher for higher ε ranges

RESULTS ANALYSIS - RESILIENCE



Best-fitting resilience models

Larger ε ranges exhibited smoother performance curves

CONCLUSION

Summary

- Demonstrated the applicability of quantitative reliability and resilience assessment methods of ML models equipped with defense measures and subject to adversarial attacks.

Results

- Software reliability growth models incorporating covariates more accurately track and predict the number of defects detected than models without covariates
- Resilience models considering negative and positive factors characterizing the deterioration and recovery of a system are also able to precisely track and predict the resilience of defensive measures for ML subject to specific attacks

Future research

- Explore the application of these models to cyber-physical systems
- Incorporate these reliability and resilience models into maintenance models

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