Comparison of Quantum & Classical Deep Learning for Critical Infrastructure Risk Modeling

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Introduction

Energy infrastructure consists of a complex network of components; any failure would have critical consequences for society. To properly assess & **mitigate risks** to energy infrastructure, it is essential to consider potential hazards. Severe weather events, such as hurricanes, tornadoes, snowstorms, earthquakes, floods, wildfires, volcanic eruptions, & landslides, pose substantial threats. Additionally, non-natural hazards, including cyberattacks, physical attacks (such as terrorism), technical failures, human errors, and supply chain disruptions, further compound the challenges faced by the energy sector.

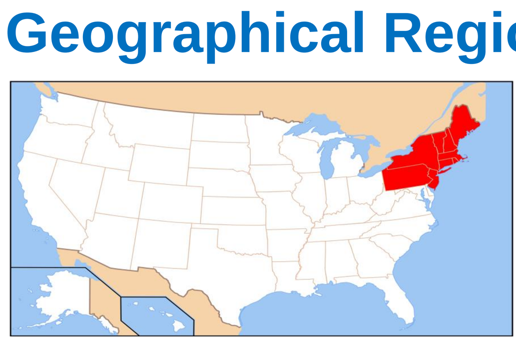
Understanding the **interdependencies and interactions** among these hazards is essential, as they often exhibit self-excitation & mutual excitation. For instance, earthquakes increase the likelihood of aftershocks, and rainstorms elevate the probability of floods or landslides. Recognizing and modeling these dynamic relationships is critical for risk assessment.

Bayesian networks are a powerful tool for modeling the vulnerability of energy infrastructure to various hazards and their subsequent influence on failures. Prior research has leveraged Bayesian networks as vulnerability models. This project builds upon this foundation, proposing a Bayesian network model that **captures the influence flow of hazards** through the vulnerability, subsequently triggering additional hazards.

Further, vulnerability is defined as the **conditional probability** of a failure occurring given the presence of a hazard. By comprehensively modeling these vulnerabilities, we gain valuable insights into how the influence of hazards propagates through the infrastructure, potentially setting off a cascade of failures. In this work, we describe the methodology employed, present the results of our risk models, and compare them against state-of-the-art methods like decision trees and neural networks.

Preliminaries

Geographical Region

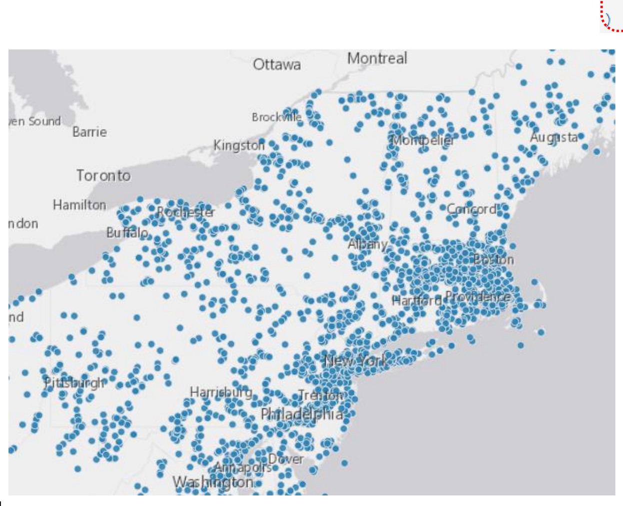


Construct the risk model by modeling the hazards and vulnerabilities present in the energy infrastructure

Region: NY, NJ, PA, CT, MA, ME, VT, NH, RI

- presents a mixture of energy resources and diverse set of regions of socio-economical scale from metropolitan areas to rural regions
- vulnerable to severe weather through snowstorms and rainstorms, while a minor earthquake risk is also present.
- availability of verified publicly data

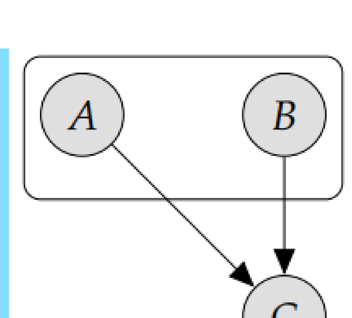
Data Sets



1. **Energy Infrastructure Data:** Homeland Infrastructure Foundation-Level Data
2. **Precipitation Data:** NASA POWER DATA
3. **Earthquake Data:** U.S Geological Survey: Earthquake Hazard Program
4. **Disaster Declarations Data:** FEMA Web Disaster Declarations
5. **Power Disturbances:** ISER Electric Disturbance Events
6. **Fire Occurrence:** National Interagency Fire Center

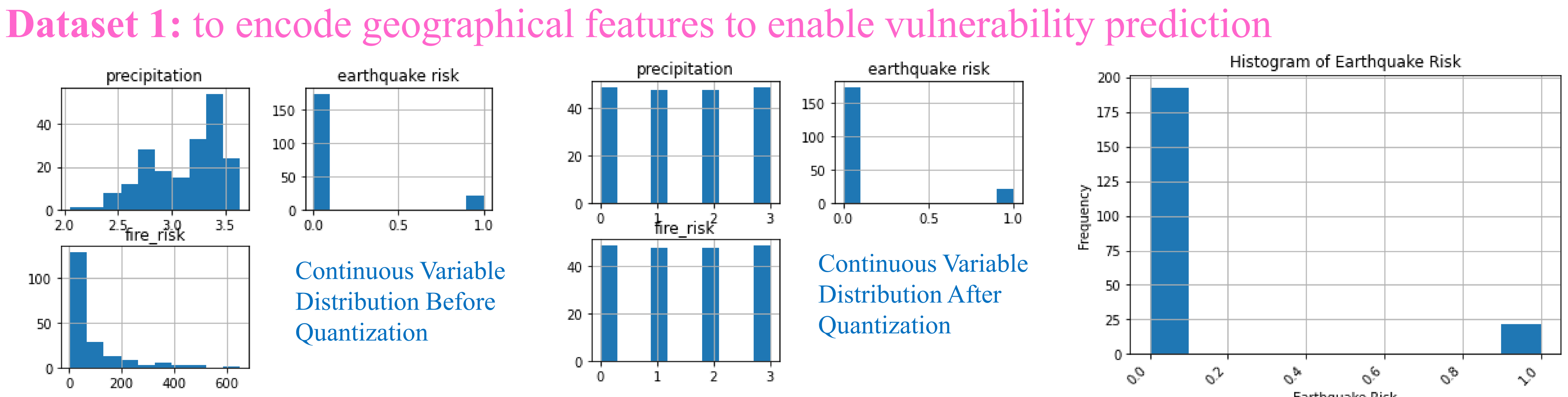
Models

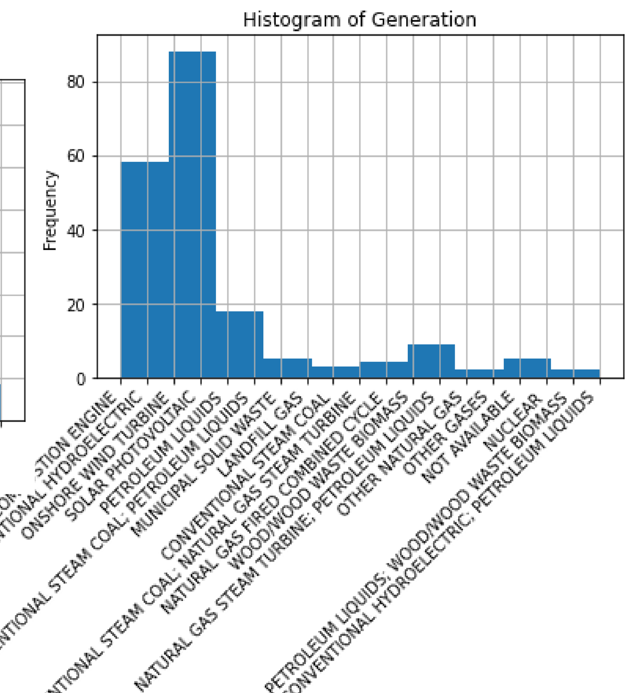
1. **Deep Neural Network (DNN)**
2. **Quantum Neural Network (QNN)**
3. **Bayesian Network (BN)**
4. **Naïve Bayes (NB)**
5. **Decision Tree (DT)**



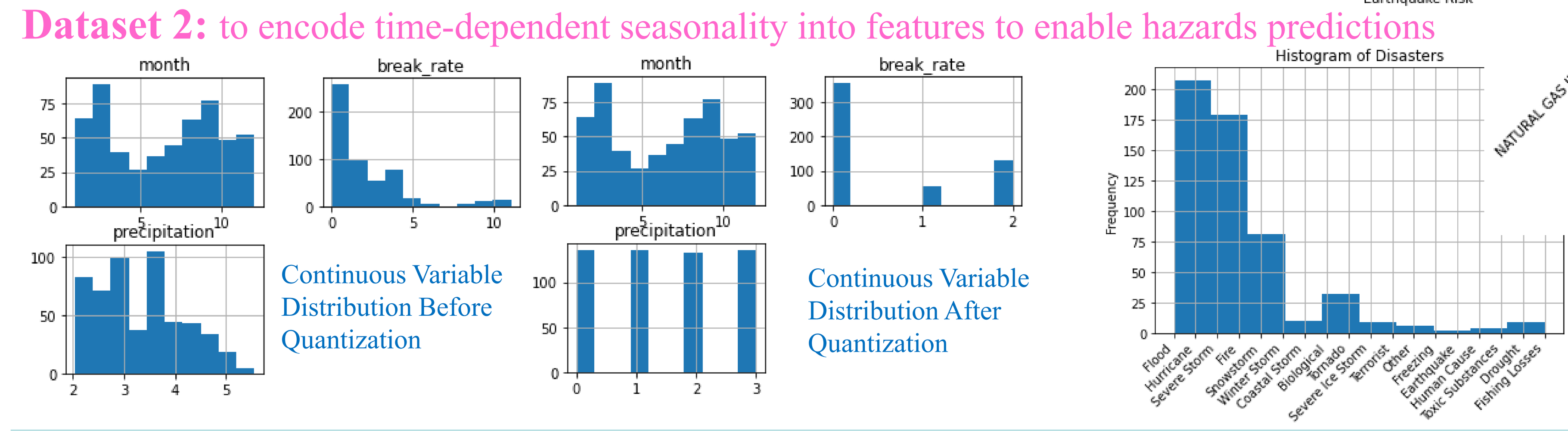
Data Analysis

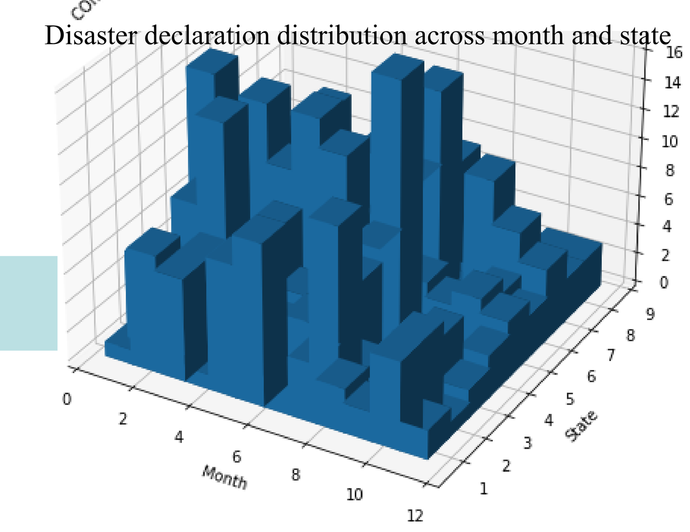
Dataset 1: to encode geographical features to enable vulnerability prediction





Dataset 2: to encode time-dependent seasonality into features to enable hazards predictions





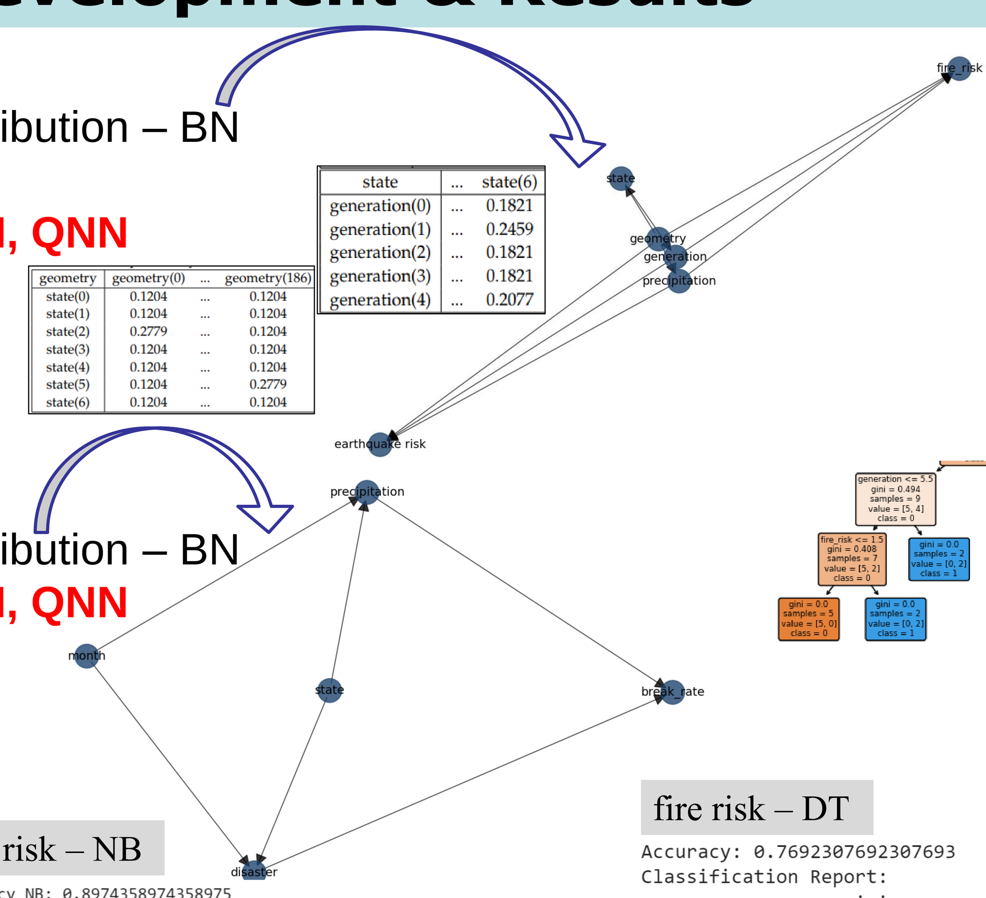
Model Development & Results

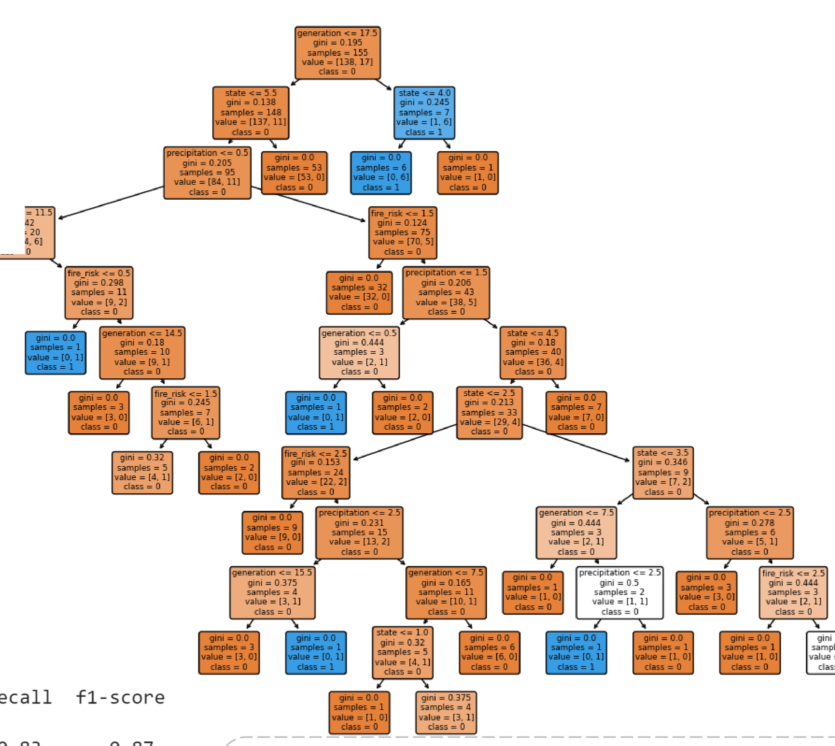
Dataset 1:

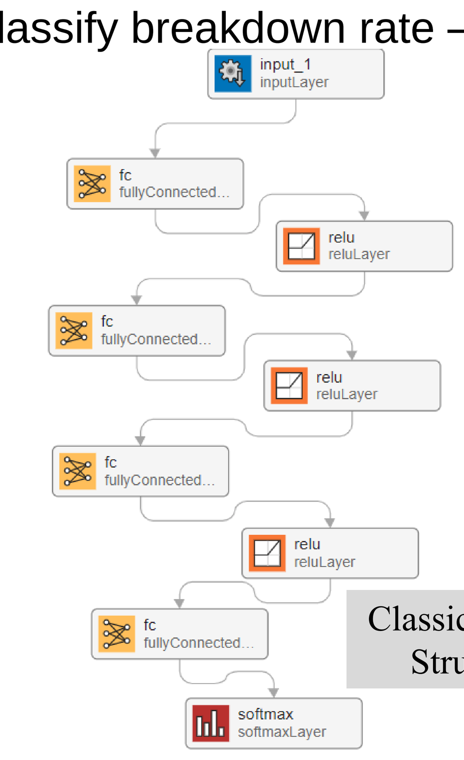
1. Learn conditional probability distribution – BN
2. **Classify fire risk – DNN, QNN**
3. **Classify earthquake risk – DNN, QNN**
4. Classify fire risk – NB
5. Classify earthquake risk – NB
6. Classify fire risk – DT
7. Classify earthquake risk – DT

Dataset 2:

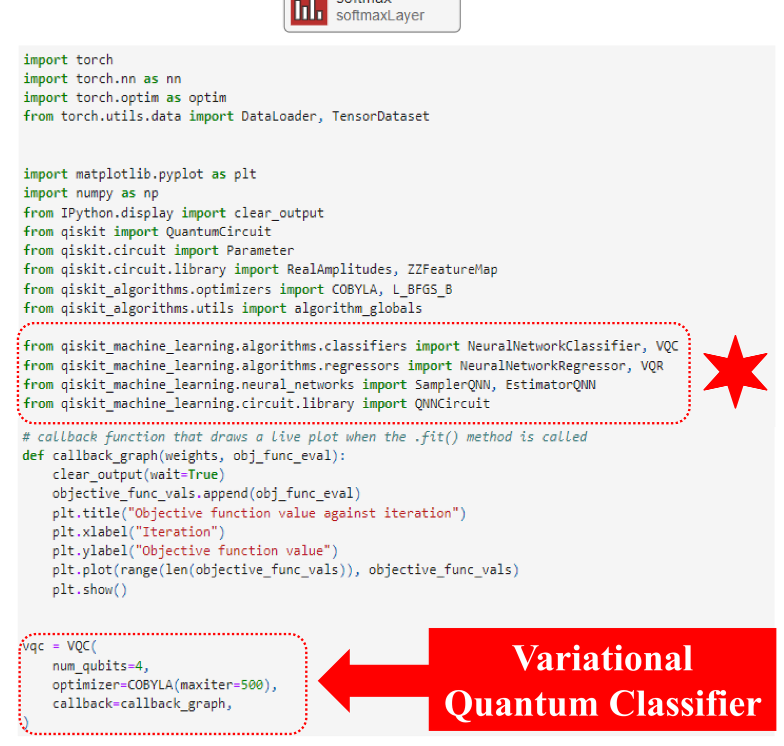
8. Learn conditional probability distribution – BN
9. **Classify breakdown rate – DNN, QNN**
10. Classify breakdown rate – NB
11. Classify breakdown rate – DT







Classical DNN Structure



Variational Quantum Classifier

fire risk – NB

Accuracy NB: 0.8974358974358975

Classification Report:

	precision	recall	f1-score	support
0	0.90	1.00	0.95	35
1	0.00	0.00	0.00	4
accuracy			0.90	39
macro avg	0.45	0.50	0.47	39
weighted avg	0.81	0.90	0.85	39

fire risk – DT

Accuracy: 0.7692307692307693

Classification Report:

	precision	recall	f1-score
0	0.91	0.83	0.87
1	0.14	0.25	0.18
accuracy			0.77
macro avg	0.52	0.54	0.52
weighted avg	0.83	0.77	0.80

$$\text{Precision} = \frac{TP}{TP+FP} \qquad \text{Recall} = \frac{TP}{TP+FN} \qquad \text{F1 Score} = \frac{TP}{TP+\frac{1}{2}(FP+FN)}$$

Classical DNN | Quantum NN

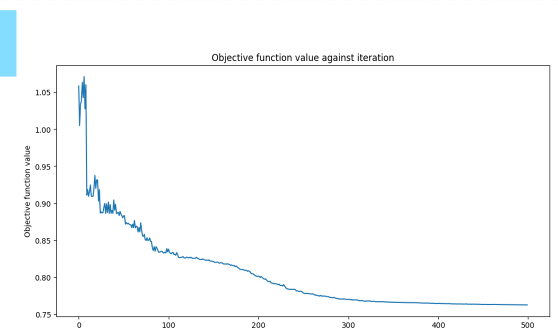
fire risk

Classical DNN — Accuracy_NN: 0.8974358974358975

	precision	recall	f1-score
0	0.90	1.00	0.95
1	0.00	0.00	0.00
accuracy			0.90
macro avg	0.45	0.50	0.47
weighted avg	0.81	0.90	0.85

Quantum NN

	precision	recall	f1-score
0	0.88	0.83	0.85
1	0.00	0.00	0.00
accuracy			0.74
macro avg	0.44	0.41	0.43
weighted avg	0.79	0.74	0.77



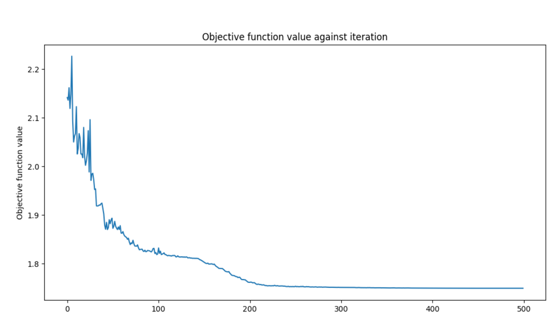
earthquake risk

Classical DNN — Accuracy_NN: 0.46153846153846156

	precision	recall	f1-score
0	0.30	0.38	0.33
1	0.25	0.18	0.21
2	0.50	0.25	0.33
3	0.65	0.92	0.76
accuracy			0.46
macro avg	0.42	0.43	0.41
weighted avg	0.43	0.46	0.43

Quantum NN

	precision	recall	f1-score
0	0.27	0.50	0.35
1	0.71	0.45	0.56
2	0.00	0.00	0.00
3	0.55	0.50	0.52
accuracy			0.38
macro avg	0.38	0.36	0.36
weighted avg	0.42	0.38	0.39



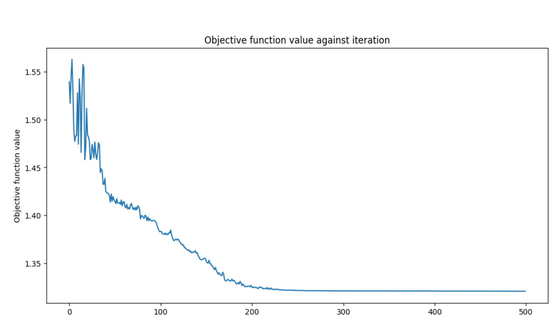
breakdown rate

Classical DNN — Accuracy_NN: 0.8055555555555556

	precision	recall	f1-score
0	0.85	0.88	0.86
1	0.83	0.45	0.59
2	0.67	0.73	0.70
accuracy			0.81
macro avg	0.78	0.69	0.72
weighted avg	0.81	0.81	0.80

Quantum NN

	precision	recall	f1-score
0	0.78	0.72	0.75
1	0.42	0.45	0.43
2	0.33	0.41	0.37
accuracy			0.63
macro avg	0.51	0.53	0.52
weighted avg	0.65	0.63	0.64

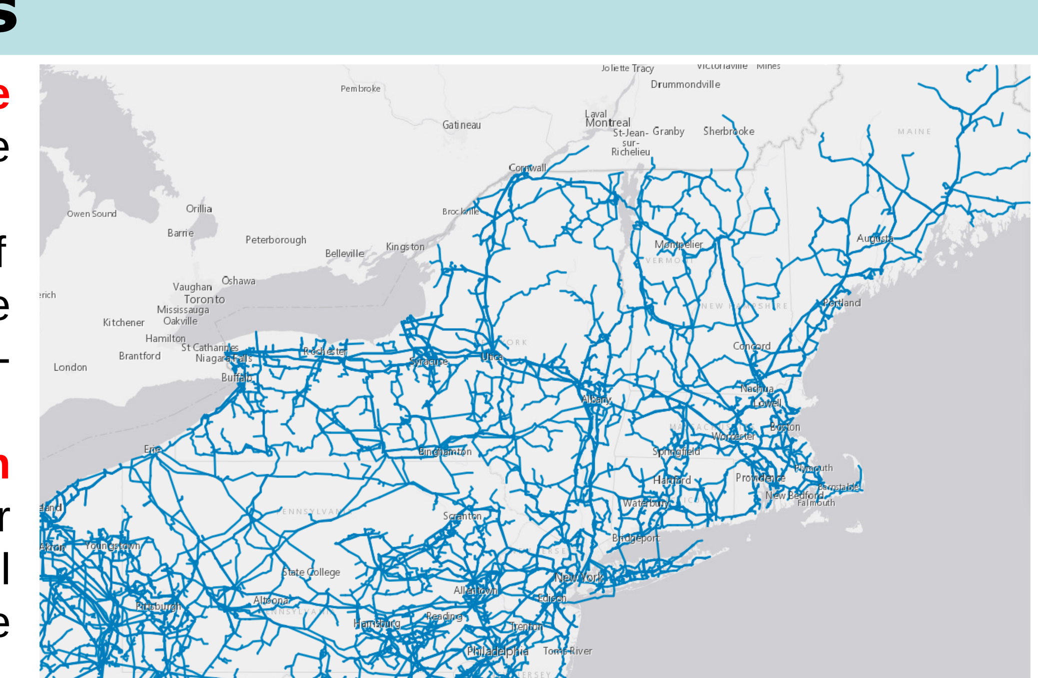


Conclusions

We explore the **impact of hazards affecting critical infrastructure** through seasonal severe weather and other events. Further, the **vulnerability** presented by geo-locations was analyzed as well.

The analysis of **Dataset 1** yields the conditional probability distributions of earthquake and fire risk through the **Bayesian network**. Thus, it can be used as an **inference method** to evaluate the vulnerability of a geo-location to the energy infrastructure.

Further, the analysis on **Dataset 2** gives the ability to **infer break down** rate conditional on the month of the year, precipitation and disaster classifications through the Bayesian network. This provides useful insights into **hazard occurrences and vulnerabilities** present in the temporal dimension.



The classification models developed for both data sets present insights into **dependencies** present in the variables and their predictability. While DNN provided acceptable accuracies, the decision tree model performed well with **explainable properties**. We believe this work can be further improved by incorporating the data on transmission lines in the region as well as shown in figure. Further, increasing the **spatial and temporal resolution** will also contribute to higher accuracy.

Glossary:

NY – New York
NJ – New Jersey
PA – Philadelphia
CT – Connecticut
MA – Massachusetts
ME - Maryland
VT – Vermont
NH – New Hampshire
RI – Rhode Island

Resources:

- Judea Pearl. "Bayesian networks". In: (2011)
- https://qiskit-community.github.io/qiskit-machine-learning/tutorials/02_neural_network_classifier_and_regressor.html
- Python bnlearn: https://erdogant.github.io/bnlearn/pages/html/index.html
- Python sklearn: https://scikit-learn.org/stable/
- https : / / hifld - geoplatform . opendata . arcgis .com/datasets/geoplatform::power-plants-2/about.
- https://power.larc.nasa.gov/, https://www.oe.netl.doe.gov/oe417.aspx
- https://www.fema.gov/openfema-data-page/fema-web-disasterdeclarations-v1