Comparison of Tornado Damage Prediction Accuracy between Classical and Hybrid Quantum Neural Networks

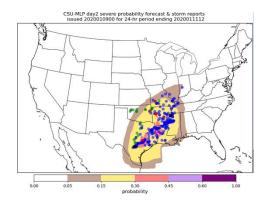
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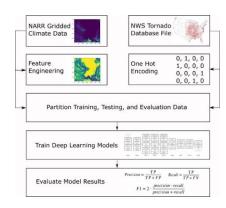
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Tornado Damage Prediction

- Tornadoes are among the deadliest and most common natural disasters worldwide
 - Approximately 1,000 tornadoes occur annually in the United States, with an average of 80 deaths, 1,500 injuries, and significant architectural damages^[1]
- Advancements in tornado prediction using machine learning models are reported to be one
 of the most effective methods in reducing tornado damage



CSU-MLP by Colorado State University [2]

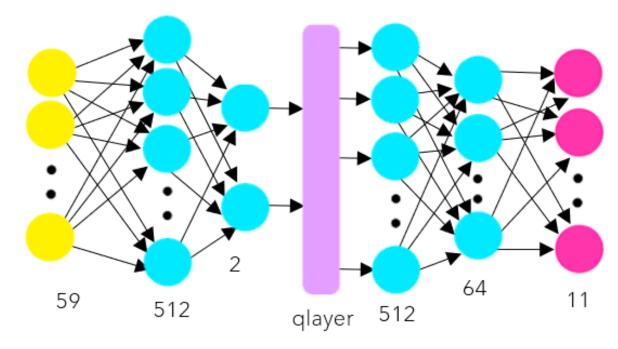


Deep-CNN by McGuire and Moore^[3]

However, machine learning fell short in processing big and complex data such as Earth's atmosphere

Project Solutions

- To enhance model prediction ability, quantum properties can be used to enhance machine learning models^[1]
 - Process and analyze more intricate data required for complex climate dynamics
 - Reduce computational cost

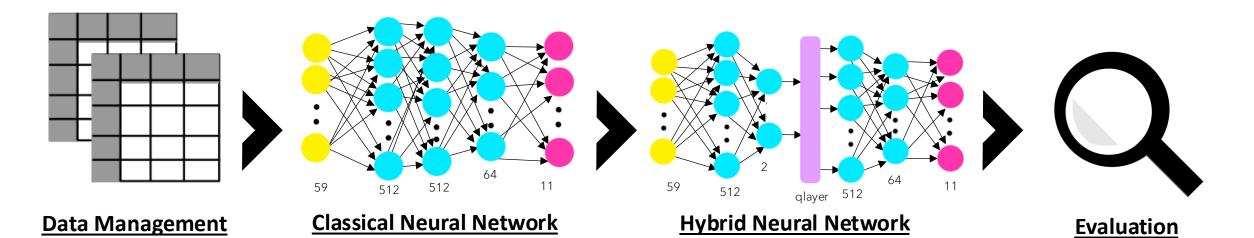


Schematics of our Hybrid Quantum-Classical Neural Network

Investigate how quantum properties, such as superpositions and entanglement, can benefit machine learning prediction



Implementation



Prepare the data obtained from Storm Prediction Center (SPC)^[1] by data pre-processing and encoding

Create multi-output classical neural network model using TensorFlow and Keras Convert quantum circuit into a layer and implement it into the neural network using PennyLane

Compare the two models and evaluate if the implementation of quantum layers increases prediction accuracy

Data

<u>Inputs</u>

- Tornado's length in miles (len)
- Width in yards (wid)
- magnitude with the scale of 0 to 5 (mag)
- year occurred (yr)
- state that was affected (st)
- and the geographical coordinates (latitude and longitude)

	st	wid	1en	mag	slat	slon	уr	ns	inj	fat	loss
0	ОК	10	15.80	1	36.7300	-102.5200	1950	1	0	0	1.0
1	NC	880	2.00	3	34.1700	-78.6000	1950	1	3	0	2.0
2	KY	10	0.10	2	37.3700	-87.2000	1950	1	0	0	2.0
3	KY	10	0.10	1	38.2000	-84.5000	1950	1	0	0	2.0
4	MS	37	2.00	1	32.4200	-89.1300	1950	1	3	0	1.0
•••											
68993	FL	5	0.01	0	29.9900	-81.6600	2023	1	0	0	0.0
68994	ОН	25	0.01	0	40.0632	-83.2430	2023	1	0	0	6.0
68995	MN	25	0.69	0	45.1051	-93.8302	2023	1	0	0	0.0
68996	LA	75	0.69	0	29.9700	-90.2500	2023	1	0	0	7.0
68997	ΑZ	10	0.10	0	34.7400	-112.4500	2023	1	0	0	0.0
68998 rows x 11 columns											

Outputs

- number of injuries (inj)
- fatalities (fat)
- number of states affected by tornadoes (ns)
- classification of the estimated property loss with the scale of 0 to 7 (loss)

```
0: n < 5,000

1: 5,000 ≤ n < 50,000

2: 50,000 ≤ n < 500,000

3: 500,000 ≤ n < 5,000,000

4: 5,000,000 ≤ n < 50,000,000

5: 50,000,000 ≤ n < 500,000,000

6: 500,000,000 ≤ n < 5,000,000,000
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7: n ≥ 5,000,000,000



Model Architecture

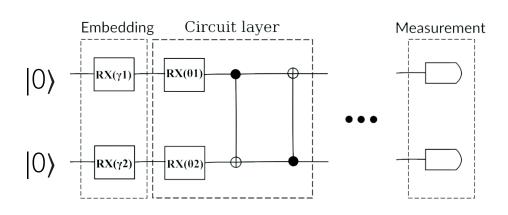
Classical NN

Hybrid Classical-Quantum NN



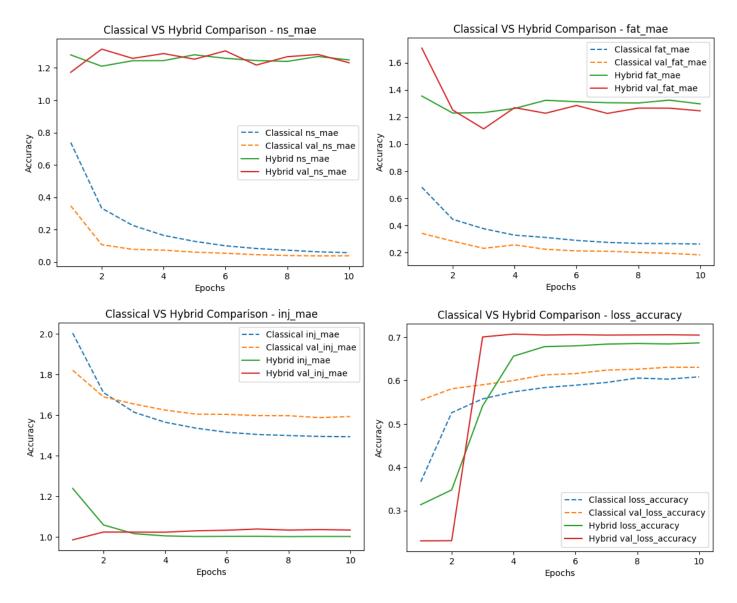
Layer (type)	Output Shape	Param #	Connected to
input_layer_21 (InputLayer)	(None, 6)	0	-
dense_66 (Dense)	(None, 512)	3,584	input_layer_21[0][0]
batch_normalization_66 (BatchNormalization)	(None, 512)	2,048	dense_66[0][0]
dropout_45 (Dropout)	(None, 512)	0	batch_normalization_6
dense_67 (Dense)	(None, 256)	131,328	dropout_45[0][0]
batch_normalization_67 (BatchNormalization)	(None, 256)	1,024	dense_67[0][0]
dropout_46 (Dropout)	(None, 256)	0	batch_normalization_6
dense_68 (Dense)	(None, 64)	16,448	dropout_46[0][0]
batch_normalization_68 (BatchNormalization)	(None, 64)	256	dense_68[0][0]
ns (Dense)	(None, 1)	65	batch_normalization_6
fat (Dense)	(None, 1)	65	batch_normalization_6
inj (Dense)	(None, 1)	65	batch_normalization_6
loss (Dense)	(None, 8)	520	batch_normalization_6

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 59)]	0	[]
dense (Dense)	(None, 512)	30720	['input_1[0][0]']
dense_1 (Dense)	(None, 2)	1026	['dense[0][0]']
keras_layer (KerasLayer)	(None, 2)	4	['dense_1[0][0]']
batch_normalization (BatchNorm alization)	(None, 2)	8	['keras_layer[0][0]']
dropout (Dropout)	(None, 2)	0	['batch_normalization[0][0]']
dense_2 (Dense)	(None, 512)	1536	['dropout[0][0]']
batch_normalization_1 (BatchNormalization)	(None, 512)	2048	['dense_2[0][0]']
dropout_1 (Dropout)	(None, 512)	0	['batch_normalization_1[0][0]']
dense_3 (Dense)	(None, 64)	32832	['dropout_1[0][0]']
batch_normalization_2 (BatchNormalization)	(None, 64)	256	['dense_3[0][0]']
ns (Dense)	(None, 1)	65	['batch_normalization_2[0][0]']
fat (Dense)	(None, 1)	65	['batch_normalization_2[0][0]']
inj (Dense)	(None, 1)	65	['batch_normalization_2[0][0]']
loss (Dense)	(None, 4)	260	['batch_normalization_2[0][0]']





Results



Based on the performance of the models for both metrics and validation metrics:

- For the number of states and fatalities, the classical neural network outperforms the hybrid model
- However, the hybrid neural network model performs better in predicting the number of injuries and property loss

Model	Classical Model	Hybrid Model		
ns_mae	0.056931101	1.249194199		
fat_mae	0.261621058	1.296267316		
inj_mae	1.492939472	1.001213972		
loss_accuracy	0.608745873	0.687100865		
val_ns_mae	0.037830908	1.231608691		
val_fat_mae	0.181522265	1.245223057		
val_inj_mae	1.592500687	1.03306623		
val_loss_accuracy	0.63061595	0.705163043		



Conclusion

- This shows that while the hybrid neural network does have an advantage in predicting some variables, it does not show superiority in all categories
- Finally, we hope to further develop our models by using GPS satellite images as inputs to complement the independent variables (width, length, latitude, longitude, magnitude, and state names, etc)

