Wildfire Prediction Using Quantum Machine Learning

Jonas Trepanier
jjtrepan@ncsu.edu

Preston Aycock
pcaycock@ncsu.edu

Andres Ayala-Lagunas
aayalal@ncsu.edu

***Abstract*—Recognizing the ongoing global threat posed by wildfires, which are increasingly exacerbated by warming global temperatures, and the potential for quantum computing to assist with it, a variational quantum classifier was trained on US wildfire data to predict positive ignition events. The results were compared with a classic classifier to determine the applicability and limitations of quantum machine learning to this task.**

I. Introduction

A. Problem Definition

Wildfires are a growing threat both in the United States and abroad. The National Oceanic and Atmospheric Administration reports that wildfires caused more than 81 billion dollars in damage between 2017 and 2021 [1], and the scale has only grown since then. For the state of California, 2025 alone has seen more than 7,000 wildfires that have destroyed 500,000 acres of property and killed at least 31 people [2]. Since these fires are predominately caused by human interference or natural phenomena, they are difficult to predict and prevent effectively [3].

Machine learning offers a potential solution. By analyzing the conditions that make a location high-risk for wildfires, preventive and responsive measures can be taken to minimize any potential catastrophe. If a model can be trained to understand such conditions, it can then identify these high-risk locations and prepare emergency services to respond quickly and decisively if a wildfire occurs. The US Government Accountability Office already reports that some machine learning tools are being utilized for exactly this purpose [4].

This paper analyzes specifically whether quantum machine learning may be a viable strategy to this end. Quantum machine learning is a burgeoning computer science field focused on applying quantum computing techniques, such as superposition and entanglement, to classical learning problems to boost performance. By training a quantum classifier on US Wildfire data and comparing its results to a classical model, conclusions on the strengths and weaknesses of quantum machine learning can be drawn, both within and beyond the scope of wildfire prevention.

B. Quantum Reasoning

The potential benefits of quantum machine learning are numerous. Quantum entanglement may map large, complex datasets into relatively few qubits; drastically speeding up traditional learning methods and allowing models to find patterns in high-dimensional spaces. Moreover, as algorithms like Shor's demonstrates, certain problems that would take exponential time to solve classically can be done in polynomial time through quantum computing. This is a dramatic increase in efficiency and, while not applicable to every problem, demonstrates how quantum machine learning carries the potential to radically reduce the timesteps needed to analyze data relationships.

In the context of wildfire prediction, these theoretical advantages are especially relevant. The wildfire dataset used in this study includes many meteorological and environmental variables whose combined effects are not easily represented in classical feature spaces. Quantum circuits naturally encode multi-variable correlations through entanglement, allowing the model to represent complex decision boundaries without the explicit engineering of higher-order interaction terms. This provides a compelling motivation for exploring quantum machine learning beyond the classical limitations of fixed feature representations.

II. Literature Review

With specific respect to wildfire prevention, quantum machine learning offers several clear advantages over current classical learning techniques. For one, the ecological data needed to train a model is complex, high-dimensional, and updates in real-time, all factors that cause traditional models to struggle [5]. Quantum Machine Learning can handle these conditions in a quicker, more reliable way. This was shown by Sankardass, Tholkapiyan, Sudhakar, and their research team when they tested two Quantum Machine Learning models: Quantum Neural Networks (QNNs) and Quantum Support Vector Machines (QSVMs) with classical models when both were trained on the same real-time environmental dataset. The study found the two quantum methods outperformed the classical in both prediction accuracy and computation time [5].

These results are bolstered by Sakar's 2025 experiment, where a hybrid classical-quantum approach utilizing Variational Quantum Algorithms (VQAs) and Convolutional neural networks (CNNs) proved more accurate than a classical neural network on its own [6]. This shows not only the feasibility of implementing Quantum Machine Learning in wildfire prediction, but how it can improve upon existing classical methods in that specific task.

III. Problem Formulation

Building off the results from Sakar and Sankardass et al's foray into comparing quantum and classical machine learning, the problem this paper seeks to address is how applicable is quantum machine learning to wildlife prediction when compared to classical machine learning.

IV. Methodology

A. Overview

This paper's approach to analyzing the effectiveness of quantum machine learning hews more towards Sakar's experiment than Sankardass'. Using a Kaggle Dataset of meteorological records that either resulted in an ignition event or not [7], this paper performed binary classification using both a purely classical model and a quantum-classical hybrid which utilizes a Variational Quantum Circuit (VQC) that is tuned classically by gradient descent.

B. Classical Model

Our classical approach began with a single baseline model trained directly on the raw wildfire data without any feature engineering. While this provided a useful benchmark, its performance was limited due to the high dimensionality of the dataset and the complex interactions between meteorological variables. To address this, we introduced targeted feature engineering, adding interaction terms and aggregated environmental indicators that improved the model's ability to capture nonlinear ignition patterns.

Building on these gains, we expanded the classical approach to a full ensemble method consisting of 6 XGBoost and 6 LightGBM models. Each base learner was trained on the complete dataset of approximately 9.7 million samples, leveraging the efficiency of gradient-boosted decision trees for large-scale tabular data. An initial meta-learning strategy using logistic regression was tested to combine the predictions of the 12 base models; however, this approach did not yield optimal results. Instead, weighting each model's output by its F1 score produced significantly better balanced accuracy and overall performance. The final classical prediction was therefore a weighted combination of all ensemble members based on their individual F1 scores.

C. Quantum Model

The hybrid classical–quantum model uses the PennyLane library to train a Variational Quantum Circuit (VQC) classifier using classical gradient descent. The input features are encoded into the first 6 qubits using amplitude embedding. The ansatz then applies parameterized RY and RZ rotations to all 12 qubits (6 data qubits + 6 ancillary/processing qubits), repeated across 2–3 layers depending on the model configuration. After the local rotations, each layer applies a sequential CNOT chain that fully entangles all qubits from qubit 0 through qubit 11. Finally, qubit 0 is measured in the Z-basis, and its expectation value serves as the model's prediction. The model is trained using a weighted mean squared error cost function, and PennyLane computes analytic quantum gradients to update the variational parameters via classical gradient descent. Several of these circuits are run, then combined into an ensemble model similar to the classical approach.

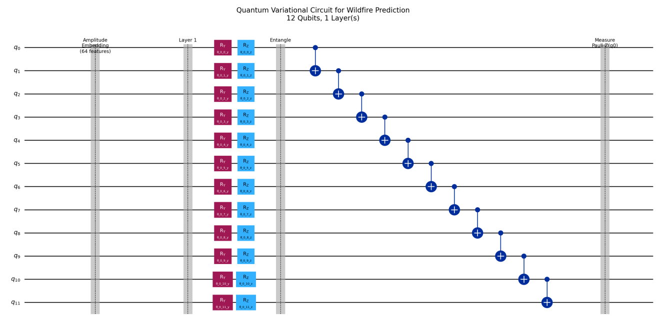

Fig. 1. Simplified diagram of a single layer of the variational quantum circuit used in the hybrid classifier. The circuit shows amplitude embedding followed by parameterized rotations and an entangling CNOT chain.

V. Results & Discussion

A. Training Comparison

Here, we present an overview of our training results. The metrics of comparison are the threshold, accuracy, balanced accuracy, F1 score, recall, specificity, false alarm rate, and finally strategy utilized for assigning weights.

Metric	Classical (Max Accuracy)	Classical (Max BA)	Quantum (BA)
Threshold	60%	48%	50%
Overall Accuracy	86.52%	76.47%	17.50%
Balanced Accuracy	77.38%	81.89%	52.88%
F1 Score	34.47%	28.91%	10.61%
Recall	67.16%	86.86%	92.45%
Specificity	87.60%	76.92%	13.31%
False Alarms	223,398	433,788	1,078,000
Strategy	Simple Average	F1-Weighted	Simple Average

For our purposes, comparisons are primarily based upon the balanced accuracy. We believe that this most accurately portrays our results due to the lopsidedness of the training data. As we can see, the accuracy of the quantum model is poor compared to classical model. In fact, every metric is significantly worse in the quantum model. There are many reasons for this, mostly consisting of computational constraints, that we will now discuss. The complex interactions that contribute to wildfires should lend themselves to entanglement correlations as well.

B. Training Summary

The performance gap between the classical and quantum models was substantial. The classical ensemble achieved significantly higher accuracy and balanced accuracy, whereas the quantum models consistently clustered around chance performance. Across all individually trained quantum classifiers, balanced accuracy remained narrowly confined between 48.8% and 52.0%, a range that did not meaningfully change even when initial weights, circuit depth, learning rate, or training schedules were varied. This tight clustering suggests that the quantum models were unable to progress toward any stable or meaningful decision boundary.

The largest barrier to effective quantum training was computational constraint. Because full-state simulation of the 12-qubit variational circuits was extremely expensive, the training process had to be split into multiple isolated sessions rather than executed as a single continuous optimization run. This fragmentation forced the optimizer to lose global context between sessions: gradients computed in one session could not build reliably on the previous session's progress, resulting in a form of "learning reset." As a result, the model was repeatedly exposed to only small fragments of the dataset and was never able to accumulate the consistent gradient information necessary for convergence.

This instability manifested clearly in the training trajectories. In one representative example, a model that had reached 42% accuracy abruptly collapsed to 17% accuracy in the next session. The loss oscillated between 1.0 and 1.1 throughout training with no sustained downward trend, further indicating that the optimization was not progressing toward a meaningful minimum. These behaviors were consistent across all circuit configurations. Modifying initialization strategies, increasing circuit depth, and adjusting learning rates had little measurable effect, implying that the model was not in a setting where such hyperparameter differences could influence learning.

The failure of individual models to meaningfully diverge also raises questions about the suitability of ensemble training under extreme data starvation. Because each model received limited and inconsistent exposure to the dataset, the ensemble's diversity was effectively superficial: different starting points did not lead to substantially different learned hypotheses. This makes it difficult to determine whether the ensemble approach itself was suboptimal, or whether the lack of computational resources overshadowed any architectural or methodological benefits. Under more favorable conditions—such as access to longer uninterrupted training runs or hardware-accelerated quantum devices—ensemble diversity and initialization strategies may have played a larger role.

Overall, the training results reflect a system dominated by resource limitations. The combination of limited per-session training time, an extremely large dataset, and the high cost of simulating many-qubit variational circuits prevented the quantum models from receiving sufficient data or optimization steps to depart from a near-random baseline. These constraints collectively explain the strong convergence toward 50% accuracy across models and the absence of any stable training dynamics.

VI. Conclusion

We believed a binary classification problem such as this would map perfectly into a quantum algorithm. Being a binary problem, the output would only be a single qubit. The features we have designed can be easily translated to quantum with amplitude encoding and are high-dimensional, potentially leading to an exponential quantum state space advantage.

Unfortunately, we did not see the improvements over classical that we expected. We believe that the biggest contributor to this was simply a lack of resources. Quantum simulation is incredibly expensive. Simulating a quantum machine learning algorithm takes more time and memory than the classical counterpart, so we encountered immense data starvation during training that forced us to train our model in several independent batches instead of all in one run, diminishing much of the feature recognition necessary for our model to be successful.

Our feature encoding also inhibited our results. As we had already defined and implemented certain feature interactions, there was a redundancy in the quantum advantage gained from these. Additionally, the normalization of features during encoding does lose some of the detail originally included. This lead to more barren plateaus that would take much more training time and other techniques (such as adaptive learning rates) to remedy. A big point of discussion can be made about the initialization of our parameters. Picking good initial parameters can help overcome these problems and drastically reduce the training necessary. We only used random initialization, but we believe research into optimal starting parameters could make a big difference in regard to barren plateaus.

Overall, our biggest limitation was in computational resources. It limited the amount of the dataset we could use, the length of training sessions, and the number of iterations per session. Without access to a real quantum computer, our algorithm was severely limited, but despite this, we were able to discover important points of failure in the algorithm itself than can be remedied in the future to hopefully improve our results even in simulation.

References

[1] Cybersecurity and Infrastructure Security Agency (2021), *Wildfires*, https://www.cisa.gov/topics/critical-infrastructure-security-and-resilience/extreme-weather/wildfires

[2] The California Department of Forestry and Fire Protection (2025) *2025 Incident Archive*, https://www.fire.ca.gov/incidents/2025

[3] National Park Service (2025) *Wildfire Causes and Evaluations*, https://www.nps.gov/articles/wildfire-causes-and-evaluation.htm

[4] US Government of Accountability Office (2023) *Artificial Intelligence in Natural Hazard Modeling: Severe Storms, Hurricanes, Floods, and Wildfires*, https://www.gao.gov/products/gao-24-106213

[5] Sankaradass, V., Tholkapiyan, M., Sudhakar, S *et al.* "Leveraging quantum machine learning for early warning systems in sudden environmental disaster prediction." *Quantum Inf Process* 24, 281 (2025). https://doi.org/10.1007/s11128-025-04894-4

[6] A. Sarda, "Implementing Hybrid Quantum Neural Networks for Accurate Wildfire Detection," *2025 17th International Conference on COMmunication Systems and NETworks (COMSNETS)* Bengaluru, India, 2025, pp. 1136-1141, doi: 10.1109/COMSNETS63942.2025.10885552.

[7] Firecast RL (2025) *US Wildfire Dataset (2014-2025)* https://www.kaggle.com/datasets/firecastrl/us-wildfire-dataset