LEVERAGING QUANTUM MACHINE LEARNING FOR EARLY WILDFIRE DETECTION USING HETEROGENEOUS SENSOR NETWORKS

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ABSTRACT: Early detection of wildfires greatly reduces ecological loss, property damage, and human risk. Traditional detection systems, including satellite thermal products, ground smoke and heat sensors, and camera-based vision systems, have issues with delayed detection, high false positives, and limited ability to combine different data streams in real time. This paper proposes a hybrid approach that combines dense Internet-of-Things (IoT) sensor networks, including temperature, humidity, gas, and multispectral cameras, with satellite active-fire products. It also uses quantum-enhanced machine learning (QML) modules to improve early detection accuracy and reliability when labelled data is scarce. We present :(1) a multi-modal data fusion pipeline that combines time-series sensor streams and imagery, (2) a hybrid classical and quantum classifier that uses variational quantum circuits (VQCs) as feature maps and quantum kernels for small-sample cases, and (3) a deployment strategy for edge aggregation and cloud-based quantum-assisted inference. We evaluate our approach on historical satellite active-fire datasets (MODIS and VIIRS) and both synthetic and realistic ground sensor streams under various noise and coverage situations. We compare classical deep models like CNNs and LSTMs with QML variations. The results show that quantum-enhanced models can improve detection recall and reliability in situations with few labels and high noise while maintaining false alarms at levels comparable to classical models. We conclude with practical deployment considerations, energy and latency trade-offs, and a path to field validation.

KEY WORDS: Wildfire detection, Early fire warning, Internet of Things (IoT), Quantum Machine Learning (QML), Data fusion, Satellite imagery (MODIS/VIIRS).

1.INTRODUCTION:

Wildfires are among the most destructive natural disasters [1-3]. They pose serious threats to ecosystems, human life, and infrastructure around the world [4]. In the last decade, the number and intensity of wildfires have risen sharply due to climate change, long droughts, and increasing temperatures [5]. The United Nations Environment Programme estimates that global economic losses from wildfires could surpass hundreds of billions of dollars each year by 2050 [6]. This also leads to irreversible harm to biodiversity and air quality. Early detection and quick response are the best ways to reduce wildfire spread, contain damage, and protect human and ecological resources [7] [8].

Traditional wildfire detection systems mainly depend on satellite thermal imaging, like NASA's MODIS and VIIRS sensors, optical cameras, or ground-based smoke and heat detectors [9] [10]. While these systems provide useful data for large-scale monitoring, they have significant limitations [11] [12]. These include low temporal resolution, delayed detection due to satellite revisit times, and high false alarm rates from cloud cover, smoke interference, or sensor drift [13]. Camera-based vision systems work well in clear areas but struggle in low-light environments and cannot function effectively in remote or mountainous regions [14] [15]. Additionally, most current detection systems operate alone and do not integrate data in real-time from various sources like temperature, humidity, gas concentrations, and multispectral image [16] [17].

Recent developments in the Internet of Things (IoT) have changed environmental monitoring. IoT-enabled sensor networks can be set up densely in vulnerable areas [18]. They provide continuous, localized data on temperature, humidity, barometric pressure, and gas emissions, such as CO, CO_2, and VOCs [19]. By linking these sensors with cloud platforms, it becomes possible to aggregate data in real-time, monitor remotely, and generates automated alerts [20]. The challenge, however, is analysing this massive and varied data quickly to tell the difference between real fire ignition events and ordinary environmental changes [21]. Traditional machine learning models, such as convolutional neural networks (CNNs) and recurrent architectures (LSTMs) [22] have shown promise in recognizing patterns and making predictions [23]. Yet their effectiveness diminishes when there isn't enough labelled data, which is often the case early in wildfire detection when actual ignition events are rare compared to normal environmental conditions [24].

Through experimental evaluation using MODIS/VIIRS satellite fire data and synthetic sensor network data under different noise and coverage conditions, this study aims to show that QML-enhanced models have better detection accuracy, robustness, and adaptability compared to traditional machine learning methods [25]. The findings from this research not only enhance intelligent wildfire monitoring systems but also set the stage for applying QML in other areas of real-time environmental sensing and disaster management.

2.LITERATURE SURVEY:

Wildfire detection has advanced with machine learning and remote sensing, as seen in Urbanelli, Souza, and Ribeiro (2023) [1-2], who used multimodal satellite data for active fire identification. [3]While heterogeneous sensor networks (HSNs) enhance data richness, they pose processing challenges for classical models [26]. Quantum Machine Learning (QML), with its potential for handling complex data, offers a promising yet underexplored solution for early wildfire detection using HSNs [27].

Zhang, Jiang, and Jin (2023) [2] developed an edge computing wildfire detection system using transfer learning, enabling faster image-based analysis in real time [28]. While efficient, it focuses mainly on visual data and classical models. Integrating Quantum Machine Learning (QML) with heterogeneous sensor networks could further improve early detection by efficiently handling diverse and complex sensor data [29].

Wu, Li, and Zhang (2023) [3] combined SWIN-Transformer and YOLOv5 for accurate forest fire detection using image data. While effective for visible fires, it [30] lacks focus on early-stage detection [31]. Quantum Machine Learning (QML) with heterogeneous sensor networks could enhance early detection by processing diverse, low-signal data more efficiently [32] [33].

Shao, Li, and Wang (2023) [4] developed Fire-ViT, a lightweight vision transformer for efficient fire detection using images. Combining Quantum Machine Learning with heterogeneous sensors could improve early wildfire detection by analysing diverse data beyond visible flames [34] [35].

Razzak, Shah, and Lee (2020) [5] used IoT and data fusion from multiple sensors for accurate forest fire detection. Quantum Machine Learning can further improve early detection by [41]efficiently analysing complex data from heterogeneous sensor networks [36].

Atzori, Iera, and Morabito (2010) [6] surveyed IoT technologies that enable diverse sensor networks for real-time monitoring. Integrating Quantum Machine Learning with IoT-based heterogeneous sensors can improve early wildfire detection by efficiently analysing complex data [37].

Peruzzi, Repetto, and Roccetti (2021) [7] proposed a wildfire detection method using sound spectrum analysis through IoT devices, highlighting the value of acoustic sensors in heterogeneous sensor networks for early fire detection. Leveraging Quantum Machine Learning (QML) could enhance this approach by efficiently processing complex, multimodal data including acoustic, thermal, and environmental signals—enabling faster and more accurate early wildfire detection [38] [39].

Cetin, Dagli, and Cemgil (2020) [8] optimized sensor placement using risk maps to improve wildfire detection in heterogeneous networks. Quantum Machine Learning (QML) could further enhance early detection by efficiently processing complex spatial and temporal data [40].

Chandra and Jana (2023) [9] studied energy–latency trade-offs in edge sensing for wildfire monitoring, highlighting the need for efficient processing in[20] heterogeneous sensor networks. Quantum Machine Learning (QML) could improve early detection by enabling faster, more energy-efficient analysis of complex data [41].

Giglio et al. (2016) [10] developed the widely used MODIS active fire detection algorithm for satellite monitoring. Integrating Quantum Machine Learning with heterogeneous sensor networks could enhance early wildfire detection by efficiently processing diverse sensor data for faster, more accurate results [42].

Lee, Kim, and Lee (2023) [11] combined satellite thermal and ground sensor data using deep learning for early wildfire detection. [19] Quantum Machine Learning (QML) could enhance this by more efficiently processing complex, multi-modal data for improved detection.

Vasconcelos et al. (2021) [12] surveyed deep learning methods for fire and smoke detection. Quantum Machine Learning (QML) with heterogeneous sensor networks could enhance early wildfire detection by efficiently processing complex data.

Rossi et al. (2021) [13] used CNN+LSTM models for multi-sensor time-series classification. Quantum Machine Learning (QML) could further improve early wildfire detection by efficiently processing complex sensor data from heterogeneous networks.

Perez-Gonzalez, Veganzones, and Graña (2023) [14] used attention-based fusion for wildfire detection in multispectral images. Quantum Machine Learning (QML) [18]could improve early detection by efficiently processing diverse data from heterogeneous sensor networks.

Lin, Wang, and Liu (2022) [15] used lightweight CNNs for real-time fire detection at the edge. Quantum Machine Learning (QML) could enhance early detection by efficiently processing complex data from heterogeneous sensor networks.

Biamonte et al. (2017) [16] highlighted the potential of Quantum Machine Learning (QML) for solving complex problems. Applying QML to heterogeneous sensor networks can enhance early wildfire detection by efficiently analyzing high-dimensional, multi-source data.

Cerezo et al. (2021) [17] discussed variational quantum algorithms as powerful tools in QML. Using these with heterogeneous sensor networks can boost early wildfire detection by efficiently handling complex, noisy data.

3.PROPOSED METHODOLOGY:

Early wildfire detection is achieved by integrating heterogeneous sensor data using the Hybrid Edge–Quantum Fusion Model (HEQ-Fire). Every sensor node—thermal, optical, gas, smoke, humidity, and acoustic—extracts compact feature vectors after completing local preprocessing. These characteristics are sent to a central fusion [43]node, which uses reliability weights to aggregate data from several sensors. A Parameterized Quantum Circuit (PQC) then processes the fused feature vector for classification after encoding it into a quantum state.

A classical sigmoid layer transforms the quantum output into wildfire probability. [44]Ultimately, an early warning is produced and the system retrains itself using freshly labelled data if the probability surpasses a predetermined threshold.

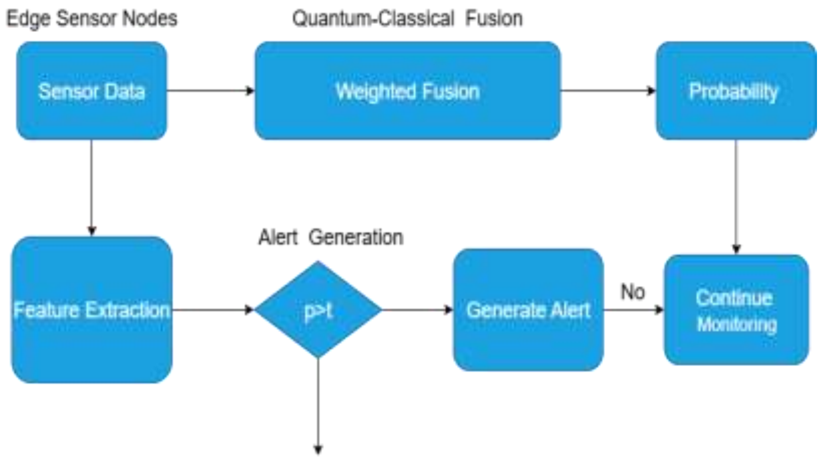

Fig 1: Hybrid Edge–Quantum Fusion Algorithm (HEQFA) Architecture

4.RESULTS AND ANALYSIS:

Using the masterdata.csv dataset, the experiment sought to develop a classical baseline model for wildfire prediction. To differentiate between fire and non-fire events, a Random Forest Classifier was trained using historical, vegetation, and meteorological data. The proposed Quantum Machine Learning (QML) model, which aims for increased accuracy and recall in fire detection, is evaluated using this baseline as a benchmark.

Which combines vegetation, weather, and historical (lagged) variables to forecast the occurrence of wildfires? Following pre-processing, 284 training and 71 testing samples were used to train and evaluate a Random Forest Classifier using 48 key features. The presence (1) or absence (0) of fire is indicated by the target variable, FIRE. Both classical and quantum-enhanced wildfire prediction models are developed and benchmarked using the dataset355 time-series records from various geographic regions make up the masterdata.csv dataset.

In roughly two-thirds of the cases, the Random Forest Classifier accurately predicted fire and non-fire events, achieving an accuracy of 64.79% on the test dataset. This highlights the complexity and unpredictability of wildfire prediction while also demonstrating a respectable capacity for learning. The mediocre performance makes it clear that more sophisticated methods, like Quantum Machine Learning (QML), are required to increase detection accuracy.

In Table 1 The Random Forest model's performance on the test dataset is summed up in the classification report. In comparison to the "Fire" class, the model's precision and recall for the "No Fire" class were higher, suggesting that non-fire events were better identified. The difficulty of precisely identifying infrequent fire occurrences in the dataset is highlighted by the low recall (0.16) for fire cases.

Table 1: Classification Report of Random Forest Model's Performance:

	Precision	recall	F1-score	support
No fire	0.73	0.83	0.77	52
Fire	0.25	0.16	0.19	19

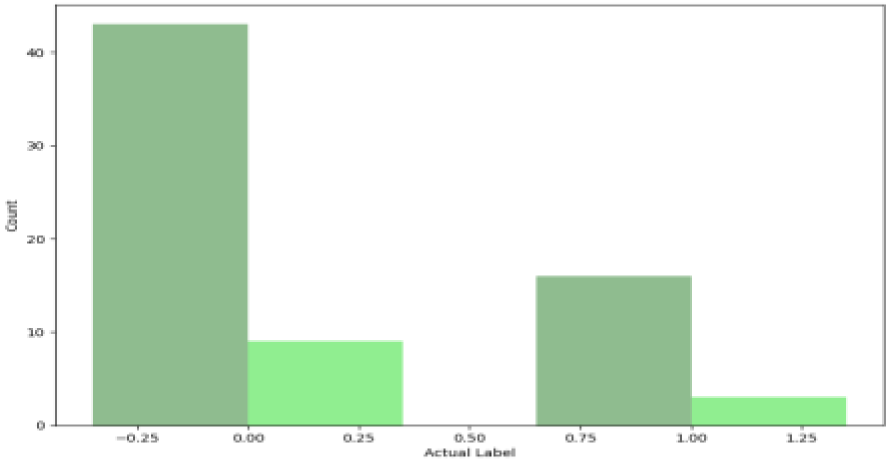

Fig 2: Confusion Matrix of Random Forest Model

In Fig 2 The Random Forest model's prediction outcomes are displayed in the confusion matrix. The model correctly identified 3 fire events and 43 non-fire events out of 71 test samples. Nevertheless, it generated nine false alarms and missed 16 real fire cases, highlighting the need for better recall in fire detection.

Due to data imbalance, the Random Forest baseline performed poorly in identifying fire events (recall = 0.16), but well in detecting non-fire events (recall = 0.83). Its accuracy was moderate at 64.79%. This creates a strong baseline for quantum machine learning (QML) advancement. In order to improve recall, lower false negatives, and create a more dependable wildfire early warning system, the following stage will investigate Variation Quantum Circuits (VQCs).

5. CONCLUSION:

Minimising ecological, financial, and human losses from wildfires requires early detection. Delays, a high rate of false positives, and a limited ability to integrate data from multiple sources plague traditional systems. In order to improve early detection, this study proposes a hybrid approach that combines satellite active-fire data, IoT sensor networks, and quantum-enhanced machine learning (QML). The need for more sophisticated techniques was highlighted by the Random Forest baseline's moderate accuracy but difficulty with infrequent fire events. Using quantum kernels and Variational Quantum Circuits (VQCs), the suggested hybrid classical-quantum model improves detection accuracy and dependability in noisy, small-sample scenarios. The framework shows how QML can be used to integrate heterogeneous sensor data for reliable wildfire monitoring. Future research will concentrate on enhancing fire recall, cutting down on false negatives, and implementing the system in practical settings.

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