Abstract—The effectiveness and dependability of real-time incident detection models directly impact the safety and operational conditions of the affected traffic routes. Recent advancements in cloud-based quantum computing infrastructure and developments in noisy intermediate-scale quantum devices have ushered in a new era of quantum-enhanced algorithms that can be utilized to enhance the accuracy of real-time incident detection. In this study, a combination of classical and quantum machine learning (ML) models is developed to identify incidents using connected vehicle (CV) data. The performance of the hybrid classical-quantum machine learning model in incident detection is compared to baseline classical ML models. The framework is evaluated using data from a microsimulation tool that simulates different incident scenarios. Results show that a hybrid neural network with a 4-qubit quantum layer outperforms all other baseline models considered in this study, even when training data is scarce. Three datasets made are DS-1 with enough training data, DS-2, and DS-3 without enough training data. The hybrid approach produces recall rates of 98.9%, 98.3%, and 96.6% for DS-1, DS-2, and DS-3, respectively. For DS-2 and DS-3, the hybrid model outperforms the classical models on average by 1.9% and 7.8%, respectively, for F2-score, a metric for the model’s ability to correctly recognize occurrences. These results indicate that in realistic scenarios with limited connected vehicles at certain times on specific roadways, the hybrid ML model performs better than classical models. As quantum computing infrastructure continues to improve, quantum ML models could offer a promising alternative for ML applications related to connected vehicles, especially when the available data is insufficient.

Index Terms—incident, real-time, connected vehicle, quantum, hybrid model.
I. INTRODUCTION

Efficiency and reliability must be ensured while detecting incidents to timely initiate an incident response to restore the desirable traffic operations in any roadway corridor. Incident detection for traffic roadways is one of the most significant problems using fundamental traffic flow diagrams, statistical, rule-based, and, more recently, machine learning models. The real-time incident detection and prediction accuracy of the models depends on the available data. Connected vehicles (CVs) can provide a plethora of real-time data, and having data from a limited number of CVs can be used to detect incidents [1,2]. In a data-driven and connected world, CVs will generate Basic Safety Messages or BSM data [3], collected by roadside units or RSUs in real-time using the available communication options. RSU, the roadside edge device, will collect data from CVs within its coverage area, and multiple RSUs can be used to create continuous and seamless coverage along a long stretch of a freeway. Data collected from the RSUs can be shared with a cloud-based traffic management system. As shown in Figure 1, once an incident occurs and BSM data are available from CVs, the incident detection algorithm runs in the cloud server. The information is shared with all approaching CVs.

![Fig. 1. Real-time incident detection with a hybrid model](image)

The widespread and successful demonstration of machine learning models and emerging CV technology have motivated the authors to use data-driven models to monitor incidents. However, machine-learning models can sometimes create false negative information due to the dynamic nature of incident occurrences. Developing a more accurate incident detection system Figure 1 Real-time incident detection with the hybrid model is always a target for transportation researchers. With the emergence of innovative quantum computing infrastructure and noisy intermediate-scale quantum devices, a series of quantum-only and hybrid (quantum and classical) models are now available to provide better incident detection accuracy. One such example of quantum computing-induced improvement is discussed in [4], where the authors have studied how to use the quantum-enhanced feature for a quantum machine learning model. Also, the quantum search space can be used for machine learning models by controlling entanglement and interference. This quantum search space is exponentially more significant than any classical computer. This research aims to develop and evaluate a hybrid neural network model, which includes classical and quantum neural networks, for traffic incident detection. In the hybrid model, a quantum layer is placed between two classical layers to improve the neural network’s performance in detecting incidents. The hybrid model will be evaluated against a classical-only neural network to measure the improvement due to the use of the hybrid model. A case study is conducted in this research using a microsimulation tool (Simulation of Urban Mobility or SUMO). With the microscopic simulation tool, multiple incident scenarios from a freeway section are simulated, and CV BSM data have been generated from a sample of the total simulated vehicles. The hybrid model is trained and later evaluated for different incident scenarios using these BSM data.

II. LITERATURE REVIEW

This section discusses the recent development of quantum machine learning models and earlier studies where classical machine learning models were used to detect an incident. To the authors’ knowledge, quantum machine learning models have not been applied for incident detection.

A. Quantum Machine Learning

Quantum deep learning gained interest in predicting atomic energies and chemical potentials [5]. Both Pang et al. and Van Nieuwenburg et al. used quantum AI to explore chromodynamics and phase transitions of matter [6] [7]. In order to verify signatures, Patel et al. deployed a Q-neural network (Q-NN) and contradicts classical machine learning techniques [8]. Q-NN achieved 95% accuracy, whereas the classical neural network (NN) model achieved 89% accuracy. Patel and Tiwari [9] utilized Quantum Binary NN (Q-BNN) model for breast cancer classification and compared it against Gaussian Processes, NNs, multilayer perceptron, support vector machine (SVM), etc. Q-BNN achieved above 95% accuracy, whereas other methods were less than 80% accurate. Li et al. used quantum-behaved particle swarm optimization with binary encoding and applied it to MNIST data [10]. The authors found that quantum-based methods provided higher accuracy compared to SVM. Chen et al.
used a quantum Convolutional Neural network (CNN) for image classification and reported higher accuracy (94%) than classical CNN (90%) [10]. Wang et al. showed that quantum stochastic networks (Q-SNN) could achieve better performance against classical networks classifying sentences [12]. Q-SNN was able to converge faster and with higher accuracy compared to classical SNN. No study has been conducted to use quantum machine learning for incident detection.

B. Traffic Incident Detection using Machine Learning

Based on our review, we have found that using machine learning models to improve incident detection accuracy is an active field of research. For example, Karim and Adeli compared the performance of the wavelet energy algorithm and California algorithm for the various rural and urban freeways [13]. They found out wavelet algorithm performed well-detecting incidents at an average 95% accuracy in under 2 minutes for urban and under 3 minutes for rural freeways. Performance was only low at 59% detection for rural two-way freeways for the 10-minute incident. Sheu [14] used fuzzy clustering-based to detect 27 types of 10-minute incidents. The author showed 100% accuracy in detecting incidents in less than a minute. The study was based on simulation data from a short 2-km 3-lane segment. Zhang and Taylor [15] proposed a data preparation and Bayesian Network-based incident detection framework that is adaptive to threshold values. The results showed a 92% detection rate with less than one false positive. The methods showed better results compared to MLF. Fang Ming and Han [16] applied BPNN using simulated data and achieved a 94% detection rate, five false positives, and less than a minute of detection time. Zheng et al. showed SVM’s detection performance in an imbalanced dataset and obtained close to 94 detection rates, two false positives, and less than a 3-minute detection time [17]. However, the authors did not compare the performance of SVM against other methods. Wang et al. [18] combined time series and SVM to detect incidents. The study reported an 80% detection rate with three false positives and less than 10 minutes of detection. Shang et al. [19] compared machine learning methods for incident detection. The authors’ hybrid method achieved a 96% detection rate, two false positives, and less than 3 minutes of detection time. Ensemble methods provided comparable above 90 detection rates, and long-short-term memory (LSTM) resulted in less than 70% detection. Jiang and Deng [20] proposed factor analysis and weighted random forest and obtained a 98% incident detection rate with one false positive. Fang et al. [21] applied deep learning methods. According to the study, deep learning models with the variable selection provided above 95% detection rate, less than one false positive, and less than a minute detection time. Chakraborty et al. [22] used semi-supervised learning to address trajectory classification for incident detection and achieved above 80 detection rates using video data. Yang et al. [23] applied an autoencoder and obtained a 90% incident detection rate, four false positives, and a 4-minute time to detection.

III. METHOD

Our incident detection framework relies on real-time CV data, which includes average CV speed and CV count. Using a simulation study, the framework is validated, and the classical-only and hybrid Q-AI models have been evaluated.

A. Incident Detection Framework

The incident detection framework relies on CV movement in specific corridor segments, referred to as zones. Zones are evenly distributed spatial segments along the corridor (as shown in Figure 2). Each RSU identifies the operational condition of each zone based on the CV data from that zone. Data are aggregated for each second. The incident detection steps are shown in Figure 3. The first stage is collecting real-time connected vehicle BSM data containing CV positions, CV speed, etc.

![Fig. 2. Incident detection using aggregated CV data](image)

![Fig. 3. Incident detection framework](image)

After that, the data is aggregated per zone. Therefore, it gives a zone-wise average value of CV speed and CV count. Six features are created for the target zone, its
upstream and downstream zones are made, and the corresponding values are extracted. These six features are the input to the incident detection model. The six features are the average speed and count of that zone, the average speed and count of the upstream zone, and the average speed and count of the downstream zone. These six features are input into the hybrid neural network containing classical and quantum layers. The model's output is a binary classification value, indicating if there has been any incident in the zone of interest. A quantum layer is used between classical fully connected neural network layers to develop the hybrid model. The quantum layer is formed using a quantum node, where a quantum function can be operated using quantum operators such as gates, quantum state preparations, measurements, and noisy channels. Using backpropagation, the parameters of the hybrid model can be optimized on a simulated or real-world quantum device. Finally, the observations from the quantum layers are measured and fed into another classical layer. This is how we create a hybrid model that contains both types of layers.

**B. Case Study**

1) **Simulation Model Creation**

![Fig. 4. I-85 road network in SUMO](image)

In this study, we have simulated a portion of the I-85 interstate between Greenville, SC, and Atlanta, GA, USA. We have gathered the road network data from OpenStreetMap. OpenStreetMap generates an OSM file containing all the information. We have used SUMO to simulate the interstate network. Netconvert and Netedit are used to design the road network appropriately. The interstate network contains three interchanges. Each interchange includes on-ramps and off-ramps for vehicles exiting and entering the interstate. Both northbound and southbound have two lanes in each direction, there are two lanes each. The arterials also have two lanes. The ramps are single lane. Figure 4 shows the road network considered in this study. After creating the network and generating traffic in SUMO, we created a method to aggregate the data by zone and collect zone-specific data. We divided the network into 56 zones, with 28 on the northbound and 28 in the southbound direction. The purpose of the simulation is to create a training dataset for the incident detection model and test the model's performance. Therefore, we first need to create incidents in the simulation.

In this study, we have simulated incidents by scheduling pairs of vehicles to halt on the roadway and block interstate lanes at different times during the simulation. When an accident happens on the road, some vehicles are usually stationary on the road, and other vehicles cannot go through the lane due to the stationary vehicles blocking their path. In this study, we have simulated this event by forcefully stopping pairs of vehicles for some time. After the incident duration has passed, the vehicles can start moving again. To show the effect of this scheduling in simulation, we show Figures 5, and 6. In Figure 5, two vehicles were halted forcefully using scheduling. Figure 6 shows the effect in the upstream and the downstream. A queue has built up in the downstream area due to the incident. In the upstream, there are no vehicles and no traffic flow. In Figure 7, we see that the downstream vehicles have started moving.

![Fig. 5. An incident happening on I-85 northbound](image)

![Fig. 6. Incident causing a queue buildup in the upstream](image)
2) Data Generation for the Incident Detection Models

After creating incidents in the simulation, we run the simulation and collect the raw CV data from the simulation. In this study, we have assumed 100 CV penetration. The data is aggregated by zone at first. This dataset contains zone-wise speed and vehicle count per second. Then we create the feature vectors by combining the data from different zones. We only consider the zone’s data, the upstream zone data, and the downstream zone data for each dataset. This creates a dataset of 70000 rows. However, this dataset is unlabeled. As we have created the scheduling of the incidents, we make a label feature and set the corresponding rows to 1, indicating the occurrence of incidents. This dataset is split into training and testing in two ways. At first, we take 40000 rows in the training set and 30000 rows in the testing set, and we call it DS-1. Next, we take 15000 rows in the training set and 55000 rows in the testing set. We call it DS-2.

The reason for creating DS-2 is that we want to evaluate the performance of a hybrid neural network when the available data is scarce. Quantum neural networks should perform well when there is a lack of training data for the model. We also create a third dataset, DS-3, by aggregating by time. In DS-1 and DS-2, we aggregate the data per second. In DS-3, we aggregate the data per minute. This gives us a shortened dataset containing only 1400 rows. We split the dataset again into training and testing, and the training set only has 150 rows, while the test set contains 1250 rows. This is done intentionally to test the machine learning models for extreme cases where there is a lack of data.

3) Incident Detection Models

The model architecture is shown in Figure 8. The input layer contains six neurons corresponding to the six inputs as discussed previously. The following three layers are dense classical layers, including 48, 32, and 4 neurons, respectively. After that, we add a 4-qubit quantum layer. The quantum layer takes the values from the 4-neuron classical layer as input and converts them to qubit values. The quantum circuit performs angle embedding and basic entangling. After that, these values need to be converted into classical values again, so we perform measurements to get classical values. Four values are extracted from 4 qubits, which are again input to the 4-neuron classical layer. The final output layer contains just one neuron, which gives a binary output corresponding to incident or no-incident. All the classical layers have rectified linear unit (ReLU) activation except the output layer, which has a sigmoid activation. Binary cross-entropy loss is used as the loss function in the model, which employs an Adam optimizer. The number of epochs is 20, and the batch size is 16. The data is normalized between 0 and 1 before it is fed to the model. The model is trained on three separate datasets, DS-1, DS-2, and DS-3. The training accuracy for the three datasets is 98, 99, and 99, respectively.

IV. DATA ANALYSIS

In this section, we will compare the performance of the hybrid (classical + quantum) neural network with other baseline models. First, we will discuss the implementation of baseline and hybrid models. Then, we will talk about evaluation metrics. As this is a binary classification task, we have searched the literature and identified the baseline models. We have used random forest (RF), support vector machine (SVM), extreme gradient boosting (XGB), and classical neural network (NN) as baseline models. We have implemented the RF and SVM models using the sci-kit-learn package in Python. For SVM, we have created two variations of the model, one with a radial basis kernel and the other with a 2nd-degree polynomial kernel. For RF, we have used 100 estimators. We have used classical layers of 48 neurons, 32 neurons, and one neuron for the classical neural network. The classical NN is implemented using Keras and PyTorch. For the quantum layer, we have used the PennyLane package in Python to simulate a quantum device in a classical computer. In PennyLane, qubit nodes
can be created using random number generators that mimic quantum qubits’ behavior. Then, it also allows the creation of quantum layers, which can be readily integrated with classical Keras layers. This allows for smooth model creation and generation. When evaluating the performance of the models, our primary focus is on the positive predictions, which signify the presence of incidents. Our evaluation metrics include true positives, false positives, false negatives, accuracy, precision, recall, and F2-score [24]. Each model is executed 30 times, and we gather the average values of these metrics for analysis.

A. Results for DS-1

First, check how the models perform for the original DS-1 dataset. As mentioned in the case study section, DS-1 is a per-second zone aggregated dataset containing 70000 rows of data, 40000 rows in training, and 30000 rows in testing. Table I shows that all the models perform very well in this scenario. This suggests that any ML model can be trained and optimized with sufficient training data to detect incidents accurately. The hybrid model achieves an F2 score of 98.7% and a recall rate of 98.9% on average. So, it is very suitable for incident detection with sufficient training data. Since the performance of other baseline models is very similar in precision, recall, and F2-score, we are not identifying any specific model in this section. All models, including the hybrid model, have good detection accuracy if sufficient training data exists.

| Incident Detection Model | TP    | FP    | FN    | Accuracy | Precision | Recall | F2-Score |
|--------------------------|-------|-------|-------|----------|-----------|--------|---------|
| RF                       | 557.9 | 0.6   | 11.1  | 0.999    | 0.999     | 0.980  | 0.984   |
| SVM (RBF)                | 545   | 0     | 24    | 0.999    | 1         | 0.958  | 0.966   |
| SVM (Poly, Degree=2)    | 556   | 3     | 13    | 0.999    | 0.994     | 0.977  | 0.981   |
| XGBoost                  | 559   | 0     | 10    | 0.999    | 1         | 0.982  | 0.986   |
| NN                       | 553   | 11.6  | 9     | 0.999    | 0.979     | 0.974  | 0.977   |
| Hybrid (2-qubit)         | 559   | 9.8   | 6     | 0.999    | 0.981     | 0.979  | 0.980   |
| Hybrid (4-qubit)         | 563   | 8.3   | 6     | 0.999    | 0.984     | 0.989  | 0.987   |

B. Results for DS-2

Since the models perform well when there is sufficient training data, we test the models for extreme cases when there is insufficient training data. We have created another dataset named DS-2, where the train-test split has been changed. There are only 15000 rows in the training set and 55000 rows in the test set. The results for this case are given in Table II. Here, we observe a notable improvement in the performance of the base models. The hybrid model with four qubits shows the most robustness by achieving an F2-score of 0.985, the highest among all the models. The hybrid model with two qubits also performs well, with an F2-score of 0.979. The XGBoost model performs well in terms of precision, but recall is more crucial in our study, so it has been compromised regarding the F2-score. On average, the hybrid model 3 with four qubits gets 936 true positives, 16 false negatives, and nine false positives. The lowest number of 4 false negatives is the most important achievement of this model. Overall, the hybrid model achieves a five-average recall of 98.3% and an F2 score of 98.5%.

| Incident Detection Model | TP    | FP    | FN    | Accuracy | Precision | Recall | F2-Score |
|--------------------------|-------|-------|-------|----------|-----------|--------|---------|
| RF                       | 14.1  | 0     | 3.9   | 0.996    | 1         | 0.783  | 0.817   |
| SVM (RBF)                | 1     | 0     | 17    | 0.984    | 1         | 0.055  | 0.068   |
| SVM (Poly, Degree=2)    | 18    | 11    | 0     | 0.989    | 0.621     | 1      | 0.891   |
| XGBoost                  | 0     | 0     | 18    | 0.983    | NaN       | 0      | NaN     |
| NN                       | 18    | 12.1  | 0     | 0.988    | 0.599     | 1      | 0.881   |
| Hybrid (2-qubit)         | 17.4  | 1.8   | 6     | 0.997    | 0.908     | 0.966  | 0.953   |
| Hybrid (4-qubit)         | 17.4  | 1.1   | 6     | 0.998    | 0.941     | 0.966  | 0.961   |

C. Results for DS-3

We have done further aggregation and aggregated the dataset by time, resulting in a per-minute dataset compared to a per-second dataset previously. This dataset is DS-3. This is the most extreme case of incident detection. Here, the number of rows has reduced significantly, and the number of positive labels is very scarce. Moreover, we have split 150 rows into training and 1250 rows into testing, so the models have very scarce data with few positive labels to learn the incident detection.
In this case, we see even more differences between the hybrid model and other baseline models. The SVM (RBF) and XGBoost models cannot learn anything from the dataset. Hence, they have recalls close to 0. The RF model has 14.1 average true positives but suffers from false negatives and lower recall. The SVM model with a 2nd-degree polynomial kernel predicts all 18 true positives but needs more precision since many false positives exist. The classical neural network also performs similarly. However, 2-qubit and 4-qubit hybrid models perform significantly better than all other models. The hybrid model with four qubits has an average false positive of 1.1 and an average false negative of 0.6. These results are promising since we are dealing with extreme cases with insufficient data to train regular machine learning models. The hybrid model with four qubits achieves an accuracy of 0.998 and an F2-score of 0.961, which shows that hybrid classical-quantum neural networks are very suitable for incident detection when there is a lack of data. Table III shows the result of this analysis.

D. Result

Numerous counterintuitive patterns are known to be mapped by quantum computing. The findings from this study demonstrate that hybrid classical-quantum neural networks provide significant advantages over classical neural networks and other machine learning models. Due to better pattern recognition provided by quantum layers, our hybrid models require relatively less training data and number of epochs to achieve higher performance with lower training time.

V. Conclusion

The utilization of quantum computing presents a promising opportunity for traffic incident detection. This study showed that, especially in the absence of training data for traffic incidents, a hybrid neural network with conventional and quantum layers outperforms previous models in terms of accuracy, precision, and F2-score. This strategy can be helpful in the real world since incident data is very scarce. Also, the hybrid model has fewer epochs, which correspond to a faster training process. This is useful for model updates and real-time applications. Overall, the hybrid model shows more robustness to different incident detection challenges, and it should be investigated more for improving roadway traffic safety.

With the continuing improvements in quantum computing infrastructure and algorithms, hybrid classical quantum machine learning models could be a promising alternative for connected vehicle-related applications when the available data for training is insufficient.

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