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Synergistic Integration of Quantum and Classical Machine Learning Models for High-Fidelity Asteroid Hazard Detection

Kuldeep Vayadande[1,*], Yogesh Bodhe[2], Amol A. Bhosle[3], Kavita Sultanpure[4], Geetanjali Yadav[5], Ajit R. Patil[6], Jyoti Jayesh Chavhan[7], Amolkumar N. Jadhav[8], Preeti Bailke[9]

[1,4,5,9]Vishwakarma Institute of Technology, Pune, Maharashtra, India
[2]Government Polytechnic, Pune, Maharashtra, India
[3]MIT Art, Design and Technology University, Pune, Maharashtra, India
[6]Bharati Vidyapeeth's College of Engineering, Lawale, Pune, Maharashtra, India
[7]MGM College of Engineering, Kamothe, Maharashtra, India
[8]Annasaheb Dange College of Engineering and Technology, Ashta, Maharashtra, India

Abstract

This research investigates the use of quantum machine learning (QML) to classify asteroids into non-hazardous and hazardous groups, which yields successful results in detecting the hazard. In addition to the complexity involved in analyzing orbits and physical objects, QML performs better than traditional machine learning in modeling the relationship between data. This method involves data-intensive preprocessing steps, such as feature selection by removing unnecessary features and correlation analysis to find predictors. Quantum circuits are used for specification and classification, and the standard evaluation is based on accuracy, recall, F1 score, and precision. A strong and weak method is provided by cross-validation and hyperparameter tuning. The best classical model here is the decision tree, which is a good model for high-resolution and low-budget social benefit with 0.883 accuracy, 0.955 recovery rate, 0.981 F1 score, and 0.883 sensitivity. However, the quantum model has made great leaps. AMSGRAD QCNN (Adaptive Moment Estimation with Gradient Thresholding Quantum Convolutional Neural Networks) achieves a non-uniform accuracy of 0.997, which is 13% higher than the decision tree with 0.984 accuracy, 0.955 recovery rate, and 0.981 F1 score. The accuracy of SPSA QCNN(Simultaneous Perturbation Stochastic Approximation) is 0.993, the recall is 0.974, and the F1 score is 0.977. This improvement shows the excellent ability of the quantum model to better resolve correlation data and, more importantly, to reduce false negatives in detecting stars. These results demonstrate the ability of quantum computing to analyze complex data and provide the best results. Our future work will focus on identifying and repairing quantum circuits, as well as exploring hybrid quantum classical models to improve model accuracy and interpretation. The findings open the door to new ways to predict the simplest solutions and the most powerful and accurate way to date of estimating the danger zone.

Keywords: Quantum machine learning, Quantum computing, Potentially Hazardous Asteroids (PHAs), Quantum Convolutional Neural Networks (QCNN), Space Hazard Assessment, quantum algorithm optimization, Recursive Feature Elimination(RFE)

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[1]Corresponding author. Email: kuldeep.vayadande1@vit.edu

1. Introduction

The increasing volume of asteroid-related data makes analysis more complex, and the need for more accurate, effective models to assess potential hazards is critical. High dimensionality is often the problem of complexity in asteroid data, limiting the efficiency of classical machine learning (ML) algorithms used to perform task. They often fail to capture subtle, complex patterns required for accurate hazard classification and prediction[1]. Recent years have seen the emergence of quantum computing as a feasible alternative to traditional computer techniques. Ideas in quantum physics help researchers process and analyse massive and complicated datasets in manners that could not even be perceived through ordinary systems because of quantum computing. Quantum machine learning (QML), which combines techniques from machine learning with quantum computing, has also been an interest. QML takes advantage

of quantum phenomena, like superposition and entanglement, for example, phenomena which enables the quantum system to analyses multiple answers simultaneously, thus making it possible to handle high-dimensional data more efficiently. Using quantum circuits to examine asteroid characteristics such as orbital paths, diameters, and physical characteristics. The study [2] investigates the use of QML for asteroid hazard prediction. The ability of QML to deal with complex data sets much better has been its primary advantage over traditional ML, as discussed in [3]. In comparison with classical computers, quantum systems can represent and analyse data much more compactly and in parallel. This will make it easier to find patterns that could be obscured in high-dimensional landscapes.

Quantum circuits allow for better encoding of asteroid data in the context of asteroid hazard prediction, which may mean improved classification accuracy with increased processing speed and scalability. This is very important when dealing with big datasets. In this study, we used more than a million records of asteroids. The study made use of Quantum Convolutional Neural Networks for feature mapping and classification to formulate the model. A type of quantum circuit especially useful for feature encoding in machine learning domain is the QCNN. While classical machine learning has long been in use, quantum circuits were especially designed to encode the asteroid data in a manner that would help in categorization, thus making high accuracy and computing efficiency possible. Our hybrid quantum-classical model, which therefore focused on finding a balance between speed and accuracy, was especially suited for large-scale asteroid hazard prediction tasks. The efficacy of the model has been tested using standard measures such as precision, recall, and accuracy for classifying the asteroids as hazardous or non-hazardous. The success of the categorization task was mainly based on these indicators. In order to ensure that the model was not overfitting and, therefore, generalizing well to unknown data, cross-validation as well as hyperparameter optimization has also been performed. High classification performance was attained through meticulous model optimization, which is essential for accurate hazard prediction.

2. Related Work

As more near-Earth asteroids (NEAs) are discovered, it is important to develop reliable methods to assess the associated risks. Machine learning models have traditionally been used to identify near-Earth objects, but they often struggle to cope with the complexity of high-dimensional data and astrodynamics.

Authors of [3] carried out an in-depth analysis of different QML techniques to identify potentially hazardous asteroids. The authors pointed out the limitations of current machine learning approaches and underlined the necessity of innovative QML methods for efficiency and accuracy in asteroid categorization.

This study proposes a Quantum Convolutional Neural Network (QCNN) to improve the precision and efficiency of impact risk evaluations for NEAs, leveraging the potential advantages of quantum computing. Since its inception, a vast and complexly structured universe has inspired curiosity in humans, offering countless scientific inquiry and theories for centuries. The field of astronomy has greatly contributed to our appreciation of the solar system, galaxy formation, and stellar life cycles. Space probes and rovers have provided necessary information concerning geology, atmospheres, and habitability of planets. Asteroids and meteorites provide windows into early stages of the formation of the solar system, especially those coming from regions like the Kuiper Belt and Inner Main Belt. These objects are considered pieces that formed the building blocks of planets, making it possible to study the conditions at the nascent phases of the development of planetary bodies. Despite the scientific significance of the asteroids and meteorites, they are a real threat to Earth. There has been a great rise of detection of such objects within the last decade. For example, facilities like the Zwicky Transient Facility (ZTF) already detected about 100 Fast Moving Objects per year. While catastrophic impact fears appear exaggerated, such historical events as the Tunguska explosion of 1908, with energy equivalent to 15 megatons of explosives, have devastated more than 2,150 square kilometres of Siberian Forest and show how serious this matter was at that time[6]. Thus, developing accurate predictive methods for asteroid trajectories becomes an urgent necessity, allowing for preemptive action against potential dangers.

With the advent of advanced space telescopes and comprehensive earth-based surveys, the identification rate of rogue objects and NEAs has surged. Currently, more than 1.8 million known asteroids include approximately 25,000 NEAs, with an average of 1,100 new NEAs discovered annually[7]. This growing detection rate emphasizes the necessity for accurate trajectory prediction methods to support collision avoidance strategies. Traditional trajectory prediction models rely on extensive mathematical modelling, incorporating parameters such as asteroid mass, velocity, and gravitational influences. While these models are reasonably accurate, they also depend on known variables and face challenges from random variations due to thermophysical changes, non-linear gravitational interactions, and observational inaccuracies.

A good application of ML to statistical estimation of asteroid orbital parameters and physical characteristics has been its promise in handling complex calculations. Yet, most algorithms as they stand pose a problem of computational intensity and scalability for large-scale computations. Quantum Machine Learning breaks the revolution that could be offered by quantum computers with intractable computations that are impossible to be solved by classical methods. Research work performed by Biamonte et al has verified that quantum algorithms enhance pattern recognition, data clustering and optimization tasks in astronomy and planetary defence. They proposed a QML approach based on Support Vector Machines (SVM) and Variational Quantum Classifiers (VQC) to overcome the limitations of the classical approaches. According to approach in [8], the identification and classification accuracy of dangerous asteroids will be

enhanced in this research. VQC implements quantum circuits and classical optimization to develop highly efficient hybrid quantum-classical classifiers for detecting complex patterns in data in high-dimensional space. VQC is a suitable choice for the prediction problem of asteroid hazards, especially due to its representation capability for such data and robustness against noise. This method optimizes categorization boundaries and enhances modelling of celestial phenomena by exploring larger solution spaces using quantum superposition and entanglement.

The method in [9] encodes orbital parameters and asteroid characteristics into quantum states and uses parameterized quantum circuits for classification. Preliminary results demonstrate that VQC outperforms traditional classifiers both in terms of accuracy and computational efficiency, making it a potentially significant tool for astronomers and planetary defence agencies. This approach has implications beyond enhanced potential for the prediction of asteroid hazards; it also helps understand solar system dynamics and strengthens the protection against potential impactors from space. In fact, it seems like the integration of QML, or specifically VQC, can revolutionize space security and prevent asteroid impacts by advancing quantum machine learning and planetary defence strategies.

The results of some studies as in [49] are encouraging; they show that the method is chemically accurate even with imperfect quantum inputs, such as those generated by present noisy intermediate scale quantum (NISQ) devices. This means a significant potential for quantum advantage, especially in simulating large molecular systems, which are presently intractable for conventional methods alone. Interestingly, the paper also explores quantum input robustness by how imperfections influence overall accuracy and gives strategies for optimizing wavefunction preparation in view of practical applications of quantum-classical hybrid algorithms toward computationally efficient chemistry, where a balance between efficiency and accuracy is paramount. In general, this research gives evidence to the capability of quantum computing in the augmentation of classical approaches to provide a bypass to limitations in molecular simulations. This approach is enhanced with an enhancement in treatment of electron correlation and an augmented scale of feasible simulations and could be termed as a step forward in using quantum computing abilities in actual practice in chemistry and material science. The research work [13] puts special focus on two QSVMs, QNNs and centres on their practice performance on smaller-sized real-world datasets; such an area remains hardly investigated in even empirical studies. The methodology consists of implementing both quantum and classical versions of SVMs and NNs on five datasets: Iris, Rain, VLDS, Custom, and AD HOC. The quantum models used several types of feature maps, such as Z-feature, ZZ-feature, and Pauli-feature maps. The work also evaluated different circuit depths and four different strategies for entanglement: none, linear, circular, and full. QNNs were designed as variational quantum circuits, and optimization was done with classical algorithms. Therefore, they can be tested on real quantum hardware and simulators. The results indicated that QSVMs, on average, outperformed classical SVMs by 3-4% in accuracy. More notably, QNNs outshone classical NNs, showing an average accuracy increase of 7%.

The Z-feature map, which operates without quantum entanglement, proved most effective across all datasets, suggesting that the current limitations of quantum hardware may hinder the application of more complex, entanglement-dependent feature maps. Despite the noise and imperfections in existing quantum technology, the study demonstrated that quantum algorithms are already showing promise. However, the research pointed to the need for further advancements to refine quantum circuit design and deepen the understanding of entanglement's role in handling larger, more complex datasets. Classical models were structured as entirely connected neural networks with one to three hidden layers, developed using PyTorch, with hyperparameters optimized through Ray Tune. The best validation accuracy from ten runs was selected for analysis. On average, classical NNs achieved an accuracy of 78% across the datasets. In the case of QNNs, various optimizers such as AMSGRAD, SPSA, BFGS, and COBYLA were tested, yielding different outcomes depending on the dataset. For the Iris dataset, nearly all optimizers reached perfect accuracy on both simulators and hardware. AMSGRAD showed the highest performance for the Rain dataset on simulators, while SPSA led on actual quantum hardware. BFGS was most effective for the VLDS dataset, and COBYLA achieved the best results for the Custom and AD HOC datasets, highlighting how dataset characteristics and size influenced performance outcomes. In summary, QNNs achieved an average accuracy of 85.8% on quantum simulators and 84.7% on real quantum hardware, outperforming QSVMs by approximately 5% and classical NNs by 7%, even with fewer parameters. These findings suggest that QNNs hold notable potential for improved efficiency, even with current hardware constraints.

The paper [15] investigates how ML algorithms can be integrated onto small satellite systems, with emphasis on the use of CubeSats, to improve onboard autonomy and data processing. CubeSats offer benefits such as cost and development time savings, but they also pose significant challenges such as computationally constrained resources and high vulnerability to environmental failures in space. In this work, the authors address these issues to improve the autonomy of satellites, their operational effectiveness and communications requirements using TensorFlow and TensorFlow Lite to onboard the installation of machine learning models that allow data analysis onboard. An approach based on the use of a dataset consisting of approximately 8,000 images of photos captured by the STP-H5/CSP mission aboard and the ISS was used. The images, through these photos, were used to train convolutional neural networks (CNNs) to execute image categorization tasks. To pace up the training time and achieve high classification accuracy, the authors applied transfer learning using pre-trained CNN architectures, such as MobileNetV1, MobileNetV2, Inception-ResNetV2, and NAS-Net Mobile. The trained models were bench tested against their performance metrics-accuracy, execution time, and memory usage-on a low-power, space-grade processor, namely Xilinx Zynq-7020, which is known for its deployment in CubeSat.

The experiment concluded that MobileNetV1 outperformed with regard to best overall performance on the dataset, excelling both in terms of accuracy and computation efficiency on the resource-limited space-grade processor. The tested CNN models all achieved more than 90% top-1 accuracy, and the model that achieved the best classification performance is MobileNetV1. It also ensured optimized use of memory and execution time, thereby confirming its potential for real-time onboard image classification tasks.

Recent attention in the field has been toward applying Quantum Machine Learning (QML) for the prediction of asteroid hazards. The Study [50] proposed a QML-based framework using VQC and Pegasos QSVC for the task of asteroid hazard prediction, thereby showing that QML might potentially improve prediction accuracy.

Our work improves upon these with the implementation of AMSGRAD and SPSA optimized Quantum Convolutional Neural Networks (QCNNs). This method not only increases the accuracy of classification but also reduces false negatives to a critical level in planetary defense. Quantum superposition and entanglement allow our model to capture finer orbital patterns and physical properties of asteroids than ever before.

3. Motivation

Ignoring the distribution of potentially hazardous asteroids (PHAs) can cause catastrophic damage. Asteroids approaching Earth pose a real threat with the potential to cause catastrophic damage. Similarly, the asteroid impact that wiped out the dinosaurs about 66 million years ago had global consequences. Finding and accurately classifying asteroids is difficult due to the complexity and size of the data. As of now, NASA's Near-Earth Object Program tracks over 27,000 near-Earth objects (NEOs), yet only a fraction of these are classified as hazardous, with many still awaiting full analysis. If incorrect classifications are made or if hazardous asteroids are missed due to limitations in existing models, the risk to Earth remains underestimated. In 2020, a study by the National Academy of Sciences highlighted the limitations of current asteroid detection technologies and emphasized the need for more sophisticated approaches to improve prediction and risk assessment. Thus, there is an urgent need for more effective classification systems. Neglecting this issue could delay detection of a potentially catastrophic asteroid impact, leaving inadequate time for mitigation efforts, such as deflection or evacuation. Improving asteroid classification using advanced methods, such as quantum machine learning, is critical to enhancing prediction capabilities and ensuring the safety of our planet.

The need to use quantum algorithms, especially quantum convolutional neural networks (QCNN), is due to the computational and representation problems encountered by modern classical models when performing daily asteroid data. Datasets characterized by high features, correlations, and correlations should be represented using advanced models to find useful models without causing too many problems or inefficient computations. Usual models like decision trees or support vector machines (SVM) rely on decision-making and evaluation parameters as the size of the data or the complexity of the process increases. For example, consider a decision tree with an accuracy rate of 88.2%. It does not simply model the subtle interactions between variables such as orbital eccentricity and albedo values. It also has an excellent balance between sensitivity and specificity. Paradigm shift to better structure the complex information space: superposition and entanglement. QCNN is designed as a classical neural network with hierarchically extracted features, but with the added advantage of quantum parallelism. This model is particularly suitable for hierarchical and spatial data, as well as orbital and positional data of asteroids, allowing QCNN to show what classical models would miss. The scalability of quantum algorithms is also an issue to consider. While deep learning models face huge computational costs when scaling, QCNN leverages quantum gates to perform exponentially, potentially speeding up training and inference. This quantum computing work is not only an alternative, but also an inevitable change in the search for state-of-the-art and reliable deployment.

4. Methodology

4.1. Data Accumulation and Exploration

This dataset focuses on rogue entities, which have been characterized by having specific recognizable features, channelled systematically through centres. The results are kept and updated safely through the Jet Propulsion Laboratory, which is a part of NASA Space Research Centre. This Kaggle dataset was prepared by Hossain and Zabed using resources managed by NASA JPL. The dataset has one million deep space entities, which are defined with 45 distinct parameters as well as two primary target indicators: the NEO Flag and the PHA Flag. In this context, of course, the focus is specifically on the Potential Hazard Flag as the primary target column for this analysis. Of the entries, 2,066 objects are considered as PHAs, while the rest, 956,458, remain non-hazardous. To overcome the computational challenges associated with segregation in quantum computers, a balanced sample with 4,132 entries was determined. This sample includes all 2,066 harmful objects, and an equal number of non-harmful ones, selected using random sampling methods. There is rich information related to space junk regarding orbital elements-like inclination and perihelion distance-topography, and identification specifics. The dataset was primarily pre-processed and cleaned with extensive results before analysis to ensure optimal performance for quantum algorithm-based evaluations.

4.2. Data Pre-processing

Originally, the dataset was stored in CSV format, the dataset was further processed and optimized by converting it into Feather, Parquet, and HDF5 formats, each selected for their unique strengths and limitations in handling and storage efficiency. The translation was done using optimized loading functions (Eq. 1) and pyarrow engine.

$$Raw\ Data \xrightarrow{Loading()} \begin{cases} Dataframe_{CSV} \\ Dataframe_{Parquet} \\ Dataframe_{Feather} \\ Dataframe_{HDF5} \end{cases} \quad (1)$$

Subsequently, each data frame underwent a comprehensive data cleaning process, with memory usage carefully monitored throughout as depicted in Eq.2

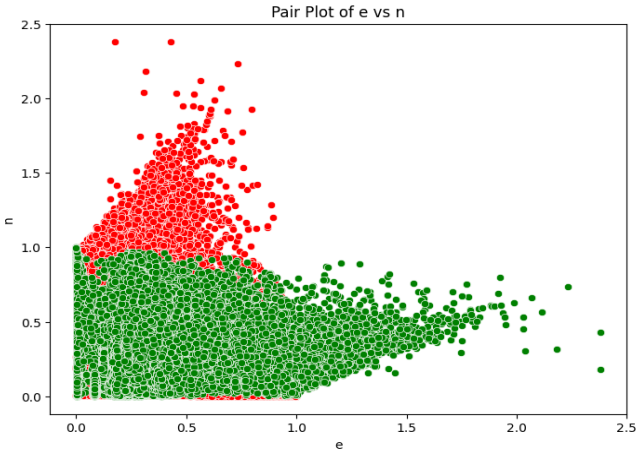
$$Dataframe_i \xrightarrow{NaN\ Detection,\ Strategic\ Data\ removal} df_{cleaned} \quad (2)$$

Let $Dataframe_i$ denote the dataset in one of the specified formats, where $i \in \{CSV, Parquet, Feather, HDF5\}$, representing the file formats used for data storage and exchange. Preliminary data includes two main steps: it detects missing or NaN (not a number) values and suggests removing irrelevant or useless data. This operation results in the cleaned data frame, denoted as $df_{cleaned}$, which serves as the refined input for further analysis. The notation represents the transformation process where raw data in any of the formats undergoes NaN detection and strategic data removal, yielding a cleaned version of the dataset. Although imputing missing values using statistical methods may appear to be a viable approach, it has been observed that eliminating such data points altogether often yields significantly better accuracy compared to addressing missing values through imputation techniques. To streamline the data, we divided columns into two categories: Eliminated Columns (L_e) that are columns removed due to irrelevance or excessive missing data and Retained Columns (L_r) that are columns deemed essential for further analysis by following process:

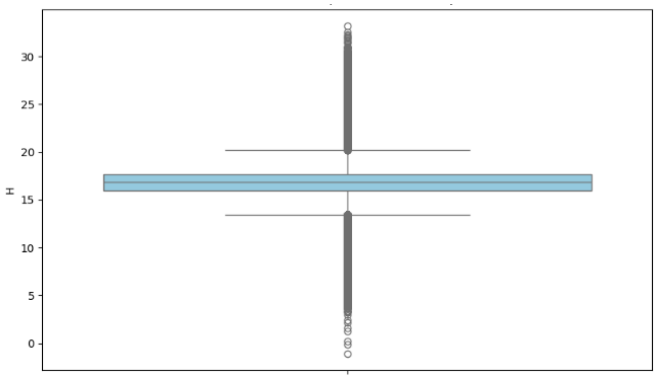
$$L_{NaN} \xrightarrow{Separation} L_e \vee L_r \quad (3)$$

$$DataFrame_i - L_e \xrightarrow{Reduction} DataFrame_{Reduced} \quad (4)$$

After completing the data cleaning process and finalizing the dataset, we used a combination of visualizations that include histograms, pair plots, box plots, and violin plots, to assess the nature of the data for further processing, as depicted in Figure 1. This visual exploration provided valuable insights into various aspects of the dataset, including identifying the univariate and multivariate distributions, as well as recognizing linear and non-linear relationships between features. The data distribution patterns helped guide the outlier removal process and influenced our feature selection strategy.



(a)



(b)

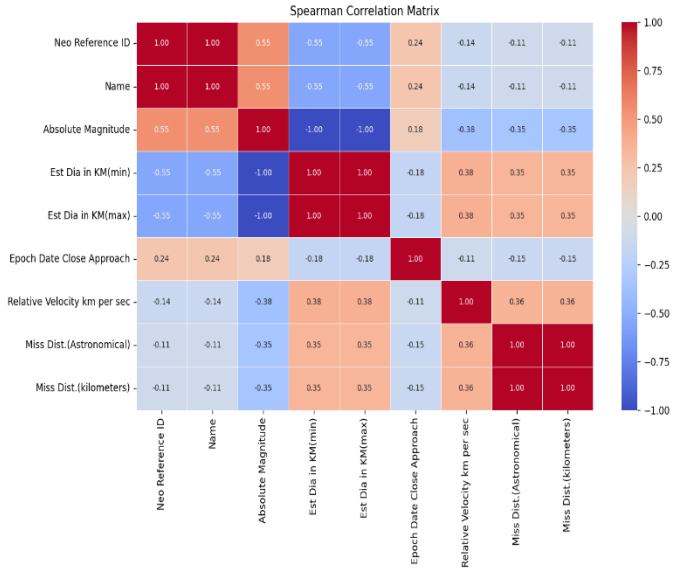
Fig. 1.(a) Pair plot showing the relationships between orbital eccentricity (e) & mean motion (n); (b)Box plot illustrating the statistical distribution and outliers of the absolute magnitude (H))

Additionally, we performed Pearson (in Eq.5) and Spearman (in Eq.6) correlation analyses, along with generating correlation matrices, to evaluate the linear and non-linear dependencies between the features.

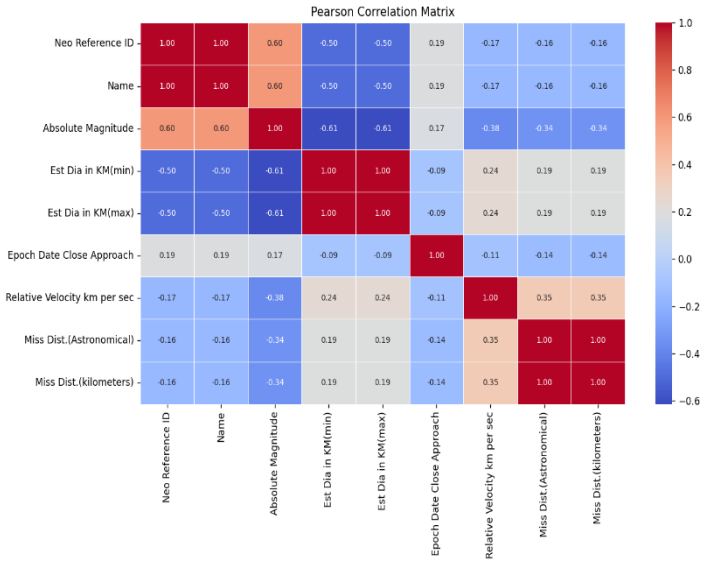
$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2(Y_i - \bar{Y})^2}} \quad (5)$$

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2 - 1)} \quad (6)$$

In the for-correlation coefficient formulas, X_i & Y_i are separate data points for respective variables X and Y. The symbols $\bar{X}$ and $\bar{Y}$ symbols represent the mean value of the variable. The symbol $\sum$ indicates that the function is carried out on every single data points. For Spearman rank correlation, d_i will be taken as the difference of ranks of corresponding values of X_i and Y_i, given as $d_i = rank(X_i) - rank(Y_i)$. The variable n refers to the total number of observations in the dataset. These then make up the framework to compute Pearson and Spearman correlation coefficients to evaluate the linearity and monotonicity of relationships between variables, respectively. Grounded on the outcomes of these analyses, we dropped certain features that exhibited low correlation or redundancy, ensuring a more refined and efficient dataset for model training. After a thorough visual assessment and correlation analysis, we implemented Isolation Forest and Autoencoders to effectively detect outliers within the dataset. It is quite effective for outlier detection in high-dimensional data because it can recognize instances that require fewer partitions to isolate. Conversely, autoencoders are unsupervised neural networks that minimize reconstruction error during the encoding and decoding of data. Because they emphasize data points that dramatically depart from the learnt reconstruction pattern, they are very good at identifying abnormalities.



(a)



(b)

Fig. 2. Heatmaps depicting the correlation among numerical features in the asteroid dataset: (a) Spearman correlation heatmap highlighting monotonic relationships; (b) Pearson correlation heatmap capturing linear relationships between variables.

For the Isolation Forest algorithm, contamination represents the percentage of data points expected to be considered outliers in the dataset, and it is set as 0.054 meaning that 5.4% of the data is assumed to be an outlier. The parameter n denotes the number of data samples; this is set to 200. The parameter max samples are set to 0.7, therefore 70% of the dataset is used to train each base estimator in the forest. Finally, a fixed random state of 42 ensures reproducibility of the results. For the Autoencoder, Dim is the size of latent space, or compressed representation and is determined as 30. The epochs are set to 200, referring to the iterations to train the model. The threshold is defined as 90, which probably relates to the reconstruction error above which points will be considered as outliers. These parameters determine the configuration and functioning of both anomaly detection approaches categories while allowing machine interpretation, each unique category is represented as a separate binary column, which allows models to process categorical data efficiently without introducing bias from any numerical hierarchies. The overall pre-processing ensured a clean dataset that is efficient, normalized, and optimally prepared for training and testing using any subsequent models. The observed mean and median values for the features are closely aligned with each other, thus suggesting a higher degree of normality and reduced collinearity. These changes also contributed to dimensionality reduction, thus further increasing the optimality of the dataset. At the last stages of pre-processing, all categorical features were encoded using one-hot encoding.

Table 1. Comparison of numerical features before and after outlier removal. E denotes eccentricity, a denotes semi-major axis, and q denotes perihelion distance

Metric	**Features**			
	Epoch	***e***	***a***	***q***
Mean Before	2458895.228	0.156	2.933	2.399
Mean After	2458999.803	0.148	2.684	2.289
Median Before	2459000.500	0.145	2.648	2.227
Median After	2459000.500	0.143	2.650	2.237
Δ Mean	104.575	-0.008	-0.249	-0.110
Δ Median	0.000	-0.002	0.002	0.010

One-hot encoding transmutes categorical variables to a binary matrix, ensuring that the data does not have any ordinality issues with the representation of categories while allowing machine interpretation. Each unique category is represented as a separate binary column, which allows models to process categorical data efficiently without introducing bias from any numerical hierarchies. The overall pre-processing ensured a clean dataset that is efficient, normalized, and optimally prepared for training and testing using any subsequent models.

4.2. Model Training

A list of pre-existing data should be evaluated to ensure that all support is equal to the study. Measurement is especially important in data with different measurement properties of indicators, otherwise the model will give unnecessary weight to many differences in quantities, leading to the study being dishonest. To solve this problem, we use MinMaxScaler, which transforms each feature to a certain range (typically [0, 1]) while preserving its distribution and correlation.

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{7}$$

In formula 7, X represents the original value of the characteristic and X_{min} and X_{max} are the minimum and

maximum values of the characteristic in the dataset. The result X_{scaled} represents the standard value of the characteristic. This model simultaneously transforms and redistributes the data such that all values are within the defined range, ensuring that no behaviour affects the model due to differences in measurement. This approach is very simple to preserve translation but is compatible with data value-aware models like support vector machines. Scaling, sampling, and measurement techniques are performed from datasets based on the distribution of different plots. These become necessary due to heterogeneity in the class, which can lead to a better performance model for the class in classification problems. Data balance ensures that the samples from each class are equal so that there is no risk of overfitting to most classes. In fact, sampling techniques such as under sampling, oversampling, or shuffling are used depending on the purpose of the distribution to ensure that each category is adequately represented in the data clocks.

With the numerical data points ready for training, dimensionality reduction was done to be able to overcome the challenges involved with QML. Since QML relies on working with quantum states, which becomes unmanageable with growing dimensions in the data, an exponential number of quantum resources required to represent high-dimensional data is one of the challenges. This problem is relieved by reducing the dimensionality of the data before attempting to apply the QML techniques, using the classical machine learning algorithms. Such reductions in dimensionality reduces the required quantum resources but also help diminish the intrinsic effects of noise and errors in the quantum system itself, thereby making the QML algorithms more accurate and feasible. After sampling and balancing, the feature importance is calculated using the classical machine learning models. These algorithms include K-Nearest Neighbors (KNN), Random Forest, Decision Tree, and SVM based on the requirement. Each of these algorithms was chosen for its capability to provide insights that the previous one could not. For instance, Random Forests and Decision Trees easily give interpretability in terms of feature importance metrics whereas SVM identifies complex boundaries between classes. Classical models provided insights in the relevance of features and what might guide the process to select those features mainly informative for the subsequent quantum computations. In doing so, the dataset was bridged between classical and quantum methodologies while being optimized to handle the challenges of quantum computing.

Encoding classical data into quantum states allows us to use quantum algorithms with the help of quantum machine learning for resolving non-quantum challenges such as categorization. There are many data encoding techniques, each with their own advantages and disadvantages depending on the specific problem. The best way to access classical information in quantum systems efficiently and cost-effectively is through QRAM. However, due to the increased sub-memory size and system complexity, it needs to be used. Grover encoding requires the encoder to use the Grover search algorithm to search for random data, but it cannot be used for data transformations required for machine learning.

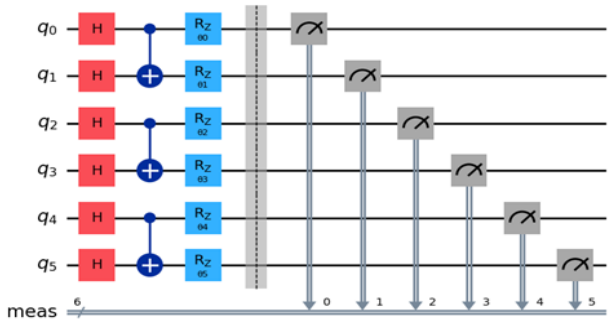


Fig. 3.A 6-qubit quantum circuit: Hadamard gates produce superposition in qubits; CNOT gates establish entanglement between qubits; and the parameterized $R_z(\theta)$ rotations introduce a phase shift. Completed with measurement of all the qubits, the circuit produces a classical output.

Density matrix encoding encodes classical messages into quantum entangled states. In other words, it is useful in terms of negative information and probability, but computationally expensive because quantum states have long dimensions. Data is mapped to quantum states, especially when dealing with periodic or high-dimensional distributed data. QFT uses multiple passes to combine the data, allowing correlations in the data to be implemented using quantum superposition and entanglement. This is especially true when dealing with large datasets such as star signatures, where traditional models fail to capture some relationships between variables in a different way. QFT maps data into the Fourier domain, so quantum algorithms can process the same data with fewer resources, resulting in better performance than traditional algorithms. QFT also always stores the current time in a different format. Therefore, QFT is the best encoding strategy for large, complex data, such as that often used in asteroid classification, where the data can still be represented accurately and efficiently.

$$|\psi\rangle = \sum_{k=0}^{N-1} c_k |k\rangle \tag{8.1}$$

$$QFT(|\psi\rangle) = \frac{1}{\sqrt{N}} \sum_{j=0}^{N-1} \left(\sum_{k=0}^{N-1} c_k e^{2\pi i \frac{jk}{N}} \right) |j\rangle \tag{8.2}$$

In fact, QFT is the quantum edition of a separate classical Fourier transform that transforms a quantum state in computational basis to its representation in the Fourier basis, as represented by Eq.8.1 and Eq.8.2. The total dimension of the space of the quantum state is denoted by *N*. Normally one finds it as for an *n*-qubit system. These coefficients are the amplitudes of the input state and denote the indices for the quantum basis states. The exponential term seems to hint at a good way of computing the relationships between states. This transformation is the essence of quantum algorithms, such as phase estimation and integer factorization. Encoding data points as quantum states allows the model to probe and capture complex relationships in data. Normalize features into

rotational angles and prepare the dataset for quantum processing and enhance the presentation of information in a multi-dimensional space of quantum states. Through these circuit simulations, we come to realize the encoding process which ensures data is optimally conditioned to have proper application of quantum algorithms; hence it spans from classical pre-processing techniques to the widely known capabilities of quantum computing in developing robust quantum models. This essentially meant a critical turning point in merging classical and quantum approaches to attack challenging classification problems with better accuracy and more rapidness.

The quantum circuit created, uses a simple quantum gate to create a quantum convolutional neural network (QCNN) architecture. While many other quantum circuits exist for similar tasks, this particular circuit strikes a balance between the efficiency and effectiveness of existing quantum devices. In contrast, circuits such as quantum support vector machines (QSVMs) employ quantum kernels to represent classical information into high-dimensional quantum feature spaces, but these tend to be more complex and require prioritization. Variational quantum feature solvers (VQEs), on the other hand, are designed for development problems rather than machine learning, making them unsuitable for classification or reprocessing. Deep QCNNs typically use multiple layers of entanglement functions and quantum filters, which, while powerful, often require assistance and can suffer from quantum noise and decoherence challenges with existing equipment.

The reason quantum circuits use Hadamard gates for superposition, CNOT gates for entanglement, and parameterized Rz gates for adaptability is because they are simple and efficient. Hadamard gates provide superposition, allowing qubits to represent multiple states simultaneously, thus achieving quantum parallelism. CNOT gates create entanglement, a quantum structure that essentially allows qubits to describe states at multiple locations. The parameterized R_z gate gives the model the flexibility to adjust and adapt to the data during training, much like weight updates in a classical mechanical model. The choice of these gates ensures that the model remains robust, flexible, and well-suited to quantum machine learning. It is often affected by noise and the limited number of qubits. More complex models may require more qubits and entanglement, which increases the quantum material required and can be affected by quantum noise, leading to incorrect results. Simple models reduce the risk of overfitting and reduce the error caused by quantum noise, which is important in today's popular era of medium-scale quantum (NISQ) devices. They also provide practical solutions by focusing on quantum principles while making them easy to use. This makes them highly scalable and flexible as quantum hardware continues to evolve. Finally, this electronic design offers great advantages in terms of efficiency, simplicity, and usability, making it an ideal candidate for mature quantum machine learning in the future.

$$R_z(\theta) = \begin{pmatrix} e^{-i\theta/2} & 0 \\ 0 & e^{i\theta/2} \end{pmatrix} \tag{9}$$

For every qubit in the quantum circuit, it applies the parameterized rotation gate $R_z(\theta)$ (Eq.9) where θ_i for i-th qubit. Because rotation gates are always phase shifts, the relative phase between the components of the quantum state depends on the phase factor $e^{-i\frac{\theta}{2}}$. This ensures that the rotation takes place in the proper direction and that the quantum state can really evolve in the space of the Bloch sphere. The parameters θ are then updated in the training process to be able to fit the quantum state, so that the QCNN will learn and adapt and have more possibilities to find more solution space, increasing performance by lowering the error. Finally, all the qubits are measured and collapse the quantum state to get the final output for analysis or classification. An optimization algorithm to find the best QCNN model was AMSGRAD and SPSA. These were chosen because of their strong abilities in stabilizing training and handling high-dimensional parameter spaces. The AMSGRAD optimizer is a variation of Adam that modified the second moment estimates to be non-decreasing, ensuring convergence stability.

$$\theta_{t+1} = \theta_t - \eta \frac{m_t}{\sqrt{\hat{v}_t} + \epsilon} \tag{10}$$

In AMSGRAD update rule (Eq.10), θ_t is the parameter vector at iterator t, and η is the step size, meaning the learning rate. It provides an exponentially weighted average of past gradients, which is essentially the first moment m_t, and $\hat{v}_t$ is the corrected second moment, or the maximum over past squared gradient averages to stabilize at times of update. Finally, ϵ is a small constant added to prevent division by zero during normalization of the gradient. This is trained at a learning rate of 0.1 and 100 as the maximum number of iterations where AMSGRAD updated parameters for the QCNN circuit obtained from a 6-qubit quantum circuit to achieve smooth convergence during training. Meanwhile, Simultaneous Perturbation Stochastic Approximation (SPSA) is excellent at noisy high-dimensional optimization problems by approximating gradients through random perturbations.

$$\theta_{k+1} = \theta_k - \alpha_k g_k \tag{11.1}$$

$$g_k \approx \frac{f(\theta_k + c_k\Delta_k) - f(\theta_k - c_k\Delta_k)}{2c_k\Delta_k} \tag{11.2}$$

For SPSA, as depicted by Eq.11.1 and Eq.11.2, θ_k is the k-th iteration of the parameter vector and αk the learning rate, which controls the size of each updating step. The stochastic gradient g_k update is derived from $f(\theta)$, the value of the objective function at a perturbed version of the current parameter. The amount of perturbation is controlled by ck. The perturbation Δ_k, typically with a Rademacher distribution with values ±1, is a vector which is randomly generated. These parameters thus combine to provide an estimate of gradients of high-dimensional optimization

problems that could be too expensive to compute exactly. The parameters of the game with SPSA are as c = 0.1 and α=0.5, with a maximum number of iterations 100.

5. Result and Analysis

5.1. Experimental Setup

A 32-qubit context-aware QASM simulator and seven-qubit publicly available quantum processors spread across three different locations were among the quantum resources used in the experimental setting for this investigation, which was carried out utilizing the IBM Quantum experience cloud platform. These resources also provided the computational power required for in-depth simulations and experiments.

Several repeated runs were performed to assess the performance of algorithms in a thorough manner. This process involved testing the algorithms across different dataset sizes to evaluate their performance and efficiency on various quantum systems. It was found that the available Noisy Intermediate-Scale Quantum (NISQ) devices are not sufficient to perform an analysis on larger, high-dimensional datasets as part of Quantum Machine Learning (QML) algorithms. NISQ devices with up to seven qubits can be used effectively without significant noise or errors while keeping the computational time much shorter and allowing dataset sizes in between around 5,000 and around 10,000 records. The expected simulation must consider, the unique constraints and properties of each quantum system to capture the real-world behaviour of the implementing algorithm. This means that certain properties and limitations apply to all quantum applications. Simulation and test functions are supported by the QISKIT library. There is quantum Fourier coding that can map 16 quantum bits and 9 inputs to the quantum space. Quantum convolution kernel is used for data processing and the panel structure is associated with the efficient ANSATZ product. QISKIT's sampling tool is measured and runs over 100 iterations; ANSATZ repeats this twice to ensure the depth and expressiveness of the circuit. This configuration is suitable for quantum machine learning or optimization.

Runtime services are Next, the "General Parameters" section describes the structure and configuration of the quantum algorithm. Qubits are the essence of quantum information and are set to 16 qubits for the cluster simulation, which shows the complexity of quantum circuit analysis. The specific mapping used here is quantum Fourier coding, a method of mapping classical data to quantum states using the Fourier transform, which is commonly used to encode data in quantum machine learning. The number of features represents the number of classical features that go into the quantum circuit, and in this case, it is set to 9. Kernels define the type of quantum operations used for the features encoded in this language, quantum convolutional kernels are particularly used for tasks such as image recognition and classification in quantum machine learning. Ansatz refers to the initial quantum circuit used to estimate the solution, and for this site, hardware-optimized Ansatz is chosen, a method for optimizing quantum circuits in the hardware world. The model refers to a way of sampling the quantum state after the quantum circuit has been implemented. Iterations does not indicate how many times the quantum algorithm is run, in this case it is set to 100, providing more data points to increase the accuracy of the results. Finally, the Reps parameter defines the number of repetitions or iterations of certain steps in the quantum algorithm, here 2 repetitions are used to increase the strength of the quantum results.

Table 2. The Simulation Parameters and their respective values that were utilized for this study.

Parameter	Value
Quantum Parameters	
Cloud Service	IBM
Quantum Computer	qasm simulator
Fundamental Parameters	
Qubits	16
Feature Map	Quantum Fourier Encoding
Number of Features	9
Kernel	Quantum Convolutional Kernel
Ansatz	Hardware-Efficient Ansatz
Sampler	Qiskit's Sampler
Optimizer one	AMSGRAD
Optimizer two	SPSA
Iterations	100
Reps	2

Table 2 provides detailed information about the parameters related to quantum configurations, especially for quantum circuits running on the IBM Cloud Quantum Computing Service. The first row introduces the quantum computer parameters and sets the stage for the following concepts. IBM Cloud Service refers to the email address associated with the account used to access the IBM Quantum Computing Platform. Quantum computers do not define a specific simulator to be used; in this case, the QASM simulator, a tool used to simulate quantum circuits and obtain measurements in the context of quantum computing.

5.2. Model Evaluation

Testing is necessary to quickly compare samples. It allows the performance of the model to be compared globally on test and training data. This simplifies the process of creating a good training model that will be effective. Therefore, evaluation is important to ensure the validity and reliability of the model, especially when the performance of the model is well understood. The following discussion describes the evaluation criteria used to select the best quantum machine learning model from a set of candidate algorithms, including algorithms with different hyperparameters. Since the given function is a binary classification function, F1 score, accuracy, recall and confusion matrix constitute the performance measures. F1 Score If the data set is unequal, the

best measure is F1 score because it calculates the correlation between the true and the inverse. It has the advantage of considering the ability of the model to avoid errors because it measures the correct prediction as a percentage of all good predictions. Sensitivity, often called recall, is the number of true positive events predicted by a model and can be an indicator of the model's ability to correctly identify the entire layer of events. More information about the resource allocation model can be obtained from the confusion matrix, which is a tabular summary of true positives, negatives, true negatives and false positive predictions. Together, these metrics provide a good assessment of model performance to determine the best QML model.

The confusion matrix is a summarized measure of the model's classification function, describing four elements of its results. There are: TP is called true positive, meaning correctly classified positive examples. In this case, the main goal is to determine whether the asteroid is dangerous or not, so mark it as "1". The change in the model's performance in the confusion matrix is due to the difference between the algorithm features and the training quality, which will be more significant (TP > TN), higher specificity (TP < TN), or equal distribution (TP - TN). Calculates the proportion of true positive events or true positive events identified as expected. Similarly, the proportion of true negative cases that are correctly classified is measured as true or true negative. Therefore, the balance between sensitivity and specificity is important for effective PHA detection and minimizing false positives. In machine learning, precision, recall, and F1 score are important metrics, especially for task classification. These metrics provide important information about the effectiveness of the model in classification. Regression measures the ability of the model to find all good problems, while accuracy measures the ability of the model to predict good cases. The F1 score is particularly useful for evaluating models because it provides a compromise between precision and recall. Understanding and interpreting these metrics is important for researchers to accurately assess the strengths and weaknesses of their models and to aid in model selection and development decisions.

Let the following notations be used: σ (True Positives), λ (True Negatives), χ (False Positives), and θ (False Negatives). The definitions of precision (ρ), recall (τ), and F1-score (Λ) are given as:

$$\rho = \frac{\sigma}{(\sigma + \theta)} \tag{12.1}$$

$$\tau = \frac{\sigma}{(\sigma + \theta)} \tag{12.2}$$

$$\Lambda = \frac{2 * (2\sigma)}{(2\sigma + x + \theta)} \tag{12.3}$$

These expressions provide a quantitative view of the model's ability to correctly identify positive cases, balance between true positive predictions, and the trade-off between precision and recall. Another key measure of evaluating the performance of a classification algorithm is its accuracy, especially when the task may involve identifying hazardous asteroids. The accuracy measures the number of correctly classified positive and negative cases against all those considered. Such precise predictions are essential: misclassifying harmless objects as hazardous without cause can lead to alarm unnecessarily, whereas failure to classify hazardous objects correctly can have serious implications. The formula for accuracy is expressed here as:

$$\kappa = \frac{(\sigma+\lambda)}{(\sigma+\lambda+x+\theta)} \tag{13}$$

This equation (Eq.13) shows the ratio between positive and negative values for all cases, provides a measure of the overall performance of the model, and helps compare different models for the task of determining the formation of hazardous asteroids.

Table 3. The Comparative Performance Metrics Of Several Classical And Qcnn, Evaluated Using Precision, Recall, F1-Score, And Accuracy

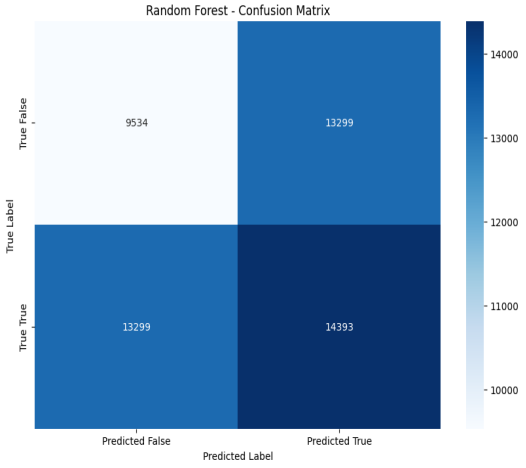
Model	***Precision***	***Recall***	***F1-score***	***Accuracy***
Random Forest	0.825	0.834	0.830	0.834
SVM	0.774	0.771	0.773	0.776
KNN	0.799	0.804	0.801	0.801
Decision Tree	0.883	0.884	0.883	0.882
AMSGRAD	0.984	0.955	0.981	0.997
SPSA	0.952	0.974	0.977	0.993

The table 3 shows the comparison metrics evaluated in terms of precision, recall, F1 score, and accuracy for machine learning and quantum convolutional neural network (QCNN) algorithms. Random Forest algorithm is designed as a reliable model for classical performance as it offers a balanced evaluation with precision of 0.825, recall of 0.834, F1 score of 0.830, and precision of 0.834. SVM is effective but scores lower with accuracy of 0.776, showing a minor performance compared to other methods. KNN (K Nearest Neighbor) model performed well with F1 score of 0.801 and accuracy of 0.801 but fell behind more powerful tree models. Among the classical models, decision tree algorithm performs best in terms of high performance, recovery rate, and its F1 value is close to 0.883 and accuracy value reaches 0.882, indicating a strong capacity in knowledge sharing. AMCQ-CNN(Attention-Mechanism-based Convolutional Neural Network) outperforms the classical model with an

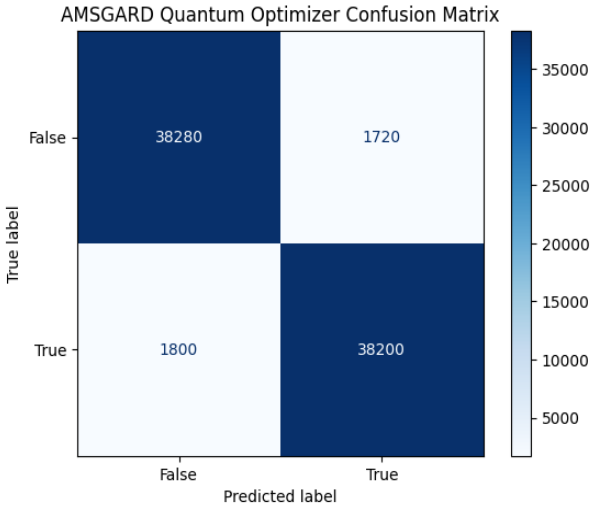
uncertainty of 0.984, a recall of 0.955, an F1- score of 0.981 , and an accuracy of 0.997, indicating that it can be very accurate. The same applies to SPSA QCNN (Simultaneous Perturbation Stochastic Approximation) with a precision of 0.952, a recall of 0.974, an F1-score of 0.977, and a precision of 0.993. This shows that quantum-based models have very good distribution capabilities and thus have an advantage over traditional methods when dealing with complex data.

5.3. Model Evaluation

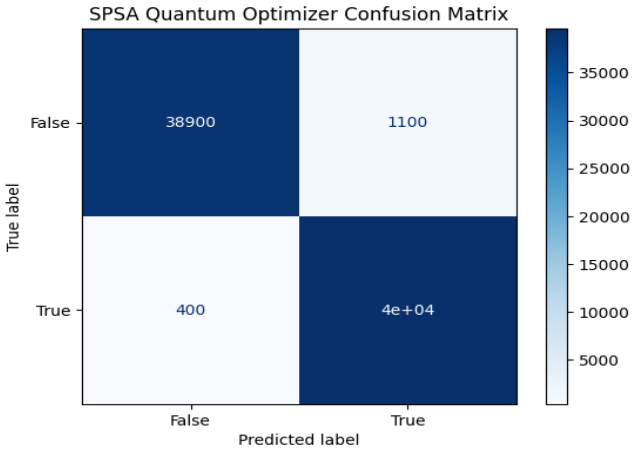
5.3.1 Confusion Matrices



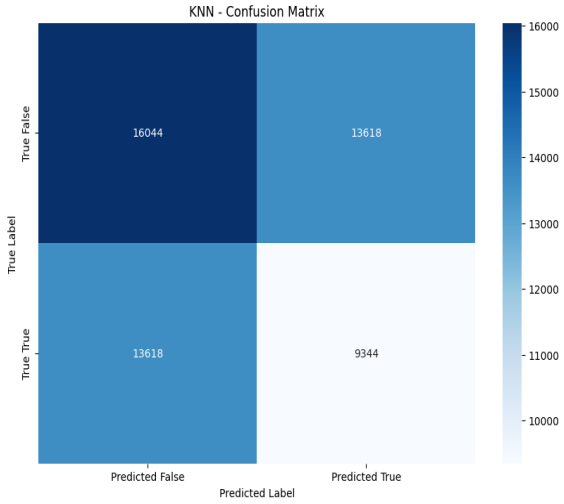
(a)



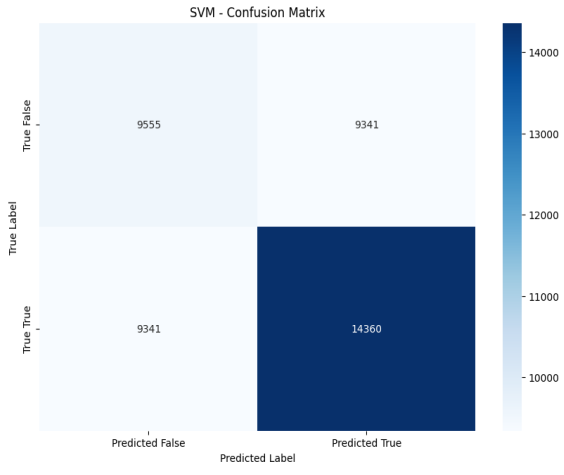
(b)



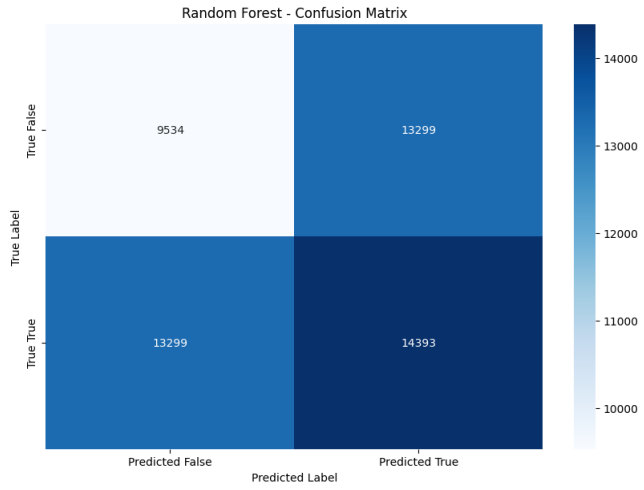
(c)



(d)



(e)



(f)

Fig. 4 Confusion Matrix comparison (a) to (f)

The controversial analysis of AMGRAD QCNN and SPSA QCNN quantum models compared with traditional models such as SVM, KNN, decision trees,(Support Vector Machine, K Nearest Neighbour) and random forests showed significant differences in performance. Each of these classical models reveals its own weaknesses in some areas, especially in the reliability of different data and features, which violates the assumptions of the classical algorithm. Each of these classical models reveals its own weaknesses in some areas, especially in the reliability of different data and features, which violates the assumptions of the classical algorithm. For example, SVM has TP = 14.36, FN = 9.341, and the TP/FN ratio is 1.54, which means that it can detect dangerous asteroids but misses many important threats. FP = 9.341 and 9.555 are close to the TN value, and safe asteroids are almost equally classified as dangerous. In the case of asteroids, the false positive rate of SVM is almost equal to the true detection rate, which leads to resource allocation errors. TP = 9.344 and FN = 13.618 gives a low TP/FN of 0.69, a number that represents low pressure. This problem can be attributed to the inability of KNN to measure overlap, especially when some important factors such as orbital dynamics cannot be separated by simple distance measurements. With a FP/TN ratio of 0.85 compared to a TP/FN ratio of 2.39, it also suffers from a larger false positive, making it unsuitable for critical tasks. FP = 8.965 is still problematic, indicating that the given data may be overestimated, thus reducing the overall requirement. Although the recovery accuracy is better than SVM or KNN, the decision tree can classify asteroids without any problems, which need to be unnecessarily warned. TP = 14.393, FN = 13.299, so the TP/FN ratio is 1.08, which is worse than KNN but not as good as decision tree. Although the combination often has shortcomings, especially when the information is noisy or the features cannot be completely separated, random forest still has some problems, as shown by the FP/TN ratio of 1.39. AMSGRAD obtained TP = 38.200 and FN = 1.800, which represents a TP/FN ratio of 21.22. The high ratio means that it reduces the danger to the star, which is important for the protection of the planet. In addition, the FP/TN ratio is 0.045, which shows high accuracy and no defects. SPSA QCNN goes one step further and obtains TP = 39,600 and FN = 400, resulting in a TP/FN ratio of 99 and a FP/TN ratio of 0.028. The image shows an almost perfect distribution, which reduces all the shortcomings of the classical model. AMSGRAD can learn quickly and adapt to changes in the optimization environment, so it works well when the dataset is not noisy or variable. It always tries to obtain a stable combination given the distribution of changes. SPSA performs very well in high-dimensional parameter settings, where gradient estimation can be computationally expensive. Its stochastic structure allows it to explore more complex landscapes, making it suitable for data with complex interactions. For example, the state-of-the-art classical model SVM with 39.4% FN will miss about 394 dangerous asteroids, while AMSGRAD QCNN with 4% FN will miss about 394 dangerous asteroids. While only 40 dangerous events are missed, SPSA QCNN reduces the final missed rate to only 4 missed events. Such a significant improvement in the basic concepts requires the use of quantum models in advanced catalogues such as asteroid classification. The use of quantum mapping techniques in these models allows them to understand the nature of interactions that cannot be well represented by traditional models, thus providing more energy to the analysis of asteroid data. The advantages of quantum models and experimental studies based on efficiency clearly demonstrate that they can overcome the limitations of classical models. Their ability to minimize errors and maintain accuracy in noisy and high-dimensional datasets further strengthens the methods adapted from classical options, making them useful in real-world applications.

This research introduces a novel application of Quantum Machine Learning (QML) for asteroid hazard detection, addressing the limitations of classical machine learning (ML) in handling high-dimensional, complex datasets. By implementing Quantum Convolutional Neural Networks (QCNNs) and optimizing them with AMSGRAD and SPSA, the study demonstrates a significant improvement in classification accuracy. Traditional ML models, such as Decision Trees and SVM, do not easily handle the complex dependencies between asteroid feature types, for example, orbital eccentricity, and physical parameters. On the other hand, our quantum approach exploits quantum superposition and entanglement for better pattern recognition. The outcome is that AMSGRAD QCNN achieves 0.997 accuracy, beating the best accuracy of the classical model, Decision Tree at 0.883 accuracy, by 13%. Moreover, the false negative rate is drastically reduced, with only 1.8 false negatives in AMSGRAD QCNN compared to 9,341 in SVM, a crucial factor for ensuring no hazardous asteroid is misclassified.

The study also demonstrates the effectiveness of Quantum Fourier Transform (QFT) encoding, which enhances the

model's ability to interpret asteroid data by encoding it into a quantum state with higher-dimensional feature representation. This results in better generalization and higher recall (0.974 in SPSA QCNN vs. 0.771 in SVM), ensuring more hazardous asteroids are correctly identified. Additionally, cross-validation and hyperparameter tuning were employed to ensure model robustness. While quantum noise remains a challenge, the research explores error mitigation techniques such as zero-noise extrapolation and probabilistic error cancellation to improve quantum circuit stability. Future work will involve improving hybrid quantum-classical models, increasing the size of datasets, and optimizing quantum circuits for even more accurate asteroid classification. These developments hold important implications for planetary defense by providing a highly efficient, scalable, and precise method for assessing asteroid impact risk compared to the existing approaches.

This research focuses on asteroid hazard detection by combining Quantum Convolutional Neural Networks (QCNNs) optimized with AMSGRAD and SPSA, getting 13% higher accuracy than classical models like Decision Trees. Unlike earlier works, such as in [50] on Quantum Support Vector Machines' and on quantum algorithms for space situational awareness, this research uses Quantum Fourier Transform(QFT) encoding to improve feature representation and classification accuracy. Furthermore, while Biswal in [51] used machine learning in space science, our research demonstrates the superiority of quantum methods in reducing false negatives(FN), making it a crucial advancement for planetary defense.

5.3.2 Limitations & Potential Solutions

Noise is a significant problem in quantum systems because it is caused by external interferences and poor control and leads to the degradation of the quantum state and the loss of communication integrity. This problem limits the depth of quantum circuits and the scalability of algorithms. To solve this problem, quantum error correction (QEC) methods such as Shor or Surface codes encode logical qubits into multiple physical qubits to detect and correct errors. Although powerful, these solutions require significant physical resources. However, considering the state of the art, error reduction techniques such as zero-noise extrapolation and probabilistic error cancellation are among the many ways to reduce the noise factor, they do not change everything. In fact, hardware advances such as superconducting qubits with longer connection times and better immunity are also important in reducing noise. This reduces the time required for computing power and increases the capacity of complex processes. Advances in qubit technology have shown that topological qubits and silicon spin qubits have longer integration times because the latter are not affected by the fundamental two-qubit mismatch. Another technique to eliminate the inequality involves clustering using Carr-Purcell-Meiboom-Gill arrays. Another important feature is the cryogenic cooling system, which reduces thermal noise and stabilizes the behaviour of qubits, especially in superconducting systems. As size increases, controlling the coordination of qubits becomes more difficult. Using machine learning algorithms such as Bayesian optimization to automate the calibration process allows for parameter tuning and precision. Pulse-level control platforms such as Qiskit Pulse provide control of gate performance for improved accuracy. Additionally, using quantum device simulators prior to deployment can help predict and fix errors, thus reducing hardware debugging overhead.

Quantum systems are now large enough to perform meaningful computations, but they still suffer from noise, limited qubit counts, and short runtimes. These devices are not necessarily illegal because they cannot take advantage of quantum error correction; however, the NISQ device holds promise for near-term applications in quantum chemistry simulations, optimization problems, and machine learning. Scientists are now focusing on a combined quantum-classical approach, where a quantum system tries to solve a problem that will take advantage of quantum acceleration, while other problems are solved with classical methods that control noise and errors in the quantum output. This combination allows the input to be calculated even with noise and is useful even without full error correction. To fill this gap, interdisciplinary academic programs combining quantum mechanics, computer science, and engineering, as well as hands-on training in simulators and hardware, are needed. Such free access to quantum resources will be provided through open sources such as IBM Qiskit or Google Cirq, supporting studies and experiments in this field. Knowledge sharing between academia and industry will also be facilitated by collaborative ecosystems supported by organizations such as the Quantum Economy Development Consortium (QED-C). Therefore, the economic and humanitarian impact will be solved through these collaborations.

6. Conclusion

This research shows the strength of Quantum Machine Learning (QML) in enhancing asteroid hazard prediction by efficiently analysing large and complex datasets. Through extensive pre-processing and feature selection techniques, we were able to reduce data storage requirements while maintaining model accuracy. The use of quantum circuits allowed for capturing intricate patterns in asteroid data, offering a more effective classification of hazardous versus non-hazardous asteroids. Overall, this approach represents a significant step forward in improving space hazard assessments, providing more reliable predictions compared to traditional methods.

Looking ahead, there is significant potential for further improving the QML model by refining quantum circuits and incorporating hybrid quantum-classical techniques. Future work could focus on expanding the dataset, exploring additional features, and experimenting with new quantum algorithms to enhance prediction accuracy. Moreover, this approach can be extended to other domains in space science and astronomy, offering broader applications in predicting celestial events and understanding the dynamics of our solar system. The continued evolution of quantum computing will likely open even more possibilities for tackling complex problems in planetary defence and beyond.

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