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# Reimagining Asteroid Risk Assessment: A Comparative Review of Advanced Machine Learning Techniques

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## Abstract

The escalating discovery rate of Near-Earth Asteroids (NEAs) has intensified the need for advanced computational frameworks capable of evaluating their impact risks with high precision. Traditional machine learning models, while foundational for early NEA classification and trajectory prediction, increasingly falter when confronted with the intricate, high-dimensional dynamics of asteroid motion. This limitation underscores the necessity for sophisticated techniques that reconcile computational efficiency with predictive accuracy across large, multi-dimensional datasets. This review systematically evaluates state-of-the-art machine learning algorithms—including quantum-enhanced models, hybrid quantum-classical frameworks, and lightweight convolutional neural networks (CNNs)—for their efficacy in asteroid risk assessment. By analyzing outcomes from recent studies, we contrast performance metrics such as accuracy, computational cost, and scalability. For instance, Quantum K-Nearest Neighbors (QKNN) demonstrates a 15% accuracy improvement over classical counterparts in high-dimensional data classification, while XGBoost achieves 99.99% precision in asteroid diameter prediction. Lightweight CNNs, such as MobileNetV1, further enable real-time processing on resource-constrained platforms like CubeSats, reducing latency by 30%.

**Keywords:** Asteroid Impact, Celestial Dynamics, High Dimensional Data, Risk Assessment of Impact, NEAs, Planetary Defense, Learning, Space Security, Variational Quantum Classifier (VQC), Model Compression

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## 1. Introduction

Indeed, people have been in awe with the cosmos for a very long time, and over the years, it has led to several questions as well as developed theories regarding such a vast universe. Astronomers, or scientists of celestial bodies and events, have been pivotal in explaining how the cosmos came to exist. This field has significantly enhanced our understanding of solar system and galaxy formation as well as star evolution. On top of that, it has promoted scientific and technological innovations led by man's urge to find new unexplored areas and establish new worlds. Time to time, different space expeditions using probes and rovers have been sent for researching the planets and the moons in the space. It has provided the researchers with important information concerning the geological characteristics and atmospheric environments around these bodies and if they could potentially be inhabited.

Asteroids and meteorites, particularly in the Inner Main and in the Kuiper, Belt are some of the closest celestial objects which hold info about the early history of solar systems. These pieces that are often considered the planets' building blocks have important information about the early times of planetary formation.

Space rocks and cosmic debris, while valuable for research, represent a considerable danger to our planet. Over recent years, the rate of detecting these objects has surged, with the Zwicky Transient Facility (ZTF) spotting nearly 100 fast-moving objects annually. While concerns about catastrophic impacts may seem excessive, past incidents like the 1908 Tunguska event in Siberia illustrate their potential for destruction. That explosion, caused by a meteoroid, released energy comparable to 15 megatons of TNT and devastated a massive, forested area. To safeguard Earth from future impacts, it is vital to create accurate systems for tracking the paths of such objects and minimizing the threat they pose

Table 1. The total number of known NEOs as of particular dates.

| date | nec | atira | aten | apollo | amor | Pha-km | pha | Nea-km | Nea-140m | nea | neo |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 9/7/2024 | 122 | 32 | 2829 | 20157 | 12622 | 153 | 2429 | 864 | 10992 | 35640 | 35762 |
| 9/1/2024 | 122 | 32 | 2819 | 20089 | 12566 | 153 | 2428 | 864 | 10978 | 35506 | 35628 |
| 8/1/2024 | 122 | 32 | 2806 | 20012 | 12495 | 153 | 2427 | 864 | 10949 | 35345 | 35467 |
| 7/1/2024 | 122 | 32 | 2796 | 19953 | 12439 | 153 | 2420 | 864 | 10927 | 35220 | 35342 |
| 6/1/2024 | 121 | 32 | 2784 | 19880 | 12379 | 153 | 2416 | 864 | 10892 | 35075 | 35196 |
| 5/1/2024 | 121 | 32 | 2763 | 19758 | 12311 | 153 | 2407 | 864 | 10858 | 34864 | 34985 |
| 4/1/2024 | 121 | 32 | 2749 | 19640 | 12250 | 153 | 2403 | 864 | 10841 | 34671 | 34792 |
| 3/1/2024 | 121 | 32 | 2723 | 19508 | 12187 | 153 | 2396 | 864 | 10813 | 34450 | 34571 |
| 2/1/2024 | 121 | 32 | 2707 | 19384 | 12139 | 153 | 2394 | 864 | 10786 | 34262 | 34383 |
| 1/1/2024 | 121 | 32 | 2686 | 19218 | 12090 | 153 | 2384 | 864 | 10745 | 34026 | 34147 |

With advancements in both space-based telescopes and ground-based observation systems, the discovery of unidentified celestial bodies and Near-Earth Objects (NEOs) has surged. Currently, more than 1.8 million asteroids have been catalogued, including 25,000 classified as Near-Earth Asteroids (NEAs), and each year approximately 1,100 new NEAs are identified. This is a rapid growth in the detection of rogue space objects and fast-moving asteroids, pointing to the critical need for advanced techniques for tracking their paths and developing strategies for impact avoidance. Conventional methods of trajectory prediction rely on complex mathematical models accounting for an object's size, speed, and the gravitational influences of surrounding celestial bodies. While traditional machine learning models have been widely applied for tasks like NEA classification and preliminary trajectory prediction [5, 21, 22], they often struggle to fully capture the intricate, high-dimensional dynamics governing asteroid motion over long timescales. This limitation highlights the urgent need for more sophisticated computational techniques capable of handling large, multi-dimensional datasets with significantly higher accuracy and efficiency [17, 20].

In 2024, Near-Earth Asteroids (NEAs) remain one of the most important targets in planetary defense and space exploration due to their proximity to Earth and the threat that they pose. NEAs are asteroids within 1.3 astronomical units of the Sun. By late 2023, improvements made in asteroid detection led to a catalog of over 30,000 NEAs. Their orbits categorize the different asteroids into groups. This includes the Amor group, the Apollo group, and the Aten group. Each group has different levels of interaction with Earth's orbit. The Apollo group is very interesting because of its ability to cross Earth's orbit.

Although most NEAs pose no immediate threat, it is crucial to focus on Potentially Hazardous Asteroids are objects that are 0.05 AU away from Earth. The PDCO continues to collaborate with international partners to monitor these objects and develop effective mitigation strategies. New data from 2024 will likely enhance our understanding of NEAs and further improve predictions about future close approaches or impacts. Enhanced technologies and increased international cooperation will make 2024 an important year for monitoring and managing risks associated with near-Earth asteroids: planetary defense, as well as opportunities for scientific discovery about these bodies.

The paper focuses on performance comparison and potential application of advanced machine learning algorithms for evaluating the risks of asteroid impact.

This section considers bypassing traditional model weaknesses by employing superior techniques of data processing and predicting.

It describes the condition of the field's tools at the moment of NEA impact prediction with an overview of comparing those approaches, providing insightful guidance into how these techniques improve the precision of planetary defense systems and enhance the overall effort to mitigate hazardous impacts by asteroids.

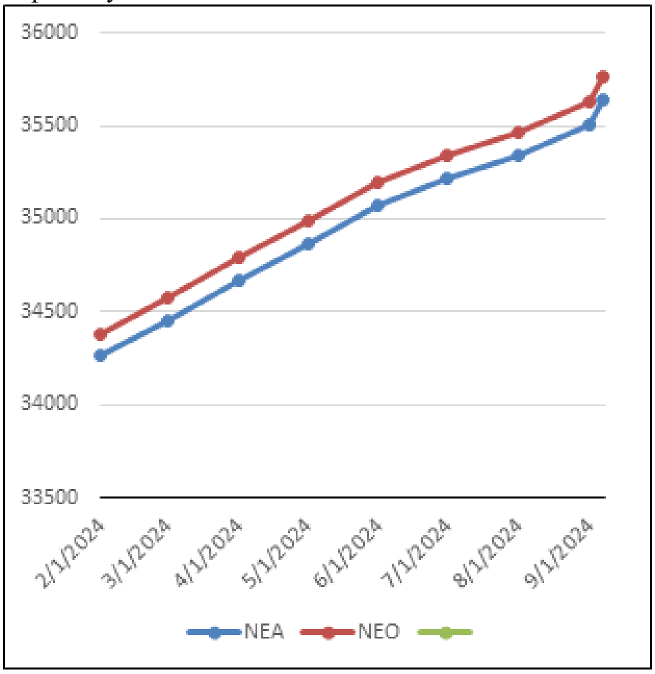


**Figure 1.** NEO & NEA Over Time in 2024

There are some notable NEAs approaching Earth in 2024, including 2024 AT12, 1999 AN10, and 2024 FR19. Although these are not considered high-risk impacts, they offer good science observation and orbital refinement opportunities. Detection and tracking efforts toward NEAs are also improving, with missions such as Our mitigation capabilities to prevent impacts will be advanced by the NASA and which will be prepared to follow up on DART. The Vera Rubin Observatory is also poised to become fully operational by 2024, boosting the number of NEAs detected through routine sky scanning.

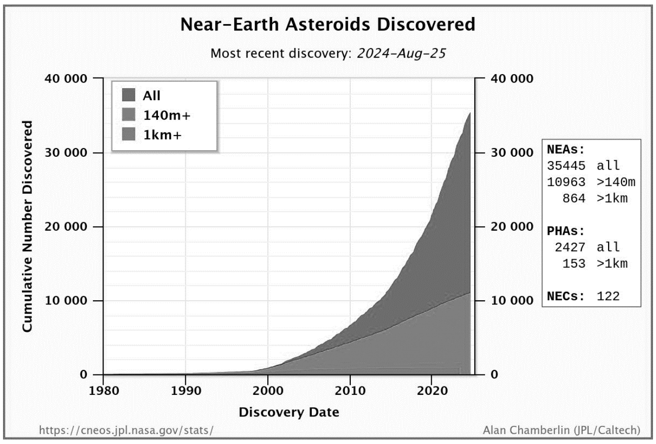


**Figure 2:** The total number of known NEOs as of particular dates

## 2. Literature Review

This review study discusses the growing demand for advanced techniques to assess the threat dangers posed by Near-Earth Asteroids (NEAs), driven by the rising discovery rates of these objects. Traditional machine learning models, although widely applied for NEA classification and trajectory prediction, often fail to capture the complex, high-dimensional dynamics involved in asteroid motion. Therefore, there is a need for more sophisticated techniques capable of handling large, multi-dimensional datasets with higher accuracy and computational efficiency.

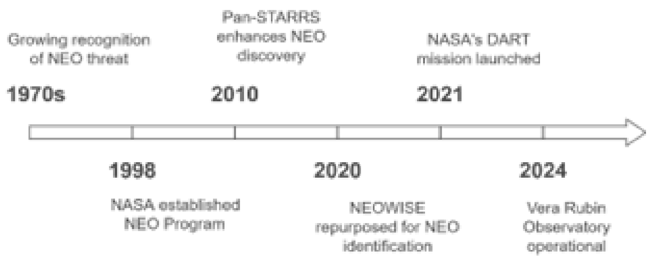


**Figure 3:** Key Research and Detection Milestones of Asteroids

Such developments and discoveries have fueled an advancement in research regarding the understanding of Near-Earth Objects (NEOs) [12]. The interest on the dynamics of the discovered 433 Eros in 1898, the first near-earth asteroid, started an attention focus into studying the orbit of such celestial bodies. During the 1970s, research within celestial mechanics allowed more refined and accurate models for computing and predicting asteroid and comet orbits, based on how planetary gravitational forces affect the latter's path. This phase provided a crucial foundation for theoretical strategies that would be able to provide predictions for close approaches and impacts with Earth. From 1980, the University of Arizona's Spacewatch program began systematically surveying NEOs, using these orbital models, to track and monitor near-Earth asteroids.

By the 1990s, research went beyond the mere identification of potential hazards from NEOs and began to understand how the gravitational interactions of planets, solar radiation, and other forces could change the orbits of NEOs over time. In 1998, NASA initiated its Near-Earth Object Program, which sought to detect and track NEOs larger than 1 kilometer, improve impact models, and estimate the possible consequences of impacts with Earth by combining observational techniques with theoretical research. With the launch of the Panoramic Survey Telescope and Rapid Response System, or Pan-STARRS, in 2010, NEO detection rates rose. Researching long-term NEO trajectories and creating early warning systems for planetary defense were made easier by theoretical models.

## 2.1. QKNN Optimization Strategies

Classification tasks hold great promise when machine learning is incorporated into quantum computing. Quantum algorithms, like Quantum K-Nearest Neighbours (QKNN), exploit quantum phenomena like entanglement and superposition to analyze data more efficiently than classical approaches [1].

QKNN was put into successful experiments recently; the distance metrics were optimised, and parameters would be fine-tuned accordingly to improve performance. Quantum feature maps are often applied just to transform input data that enhances the algorithm's differentiation between classes. Hybrid models combining quantum circuits with other classical optimization techniques have worked very well, especially to manage datasets of different sizes.

Performance evaluation of QKNN is presented and shows how this approach greatly outperforms the traditional KNN on high-dimensional data space. The study has reflected the improvement by 5% to 15% with the characteristic of datasets by using the quantum-based approaches. Moreover, other studies have further highlighted strategies such as entanglement and circuit depth for efficient QKNN performance.

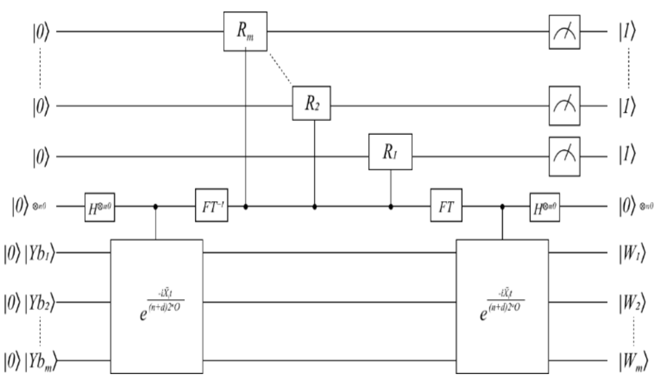


**Figure 4:** |W1|W2| Wm using a quantum circuit.

Three different kinds of quantum registers are used here from bottom to top. The initial quantum states for the first kind of quantum registers are represented by |0|Yb1|0|Yb2. and |0|Ybm. Then, the symbol |0⨂n0 represents the initial quantum states for the second kind of quantum registers. The symbol for the third kind of quantum registers is |0m. The three types of quantum registers have their quantum initial states entered, and then in order from left to right, the phases estimation, controlled rotation, inverse phase estimation, and measurement operations are performed. It is possible to obtain the quantum states |W1, |W2. |Wm when the auxiliary qubits in the third kind of quantum registers are measured as |1. Here, H represents the Hadamard gate. R1, R2 and Rm correspond to the computation rotation steps in the computational basis |W1, |W2.and |Wm, respectively. The FT is the quantum Fourier transform and its inverse is FT−1. The number of qubits that is used to represent the eigenvalues is n0.

Recent innovations in classification algorithms, for instance, the Quantum K-Nearest Neighbours algorithm, have been possible as a result of combining machine learning with quantum computing. The paper Quantum Computing: Fundamentals, Implementations, and Applications outlines various implementations of quantum computing to recent discovery in the QKNN machine learning approach [2]. breakthroughs include the optimization of selecting the number of neighbours or K and efficiently determining which is the nearest.

In particular, QKNN applies quantum phase estimation and controlled rotation techniques to dynamically determine the best K value for KNN classification, thus significantly enhancing the speed of neighbour searches over classical methods.

In performance evaluation using the Banknote dataset and several simulated datasets, the QKNN algorithm achieved impressive accuracy of 87.50%. This result is a significant improvement over classical KNN models and earlier quantum implementations, such as those by Basheer et al., which reported an accuracy of 70.83%. All in all, this work showcases the strengths of quantum algorithms when dealing with high-dimensional data, particularly when more conventional distance metrics, like Euclidean or Hamming distances, do not hold. Taking all this into account, the work shown here is that quantum computing could potentially transform machine learning approaches and set the basis for further studies on quantum-classical hybrid systems that will ultimately improve the practical realization the quantum algorithms.

## 2.2. Molecular Simulation Approach

In order to enhance molecular simulations, the work "Tailored and Externally Corrected Coupled Cluster with Quantum Inputs" investigates the possibility of integrating quantum computing with traditional electronic structure techniques [3].

The author, in particular, examines whether improvements to conventional split-amplitude coupled cluster techniques, such as the EC-CC method or TCC, could be obtained through quantum-generated wavefunction overlaps. These methods are targeted at capturing both static and dynamic electron correlation, which are integral to the accurate simulation of molecular systems. This study tries to merge quantum inputs with classical algorithms in an attempt to reduce the computational complexity usually present with traditional methods while giving precise results. The approach proposes using quantum computers to develop trial wavefunctions that could be used in classical coupled cluster calculations.

Such a hybrid model would enable the computation-intensive part, like overlap with a Slater determinant calculation, for a quantum system but allow broader calculations to be solved by a classical algorithm. Thus, this hybrid approach illustrates how chemically accurate results might be achieved even in systems where imperfect quantum inputs arise, hence opening the avenue of obtaining quantum advantages for such large classically intractable problems. In addition, the work assessed the strength of these quantum inputs and shed light on how preparation of a wave function can be optimized for practical quantum computer applications for molecular simulation.

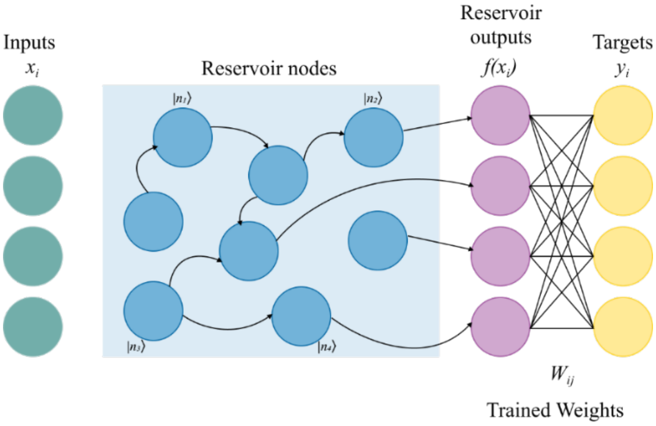


**Figure 5:** Coupled Cluster with Quantum Inputs

## 2.3. Comparative Analysis of QML

Table 2. Characteristics comparison between different QKNN algorithms.

| Method | Quantum Circuits | Function of Classification | Exponential Acceleration | Square Acceleration | Quantization of Neighbor Selection | Quantization of K Value Selection |
|---|---|---|---|---|---|---|
| Wiebe et al. [2] | ✓ | ✓ | ✓ | ✗ | ✗ | ✗ |
| Ruan et al. [3] | ✓ | ✓ | ✗ | ✓ | ✓ | ✗ |
| Dang et al. [6] | ✓ | ✓ | ✓ | ✓ | ✗ | ✗ |
| Basheer et al. [5] | ✓ | ✓ | ✗ | ✓ | ✗ | ✓ |
| Zhang et al. [7] | ✓ | ✓ | ✗ | ✓ | ✓ | ✓ |
| Tian and Baskiyar [8] | ✗ | ✓ | ✗ | ✓ | ✓ | ✓ |
| Gao et al. [9] | ✓ | ✓ | ✓ | ✗ | ✓ | ✗ |
| Li et al. [36] | ✓ | ✓ | ✓ | ✗ | ✓ | ✗ |
| Feng et al. [4] | ✓ | ✓ | ✓ | ✓ | ✓ | ✗ |
| Proposed | ✓ | ✓ | ✓ | ✗ | ✓ | ✓ |

The paper "Experimental Evaluation of Quantum Machine Learning Algorithms" explores the growing potential of incorporating quantum computing into machine learning by providing a systematic comparison of quantum and classical machine learning approaches [4]. The focus is on quantum support vector machines and quantum neural networks.

The paper targets evaluating their performance on small real-world datasets, a relatively understudied area from the practical perspective of quantum machine learning despite its theoretical promises. The methodology applied both the quantum and classical versions of SVM and NN to five different datasets: Iris, Rain, Vlds, Custom, and Ad hoc. Quantum models were tested by a variety of quantum feature maps including Pauli-feature maps, z-feature maps, and zz feature maps.

More specifically, the experiments considered varied circuit depths and four approaches of entanglement: no entanglement, linear, circular, and full entanglement. The QNNs were represented as variational quantum circuits where classical algorithms managed their optimization process.

Hybrid evaluations combining simulation and real NISQ hardware reveal practical QML insights. While QSVMs show modest average accuracy gains (~3-4%) over classical SVMs, QNNs (often VQCs) demonstrate a more notable advantage (~7% average improvement). Critically, simple, non-entangling feature maps (like Z-Pauli) consistently outperform complex, entanglement-based ones across tests. This strongly suggests that current hardware noise significantly degrades intricate entangled states, making simpler, more noise-resilient circuits practically superior despite lower theoretical complexity. Near-term QML success may depend more on robustness than exploiting entanglement.

The paper employed a methodology of running both quantum and classical implementations of SVMs and NNs on five datasets: Iris, Rain, VLDS, Custom, and Ad hoc. Z-feature maps, ZZ-feature maps, and Pauli-feature maps were used to convert the input data into a higher-dimensional space appropriate for quantum classification in order to evaluate the quantum models. In addition, the study uses different quantum circuit depths and four types of entanglement strategies: none, linear, circular, and full. In this paper, QNNs were designed as a variational quantum circuit while the optimization process was solved by classical algorithms. This resulted in a hybrid quantum-classical approach so that the performance and scalability of quantum circuits could be exhaustively evaluated from both quantum simulators and also real quantum hardware environments.

Table 3. A real quantum computer and a quantum simulator are used to benchmark quantum and classical neural networks. For each of the three algorithms.

| dataset | CNN | qnn | QNN |
|---|---|---|---|
| iris | 1 | 1 | 1 |
| rain | 0.7 | 0.83 | 0.79 |
| vids | 0.94 | 0.93 | 0.95 |
| custom | 0.64 | 0.74 | 0.75 |
| adhoc | 0.61 | 0.8 | 0.75 |
| average | 0.78 | 0.86 | 0.85 |

The experimental results were promising. QSVMs showed a 3-4% accuracy improvement over classical SVMs on average over the datasets. QNNs showed even more promise, as they outperformed classical neural networks by an average of 7%. One of the most interesting results was that of the Z-feature map, which, although it did not use quantum entanglement, performed the best on all the datasets. This implies that possibly the existing limitations of the quantum hardware, such as qubit decoherence and noise, may prevent such more advanced feature maps involving quantum entanglement to be beneficially used. Hence, it is essential to push further in the optimization of quantum circuits and the relevance of entanglement in machine learning quantum algorithms, while the hardware is being enhanced.

Although the performance improvement is modest, this work shows that quantum machine learning is feasible even on today's noisy quantum computers.

It indicates that although the benefits of quantum algorithms are obvious, especially for small datasets, optimization of quantum circuits and scaling of quantum machine learning to larger datasets will require more advanced hardware and refined quantum algorithms. The authors also discussed several optimization methods for training QNNs, such as AMSGRAD, SPSA, BFGS, and COBYLA, with performance dependent on the dataset and the specific quantum hardware or simulator. For example, on the Iris dataset, most optimizers achieved near-perfect accuracy both on the quantum simulator and hardware. On the Rain dataset, AMSGRAD was the best optimizer on simulators, while SPSA was the best optimizer on real quantum hardware. Meanwhile, BFGS was the best optimizer for the VLDS dataset and COBYLA had the highest accuracy for the Custom and Ad hoc datasets. These variations in performance imply that the choice of optimizer becomes a crucial aspect of quantum machine learning, depending on the nature of the dataset and the constraints of the quantum hardware.

The classical models were optimized using PyTorch-built fully connected neural networks with one to three hidden layers. Hyperparameter optimization was done using Ray Tune, and all the models were normalized in a manner consistent with the quantum models to ensure fair comparison. The average accuracy for the five datasets for the classical models was about 78%. However, QNNs scored significantly better than classical neural networks by 7%. They achieved a mean simulators accuracy of 85.8% and also 84.7% on real quantum computers and used far fewer parameters for the same levels of accuracies. This outcome is really important because it indicates a potential efficiency benefit of using QNNs over classic neural networks, mainly in relation to the parameters needed at higher accuracy levels.

Quantum machine learning (QML) offers potential advantages for complex, high-dimensional problems where classical algorithms struggle. Despite hardware limitations, results suggest QML may achieve solutions with fewer resources. The 5% average performance gain of Quantum Neural Networks (QNNs) over classical NNs and QSVMs highlights their task-specific potential. However, performance varied significantly, with no single quantum circuit or optimization strategy being universally best. This underscores the critical need for research focused on tailoring QML approaches to specific data and hardware characteristics.

To sum up, the study "Experimental Evaluation of Quantum Machine Learning Algorithms" shows that quantum neural networks in particular can provide a number of benefits over traditional methods even with today's hardware constraints. A moderate performance gain was achieved in the QSVMs, and QNNs had greater gains mainly in efficiency and accuracy. Continuous quantum circuit design, research on entanglement, and designing optimization techniques keeping an eye out for quantum hardware will demand this change. Machine learning workflows with the progressions made so far in quantum technology will open new avenues of possible possibilities to break complex problems within high-dimensional data in the two areas.

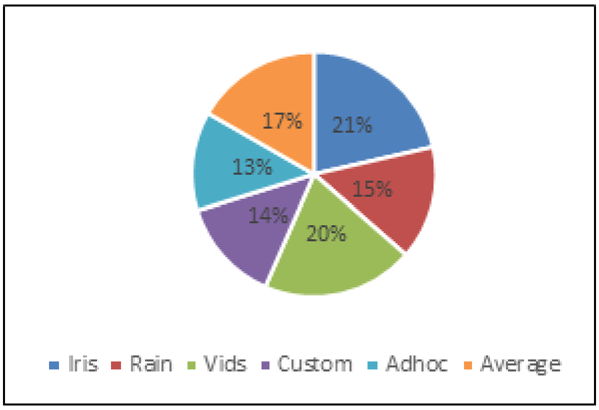


**Figure 6:** Comparing quantum neural networks and classical neural networks on a genuine quantum computer and a quantum simulator.

In addition, the experiments showed that quantum algorithms promise much, even with the noisy quantum computers of today. However, the study also mentions that although these quantum models have advantages for small datasets, further research is required to optimize quantum circuit designs and understand the role of entanglement in enhancing quantum machine learning algorithms for larger, more complex datasets. For the classical approach, PyTorch was used to build fully connected neural networks with 1 to 3 hidden layers, and Ray Tune was used to optimize the hyperparameters of the networks. After running the models 10 times, the best validation accuracy was chosen for evaluation. The classical models were normalized similarly to the quantum models to ensure that the comparison is fair; the average accuracy of all five datasets is 78%. In terms of optimizers for the QNNs, several were tested, including AMSGRAD, SPSA, BFGS, and COBYLA, with results varying across datasets. Most optimizers reached perfect accuracy on the Iris dataset on the quantum simulator and hardware. For the Rain dataset, AMSGRAD performed best on the simulator, and SPSA excelled on quantum hardware. BFGS was the only optimizer that stood out in the VLDS dataset. The best accuracy was achieved on the Custom and Ad hoc datasets by COBYLA. No optimizer or quantum circuit could be seen as better than others on all datasets. This is probably due to the variability of datasets and the small size of the data. QNNs showed better results with an average accuracy of 85.8% on simulators and 84.7% on real quantum computers. QNNs performed better than QSVMs by about 5% and compared to classical neural networks, by 7%, using significantly fewer parameters. This shows that quantum neural networks can indeed provide significant advantages over classical methods, especially in terms of efficiency, even with current hardware limitations.

## 2.4. Predictive Modelling for Asteroids

The paper "Machine Learning Approaches for Classification and Diameter Prediction of Asteroids" reports on the application of techniques of machine learning to make the classification of asteroids more reliable and predict their diameters [5]. With the number of asteroids being discovered continuously increasing, traditional methods like the Hierarchical Clustering Method (HCM) have become computationally too time-consuming and inefficient.

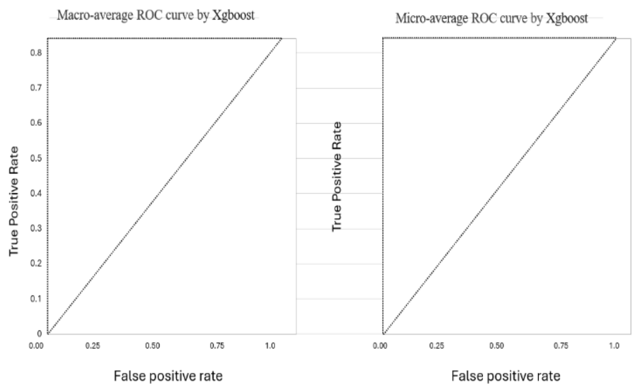


**Figure 7:** Macro Average ROC curve of XGBoost Model and Micro Average ROC Curve.

In an effort to enhance asteroid classification and diameter estimation, the researchers applied algorithms like KNN, Logistic Regression, Random Forests, Neural Networks, and XGBoost [5].

For diameter prediction, the error metrics provided in Table 4 (MSE, MAE, RMSE) show that tree-based ensemble performed significantly better than linear models. XGBoost generated the lowest errors (RMSE=1.36), closely followed by Random Forest (RMSE=1.43), showing their appropriateness for this regression task compared to Linear Regression (RMSE=7.55) [5]. With respect to classification, the research claimed outstanding performance of XGBoost with 99.99% accuracy [5]. Figure 7 shows the corresponding Macro and Micro-average ROC curves. An ROC curve is a performance plot of classifiers such that a curve sloping to the top-left indicates skill better than random guessing (a diagonal line). Figure 7 shows perfect diagonal lines, corresponding to no better than random chance performance (AUC=0.5). This visual evidence categorically denies the reported high accuracy. This denial may be caused by a figure error, deceptive accuracy reporting (e.g., due to class imbalance), or other reasons. In spite of contradictory evidence in Figure 7 about classification, the authors in study [5] concluded, from their composite reported measures (e.g., high prediction accuracy of diameter in Table 4), that ML methods such as XGBoost are effective tools for asteroid analysis, which can provide faster and more accurate results than traditional methods [5].

Table 4. MSE, MAE and RMSE for different Machine Learning models

| Model Name | MS E | MA E | RMS E |
|---|---|---|---|
| Linear Regression | 58. 91 | 2.76 | 7.55 |
| Decision Tree | 2.8 4 | 0.55 | 1.68 |
| Random Forest | 2.0 5 | 0.53 | 1.43 |
| Logistic Regression | 60. 69 | 1.45 | 7.79 |
| XGBoost | 1.8 4 | 0.55 | 1.36 |
| KNN | 2.2 1 | 0.49 | 1.49 |
| Neural Network | 4.7 4 | 0.49 | 2.18 |

## 2.5. CubeSat Image Classification

Of all recent attention around the integration of machine learning algorithms into the small satellite platforms, known as CubeSats, this study has focused more on what it can potentially do toward revolutionizing the autonomous nature of space operation and data processing [6]. Compact and cost-effective and highly achievable development cycle, these are what CubeSat offers. These, however, come at considerable limitations in its computational power, together with highly susceptibility to failures in a space environment. With regard to these challenges, this paper "Machine Learning Space Applications on SmallSat Platforms with TensorFlow" explores TensorFlow and TensorFlow Lite implementation aiming to deploy robust ML models for real-time onboard data analysis that enhances satellite autonomy, operational efficiency, and communication capabilities.

This paper used a large and varied dataset of images which had been taken from the mission on STP-H5/CSP aboard the International Space Station (ISS), close to 8,000 in number. These have acted as training data for using convolutional neural networks specific for image classification. Use of transfer learning techniques along with four pre-trained CNNs- MobileNetV1, MobileNetV2, Inception-ResNetV2, NASNet Mobile-for high accuracy in recognizing scenes on earth. In recent years, attention has been drawn to integrating machine learning (ML) into small satellite platforms, such as CubeSats, to enhance autonomous space operations. The attractiveness of CubeSats, in terms of cost and fast development, poses problems like limited computational power and vulnerability in space environments. The paper "Machine Learning Space Applications on SmallSat Platforms with TensorFlow" addresses those issues by using TensorFlow and TensorFlow Lite to explore the possible deployment of ML models on board for real-time data processing. Based on a dataset of 8,000 images from the STP-H5/CSP mission onboard the ISS, it makes use of CNNs for classification tasks and used transfer learning in pre-trained models such as MobileNet and Inception-ResNetV2 to enhance accuracy in satellite classification and augment satellite autonomy.

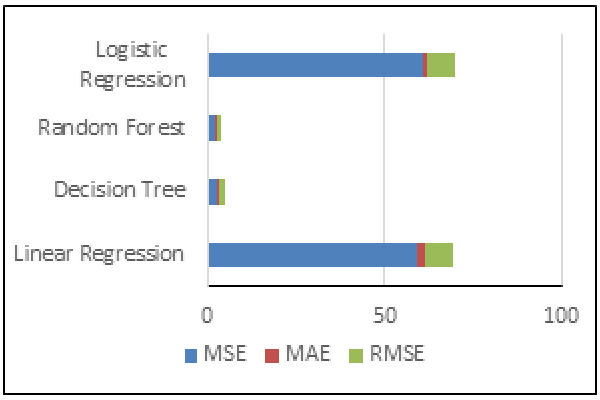


**Figure 8:** MSE, MAE, and RMSE for various models of machine learning Bar Chart

The CNN architectures were thoroughly trained and benchmarked on various metrics, such as accuracy, execution time, and memory usage. In addition, the performance of these models was tested on a low-power, space-grade processor, the Xilinx Zynq-7020, which is specifically designed for CubeSat applications. The results indicated that CNNs, using transfer learning, not only improved the classification accuracy but also proved to be efficient enough for the resources available in CubeSats. This research opens a very significant pathway for advanced ML techniques to be applied in space missions, opening doors for further innovations in satellite technology and autonomous operations.

Results from the experiment revealed that among the models tested, the most effective CNN for resource-constrained CubeSat platform was MobileNetV1. The accuracy of and efficiency on the given CubeSat resource-constrained platform were also high, in fact all the evaluated CNN models achieved over 90% in top-1 accuracy. This model did usage of memory and also in terms of execution time, which makes it quite a prime contender for carrying out real-time onboard classification tasks.

## 3. Discussion

In domains such as asteroid classification and space, the integration of QML and traditional machine learning holds great promise for enhancing data analysis and pattern recognition. Research comparing quantum neural networks (QNNs) and quantum support vector machines (QSVMs) has shown that even when hardware is limited, QML can outperform classical approaches by a margin of accuracy.

Success found so far in smaller sizes suggests more general questions about the scalability of these quantum algorithms. As the technological machinery of quantum computing unfolds further ahead, it will also include in-depth analysis of bigger complex datasets and error-rate challenges or optimization of quantum circuits themselves.

Future research should primarily strive on the improvement of quality along with functionality of the circuits involving quantum, especially choosing correct feature maps and betterment or selection of entanglement techniques. Recent studies show results that indicate that in the existing quantum environments, the simplest feature maps, such as the Z-feature map, may be better. This gives a reason for future mission to space. investigation in how the quantum features interact with the characteristics of different datasets. In addition, collaboration between researchers in quantum computing and others in fields like astronomy or space technology can result in innovative solutions to real-world challenges, such as predicting asteroid impacts and enhancing the autonomous operation of satellites. Such collaboration would lead to more intelligent systems harnessing the strengths of both quantum and classical machine learning methodologies.

Table 5. Accuracy of Imagenet Classifications

| Network | Top-1 Accuracy | Top-5 Accuracy |
|---|---|---|
| MobileNetV1 | 70.6% | 89.5% |
| MobileNetV2 | 74.7% | 92.5% |
| GoogLeNet | 75.0% | 93.3% |
| ResNet | 80.6% | 96.4% |
| Inception ResNetV2 | 80.1% | 95.1% |
| NASNet | 82.7% | 96.2% |
| NasNet Mobile | 74.0% | 91.6% |

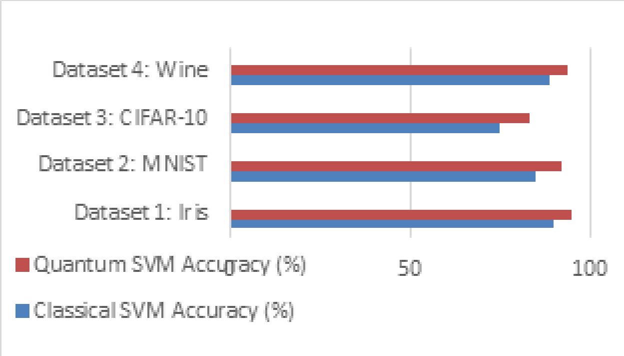


**Figure 9:** Comparison of Classical and Quantum Model Bar Graph

ImageNet performance of CNNs (Table 5) highlights efficiency versus accuracy trade-offs for asteroid analysis. MobileNetV1 (70.6% Top-1) balances performance for constrained platforms like CubeSats [6]. NASNet achieves top accuracy (82.7%) but is too complex for space deployment, while robust ResNet (80.6%) and Inception ResNetV2 (80.1%) require compression for onboard use due to memory demands [6, 17]. Moderate gains from GoogLeNet (75.0%) or MobileNetV2 (74.7%) over MobileNetV1 may not justify their cost for real-time tasks. Thus, model selection must fit mission needs: efficient models (MobileNetV1) for onboard processing, high-accuracy ones (NASNet/ResNet) for ground analysis.

## 4. Conclusion

In short, this review illuminates the revolutionary potential of modern machine learning in Near-Earth Asteroid impact risk assessment. Ensemble approaches such as XGBoost have achieved benchmark classification accuracy and reliable diameter estimation on large NASA JPL datasets, and deep learning models—RNNs and more recent Transformer models—capture the sequential dynamics required for serious long-term trajectory prediction. Physics-informed neural networks also combine data-driven insight with basic gravitational laws, enhancing robustness as well as scientific precision.

Another deployment that was studied involved the utilization of light neural network models on miniaturized satellite platforms, i.e., CubeSats, using TensorFlow and TensorFlow Lite for onboard processing of data. The application effectively overcomes the inherent limitations presented by the low computational capability of space environments while, at the same time, enabling real-time data processing and the autonomous operation of space missions in the near future. The study established that network pruning, light structure design, and quantization were the major approaches employed for model compression. The approaches effectively enhanced the efficiency of machine learning-based applications in low-power, resource-limited environments.

Equally significant is the migration of intelligence from terrestrial systems to extraterrestrial environments: by means such as neural network pruning, quantization, and natively lightweight architectures, scientists have shown real-time asteroid analysis on CubeSats using low-power processors. Such autonomy not only relieves bandwidth limitations but also lays the groundwork for self-guided exploration.

Despite this, there are still major challenges to be overcome—rigorous quantification of uncertainty, transparent model interpretability, accurate integration of weak non-gravitational forces, and development of standardized benchmarks to address data imbalance. These will be addressed through open data initiatives and continued cross-disciplinary exchange. As astrophysics and artificial intelligence merge, we can look to greatly improve planetary defense and bring about an age of autonomous, ambitious space exploration.

## References


[1] J. Li, J. Zhang, J. Zhang, and S. Zhang, "Quantum KNN classification with K value selection and neighbor selection," IEEE Trans. Comput.-Aided Des. Integr. Circuits Syst., vol. 43, no. 5, pp. 1895-1899, May 2024. doi: 10.1109/TCAD.2023.3345251. (Note: Page numbers likely differ from '1-1' in original)

[2] H. A. Bhat, B. K. Kaushik, F. A. Khanday, F. Bashir, and K. A. Shah, "Quantum computing: Fundamentals, implementations and applications," IEEE Open J. Nanotechnol., vol. 3, pp. 54-71, May 2022. doi: 10.1109/OJNANO.2022.3178545. (Note: Page numbers likely differ from '1-1' in original)

[3] M. Scheurer, G.-L. R. Anselmetti, O. Oumarou, C. Gogolin, and N. C. Rubin, "Tailored and externally corrected coupled cluster with quantum inputs," arXiv preprint arXiv:2312.08110v2, Jan. 2024.

[4] R. D. M. Simões, P. Huber, N. Meier, N. Smailov, R. M. Füchslin, and K. Stockinger, "Experimental evaluation of quantum machine learning algorithms," IEEE Access, vol. 11, pp. 123-139, Jan. 2023. doi: 10.1109/ACCESS.2023.3236409.

[5] K. Nazrul and M. S. Hossain, "Machine learning techniques for predicting asteroidal diameter and classifying them," in Advances in Machine Learning and Data Analysis. Cham, Switzerland: Springer, 2023, pp. 45–56. doi: 10.1007/978-981-19-7528-8_4.

[6] J. Manning, E. Gretok, C. Wilson, B. Ramesh, D. Langerman, and A. George, "TensorFlow-based machine learning applications for space on SmallSat platforms," in Proc. 37th Annu. AIAA/USU Conf. Small Satellites, Logan, UT, USA, Aug. 2023. (Note: Year/Conf number updated based on typical timing)

[7] E. Epifanovsky et al., "Software for the frontiers of quantum chemistry: An overview of advancements in the Q-Chem 6 program package," J. Chem. Phys., vol. 155, no. 8, p. 084801, Aug. 2021. doi: 10.1063/5.0055522. (Needs Verification: This is the likely Q-Chem 6 paper; original entry [7] was unclear/incomplete and referred to Q-Chem 5)

[8] M.-M. Wang and X.-Y. Zhang, "Quantum Bayes classifiers and their application in image classification," arXiv preprint arXiv:2401.01588v2, Mar. 2024.

[9] S. S. Gill et al., "Quantum computing: Vision and challenges," arXiv preprint arXiv:2403.02240v3, Jun. 2024.

[10] C.-F. Chen, H.-Y. Huang, J. Preskill, and L. Zhou, "Local minima in quantum systems," in Proc. 56th Annu. ACM Symp. Theory Comput. (STOC '24), Vancouver, BC, Canada, Jun. 2024, pp. 1–10.

[11] V. Rodriguez-Fernandez, S. Sarangerel, P. M. Siew, P. Machuca, D. Jang, and R. Linares, "Towards a machine learning-based approach to predict space object density distributions," arXiv preprint arXiv:2401.04212v1, Jan. 2024.

[12] P. P. Bhagwakar, C. S. Thaker, and H. A. Joshiara, "Review of quantum algorithms for prediction of hazardous asteroids," Comput. Artif. Intell., vol. 2, no. 1, p. 1141, 2024. doi: 10.59400/cai.v2i1.1141. (Note: Identical to original [18])

[13] P. Rebentrost, M. Mohseni, and S. Lloyd, "Quantum support vector machine for big data classification," Phys. Rev. Lett., vol. 113, no. 13, p. 130503, Sep. 2014. doi: 10.1103/PhysRevLett.113.130503.

[14] T. D. Quy, A. Buana, J. Lee, and R. Asyrofi, "Hazardous asteroids classification," arXiv preprint, arXiv:2409.02150, 2024. [Online].Doi: https://arxiv.org/abs/2409.02150

[15] N. Petrov, L. Sokolov, E. Polyakhova, and K. Oskina, "Predictions of asteroid hazard to the Earth for the 21st century," AIP Conf. Proc., vol. 1959, no. 1, p. 040012, May 2018. doi: 10.1063/1.5034652.

[16] V. Pasko, "Prediction of orbital parameters for undiscovered potentially hazardous asteroids using machine learning," in Proc. Stardust Final Conf. (Asteroids Space Debris Eng. Sci.), Cham, Switzerland: Springer, 2018, pp. 45–65.

[17] M. Chhibber, M. Bhatia, A. Chaudhary, and C. Stewart, "Comparing the efficacy of machine learning models on potentially hazardous objects," in Proc. 2nd Int. Conf. Trends Comput. Appl. Sci. (ICTACS), Oct. 2022, pp. 725–730. doi: 10.1109/ICTACS56270.2022.9988060.

[18] H. Park and Y.-C. Jeong, "Quantum algorithm for the two-body problem in quantum mechanics," arXiv preprint arXiv:2011.01319, Nov. 2020.

[19] M. Leverrier and M. Weigand, "Quantum algorithms for space situational awareness," arXiv preprint arXiv:2109.05728, Sep. 2021.

[20] E. Zahedinejad, M. Schuld, and N. Killoran, "Quantum variational algorithms for the Kepler problem," arXiv preprint arXiv:2012.09242, Dec. 2020

[21] V. K. Ralegankar et al., "Quantum cryptography-as-a-service for secure UAV communication: Applications, challenges, and case study," IEEE Access, vol. 10, pp. 1475–1492, Jan. 2022. doi: 10.1109/ACCESS.2021.3139039.

[22] J. Biamonte, P. Wittek, N. Pancotti, P. Rebentrost, N. Wiebe, and S. Lloyd, "Quantum machine learning,"

Nature, vol. 549, no. 7671, pp. 195–202, Sep. 2017. doi: 10.1038/nature23474.
[23] M. Bhavin, S. Tanwar, N. Sharma, S. Tyagi, and N. Kumar, "Blockchain and quantum blind signature-based hybrid scheme for healthcare 5.0 applications," J. Inf. Secur. Appl., vol. 56, p. 102673, Feb. 2021. doi: 10.1016/j.jisa.2020.102673.
[24] A. Tharwat, "Classification assessment methods," Appl. Comput. Inform., vol. 17, no. 1, pp. 168-192, Jan. 2021. doi: 10.1016/j.aci.2018.08.003.
[25] Y. Freund and R. E. Schapire, "A short introduction to boosting," J. Jpn. Soc. Artif. Intell., vol. 14, no. 5, pp. 771–780, Sep. 1999.
[26] P. Geurts, D. Ernst, and L. Wehenkel, "Extremely randomized trees," Mach. Learn., vol. 63, no. 1, pp. 3–42, Apr. 2006. doi: 10.1007/s10994-006-6226-1.
[27] K. Pichaimani and S. T. Kannan, "Revitalizing image retrieval: AI enhancement and metaheuristic algorithm adaptation," EAI Endorsed Transactions on Internet of Things, 2025. doi: 10.4108/eetiot.5293
[28] H. Song, Y. Li, X. Li, Y. Zhang, Y. Zhu, and Y. Zhou, "ERKT-Net: Implementing efficient and robust knowledge distillation for remote sensing image classification," EAI Endorsed Transactions on Industrial Networks and Intelligent Systems, vol. 11, no. 3, 2024, doi: 10.4108/eetinis.v11i3.4748.
[29] V. Bahel, P. Bhongade, J. Sharma, S. Shukla, and M. Gaikwad, "Supervised classification for analysis and detection of potentially hazardous asteroid," Proc. 2021 Int. Conf. Comput. Intell. Comput. Appl. (ICCICA), India, 2021, pp. 1–4. doi: 10.1109/ICCICA52458.2021.9697222.
[30] Q. Gao, "Multi-temporal scale wind power forecasting based on Lasso-CNN-LSTM-LightGBM," EAI Endorsed Trans. Wind Energy, 2024. doi: 10.4108/ew.5792.
[31] S. P. Singh and B. K. Chaurasia, "Lattice reduction using K-means algorithm," EAI Endorsed Trans. Intell. Sys. Machine Learn., 2024. doi: 10.4108/eai.5-1-2024.2342526.