Research Proposal by Sajid Aman - Sajid Aman.pdf

by Sanaul Haque

Submission date: 13-Oct-2025 11:24PM (UTC+0700)
Submission ID: 2779973335
File name: Research_Proposal_by_Sajid_Aman_-_Sajid_Aman.pdf (275.85K)
Word count: 2926
Character count: 16900

Research Proposal
on

JNI-SQP: A Quantum Machine Learning Model for Asteroid Selection in Space Mining Using Spectral Data

Scholar's Name
SAJID AMAN

Scholar's Affiliation
NOTRE DAME COLLEGE

Scholar's Email
sajidaman01@outlook.com

Category
JUNIOR

Country
BANGLADESH

Submission Time
30 SEPTEMBER 2025

ABSTRACT

The JNI-SQP (Jamal Nazrul Islam Spectral Quantum Prospector) is a hybrid Quantum Machine Learning model to optimise asteroid selection towards space mining. This work explores whether it is possible to improve efficiency, accuracy and computation time reduction through classical preprocessing combined with quantum simulators compared to complete classical approaches, examining visible and NIR reflectance spectra of near-Earth asteroids drawn from MIT/SMASSII. The hypothesis aims to drastically minimise computation time and achieve higher than 95% accuracy to high-value asteroids (e.g., M-type, C-type), irrespective of NISQ hardware constraints (noise, qubit limitations, etc.). Within 9 months of duration, the approach will be to preprocess data, design hybrid models, and test against SVM/CNN baselines. Scalable QML prototype development to improve resource yield forecasting is anticipated as an output. This work will change mining efficiency as well as the applications of quantum computing. This proposal seeks funding to commence this work within a proposed budget to present a viable prospecting framework.

RESEARCH PROBLEM

Near-Earth asteroids (NEAs) offer vital resources—metals, water, and propellants [1]—for space missions, with mining feasibility established [2, 3]. Yet, selecting high-value asteroids (e.g., M-type, C-type) from vast datasets remains challenging due to spectral data complexity [4-6]. Classical machine learning methods like SVM and CNN achieve 85–95% accuracy but lag in efficiency [7]. Quantum Machine Learning promises faster, more precise analysis [8], though NISQ hardware limitations—noise and limited qubits —pose barriers [9, 10]. The JNI-SQP model proposes a hybrid solution, combining classical preprocessing with quantum simulators. The research question asks: Can this approach improve efficiency and accuracy in selecting high-value asteroids compared to classical methods? The hypothesis predicts a great computation time reduction and >95% precision, tested with spectral data. This study's significance lies in enhancing mining efficiency and advancing QML in astronomy .

RESEARCH QUESTION

Can a hybrid Quantum Machine Learning approach, incorporating classical preprocessing and quantum simulators to address hardware limitations, improve the efficiency and accuracy of selecting high-value asteroids for space mining from high-dimensional spectral datasets compared to fully classical machine learning methods?

HYPOTHESIS

Integrating Quantum Machine Learning algorithms with classical preprocessing will reduce computation time and improve classification precision to above 95% for selecting optimal asteroids from high-dimensional spectral datasets using current Quantum Hardware with limitations (e.g., noise, limited qubits), outperforming entirely classical machine learning approaches.

LITERATURE REVIEW

Asteroids, particularly Near-Earth Asteroids (NEAs), are unstable and rich in rare earth materials, offering possible supplements to materials found on Earth [1]. DeMeo and Carry [11] mapped the compositional diversity of the asteroid belt using reflectance spectra. Meanwhile, Reddy et al. [12] showed how the spectra of minerals indicate relative abundances, which helps in data-based classification. Hein et al. [2] created a techno-economic model for asteroid mining as a feasible venture and pointed out that effective methods for material excavation are necessary. Identifying which asteroids to mine relies on understanding their compositions and chemical makeups, confirming that spectral analysis is the most important remote sensing method [4, 10]. Machine learning has improved how spectral data is interpreted to characterize asteroids. Breitenfeld et al. [13] demonstrated that traditional machine learning methods can achieve high precision in predicting mid-infrared asteroid spectra compositions. However, these traditional models (e.g., SVM and CNN) struggle with high-dimensional datasets as computational time increases and the risk of overfitting rises with larger data volumes, especially with extensive spectroscopy databases [4-6]. Recent studies address this issue through feature reduction methods like PCA. Still, performance stagnates when dimensionality increases [14]. Quantum machine learning (QML) presents a promising alternative. Its algorithms show potential to surpass traditional techniques in speed and efficiency when addressing complex pattern recognition tasks with large dimensions [6, 7, 11, 15]. Biamonte et al. [8] highlighted the theoretical advantages of QML, including exponential speedups in specific optimization problems, which could aid in asteroid selection by speeding up the processing of spectral features. Havlíček et al. [9] developed a hybrid QML model using variational circuits for classification and showed improved accuracy with high-dimensional datasets, a method suitable for asteroid spectral analysis. Despite this potential, QML faces limitations due to noisy intermediate-scale quantum (NISQ) devices exhibiting high error rates and short coherence times [16]. Additionally, QML models lack interpretability and encounter challenges in new hybrid frameworks that merge the strengths of quantum methods with traditional ones [7]. Comparing machine learning models shows strong evidence that factors beyond just accuracy should be considered. Breitenfeld et al. [13] recorded F1-scores to assess precision-recall balances in mineral predictions. These metrics highlight the need for thorough evaluations to validate QML's advantages over traditional methods like SVM and CNN. This work builds on previous research by proposing a hybrid quantum-classical model (JNI-SQP) to address the limitations of traditional ML and current QML methods. Based on existing literature, integrating supervised machine learning models with quantum enhancements, as attempted by Havlíček et al. [9], shows promise for improving asteroid selection. This study aims to bridge this gap by testing spectral data from MIT/SMASSII against traditional baseline methods.

PROPOSED METHODOLOGY

A. Data Loading and Initial Cleaning

Visible and Near Infra-red reflectance spectra of Near Earth Asteroids will be ingested. Missing values will be imputed using a mean strategy, preserving data integrity.

B. Data Preprocessing

1. *Outlier Removal:* Firstly, spikes will be detected visually using plots and removed outside of the preferred Median Absolute Deviation range. Wavelengths will be aligned to the preferred range, and noise will be smoothed. Final visual verification will refine parameters to safeguard absorption features.
2. *Continuum Removal:* Spectra will be normalised using a continuum-removal technique to minimise slope effects and enhance the visibility of diagnostic absorption features.
3. *Data Splitting:* The dataset will be randomly split into training and testing subsets. Scaling and dimensionality reduction will be applied based only on the training set to prevent information leakage.
4. *Scaling:* Reflectance and the associated measurement uncertainties will be normalised ([0, 1]) and standardised (mean 0, SD 1) to a common reference by the same factor to enable direct comparison between asteroid samples. The factor will be either a reference wavelength or the maximum reflectance.
5. *Dimensional Reduction:* Principal Component Analysis (PCA) will compress the high-dimensional spectral data into a smaller set of uncorrelated variables. This will enhance noise robustness, improve computational efficiency, and highlight the most significant spectral variations for classification and interpretation.
6. *Quantum Encoding:* Quantum Encoding will be implemented using Qiskit's feature maps, enabling amplitude and angle-based encodings, allowing asteroid reflectance spectra to be represented as quantum states.

C. Model Design

JNI-SQP features a Variational Quantum Classifier (VQC) [30] implemented in Qiskit [23], used to classify asteroid types. Classical baselines such as SVM [31] and CNN [32] will be employed for comparison.

D. Training

Training leverages Google Colab's [25] free GPU/TPU resources. Classical baselines, including SVM and CNN models, will also be trained for comparison. Hyperparameters for the classical models and VQC will be optimised using a validation set, ensuring robust performance and preventing overfitting, with the VQC iteratively tuning circuit parameters to maximise classification accuracy and F1-score.

E. Evaluation

The models will be evaluated on a 10% hold-out validation set using accuracy and F1-score, targeting values above 95%. Five-fold cross-validation will be employed to ensure robustness. Runtime efficiency will be assessed, with the expectation of measurable improvement over classical baselines. Results will be visualised using confusion matrices and ROC curves.

F. Risks and Mitigation

1. NISQ Constraints: Noise and qubit limitations are relaxed by Qiskit Aer simulators.
2. Data Misalignment: Corrected through strict visual alignment verification.
3. Hardware availability/queue time: Mitigation: Executing locally or on IBM Qiskit simulators prior to executing efficiently on real hardware.

4. Limited size of a sample/overfitting: Mitigation: Performing dimensionality reduction (PCA) to lower feature number, and utilize cross-validation when training a model.

EXPECTED OUTCOME

Validation of the hypothesis will enable the JNI-SQP model to reduce asteroid selection computation time by a great amount and achieve classification precision above 95% using quantum simulators, facilitating faster identification of high-value asteroids for space mining. This will yield a hybrid quantum-classical prototype, validated spectral datasets from MIT/SMASSII archive. Despite NISQ limitations (noise, limited qubits), the simulator-based framework will provide a scalable blueprint for future hardware adaptations, enhancing resource yield predictions for space missions.

OPERATIONAL FRAMEWORK

A. Resource

1. *Data Sets:* NEAs' (Near Earth Asteroid) reflectance spectral datasets from MIT/SMASSII archive (Small Main-Belt Asteroid Spectroscopic Survey) [17-22].
2. *Preprocessing Tools:* Preprocessing is conducted in Google Colab [25] using Matplotlib [26] for visualisation, scipy.stats [27] for Median Absolute Deviation, scipy.signal [27] for median filtering and scipy.signal.savgol_filter [27] for Savitzky-Golay Smoothing [27] for smoothing, sklearn.Preprocessing [29] for scaling and vector normalization, sklearn.decomposition [29] for PCA, and Qiskit [23] for quantum encoding.
3. *Quantum Computing Tools:* Open-source and cloud-based tools are utilized to implement quantum aspects for conducting simulations of the problem of interest.

    Qiskit [23]*:* An open-source Python library to design, simulate, and run quantum circuits.

    IBM Quantum Lab [24]*:* An online platform that allows users to execute quantum circuits on actual quantum processors as well as simulators.

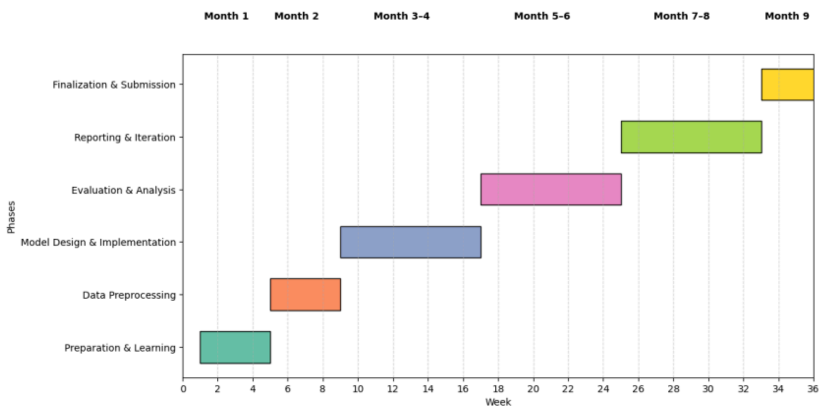
    Google Colab [25]*:* A cloud-hosted platform to run Python code in Jupyter notebook provided with free GPU/TPU to run simulations, Qiskit, and traditional tools to make it viable without specialized local hardware.

B. Budget

Category	Estimated Cost	Notes
Datasets Access	$0	Open-source
Software/Tools	$0	Open-source
Quantum Hardware Access	$500–$2000	Quantum hardware fees are not fixed because the runtime is variable and the cost is contingent on the execution time.
Compute (Colab Pro)	0$-$100	Free tier primary; upgrade if needed

Cloud Storage	$0	free
Contingencies	$200	When there are needs
Total	$2300 (approx.)	-

C. Timeline



CONCLUSION

This project proposes an innovative hybrid Quantum Machine Learning framework to transform asteroid selection for space mining. It provides a scalable way to achieve higher precision and efficiency, even with the limitations of NISQ, by overcoming current computational bottlenecks and using quantum-classical synergy. The expected improvements will not only make predictions about asteroid resource yields more accurate, but they will also lay the groundwork for using quantum technologies more widely in astronomy. We ask for support for this effort, which will speed up sustainable space exploration and help us stay ahead in quantum-driven innovation.

REFERENCE

[1] K. M. Cannon, “Precious and structural metals on asteroids,” *Journal of Materials Science*, vol. 58, no. 12, pp. 103256, 2023, doi: 10.1016/j.jms.2022.103256.

[2] A. M. Hein, R. Matheson, and D. Fries, "A techno-economic analysis of asteroid mining," in *Proc. Int. Astronautical Congress*, Bremen, Germany, Oct. 2018. [Online]. Available: https://hal.archives-ouvertes.fr/hal-01910095

[3] Mark J Sonter, "The Technical and Economic Feasibility of Mining the Near-Earth Asteroids" https://nss.org/wp-content/uploads/2017/07/Mining-Near-Earth-Asteroids-Sonter.pdf

[4] S. Fornasier, B. E. Clark, E. Dotto, A. Migliorini, M. Ockert-Bell, and M. A. Barucci, “Spectroscopic survey of M-type asteroids,” *Icarus*, vol. 210, no. 2, pp. 655–673, 2010.

[5] Jiayi Ge *et al.*, “Asteroid material classification based on multi-parameter constraints using artificial intelligence**”**
Available: https://www.aanda.org/articles/aa/full_html/2024/12/aa51971-24/aa51971-24.html

[6] J. P. Emery and L. F. Lim, “Thermal Emission Spectroscopy of M-type Asteroids: How Many Are Metallic?,” in *EPSC-DPS Joint Meeting*, 2011.

[7] Z. Wang, R. Zuo, X. Liu, et al., “An Evaluation of Convolutional Neural Networks for Lithological Mapping Based on Hyperspectral Images,” *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 17, pp. 1-14, Mar. 2024, doi:10.1109/JSTARS.2024.3372138.

[8] J. Biamonte, P. Wittek, N. Pancotti, P. Rebentrost, N. Wiebe, and S. Lloyd, "Quantum machine learning," *Nature*, vol. 549, pp. 195–202, Sep. 2017. doi: 10.1038/nature23474

[9] V. Havlíček et al., "Supervised learning with quantum-enhanced feature spaces," *Nature*, vol. 567, no. 7747, pp. 209–212, Feb. 2019. [Online]. Available: https://doi.org/10.1038/s41586-019-0980-2

[10] M. Schuld, I. Sinayskiy, and F. Petruccione, "An introduction to quantum machine learning," *Contemp. Phys.*, vol. 56, no. 2, pp. 172–185, 2015. [Online]. Available: https://doi.org/10.1080/00107514.2014.964942

[11] F. E. DeMeo and B. Carry, "Solar system evolution from compositional mapping of the asteroid belt," *Nature*, vol. 505, no. 7485, pp. 629–634, Jan. 2014. doi: 10.1038/nature12908

[12] V. Reddy, T. L. Dunn, C. A. Thomas, N. A. Moskovitz, T. H. Burbine, and B. E. Clark, "Mineralogy and surface composition of asteroids," in *Asteroids IV*, P. Michel, F. E. DeMeo, and W. F. Bottke, Eds. University of Arizona Press, pp. 43–63, 2015.

[13] L. Breitenfeld et al., "Machine learning applied to mid-infrared spectra of asteroids: Predicting mineral abundances," *J. Geophys. Res. Planets*, vol. 126, no. 10, Oct. 2021. [Online]. Available: https://agupubs.onlinelibrary.wiley.com/doi/epdf/10.1029/2021JE007035

[14] Guo, T., Lu, X.-P., Zhang, Y.-X., & Yu, K. "Neighboring Discriminant Component Analysis for Asteroid Spectrum Classification," *Remote Sensing*, vol. 13, no. 16, article 3306, 2021, doi:10.3390/rs13163306.

[15] D. P. García et al., "Systematic literature review: Quantum machine learning and its applications," *Quantum Sci. Technol.*, 2023. [Online]. Available: https://arxiv.org/pdf/2201.04093

[16] Gujju, Y., Matsuo, A., & Raymond, R., "Quantum Machine Learning on Near-Term Quantum Devices: Current State of Supervised and Unsupervised Techniques for Real-World Applications," *Phys. Rev. Applied*, vol. 21, art. 067001, 2024.

[17] R. P. Binzel, A. W. Harris, S. J. Bus, and T. H. Burbine, "Spectral properties of Near-Earth objects: Palomar and IRTF results for 48 objects including spacecraft targets (9969) Braille and (10302) 1989 ML," Icarus, vol. 151, pp. 139–149, 2001. [Data set]. Available: http://smass.mit.edu/smassneodata.tar.gz

[18] R. P. Binzel, A. S. Rivkin, S. J. Bus, J. Sunshine, and T. Burbine, "MUSES-C Target Asteroid (25143) 1998 SF36: A reddened ordinary chondrite," Meteoritics Planet. Sci., vol. 36, pp. 1167–1172, 2001. [Data set]. Available: http://smass.mit.edu/smassref5.tar.gz

[19] R. P. Binzel, M. Birlan, S. J. Bus, A. W. Harris, A. S. Rivkin, and S. Fornasier, "Spectral observations for Near-Earth objects including potential target 4660 Nereus: Results from Meudon remote observations at the NASA Infrared Telescope Facility (IRTF)," Planet. Space Sci., vol. 52, pp. 291–296, 2004. [Data set]. Available: http://smass.mit.edu/smassref6.tar.gz

[20] R. P. Binzel, E. Perozzi, A. S. Rivkin, A. Rossi, A. W. Harris, S. J. Bus, G. B. Valsecchi, and S. M. Slivan, "Dynamical and compositional assessment of Near-Earth object mission targets," Meteoritics Planet. Sci., vol. 39, pp. 351–366, 2004. [Data set]. Available: http://smass.mit.edu/smassref7.tar.gz

[21] R. P. Binzel, A. S. Rivkin, J. S. Stuart, A. W. Harris, S. J. Bus, and T. H. Burbine, "Observed spectral properties of Near-Earth objects: Results for population distribution, source regions, and space weathering processes," Icarus, vol. 170, pp. 259–294, 2004. [Data set]. Available: http://smass.mit.edu/smassref8.tar.gz

[22] A. S. Rivkin, R. P. Binzel, J. Sunshine, S. J. Bus, T. H. Burbine, and A. Saxena, "Infrared spectroscopic observations of 69230 Hermes (1937 UB): Possible unweathered endmember among ordinary chondrite analogues," Icarus, vol. 172, pp. 408–414, 2004. [Data set]. Available: http://smass.mit.edu/smassref9.tar.gz

[23] H. Abraham *et al*., "Qiskit: An Open-source Framework for Quantum Computing," Zenodo, 2025. [Online]. Available: https://doi.org/10.5281/zenodo.15530001.

[24] IBM Quantum Team, "IBM Quantum Lab," IBM Quantum Experience Documentation, 2023. [Online]. Available: https://quantum-computing.ibm.com/docs

[25] Google, "Colab: Collaborative Jupyter Notebooks," Google Colab Documentation, 2023. [Online]. Available: https://colab.research.google.com/notebooks/intro.ipynb

[26] J. D. Hunter, *Matplotlib: A 2D Graphics Environment*, Computing in Science & Engineering, vol. 9, no. 3, pp. 90–95, 2007. [Online]. Available: https://matplotlib.org/

[27] P. Virtanen *et al*., "SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python," *Nature Methods*, vol. 17, pp. 261–272, 2020. [Online]. Available: https://doi.org/10.1038/s41592-019-0686-2

[28] A. Savitzky and M. J. E. Golay, "Smoothing and Differentiation of Data by Simplified Least Squares Procedures," *Analytical Chemistry*, vol. 36, no. 8, pp. 1627–1639, 1964.

[29] F. Pedregosa *et al*., "Scikit-learn: Machine Learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011. [Online]. Available: https://scikit-learn.org/

[30] P. Sen, A. S. Bhatia, K. S. Bhangu, and A. Elbeltagi, “Variational quantum classifiers through the lens of the Hessian,” *PLOS ONE*, vol. 17, no. 1, p. e0262346, Jan. 2022, doi: 10.1371/journal.pone.0262346.

[31] C. Cortes and V. Vapnik, “Support-vector networks,” *Machine Learning*, vol. 20, no. 3, pp. 273–297, Sept. 1995, doi: 10.1007/BF00994018.

[32] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, “Gradient-based learning applied to document recognition,” *Proceedings of the IEEE*, vol. 86, no. 11, pp. 2278–2324, Nov. 1998, doi: 10.1109/5.726791.

Research Proposal by Sajid Aman - Sajid Aman.pdf

ORIGINALITY REPORT

22%	21%	18%	0%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	arxiv.org Internet Source	3%
2	e-archivo.uc3m.es Internet Source	2%
3	d197for5662m48.cloudfront.net Internet Source	1%
4	S Suhas, S Divya. "Quantum-Improved Weather Forecasting: Integrating Quantum Machine Learning for Precise Prediction and Disaster Mitigation", 2023 International Conference on Quantum Technologies, Communications, Computing, Hardware and Embedded Systems Security (iQ-CCHESS), 2023 Publication	1%
5	jgit.kntu.ac.ir Internet Source	1%
6	hal.archives-ouvertes.fr Internet Source	1%
7	upcommons.upc.edu Internet Source	1%
8	repository.tudelft.nl Internet Source	1%
9	theses.gla.ac.uk Internet Source	1%
10	par.nsf.gov Internet Source	1%

11	spj.science.org Internet Source	1 %
12	etheses.lib.ntust.edu.tw Internet Source	1 %
13	export.arxiv.org Internet Source	1 %
14	tel.archives-ouvertes.fr Internet Source	1 %
15	agupubs.onlinelibrary.wiley.com Internet Source	1 %
16	ltu.diva-portal.org Internet Source	1 %
17	Moez Krichen, Mohamed S. Abdalzaher. "Performance enhancement of artificial intelligence: A survey", Journal of Network and Computer Applications, 2024 Publication	1 %
18	ntnuopen.ntnu.no Internet Source	<1 %
19	tikalon.com Internet Source	<1 %
20	Cong Yang, Yanni Dong, Bo Du, Liangpei Zhang. "Attention-Based Dynamic Alignment and Dynamic Distribution Adaptation for Remote Sensing Cross-Domain Scene Classification", IEEE Transactions on Geoscience and Remote Sensing, 2022 Publication	<1 %
21	iris.unito.it Internet Source	<1 %
22	1login.easychair.org Internet Source	<1 %

23	Jing Liang, Fangqi Zhu. "Soil Moisture Retrieval From UWB Sensor Data by Leveraging Fuzzy Logic", IEEE Access, 2018 Publication	<1 %
24	cs.petrsu.ru Internet Source	<1 %
25	pypi.org Internet Source	<1 %
26	www.ijcaonline.org Internet Source	<1 %
27	Pushpa Choudhary, Sambit Satpathy, Arvind Dagur, Dhirendra Kumar Shukla. "Recent Trends in Intelligent Computing and Communication", CRC Press, 2025 Publication	<1 %
28	Amin Yahyaabadi, Matthew Driedger, Nathalie Turenne, Stephanie Connell et al. "ManitobaSat-1: A Novel Approach for Technology Advancement", IEEE Potentials, 2020 Publication	<1 %
29	Muhamad Akrom, Supriadi Rustad, Pulung Nurtantio Andono, Guruh Fajar Shidik et al. "Predicting lattice constant in ABX3 perovskite via quantum machine learning", Computational Materials Science, 2025 Publication	<1 %
30	quantum-journal.org Internet Source	<1 %
31	www.coursehero.com Internet Source	<1 %
32	Y.R. Fernández, J.-Y. Li, E.S. Howell, L.M. Woodney. "Asteroids and Comets", Elsevier BV, 2015	<1 %

Publication

33	Jiayi Ge, Xiaoming Zhang, Juan Li, Mingtao Li, Yijun Tang, Yunxiao Jiang, Chengzhi Liu, Zhe Kang, Xianqun Zeng, Xiaojun Jiang. "Asteroid material classification based on multi-parameter constraints using artificial intelligence", Astronomy & Astrophysics, 2024 Publication	<1 %

Exclude quotes	On	Exclude matches	Off
Exclude bibliography	Off		