Dark Web Image Classification Using Quantum Convolutional Neural Network

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Abstract - Image data is present in about 75% of black marketplace postings, underscoring the need of taking this into account when doing investigative investigation. However, manually scanning tens of thousands of websites for visual evidence of criminal activity is time and resource intensive. Therefore, use of Quantum Computing is propagated to classify the images using Quantum Convolutional Neural Network. Current studies concentrate on certain fields, such as locating dark marketplace based on image identification. The images are classified based on the scrapped data from the dark marketplace such as alcohol, devices, cards, drugs, etc.

The provided dataset for this project consists of around 1242 files and 4 folders comprising picture data, and is comprised of hidden services. Identifying and implementing a model that can identify the objects in an existing dataset with the best possible accuracy will aid future researchers working with datasets containing classes with comparable characteristics. The dataset that will be utilised in this study will be made accessible to the scientific community so that they may do further analysis.

I. Introduction

Keywords: Dark Web, Tor, Images, Quantum Circuit, Quantum Computing for Cyber Security, Quantum Convolutional Neural Network.

Anonymity networks like Tor enable the hosting of covert internet markets where dark vendors may deal illegal goods including narcotics, firearms, and hacking services. Dark picture classification and analysis algorithms that work well assist dark web investigations that aid in locating and identifying these markets. Existing automated systems only take into account text, ignoring non-textual objects like images. Despite the fact that image data can enhance investigative analysis, there are two main obstacles to overcome when analysing dark web images: (a) moral concerns about the existence of child exploitation imagery in illicit markets, and (b) the computational burden of downloading, processing, analysing, and storing image content.

Quantum machine learning (QML), an interdisciplinary area of research in the realm of quantum artificial intelligence, has drawn growing attention. Machine learning methods are mostly implemented using QML on quantum hardware such quantum annealers and quantum circuits. QML, which is based on quantum features including superposition, entanglement, and quantum parallelism, offers the ability to more effectively address the issues associated with huge data and the sluggish training process in existing conventional machine learning.
CNNs that dealt with quantum data could be used to recognise stages of quantum states and create a quantum error correcting system. Quantum gates with controllable parameters were used to approximate the pooling and convolutional layers.
In this research, we present a novel quantum convolutional neural network model based on parameterized quantum circuits for image classification applications, driven by the network structure in and current research on the expressive power as well as quantum benefits on low-depth quantum circuits. First of all, unlike other models, this one categorises classical picture data rather than quantum data. To be processed by quantum technology, image data must be encoded into quantum states.
In this research, authors developed the quantum convolutional layers and pooling layers built on the amplitude encoding using more expressive universal quantum gates, which allows us to use the QCNN model to handle grid-type input, such as photographs. Lastly, compared to various finite-difference based optimization algorithms, the learning algorithm of this model is based on the parametric rule, which can effectively calculate the analytical gradients of loss functions on quantum

circuits and obtain a faster yet more stable rate of convergence. [2]

II. ORGANISATION OF PAPER

A. Related Work

Introduction to Quantum Computing

Quantum computers, which are very potent and secure, will be advantageous for information and communication technology. Quantum computing is a developing technology that employs quantum physics to tackle issues that traditional computer cannot. Because quantum computers employ probability rather than merely 1s and 0s, they can process exponentially more data than conventional computers. Qubits, or fundamental memory units, are formed in quantum computing by using the spin or photon orientation of physical systems. The concept of quantum superposition refers to the notion that physical systems can exist in a variety of configurations at the same time. The quantum entanglement phenomenon is also capable of inextricably joining qubits.

Millions of low error rate and long coherence time qubits can be used in fault-tolerant quantum computers to handle issues like integer factorization and unstructured database searches. Although it may take decades for experiments to lead to the realisation of noisy intermediate-scale quantum (NISQ) computers, these systems are now in production. Numerous uncorrected quantum bits are used in noise qubit computers, which leads to faulty computations within a constrained window of coherence. Numerous methods have been put forth by researchers to take use of these devices' quantum properties.

Contrary to traditional computing, quantum computing has a clear benefit. The current generation of supercomputers might be surpassed by quantum computers. Researchers are still figuring out which kinds of traditional computing issues quantum computing can tackle. Researchers also looked into quantum machine learning.

Data processing is done at the quantum level by quantum computers. Machine learning technology developed more quickly on quantum software than on traditional computers. In quantum machine learning, conventional data is initially loaded into the states of the qubits. Encoding or embedding quantum data allows for the creation of quantum states. For optimal performance, quantum machine learning algorithms (QML) mainly rely on conventional data encoding. Encoding, processing, and measurement are the three stages of quantum machine learning. Quantum machine learning involves three stages: encoding, processing, and measurement. The three points in the list of points below are briefly discussed.

- **Encoding:** putting conventional information into a quantum state.
- **Processing:** At this stage, the quantum device processes the embedded input, which will be a variational circuit or a quantum routine.
- **Measurement:** This phase evaluates the anticipated outcome to provide the prediction for QML.

Quantum Computing for proactive cybersecurity

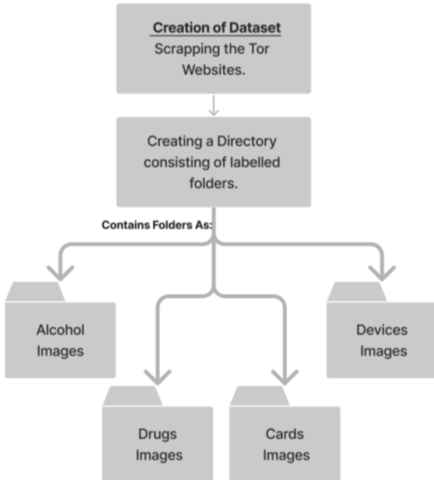
Numerous computer science research have been affected by the idea of quantum computation, particularly those in the fields of computational modelling, cryptography theory, and information theory. Information security may benefit from quantum computers, or it may suffer a detrimental effect.The advantages of quantum computing in cybersecurity have been thoroughly examined by many researchers. Njorbuenwu, The use of a quantum computer has the potential to be advantageous in a number of domains, according to M et al.
A research on the application of many quantum concepts was given by Laxminarayana N et al. Intruder detection systems for healthcare systems may be trained using mechanics and neural networks. On the KDD99 dataset, scientists tested the suggested method.

Researchers investigated how quantum computing may reduce the need for domain-specific security. Ko K. K. & Jung, E. S. provided quantum computing-based representations of standard AES and modified AES algorithms to underline that quantum computing will be a viable solution to improve cybersecurity. To protect cyber-physical systems, Tosh D et al. suggested utilising quantum cryptography to encrypt communication between sensors and computers. Ali, A looked at the viability of fusing quantum and conventional computers.
Musashi, Y., and Suryotrisongko, H. suggested an unique hybrid quantum-classical deep learning model for botnet detection using domain generation algorithms (DGA).

Researchers are also examining if applying quantum mechanical concepts to machine learning issues might enhance the outcome. The most recent research results in quantum machine learning were compiled by Abohashima Z et al. A classification with Quantum Convoltional Neural Network strategy were suggested by the authors.

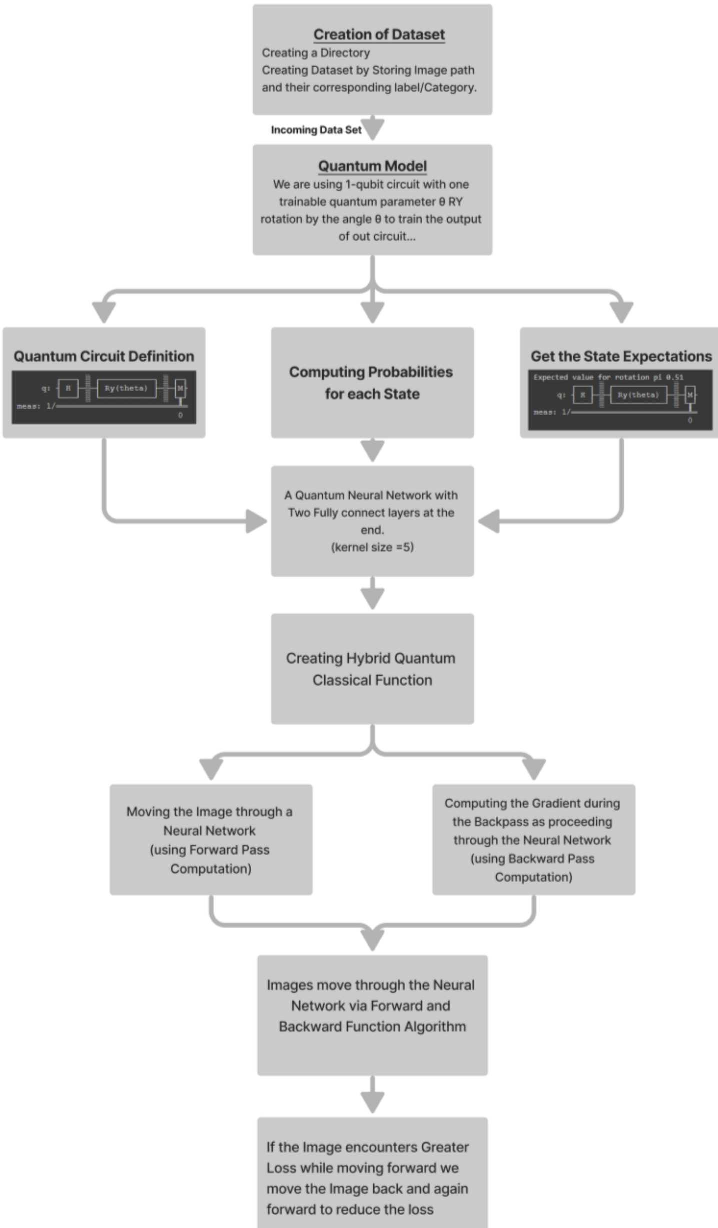
B. Proposed Approach

Figure1 Depicts the proposed methodology to create the dataset



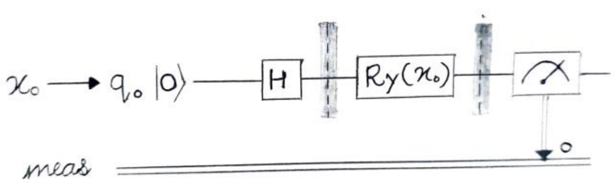
*(**to be written about how the dataset has been prepared how from which source it has been created**)*

Figure 2 depicts the proposed methodology for classifying onion services market images with quantum convolutional neural network.



Quantum Circuit Used

Authors has built and implemented 1-qubit Quantum Circuit



About Quantum Convolutional Neural Network

1. ***Neurons and Weights***

A neural network is essentially merely a complex function constructed from smaller building components known as neurons. A neuron is often a nonlinear function that translates one or more inputs to a single real number. It is also typically simple, straightforward to compute, and nonlinear. Normally, neurons copy their single output and provide it to other neurons as input. In order to visually depict how the output of one neuron will be utilised as the input to other neurons, we represent neurons as nodes in a graph and draw directed edges between nodes. Also noteworthy is the fact that each edge in our graph frequently has a scalar number called a weight attached to it. Each input to a neuron will be multiplied by a separate scalar before being gathered and processed into a single result, according to this theory. In order to train a neural network, our main goal is to select weights that will cause the network to act a certain manner.

2. **Input Output Structure of neural network**

A traditional (real-valued) vector serves as the input to a neural network. According to the network's graph topology, a layer of neurons receives each component of the input vector multiplied by a distinct weight. The findings are compiled into a new vector, where the i'th component stores the output of the i'th neuron, after each neuron in the layer has been assessed. After that, a new layer can use this new vector as an input, and so on. Except for the initial and last levels of our network, we shall refer to all other layers as hidden layers.

3. **Feed Forward Neural Network**

A feed-forward neural network is the name given to the type of neural network we will be working with (FFNN). This means that information will never hit a cell again as it passes through our brain network. We may call the graph that represents our neural network a directed acyclic graph (DAG). Furthermore, no edges will be allowed between neurons in the same layer of our neural network.

4. **Backend**

Backend act as either a simulator or an actual quantum computer, operating quantum circuits and/or pulse schedules and providing results.

5. **Shots**

1. A single trip through each step of a full quantum circuit on an IonQ, Rigetti, or OQC gate-based QPU is referred to as a "shot."

A Mathematical Approach to Quantum Convolutional Layer

Let X^l be the input and K^l be the Kernel for the layer l of a convolutional neural network, And f: R $\rightarrow$[0, C] with C > 0 be a non-linear function so that $f(X^{l+1}) := f(X^l * K^l)$ is the output for layer l. The given X^l and K^l are stored in Quantum Random Access Memory (QRAM), there is a quantum algorithm that for precision parameters $\varepsilon > 0$ and $\eta > 0$, creates quantum state $|f(\overline{X}^{l+1})\rangle$ such that $\| f(\overline{X}^{l+1}) - f(X^{l+1}) \|_\infty \leq 2\varepsilon$ and retrieves classical tensor χ^{l+1} such that for each pixel j. [25]

$$\begin{cases} \left|\chi_j^{l+1} - f\left(\chi_j^{l+1}\right)\right| \leq 2\varepsilon & if\ f\left(\chi_j^{l+1}\right) \geq \eta \\ \chi_j^{l+1} = 0 & if\ f\left(\chi_j^{l+1}\right) < \eta \end{cases}$$

The Algorithm has the time complexity as

$$O\left(\frac{1}{\varepsilon\eta^2} \cdot \frac{M\sqrt{C}}{\sqrt{E\left(f\left(\overline{X}^{l+1}\right)\right)}}\right)$$

O hides the poly-logarithmic in the size of X^l and K^l.

Algorithms Used

1. Forward Pass for QCNN

The quantum analogue of a single quantum convolutional layer is implemented in the QCNN forward pass method. To prepare the input for the following layer, it first applies a convolutional function to an input and a kernel, then applies a nonlinear function and performs pooling operations.

2. Quantum Backpropagation Algorithm (Backward Pass)

It is widely used algorithm to train feed forward neural network is backpropagation. The algorithm required for quantum convolutional neural network is quantum backpropagation algorithm. Like in classical feed forward neural network we have classical backpropagation algorithm which updates all kernels weights according to the derivative of a given loss function *L*.

The algorithm calculates each element of the gradient tensor $\frac{\partial L}{\partial F^l}$ within additive error $\delta \, \| \frac{\partial L}{\partial F^l} \|$ which updates F^l as per the gradient descent update rule.

The time complexity of a single layer l for quantum backpropagation is [25]:

$$O\left(\left(\left(\mu(A^l) + \mu\left(\frac{\partial L}{\partial Y^{l+1}}\right)\right)\kappa\left(\frac{\partial L}{\partial F^l}\right) + \left(\mu\left(\frac{\partial L}{\partial Y^{l+1}}\right) + \mu(F^l)\right)\kappa\left(\frac{\partial L}{\partial Y^l}\right)\right)\frac{\log {}^1/_\delta}{\delta^2}\right)$$

The gradient is calculated as:

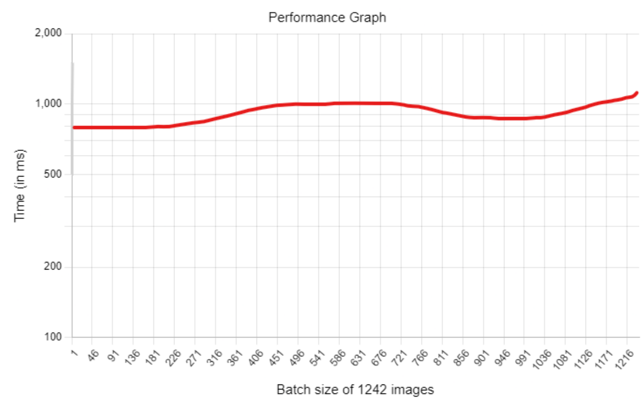
$$\Delta_{x_0}\, QuantumCircuit(x_0) = QuantumCircuit(\alpha + \beta) - QuantumCircuit(\alpha - \beta)$$

Here x_0 and α represented as parameter for Quantum Circuit and β as macroscopic shift. Thus the gradient is simply the difference the Quantum Circuit evaluated at $\alpha + \beta$ And $\alpha - \beta$.

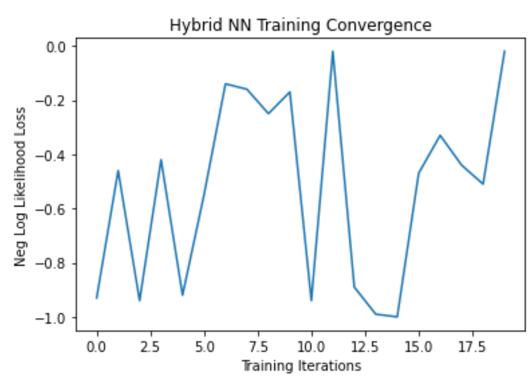
IV. RESULT AND DISCUSSION

(**this has to be wrtiten**)

Performance graph with the batch size of 1242



Epoch graph



Pseudo Code for QCNN

Function to create dataset by storing image path and corresponding label:

return dictionary with key as image path and value as label index

Class for QuantumCircuit:

constructor taking input as n_qubits, shots, backend:

defining circuit parameters

Function to run the circuit taking parameter as rotating angle:

counting the result of each Iteration through the backend,

getting the states of each count

computing the probabilities of each state

getting the state expectation

return an array of state expectation

Class for HybridFunction

Static Function for forward pass computation taking context, input, quantum_circuit, and shift as parameters:

getting the shifts from context

getting the shifts from quantum_circuit

getting the expectations along Z-axis of rotation

calculating the result as tensors of expectations

storing the input and result for further backward pass computation

Static Function for backward pass computation taking context and gradient_output as parameters:

destructuring input and expectations along Z-axis to save as tensor pair

taking list of input from previous gradient

calculating the amount of shift shape

adding to the calculated shift to input_list to shift right

subtracting the calculated shift from input_list to shift left

a loop to append values of gradient after subtracting left and right side expectations

CONCLUSION

(**has to be written**)

REFERENCES

[1] Cong, I., Choi, S., \& Lukin, M. D. (2019). Quantum convolutional neural networks. Nature Physics, 15(12), 1273-1278.

[2] Lü, Y., Gao, Q., Lü, J., Ogorzałek, M., \& Zheng, J. (2021, July). A Quantum Convolutional Neural Network for Image Classification. In 2021 40th Chinese Control Conference (CCC) (pp. 6329-6334). IEEE.H. Simpson, *Dumb Robots*, 3rd ed., Springfield: UOS Press, 2004, pp.6-9.

[3] Oh, S., Choi, J., Kim, J. K., \& Kim, J. (2021, January). Quantum convolutional neural network for resource-efficient image classification: A quantum random access memory (QRAM) approach. In 2021 International Conference on Information Networking (ICOIN) (pp. 50-52). IEEE.

[4] Kerenidis, I., Landman, J., & Prakash, A. (2019). Quantum algorithms for Trochun, Y., Stirenko, S., Rokovyi, O., Alienin, O., Pavlov, E., & Gordienko, Y. (2021, September). Hybrid Classic-Quantum Neural Networks for Image Classification. In *2021 11th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS)* (Vol. 2, pp. 968-972). IEEE.

[5] Wei, S., Chen, Y., Zhou, Z., & Long, G. (2022). A quantum convolutional neural network on NISQ devices. *AAPPS Bulletin*, *32*(1), 1-11.

[6] Liu, J., Lim, K. H., Wood, K. L., Huang, W., Guo, C., & Huang, H. L. (2021). Hybrid quantum-classical convolutional neural networks. *Science China Physics, Mechanics & Astronomy*, *64*(9), 1-8.

[7] Li, Y., Zhou, R. G., Xu, R., Luo, J., & Hu, W. (2020). A quantum deep convolutional neural network for image recognition. *Quantum Science and Technology*, *5*(4), 044003.

[8] Mari, A., Bromley, T. R., Izaac, J., Schuld, M., & Killoran, N. (2020). Transfer learning in hybrid classical-quantum neural networks. *Quantum*, *4*, 340.

[9] Zhao, C., & Gao, X. S. (2021). Qdnn: deep neural networks with quantum layers. *Quantum Machine Intelligence*, *3*(1), 1-9.

[10] Nguyen, N. T., & Kenyon, G. T. (2018, November). Image classification using quantum inference on the d-wave 2x. In *2018 IEEE International Conference on Rebooting Computing (ICRC)* (pp. 1-7). IEEE.

[11] Hur, T., Kim, L., & Park, D. K. (2022). Quantum convolutional neural network for classical data classification. *Quantum Machine Intelligence*, *4*(1), 1-18.

[12] Shi, S., Wang, Z., Cui, G., Wang, S., Shang, R., Li, W., ... & Gu, Y. (2022). Quantum-inspired complex convolutional neural networks. *Applied Intelligence*, 1-10.

[13] Li, W., Chu, P. C., Liu, G. Z., Tian, Y. B., Qiu, T. H., & Wang, S. M. (2022). An Image Classification Algorithm Based on Hybrid Quantum Classical Convolutional Neural Network. *Quantum Engineering*, *2022*.

[14] Verdon, G., McCourt, T., Luzhnica, E., Singh, V., Leichenauer, S., & Hidary, J. (2019). Quantum graph neural networks. *arXiv preprint arXiv:1909.12264*.

[15] Mogalapalli, H., Abburi, M., Nithya, B., & Bandreddi, S. K. V. (2022). Classical–quantum transfer learning for image classification. *SN Computer Science*, *3*(1), 1-8.

[16] Mattern, D., Martyniuk, D., Willems, H., Bergmann, F., & Paschke, A. (2021). Variational quanvolutional neural networks with enhanced image encoding. *arXiv preprint arXiv:2106.07327*.

[17] Bokhan, D., Mastiukova, A.S., Boev, A.S., Trubnikov, D.N. and Fedorov, A.K., 2022. Multiclass classification using quantum convolutional neural networks with hybrid quantum-classical learning. *arXiv preprint arXiv:2203.15368*.

[18] Henderson, M., Shakya, S., Pradhan, S. and Cook, T., 2020. Quanvolutional neural networks: powering image recognition with quantum circuits. *Quantum Machine Intelligence*, *2*(1), pp.1-9.

[19] Skolik, A., McClean, J.R., Mohseni, M., van der Smagt, P. and Leib, M., 2021. Layerwise learning for quantum neural networks. *Quantum Machine Intelligence*, *3*(1), pp.1-11.

[20] Garcıa-Hernandez, H.I., Torres-Ruiz, R. and Sun, G.H., 2020. Image classification via quantum machine learning. *arXiv preprint arXiv:2011.02831*.

[21] Abohashima, Z., Elhosen, M., Houssein, E.H. and Mohamed, W.M., 2020. Classification with quantum machine learning: A survey. *arXiv preprint arXiv:2006.12270*.
[22] Farhi, E., & Neven, H. (2018). Classification with quantum neural networks on near term processors. *arXiv preprint arXiv:1802.06002*.
[23] Kerenidis, I. and Prakash, A., 2020. Quantum gradient descent for linear systems and least squares. *Physical Review A*, *101*(2), p.022316
[24] Crooks, G.E., 2019. Gradients of parameterized quantum gates using the parameter-shift rule and gate decomposition. *arXiv preprint arXiv:1905.13311*.
[25] Kerenidis, I., Landman, J., & Prakash, A. (2019). Quantum algorithms for deep convolutional neural networks. *arXiv preprint arXiv:1911.01117*.