**Dark Web Image Classification Using Quantum Convolutional Neural Network**

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**ABSTRACT**

Researchers and security professionals regard dark web data as one of the methods for proactive cyber protection. As a result, the classification of dark web picture material using methodologies ranging from machine learning to deep learning is intensively investigated in the literature. However, certain issues exist with categorising dark web image services, such as the dataset's restriction to identify hidden services and the need for significant computational and storage resources to store raw and unlabelled dark web data.

The proposed work presented a Quantum Convolutional Neural Network based approach to classify the images found on dark web hidden services. First, the dark web crawler crawled the Tor dark web to fetch the hidden services images.

(\*\*do we have to mention about dataset preparation? And how to explain the working or neural network\*\*)

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

1. **INTRODUCTION**

(\*\*confirmation of which to be added\*\*)

**ORGANISATION OF PAPER**

The organisation of the chapter includes related work in section II. Section III covers methodologies and result discussion, and the paper concludes with limitation and future scope.

1. **RELATED WORK**

(\*\*do we need an exact data from related works para\*\*)

**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.

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

**Quantum Computing for proactive cybersecurity**

(\*\*do we need to include this info as well?\*\*)

**3. PROPOSED APPROACH**

(\*\*dataset details verification needed\*\*)

Figure 1 depicts the proposed methodology to create the dataset.

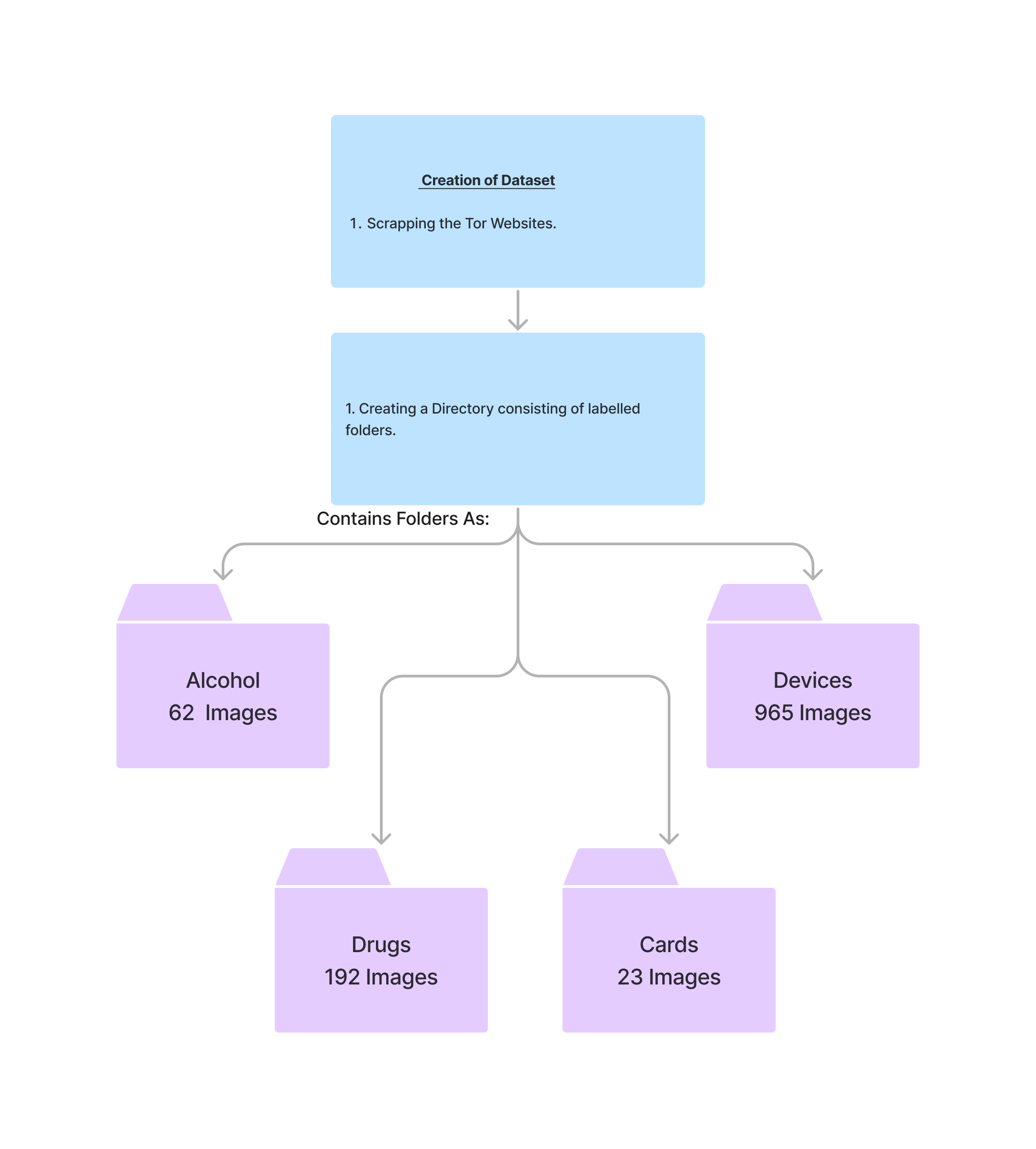
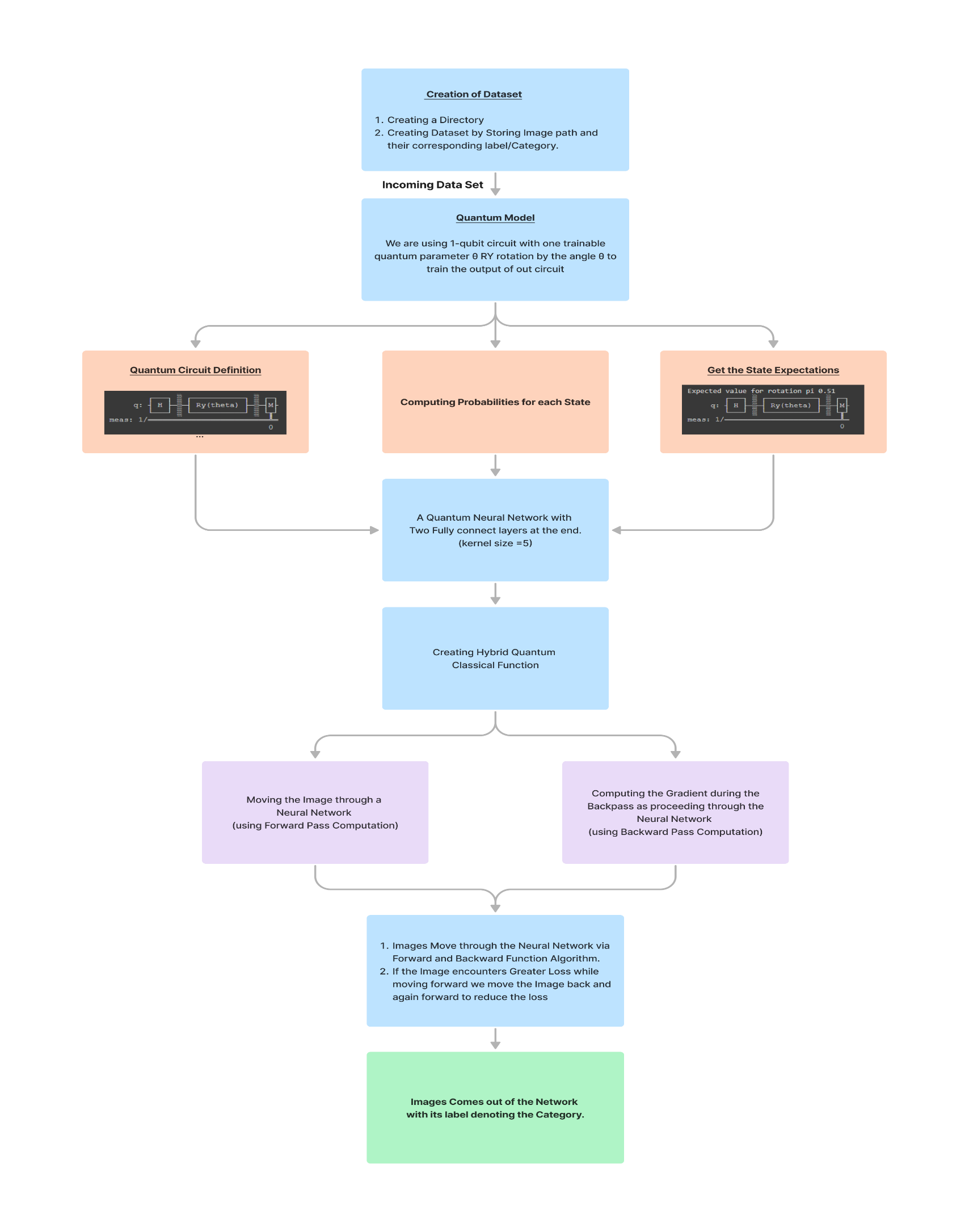


Fig.1 Proposed Methodology for dataset creation

Figure 2 depicts the proposed methodology for classifying onion services market images with quantum convolutional neural network.Fig.2 Proposed Methodology for Image Classification

(%%to be written as what actually happens in the model%%)

[{ask mam about this reference}](https://qiskit.org/textbook/ch-applications/image-processing-frqi-neqr.html), [{ask this too}](https://qiskit.org/textbook/ch-applications/quantum-edge-detection.html)

**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.

1. 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.

1. 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. You 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.

**A Mathematical Approach to Quantum Convolution Layer**

Let *Xl* be the input and *Kl* be the Kernel for the layer l of a convolutional neural network,

And *f*: R →[0, C] with C > 0 be a non-linear function so that *f* (*Xl+1*) := *f* (*Xl \* Kl*) is the output for layer l. The given *Xl* and *Kl*  are stored in Quantum Random Access Memory (QRAM), there is a quantum algorithm that for precision parameters ε > 0 and η > 0, creates quantum state | *f*(l+1 ) such that *f*(l+1 ) - *f*(*X* l+1 ) ≤ 2 ε and retrieves classical tensor

l+1 such that for each pixel *j*.



The Time Complexity of the algorithm is

hides the poly-logarithmic in the size of *Xl* and *Kl* .

**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.

1. Quantum Backpropagation Algorithm

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

**REFERENCES**

1. Cong, I., Choi, S. and Lukin, M.D., 2019. Quantum convolutional neural networks. *Nature Physics*, *15*(12), pp.1273-1278.
2. Lü, Y., Gao, Q., Lü, J., Ogorzałek, M. and Zheng, J., 2021, July. A Quantum Convolutional Neural Network for Image Classification. In *2021 40th Chinese Control Conference (CCC)* (pp. 6329-6334). IEEE.
3. Oh, S., Choi, J., Kim, J.K. and 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. and Prakash, A., 2019. Quantum algorithms for deep convolutional neural networks. *arXiv preprint arXiv:1911.01117*.
5. Trochun, Y., Stirenko, S., Rokovyi, O., Alienin, O., Pavlov, E. and 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.
6. Wei, S., Chen, Y., Zhou, Z. and Long, G., 2022. A quantum convolutional neural network on NISQ devices. *AAPPS Bulletin*, *32*(1), pp.1-11.
7. Liu, J., Lim, K.H., Wood, K.L., Huang, W., Guo, C. and Huang, H.L., 2021. Hybrid quantum-classical convolutional neural networks. *Science China Physics, Mechanics & Astronomy*, *64*(9), pp.1-8.
8. Li, Y., Zhou, R.G., Xu, R., Luo, J. and Hu, W., 2020. A quantum deep convolutional neural network for image recognition. *Quantum Science and Technology*, *5*(4), p.044003.
9. Mari, A., Bromley, T.R., Izaac, J., Schuld, M. and Killoran, N., 2020. Transfer learning in hybrid classical-quantum neural networks. *Quantum*, *4*, p.340.
10. Zhao, C. and Gao, X.S., 2021. Qdnn: deep neural networks with quantum layers. *Quantum Machine Intelligence*, *3*(1), pp.1-9.
11. Nguyen, N.T. and 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.
12. Hur, T., Kim, L. and Park, D.K., 2022. Quantum convolutional neural network for classical data classification. *Quantum Machine Intelligence*, *4*(1), pp.1-18.
13. Shi, S., Wang, Z., Cui, G., Wang, S., Shang, R., Li, W., Wei, Z. and Gu, Y., 2022. Quantum-inspired complex convolutional neural networks. *Applied Intelligence*, pp.1-10.
14. Li, W., Chu, P.C., Liu, G.Z., Tian, Y.B., Qiu, T.H. and Wang, S.M., 2022. An Image Classification Algorithm Based on Hybrid Quantum Classical Convolutional Neural Network. *Quantum Engineering*, *2022*.
15. Verdon, G., McCourt, T., Luzhnica, E., Singh, V., Leichenauer, S. and Hidary, J., 2019. Quantum graph neural networks. *arXiv preprint arXiv:1909.12264*.
16. Mogalapalli, H., Abburi, M., Nithya, B. and Bandreddi, S.K.V., 2022. Classical–quantum transfer learning for image classification. *SN Computer Science*, *3*(1), pp.1-8.
17. Beer, K., Bondarenko, D., Farrelly, T., Osborne, T.J., Salzmann, R., Scheiermann, D. and Wolf, R., 2020. Training deep quantum neural networks. *Nature communications*, *11*(1), pp.1-6.
18. Mattern, D., Martyniuk, D., Willems, H., Bergmann, F. and Paschke, A., 2021. Variational quanvolutional neural networks with enhanced image encoding. *arXiv preprint arXiv:2106.07327*.
19. 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*.
20. 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.
21. 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.
22. Garcıa-Hernandez, H.I., Torres-Ruiz, R. and Sun, G.H., 2020. Image classification via quantum machine learning. *arXiv preprint arXiv:2011.02831*.
23. Abohashima, Z., Elhosen, M., Houssein, E.H. and Mohamed, W.M., 2020. Classification with quantum machine learning: A survey. *arXiv preprint arXiv:2006.12270*.
24. Peng, S.P. and Zhao, Y., 2019. Convolutional neural networks for the design and analysis of non-fullerene acceptors. *Journal of Chemical Information and Modeling*, *59*(12), pp.4993-5001.
25. Allcock, J., Hsieh, C.Y., Kerenidis, I. and Zhang, S., 2020. Quantum algorithms for feedforward neural networks. *ACM Transactions on Quantum Computing*, *1*(1), pp.1-24.
26. Kerstin, B., Dmytro, B., Terry, F., Tobias, O., Robert, S. and Ramona, W., 2019. Efficient learning for deep quantum neural networks. *Nature*.
27. Farhi, E. and Neven, H., 2018. Classification with quantum neural networks on near term processors. *arXiv preprint arXiv:1802.06002*.
28. Kerenidis, I. and Prakash, A., 2020. Quantum gradient descent for linear systems and least squares. *Physical Review A*, *101*(2), p.022316.