**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.

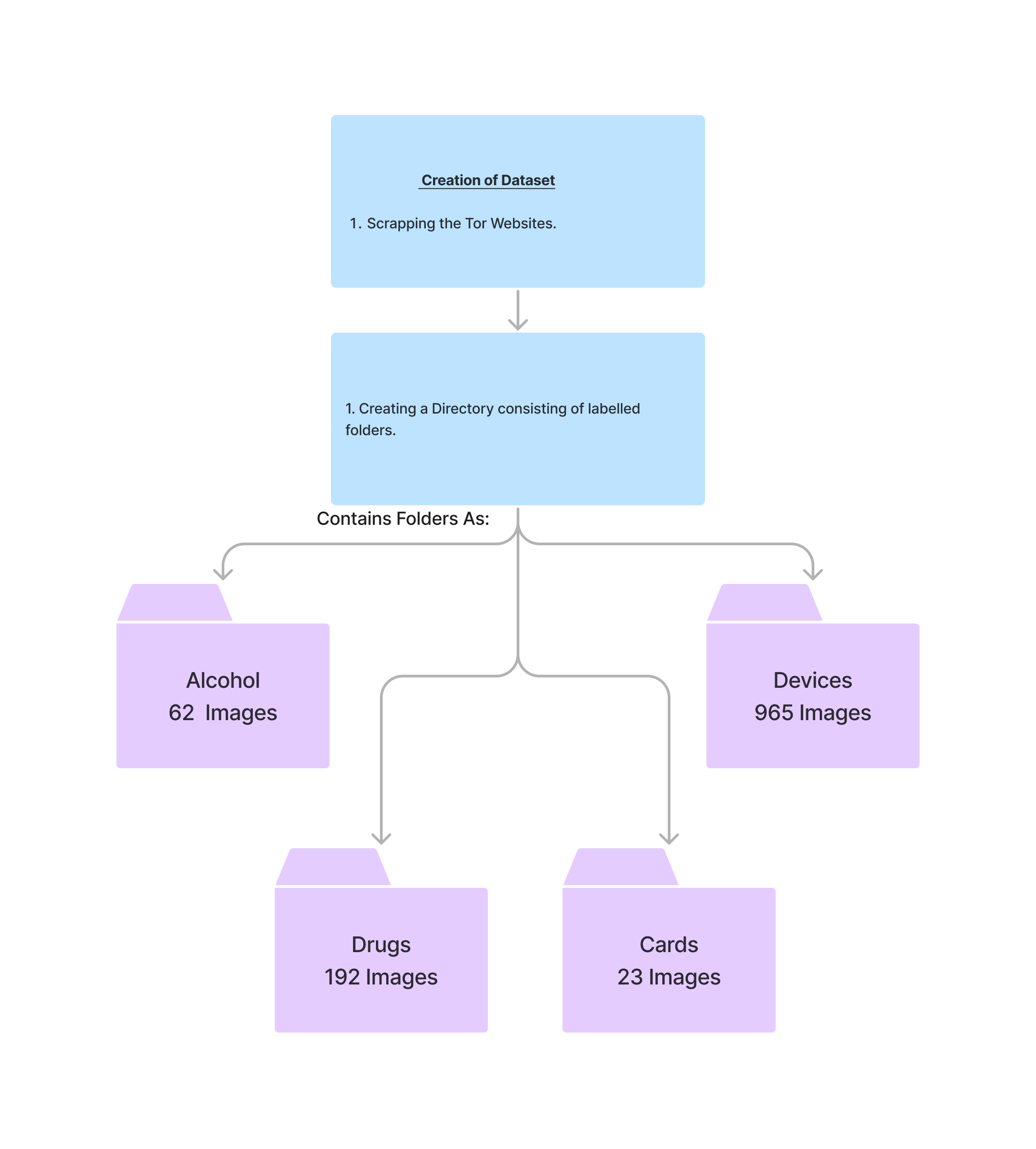
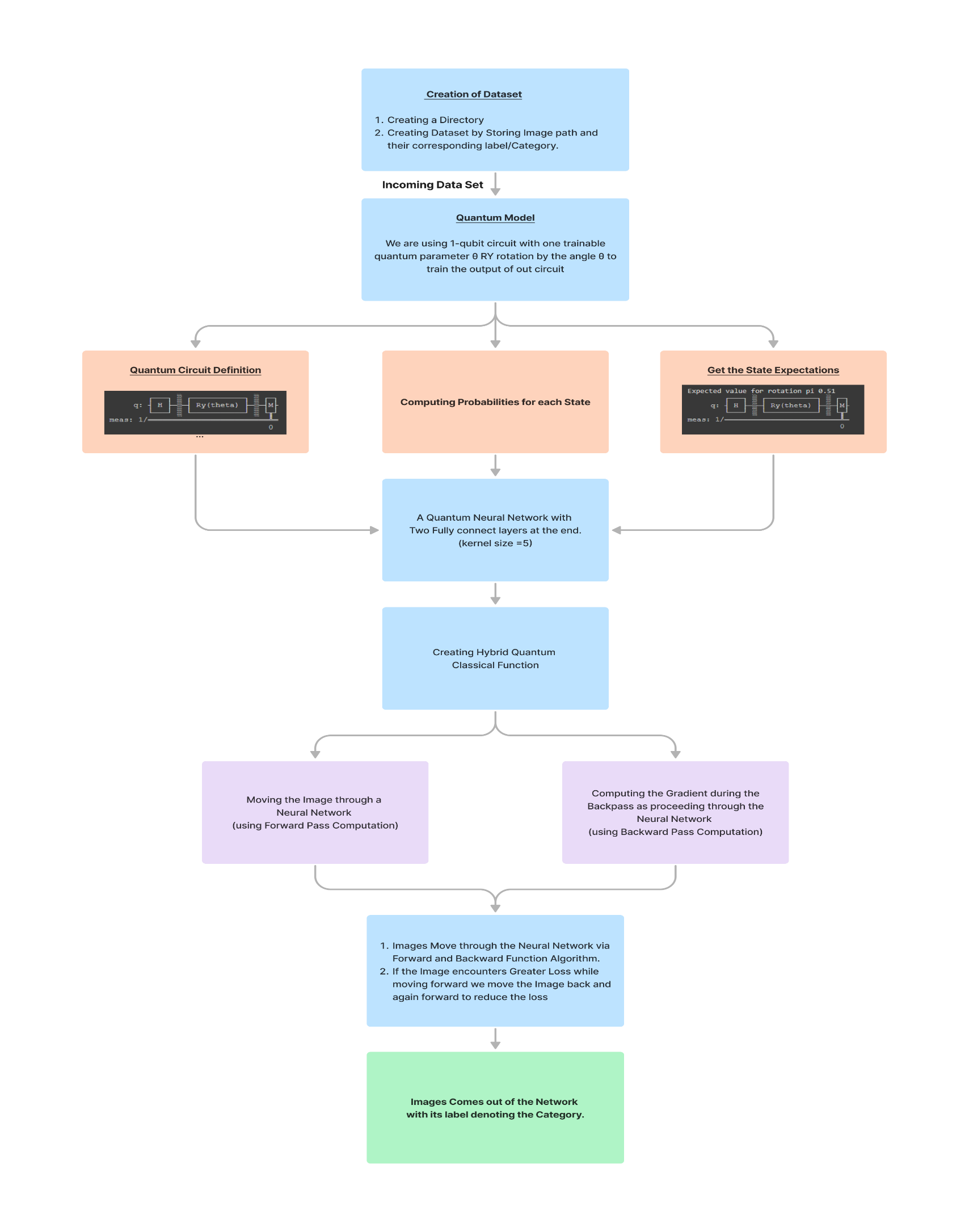


Fig.1 Proposed Methodology for dataset creation

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. 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.

**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 (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 within additive error || || which updates *Fl* as per the gradient descent update rule.

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

**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

1. **RESULT AND DISCUSSION**
2. **CONCLUSION**

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