**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.

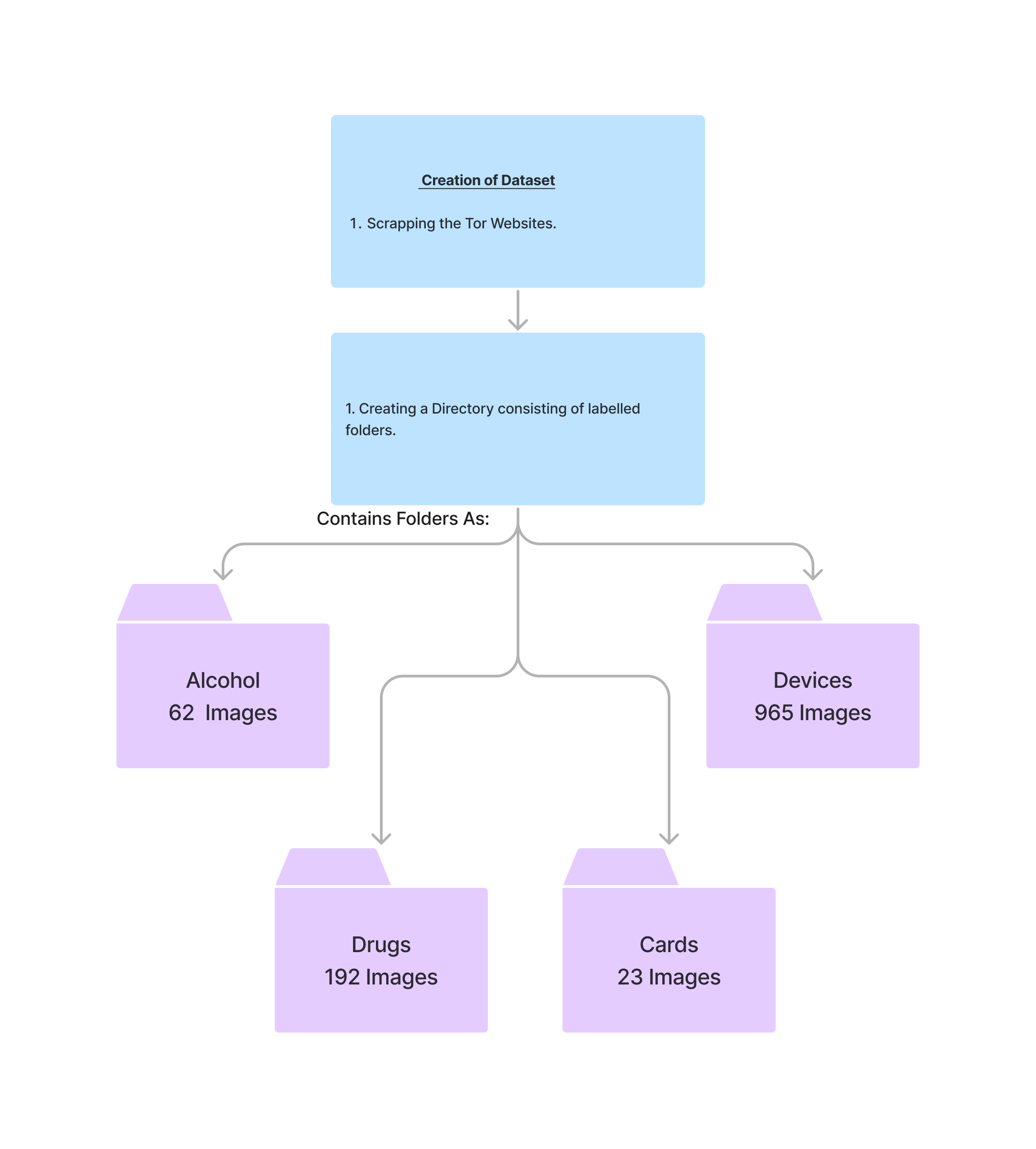
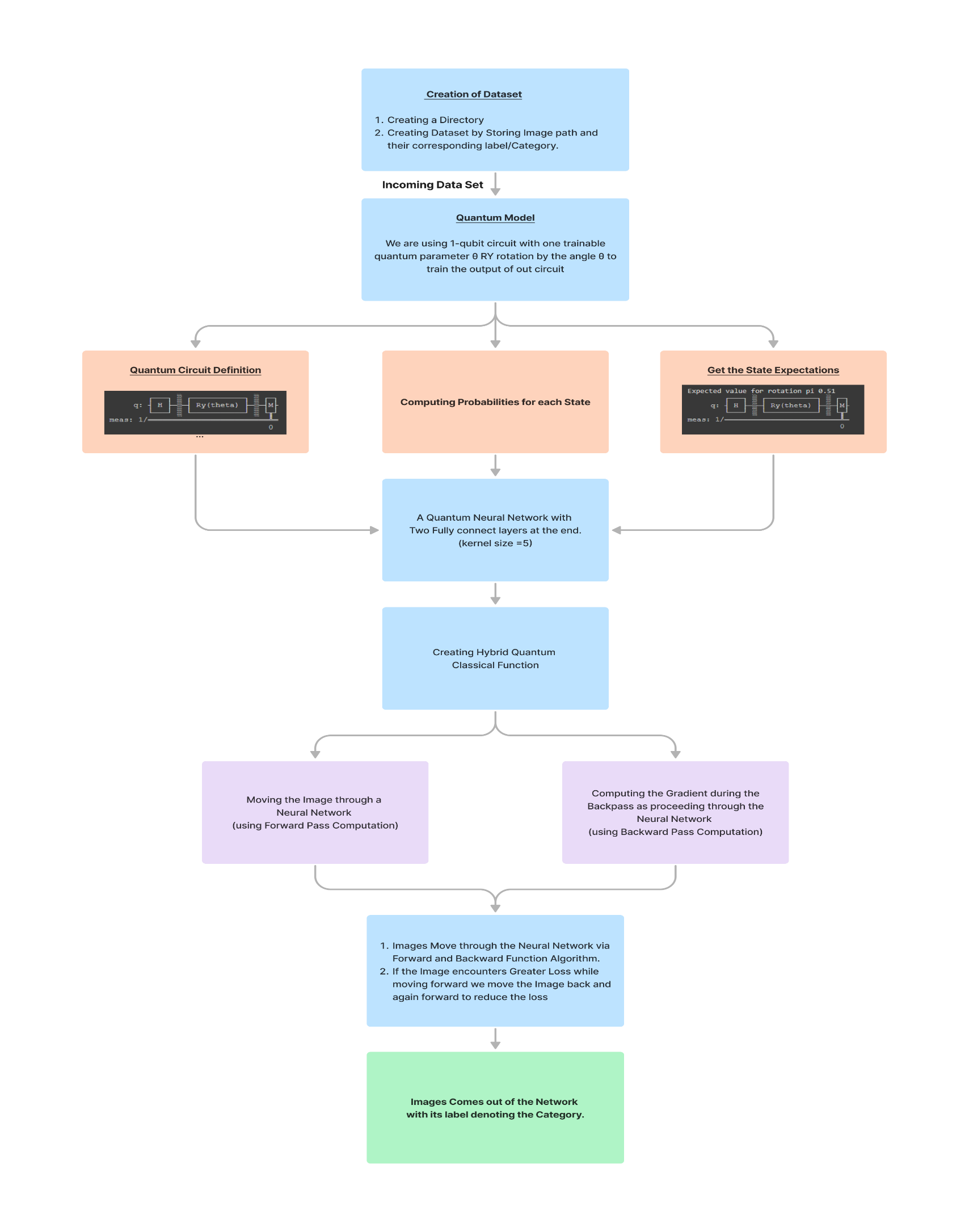


Fig.1 Proposed Methodology for dataset creation

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%%)

(%%mentioning scrambled data which has to be paraphrased%%)

[[major reference ]](https://qiskit.org/textbook/ch-machine-learning/machine-learning-qiskit-pytorch.html)

[{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
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.

**Neurons and Weights**

A neural network is ultimately just an elaborate function that is built by composing smaller building blocks called neurons. A ***neuron*** is typically a simple, easy-to-compute, and nonlinear function that maps one or more inputs to a single real number. The single output of a neuron is typically copied and fed as input into other neurons. Graphically, we represent neurons as nodes in a graph and we draw directed edges between nodes to indicate how the output of one neuron will be used as input to other neurons. It's also important to note that each edge in our graph is often associated with a scalar-value called a [***weight***](https://en.wikipedia.org/wiki/Artificial_neural_network#Connections_and_weights). The idea here is that each of the inputs to a neuron will be multiplied by a different scalar before being collected and processed into a single value. The objective when training a neural network consists primarily of choosing our weights such that the network behaves in a particular way.

###### Feed Forward Neural Networks

It is also worth noting that the particular type of neural network we will concern ourselves with is called a **feed-forward neural network (FFNN)**. This means that as data flows through our neural network, it will never return to a neuron it has already visited. Equivalently, you could say that the graph which describes our neural network is a **directed acyclic graph (DAG)**. Furthermore, we will stipulate that neurons within the same layer of our neural network will not have edges between them.

###### IO Structure of Layers

The input to a neural network is a classical (real-valued) vector. Each component of the input vector is multiplied by a different weight and fed into a layer of neurons according to the graph structure of the network. After each neuron in the layer has been evaluated, the results are collected into a new vector where the i'th component records the output of the i'th neuron. This new vector can then be treated as an input for a new layer, and so on. We will use the standard term **hidden layer** to describe all but the first and last layers of our network.

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