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ORIGINAL RESEARCH

Quantum-inspired Arecanut X-ray image classification using transfer learning

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Abstract

Arecanut X-ray images accurately represent their internal structure. A comparative analysis of transfer learning-based classification, employing both a traditional convolutional neural network (CNN) and an advanced quantum convolutional neural network (QCNN) approach is conducted. The investigation explores various transfer learning models with different sizes to identify the most suitable one for achieving enhanced accuracy. The Shufflenet model with a scale factor of 2.0 attains the highest classification accuracy of 97.72% using the QCNN approach, with a model size of 28.40 MB. Out of the 12 transfer learning models tested, 9 exhibit improved classification accuracy when using QCNN models compared to the traditional CNN-based transfer learning approach. Consequently, the exploration of CNN and QCNN-based classification reveals that QCNN outperforms traditional CNN models in accuracy within the transfer learning framework. Further experiments with qubits suggest that utilising 4 qubits is optimal for classification operations in this context.

KEYWORDS

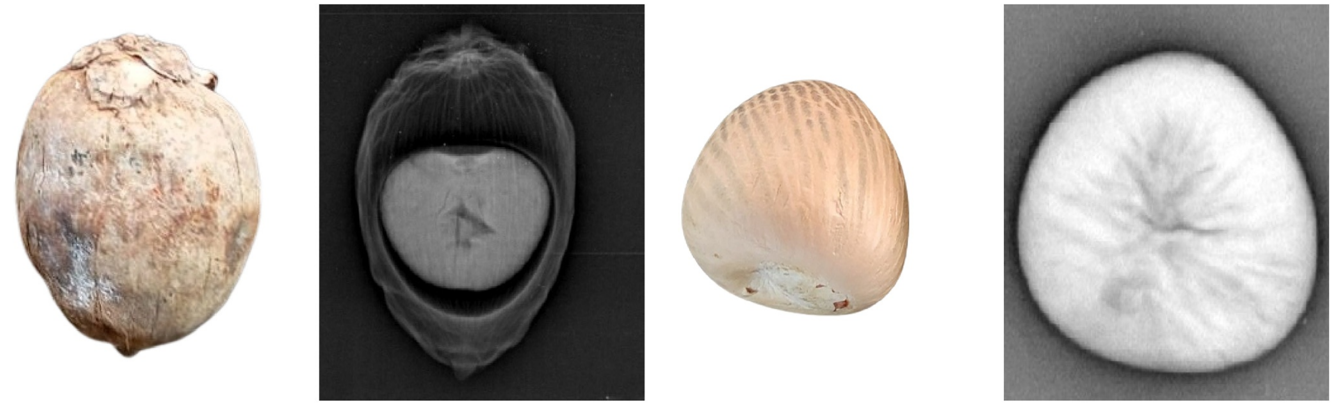
quantum computing, quantum information

1 | INTRODUCTION

Arecanut is one of the commercial crops grown in many parts of India. Arecanut is embraced with a set of unique methodologies and cultural significance when it comes to its cultivation and usage [1]. It is used in many forms, such as tea, supari, ice cream, paints etc. Grading or classification of Arecanuts are performed based on externally appearing characters. Some authors used raw Arecanuts for classification purpose. However, Arecanut industry uses dried Arecanuts, since they can be preserved for longer duration. Dried Arecanuts are categorised into two major forms based on the processing post harvesting, namely the red-boiled type arecanut and the sun-dried type arecanut. In this study, we consider sun-dried type of arecanut and its X-ray images for grading/classification. Figure 1 shows Arecanuts in various forms representing feasibility of using non-destructive approach for grading them. Hence X-ray imaging is a potential imaging tool for examining the quality of an Arecanut using non-destructive approach.

Many works were performed for the classification of Arecanuts using image processing and machine learning techniques [2–7]. However, these approaches cannot determine the true quality of arecanut, since classification is performed based on external appearance. We need a method to determine the grade of an Arecanut by examining internal structure. Srimany et al. examined the internal structure of Arecanut using magnetic resonance imaging (MRI) imaging technique [8]. However, the use of MRI is not suitable for classification of Arecanut due to high cost involved in imaging and only one sample can be examined at a time. Naik and Rudra proposed a non-destructive approach of grading and localisation of Arecanut using X-ray imaging. The authors proposed a lightweight deep learning model using adaptive genetic algorithm-based approach for the detection of three Arecanut grades [9].

Researchers widely use neural networks and transfer learning methods due to their effectiveness and computational power [10–15]. These models eliminate the need for manually extracting features, making deep learning techniques adept at



(a) (b) (c) (d)

FIGURE 1 Various representation of an Arecanut. (a) A Husk covered Arecanut. (b) An X-ray image of husk covered Arecanut. (c) An Arecanut kernel. (d) An X-ray image of Arecanut kernel.

automating binary or multi-class classification tasks. The increase in image data and harder computing tasks are pushing us to make image processing better. Using quantum computing for image processing could be a key strategy to address the increasing volume of data and accelerate the classification process. Quantum information processing harnesses special traits of quantum mechanics, such as superposition, entanglement, and parallelism, to speed up classical tasks. It aids with things, such as factoring large numbers, searching databases, and more. These unique quantum features can also fasten the signal processing and data processing.

Various researchers applied quantum-based classification on their datasets. Subbiah et al. used ‘ant and bee’ and ‘potato leaf disease’ datasets for the classification using transfer learning approach [16]. Huang et al. [17] proposed hybrid quantum-classical neural network for the classification of handwritten images in MNIST dataset [18]. Alsharabi et al. performed classification of disorders in brain MRI images using alexnet-based quantum variational circuit [19]. Mir et al. performed detection of diabetic retinopathy using classical-quantum transfer learning-based approach [20]. The appropriateness of these models and pre-trained models employed in transfer learning can differ based on individual datasets and their sizes. We conduct an investigation to identify the best-performing transfer learning model for our specific dataset of Arecanut classification.

In our study, we employ transfer learning techniques in quantum processing by utilising various pre-trained models for our dataset. Our goal is to investigate their effectiveness in classifying Arecanut X-ray images, aiming for superior performance within this specific domain. By harnessing transfer learning, we capitalise on the knowledge and features acquired by these pre-trained models from extensive datasets. We apply these models to Arecanut X-ray images to explore their potential for achieving high-performance classification tasks in this specialised field. This exploration into their adaptability and accuracy within this context offers valuable insights into the potential of transfer learning-based quantum image processing techniques for efficiently and accurately classifying Arecanut X-ray images.

2 | MATERIALS AND METHODS

2.1 | Dataset and pre-processing

This study employed a dataset comprising Arecanut X-ray images with three distinct classes. The dataset includes a total of 900 images, evenly distributed with 300 images representing each class. These images are divided into two sections designated for training and validation. Within each section, there are three classes—Grade 1, Grade 2, and Grade 3—each containing images specific to their respective classes. Final version of dataset is distributed in the ratio of 4:1 for training and validation respectively.

The images in the dataset differs in resolution, thus we resized them to 256×256 pixels to ensure that all images in the dataset have a consistent size. Further the centre cropping of 224×224 is applied to resize the images to a larger size and then cropping the central region to a smaller, standardised size. This can help the model generalise better during training by providing it with variations of the input data. Finally, to load the images in the range [0, 1] the images are normalised according to mean [0.572291, 0.572291, 0.572291] and standard deviation [0.20683911, 0.20683911, 0.20683911] as per our dataset images.

2.2 | Using hybrid quantum transfer learning model

Transfer learning involves transferring knowledge gained from a source task to a target task. Initially, the algorithm is trained to master and execute a specific source task, after which this acquired knowledge is applied or transferred to a different target task. The necessity for employing transfer learning arose from encountering real-world scenarios where adequate training datasets are not available for specific tasks. This approach allows leveraging existing knowledge from one domain to improve learning and performance in another domain, thereby addressing the limitations posed by insufficient data availability in various practical applications. We utilised various standard transfer learning models for our study with its alternates, such as Shufflenet-V2 [21], ResNet [22], RegNet [23], WideResnet [24], Googlenet [25] as indicated in first part of the Figure 2 which were trained on the ImageNet dataset that is a widely used large-scale dataset in the field of computer vision.

Quantum transfer learning, utilising variational circuits, offers a promising approach to enhance the analysis of image datasets. Variational circuits serve as the foundation for quantum machine learning models. The transfer learning process initiates with pre-training the variational circuit on a related quantum task, enabling the model to capture generic features common to quantum image classification. The variational quantum circuit comprises three layers: embedding, variational, and measurement layers. The embedding layer initialises all qubits in a superposition of up and down states, followed by rotations based on input parameters. Variational layers apply a combination of trainable rotation and constant entangling layers. The measurement layer calculates the local expectation value of the ZZ operator for each qubit, yielding a classical output vector for further processing. Subsequently, a dressed quantum circuit is created, incorporating classical pre-processing, a classical activation function, constant scaling, the earlier defined quantum circuit, and classical post-processing layers. Transfer learning is employed by downloading a classical pre-trained network and replacing the final fully connected layer with our trainable dressed quantum circuit. While quantum machine learning is a dynamic field, these principles provide a conceptual framework for leveraging quantum transfer learning in the realm of image analysis. Thus, we have utilised transfer learning technique on our dataset for classification using quantum convolutional neural network (QCNN) approach as mentioned in the lower part of the Figure 2.

In our performance evaluation, we employ well-established standard transfer learning models with its alternates, such as Shufflenet-V2, ResNet, RegNet, WideResnet, Googlenet. Our approach involves constructing these models by incorporating pre-trained weights derived from the ImageNet dataset. We optimise the imported models by integrating additional layers, such as global average pooling, batch normalisation, and dense output layers. The primary objective behind integrating the global average pooling layer is to obviate the necessity of fine-tuning hyperparameters in the classical transfer learning models. During the model training phase, we initiate the process by freezing all base layers and solely training the output layer using a relatively high learning rate. Subsequently, to enhance model accuracy, we strategically reduce the learning rate after an initial set of epochs. Thus, it offers the advantage of maintaining the base layer weights without significant alterations during the early epochs when the final layers are yet to stabilise. The implementation details for Arecanut grade classification is illustrated in Figure 2.

3 | RESULTS

In our study, the Quantum Computing devices utilised include the Penny-lane default device and IBM Qiskit Basicaer simulator device. The simulator was chosen for the noiseless characteristics to mitigate any potential errors during computations. The experiments are performed on 11th Gen Intel(R) Core(TM) i7-11700 @ 2.50 GHz device. The images are resized to 256 × 256 and normalised during run time. All the experiments are trained for 40 epochs using transfer learning.

In our investigation, we conducted analysis for various models of transfer learning for both classical and quantum-based approaches. Prior to training, hyperparameters are defined as specified in Table 1, with Adam as the optimiser.

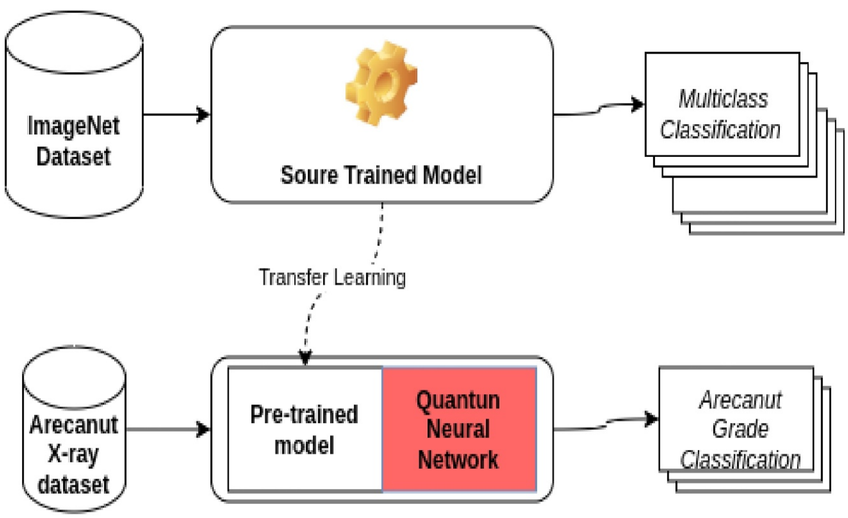


FIGURE 2 Block diagram illustrating the implementation of quantum transfer learning for classification using Arecanut X-ray images.

3.1 | Classification performance of hybrid quantum transfer learning model

To gauge the effect of classification, we consider various transfer models that exhibits various model sizes as illustrated in Figure 3. Additionally, we are considering various model sizes that illustrates the change in classification accuracy for the dataset that is considered. Figure 3 represents the lowest model used for classification is Shufflenet-V2 with network scale factor of 0.5 of size 5.28 MB, whereas the largest model used is Resnet-101 with model size of 172 MB.

Transfer learning-based classification of Arecanut X-ray images are performed using classical Convolutional Neural Network (CNN) models and on QCNN models. The result of classification is represented in Figure 4. Among the models, shufflenet with scaling of 0.5 model has shown least accuracy of 72.38% for traditional CNN model and 73.29% accuracy for QCNN model. This indicates the smaller model size with few layers contributes to the poor classification performance. However, its worth noting that the largest model, Resnet-101, of model size 171 MB does not guarantee the best classification accuracy for CNN as well as QCNN transfer learning approach. Thus, there is a necessity of exploring an optimal model which is smaller in size and yet provides better classification accuracy. In this search, we got a best accuracy of 97.72% for the model shufflenet whose scaling is 2.0, and also note that its model size is only 28.40 MB using QCNN transfer learning technique.

Our study shows that, among the 12 transfer learning models used for classification of Arecanut X-ray images, 9 models have performed better using QCNN-based approach, as compared to that of traditional CNN models. The models Resnet-34 and Googlenet has shown superior classification accuracy in CNN model as compared to QCNN models. However, the difference in classification accuracy using CNN versus QCNN-based transfer learning is small. It is worth noting that, the classification accuracy for our dataset has outperformed using transfer learning-based QCNN approach. Figure 5 compares the classification accuracy obtained using transfer learning-based approach on best performing model (Shufflenet-V2 of scale 2) for classical CNN versus Quantum-based approach. It is to be observed that using Quantum-based transfer learning, we have achieved an accuracy of 97.72%, while classical CNN-based approach has shown accuracy of 85.58% only. Similarly, Figure 6 represents the loss curve obtained during the training of best performing model (Shufflenet-V2 of scale 2) with classical CNN versus Quantum-based approach. Therefore, we have determined that the Shufflenet-V2 model with a scale of 2 is the most optimal choice for our dataset when employing transfer learning techniques with Quantum for image analysis.

We further performed investigation on the possibility of improving the accuracy for the best performed QCNN model for various qubit sizes of 2, 4, 8, 12 and 16. Through this investigation, we sought to explore any correlations between the number of qubits and the efficacy of classification tasks. It is worth noting that while 4 qubits emerged as the optimal choice in our experimentation, variations in qubit numbers have not contributed for better accuracy. It is observed that higher numbers of qubits may offer increased computational capacity and the ability to represent more complex data structures and the practical implementation of models with higher qubit counts may present challenges in terms of resource requirements and computationally are very expensive. Conversely, using a lower number of qubits could lead to simplified model architectures and reduced computational overhead. However, this may come at the expense of diminished representational capacity and may lower classification accuracy, particularly for datasets with intricate patterns or features. The classification accuracy for various qubits is

Hyperparameters	Qubits	Quantum depth	Cost function	Batch size	Learning rate	Epochs
Values	4	6	Cross-entropy	40	0.0004	40

TABLE 1 Hyperparameters used for quantum convolutional neural network.

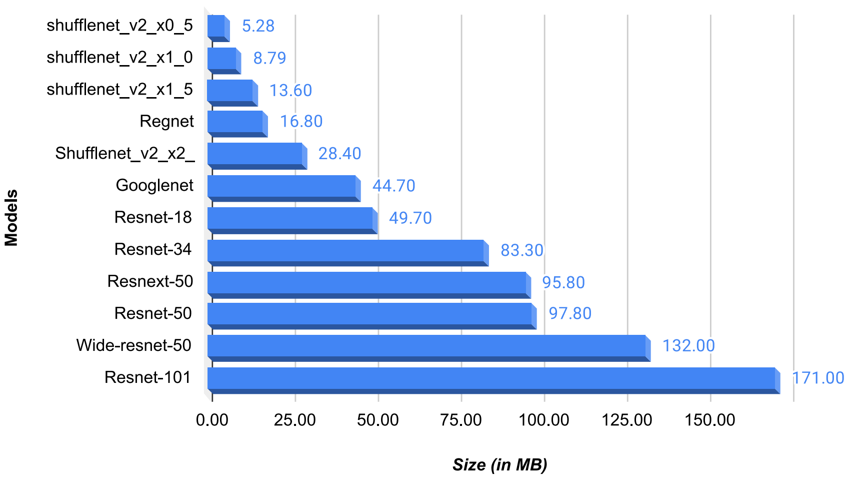


FIGURE 3 Comparison of transfer learning models and their respective sizes.

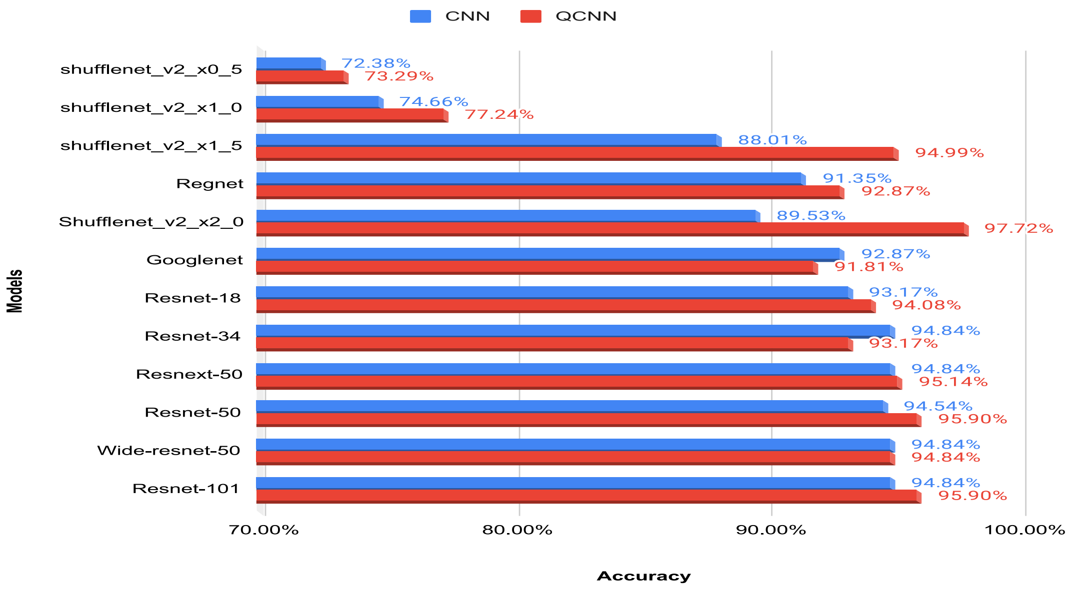
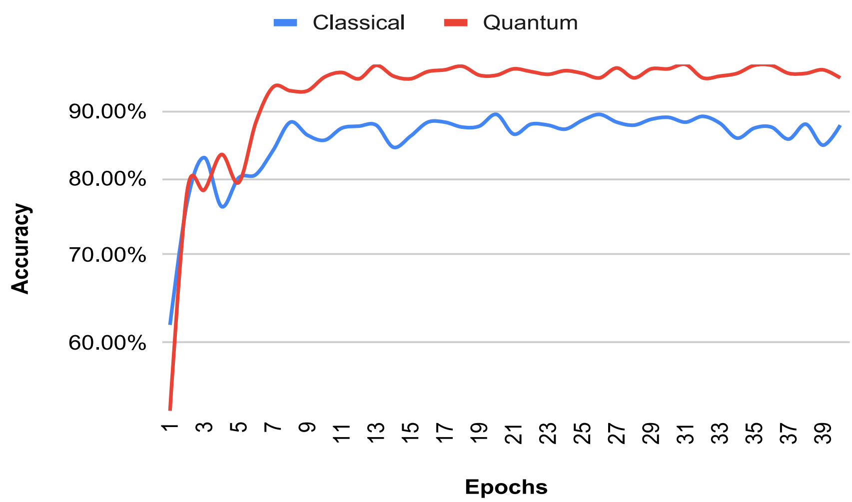


FIGURE 4 Comparing accuracies achieved through transfer learning: CNN versus QCNN approach. CNN, convolutional neural network; QCNN, quantum convolutional neural network.

FIGURE 5 Comparing accuracy curves for transfer learning with Shufflenet-V2 at scale 2: CNN versus QCNN. CNN, convolutional neural network; QCNN, quantum convolutional neural network.



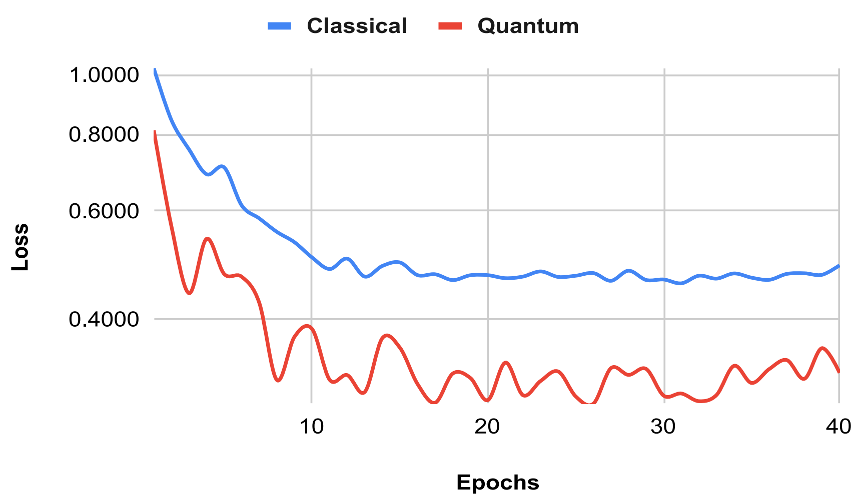


FIGURE 6 Comparing loss curves for transfer learning with Shufflenet-V2 at scale 2: CNN versus QCNN. CNN, convolutional neural network; QCNN, quantum convolutional neural network.

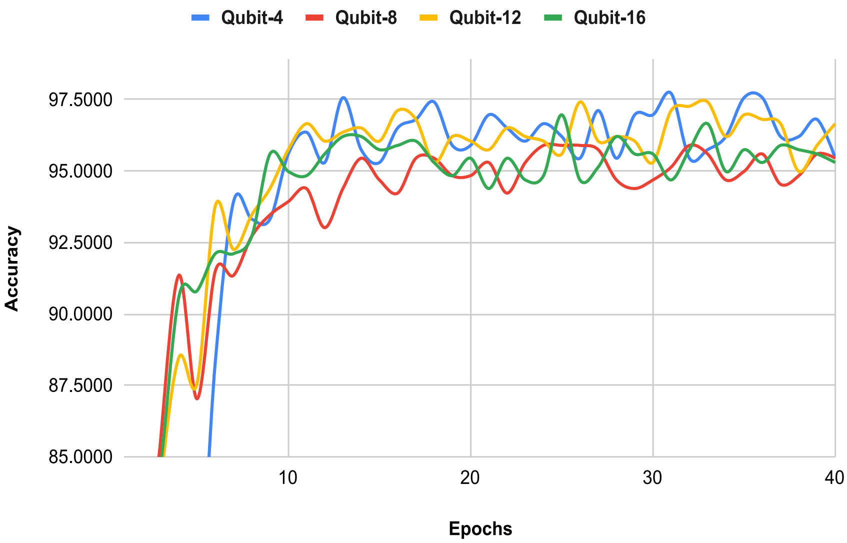


FIGURE 7 Comparison of accuracy obtained using transfer learning for various qubits on Shufflenet-V2 of scale 2.

represented experimented on our dataset is represented in Figure 7. However, there is no improvement in classification accuracy found as compared to the initial experiment performed for qubit 4, for qubit of 12 size near best accuracy of 97.42% was found with the expense of delay in computation.

4 | CONCLUSION

In our investigation, we conducted a thorough study of various transfer learning model-based approach for classifying Arecanut X-ray images using both CNN and QCNN. We employed 12 transfer learning models in our experiments. We observed that the QCNN consistently outperformed the CNN-based approach among the nine models. Notably, the Shufflenet model with a scale factor of 2 emerged as the top performer, achieving an impressive accuracy of 97.72% with a compact model size of 28.40 MB through the QCNN approach. We explored identifying suitable qubit values for the classification of Arecanut. However, after testing various qubit sizes, we found that the best accuracy was obtained with a qubit value of 4, and further exploration did not lead to improvements in classification accuracy. It is crucial to note that the computational cost of quantum processing, particularly through simulation, led to longer training times compared to traditional CNN approaches. Nevertheless, the implementation of these models on actual quantum-based hardware is anticipated to significantly expedite processing, showcasing the potential for faster and more efficient computations in a quantum computing environment. Techniques for feature engineering and representation learning-based image analysis using Quantum approach is necessary. This could involve designing quantum algorithms for extracting and representing salient features from Arecanut X-ray images. This study underscores the promising prospects of quantum-enhanced transfer learning for image classification, offering enhanced accuracy and the potential for acceleration in real-world quantum processing scenarios.

AUTHOR CONTRIBUTIONS

Praveen M. Naik: Conceptualization; data curation; formal analysis; investigation; methodology; visualization; writing – original draft; writing – review & editing. **Bhawana Rudra**: Supervision.

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CONFLICT OF INTEREST STATEMENT

There is no conflict of interest.

DATA AVAILABILITY STATEMENT

X-ray sample images are provided and a complete set of X-ray images is available upon reasonable request at the following GitHub repository: https://github.com/PraveenMNaik/Xray-Arecanut-Dataset.

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