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Deep Learning with Quantum Computing for Coconut Disease and Nutrient Deficiency Detection.

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ABSTRACT :

Crops can be impaired in quality and yield due to coconut diseases, pest damage and nutrient deficiencies. These conditions can be difficult to diagnose, especially at an early stage, as their symptoms often overlap and/or expert help is not available to support the diagnosis. In this paper, a hybrid architecture between CNN and Variational Quantum Circuit (VQC) is proposed for the classification of healthy and unhealthy images of coconut. A classical CNN is used to obtain four numerical features from the images of a coconut, which are then processed by a four-qubit variational quantum circuit. This quantum circuit's output is fed into a classical prediction head for final classification. The framework also includes recommended treatment and preventive measures and a suggested process for severity determination and treatment. The results of the experimental evaluation show that the hybrid model outperformed the classical CNN baseline model in terms of aggregate classification accuracy on the dataset used. The results indicated that the approach proposed may be useful to the development of intelligent image-based coconut health assessment systems. More detailed measurements using class-wise metrics and experiments should be conducted to determine its reliability.

Keywords: *Real-Time Coconut Disease and Nutrient Deficiency Detection, Deep Learning, Convolutional Neural Networks (CNN), Simple Quantum Computing, Precision Agriculture.*

1.Introduction

Coconut (Cocos nucifera L.) is an economically significant tropical plantation crop which is used for food, domestic products, and industrial applications. Considering the coconut health is a matter associated with agricultural productivity and coconut farmers' livelihoods. My problem is to know the condition of the fruit and the disease symptoms, as well as the damage caused by pests and nutrient deficiencies, and to have them inspected in good time to maintain the quality of crops. Typical diagnosis is mostly based on visual assessment and agricultural knowledge. This can be problematic if symptoms are not very clear, if several conditions look similar, or if the diagnosis is a specialist topic and the available expert advice is not readily accessible. Artificial Intelligence based on images is a solution to help plant-health preliminary assessments. CNNs are able to learn visual features directly from the images, such as colour change, texture, shape, and surface appearance. CNNs are able to capture these features and are, therefore, helpful in dealing with agricultural images. But the results of classification will vary with the quality of the data sets, the extent of class coverage, the image acquisition conditions, and the separation of training and test data. Hybrid quantum–classical learning involves using a small quantum circuit to transform a reduced feature representation, while utilizing classic image processing. The parameterized gates in a variational quantum circuit (VQC) have parameters that can be optimized during training. The proposed framework involves a CNN extracting image features, and a four value QNN, called a four-qubit VQC, processing a four value representation. Pauli-Z expectation values are then used as input to a classical prediction head for multiclass classification. This design allows for comparison of a classical CNN vs a hybrid CNN–VQC model. The study emphasizes ten categories found in the project data set: nutrient deficiencies, fruit conditions, pest damage, healthy reference category and sooty mold. A proposed post-classification workflow for estimating the visible symptom severity and providing general recommendations is also part of the framework. The classification, the severity estimation and the agronomic advice are independent functions because it is not directly possible to measure the affected area by a forecasted class probability, and the image-based forecasts do not replace the expert diagnosis.

1.1. Objectives and contributions

- Construct an image-based CNN model to learn the visual representations of the ten given coconut health classes.
- Using a four-value feature bottleneck, embed a four-qubit VQC with the CNN feature extractor.
- Compare the performance of the following two models on accuracy, precision, recall and macro F1-score for the project.
- To introduce another approach for estimating severity, using a provisional scale of mild, moderate, and severe.
- To offer a structured approach to the recommendation process that can be checked and localised by the agricultural specialist.

2. Related Work

2.1. Plant Disease Diagnosis Using Deep Learning

Devarajan et al. [1] investigated CNN-based plant disease diagnosis, while Murugavalli and Gopi [2] explored Vision Transformers for leaf disease detection. Pal et al. [3] developed a lightweight

and explainable CNN. Sahu et al. [4] combined dilated CNNs, attention, and Mask R-CNN segmentation. Zeng et al. [5] proposed a Transformer–CNN framework, while Zhang et al. [6] explored multiscale CNNs with state-space models. Arshad et al. [7] introduced ConvGeM-Next for plant disease detection. Other studies focused on efficient citrus disease classification [9], robust plant disease identification [10], and CNN–Vision Transformer-based maize disease detection [11].

2.2. Coconut Disease and Nutrient Deficiency Assessment

Saleema et al. [8] studied deep learning for coconut disease detection and classification. Manoharan et al. [12] investigated early identification and severity assessment of nutrient deficiencies in coconut trees. Muthusamy and Ramu [13] proposed a lightweight attention-based ensemble for nutrient deficiency detection and severity assessment across different crop leaves. These studies emphasize the importance of automated disease identification and severity evaluation in agriculture.

2.3. Quantum and Hybrid Learning for Image Classification

Kulkarni et al. [14] proposed a hybrid QFT–QCNN framework for coffee leaf disease detection. Al-Shamayleh and Ibrahim [15] explored quantum-deformation-based deep learning features for grapevine disease classification. These studies demonstrate the exploration of quantum and hybrid approaches in agricultural image analysis.

2.4. Research Gap

Previous studies have explored deep learning, attention mechanisms, transformers, severity assessment, and quantum-based approaches for agricultural image analysis. However, this study investigates a hybrid CNN–VQC framework using a four-feature bottleneck and a four-qubit quantum circuit for classifying ten coconut categories. Its performance is compared with a classical CNN baseline.

3. Materials and methods

3.1. Dataset and class definition

The project dataset was obtained from Kaggle and contains 1,500 real coconut images. The supplied class names are listed in Table 1. The ten labels are treated as ten output categories in this manuscript.

No.	Supplied class label	Category represented by the label
1	Boron_Deficiency	Nutrient deficiency
2	Fruit_Cracking	Fruit disorder / visible cracking
3	Fruit_Rot	Fruit disease / decay
4	Healthy_Fruit	Healthy reference category
5	Immature_Fruit_Fall	Fruit-development disorder
6	Magnesium_Deficiency	Nutrient deficiency

7	Mite_Damage	Pest-related damage
8	Nitrogen_Deficiency	Nutrient deficiency
9	Potassium_Deficiency	Nutrient deficiency
10	Sooty_Mold	Sooty fungal growth / coating

Table 1. Ten class labels supplied for the 1,500-image project dataset.
The dataset contains 1,500 coconut images across ten supplied categories. Images from the same fruit, tree, or capture session are kept within the same subset to reduce data leakage.

3.2. Image Preprocessing

Images are loaded with their associated labels and then preprocessed for CNN input by converting to
the desired colour space, resizing to the CNN input shape and normalizing pixel values. The training augmentation can be a slight rotation, flip, zoom or brightness adjustment, but only once the dataset is split.

3.3. Data Set Partition and Assessment Command Control

The data splitted into three sets: training, validation, held-out test. Split ratios, random seed, method of stratification. Fruits, trees, or captured sessions are not be mixed between the subsets to avoid leakage.

3.4. Classification Formulation

Each image of coconut is classified into one of ten coconut categories; this is a single-label classification problem. During the model estimation, a probability is calculated for each class and the class with the highest probability is predicted. In the case of an image having more than one condition, a multilabel classification would be needed.

4. Proposed hybrid CNN–VQC architecture

The proposed architecture includes image input, image preprocessing, CNN feature extraction, reducing to 4 features, 4-quantum processing, and multiclass classification in the classical world. The same image split and evaluation protocol should be followed in the classical baseline and the hybrid model to make meaningful comparisons.

4.1. This is a classic CNN Feature Extractor

This is a classic Feature Extractor for CNN. Preprocessed coconut images are processed by CNN and features obtained include edge, colour difference, spots, crack, lesion and texture. These patterns are learned by convolutional layers, while the activation and pooling operations help to extract useful features and to shrink spatial dimensions. The extracted features are then given to the next step of the model.

4.2. Four-Feature Bottleneck

The CNN feature representation will be collapsed into four numbers: $z = [z_1, z_2, z_3, z_4]$.
These values are scaled and encoded in four qubit, so that there is a compact connection between the CNN and the quantum circuit.

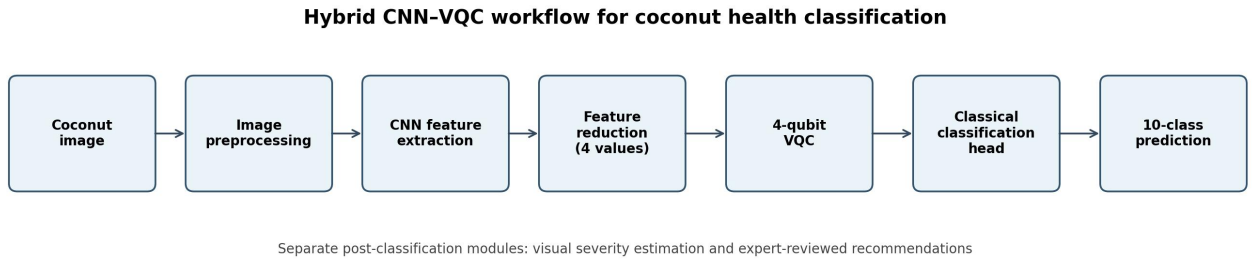


Fig. 1. Overall hybrid CNN–VQC workflow for the ten-category coconut image-classification task.

4.3. The four-qubit variational quantum circuit (VQC)

There are four qubits and trainable parameters in the VQC for the four CNN features. RY gates encode the input features, trainable rotations are applied by the RZ gates, and CNOT gates allow interactions between qubits. Additional RY rotations are made prior to measurement.

4.4. Classical Measurement and Prediction Head

The Pauli Z is used to measure each qubit. The value of the measurement is:

Measurement value = Probability(0) − Probability(1)

The four outputs are the quantum feature vector, $q = [q_1, q_2, q_3, q_4]$

This is fed into a classical prediction head that computes the ten class scores. The score is first converted into probabilities by computing the exp(class score) / Sum of exp(all class scores) for each class. The highest probability class is chosen to be the predicted coconut class.

4.5. Baseline and comparison networks based on CNN

A classical CNN trained from scratch is used as the baseline. Both models are tested with the same data partitions, data preprocessing and metrics (accuracy, precision, recall and F1-score). They then compare their results to test the classification performance under the proposed experimental conditions.

5. Workflow for severity assessment and recommendations

The severity module is independent of the ten-class classifier: the ten-classifier identifies the category of the visible affected area while the severity module estimates the area. Class confidence does not

indicate damage percentage. A segmentation mask or annotated region is needed or an image processing method that has been validated.

5.1. Affected-Area Ratio

Suppose that A is the area of the entire target-region, and A_e is the estimated area of the symptomatic part of the target-region. The ratio of the area of the affected area to the area, $S = 100 \times A_e / A$.

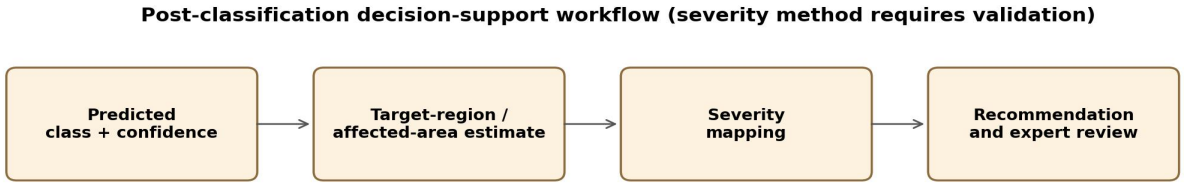


Fig. 2. Proposed severity and recommendation workflow after classification.

5.3. Recommendation logic Predicted categories are correlated to recommendations

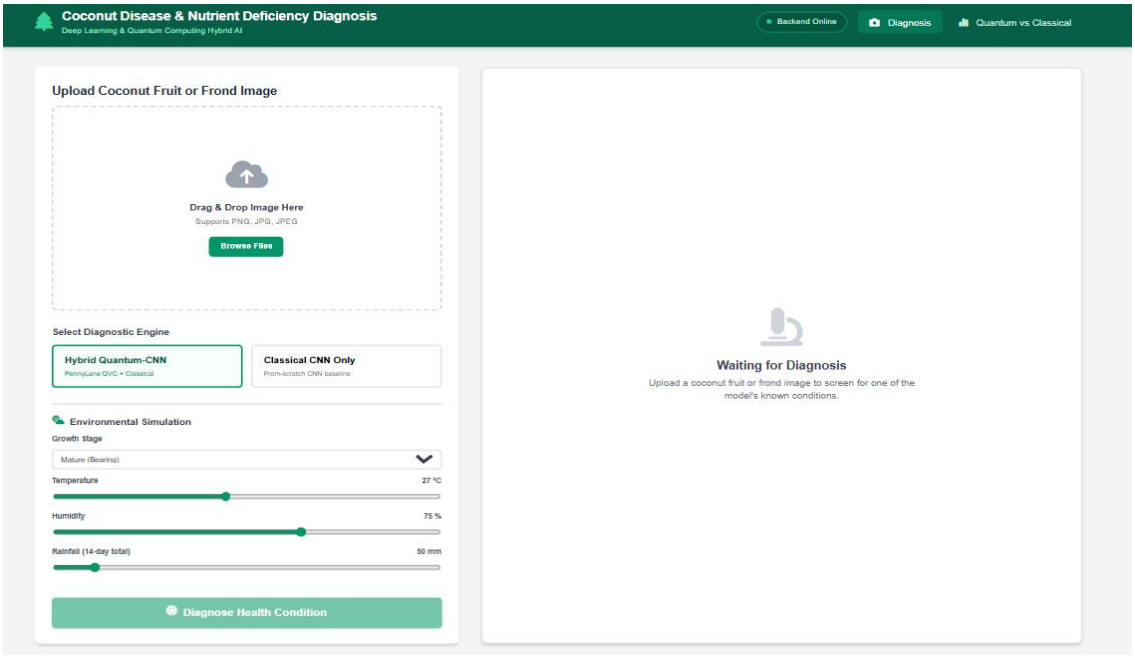
Before fertilizer selection, soil or leaf-tissue testing and expert advice are necessary to overcome nutrient deficiencies. Sooty mold and mites can cause fruit rot; they must be inspected, sanitized and managed according to recommended local advice. Growers should consider irrigation, nutrition, weather, and fruit development when dealing with fruit cracking and immature fruit fall, but not necessarily these are the only causes. Recommendations must be based on a regional and specialist schedule and quantities of fertilizers or doses of pesticides must be based on established local advice. Outputs are not diagnoses, but decision support.

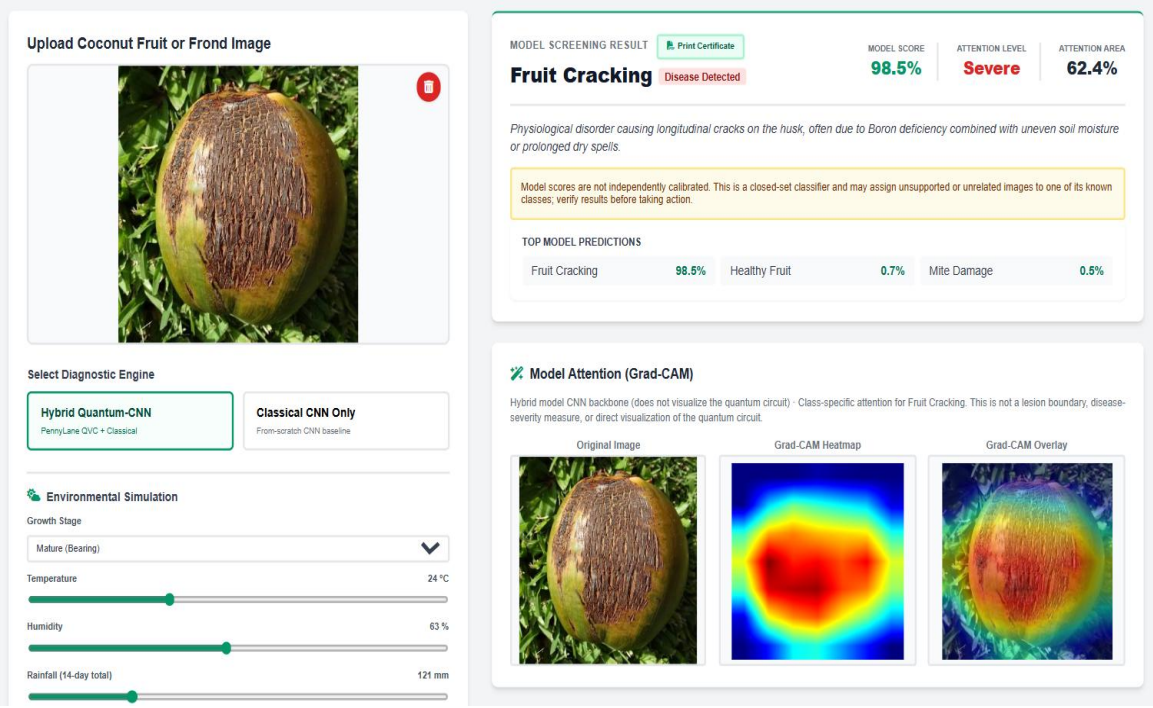
5.4. Uncertainty Handling

The reliability of prediction may be affected by poor lighting, blur, occlusion, unfamiliar varieties and/or absent symptoms. A level of confidence should be determined with the help of validation data. If a prediction falls below this threshold, it should be classified as uncertain and not be reported as a potentially misleading prediction.

6. Experimental results

CNN–VQC model achieved better accuracy and the macro F1-score compared to the classical CNN baseline model. The results indicate that the hybrid model has achieved better classification results for the settings evaluated.





6.1. Performance Metrics

The accuracy rate is the percentage of correct classifications of images in the test set. Precision (TP/(TP+FP)) and Recall (TP/(TP+FN)) represent the true positive and true negative rates respectively. The F1 score is the harmonic mean of precision and recall: $F1 = 2 \times P \times R / (P + R)$. Macro F1 is the average of all 10 classes but weights them equally, irrespective of class size. Reported precision and recall should also be reported using the averaging technique.

6.2. Further Evaluation

A confusion matrix, class-wise performance metrics and repeated experiments should also be used for further evaluation to check the consistency of the model. The contribution of the quantum component should also be investigated through training time, inference latency and also an ablation study should be reported.

7. Discussion

The experimental results show that the proposed CNN–VQC model achieved better classification
performance than the classical CNN. The four-qubit quantum circuit offers an extra feature-processing layer in between CNN extraction and final classification. The results demonstrate the feasibility of integration of classical deep learning with quantum computing in coconut disease and nutrient deficiency detection. The model needs to be evaluated with a variety of coconut image datasets and further experiments are needed to gauge the reliability and practicality of the model for agricultural applications.

8. Conclusion and Future Work

This paper proposed a hybrid CNN–VQC system for coconut disease, coconut fruit disorder, pest attack and nutrient deficiency classification of 1,500 images from 10 categories. The model consists of a CNN feature extractor, a quantum circuit with four qubits, and a classical prediction head. The classification
results reported are better than the classical CNN baseline. The next steps are to increase the number of
images labeled by experts, to further develop the severity estimation, to validate the recommendations with agricultural experts, to assess the prediction uncertainty, and to test the system in real field conditions. After external validation, mobile or web deployment can be considered.

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