Quantum-Optimized Deep Feature Framework for Multi-Class Mushroom Image Recognition

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***Abstract*—Accurate differentiation of mushroom species is critically important for both biological applications and safety-critical contexts, where misclassification can lead to significant negative consequences. Conventional identification techniques often face limitations due to the striking visual similarities among numerous species. To address this, automated image-driven categorization systems have emerged as a vital area of research. This study leverages quantum-driven learning paradigms, which operate within classical computational frameworks by utilizing probabilistic representations inspired by quantum theory, to efficiently capture intricate feature relationships and enhance classification outcomes. We propose a novel framework that integrates a quantum mechanics-inspired, neighborhood-based classifier with deep visual feature learning via MobileNetV2. To further improve classification reliability, an automatic parameter adjustment approach based on quantum-behaved particle swarm optimization is incorporated. Experimental results demonstrate a high classification accuracy of 98.75%, highlighting the framework's effectiveness and scalability for multi-class mushroom image analysis.**

***Index Terms*—Image Classification, Feature Extraction, MobileNetV2, Quantum K-NN, QPSO.**

I. INTRODUCTION

The automatic identification of mushroom types in digital images is a complex problem within computer vision. Accurate classification is essential for diverse applications, such as avoiding poisoning, ecological surveillance, and biodiversity studies, particularly because visual similarities between species and environmental variations hinder manual identification. To address these complexities, automated image-based techniques employ machine learning and deep learning models that can extract discriminative morphological features directly from images [1], [2].

Accurately categorizing mushrooms in biological image analysis is a difficult task. The primary reason is that species looking almost the same can differ greatly in their edibility or toxicity. As a result, relying on visual cues for identification, even by experienced individuals, is unreliable and susceptible to mistakes [3], [4]. This ambiguity has driven rapid advancements in computational image analysis, aiming to uncover patterns beyond human perception.

Deep learning, specifically convolutional neural networks (CNNs), have changed how images are categorized. CNNs create hierarchical feature representations directly from unprocessed input [5]. Transfer learning with pre-trained models like MobileNetV2 has shown potential for extracting important characteristics at a lower computational cost, especially when the datasets are small [6], [7]. Recent studies on mushroom classification show that deep learning models can achieve high accuracy. Hybrid and advanced architectures have shown good results on difficult picture datasets [8, 9].

Conventional classifiers have a hard time recognizing fine-grained multi-class mushrooms because species look very similar to each other. K-nearest neighbor (k-NN) is easy to use and works well, but the way you choose the neighborhood and the distance measures can affect how well it works. This research introduces a hybrid system that integrates MobileNetV2 feature extraction with a quantum-inspired k-NN classifier, optimized by quantum-behaved particle swarm optimization to address these challenges. The proposed method for dependable multi-class mushroom picture classification is validated by its 98.75% accuracy rate. [10], [11], [12].

The suggested method improves the classification of mushroom species by using quantum-inspired machine learning and optimization along with deep feature extraction. Standardization and PCA reduce dimensionality and increase feature resilience, whilst MobileNetV2 effectively captures discriminative visual patterns. By leveraging cosine similarity, a quantum-inspired k-NN classifier enhances the distinction between classes. Quantum-Behaved Particle Swarm Optimization is then used to automatically tune the 'k' parameter, leading to higher classification accuracy. This hybrid strategy effectively and reliably finds multi-class mushrooms by integrating the advantages of both methodologies.

II. PROPOSED METHODOLOGY

This section describes a hybrid image classification approach that classifies multi-class mushroom images using quantum-inspired classification and optimization techniques with deep learning to extract features.

A. DATASET PREPARATION AND PREPROCESSING

The dataset utilized in this study has taken from Kaggle which included 27,436 images of 94 distinct kinds of mushrooms. The species were originally classified at the species level in the dataset, but for the purposes of this study, they were divided into four high-level groups: edible, hallucinogenic, medicinal, and poisonous. There are 4,000 pictures in all, with 1,000 in each category. To keep things the same, all photos are downsized to 128 by 128 pixels. The MobileNetV2 preprocessing function does image preprocessing by scaling pixel values to the ImageNet standard.

B. FEATURE EXTRACTION USING MOBILENETV2

A pre-trained MobileNetV2 network is used as a feature extractor by removing the last classification layers and using global average pooling to make fixed-length feature vectors for each input image. The retrieved features efficiently capture discriminative visual properties such as texture, shape, and structural patterns of mushrooms. Using a pre-trained model makes transfer learning more efficient, cutting down on training time and improving the quality of feature representation without having to train a deep network from scratch [13].

C. FEATURE SCALING AND DIMENSIONALITY REDUCTION

To make the recovered feature vectors more stable and increase the classifier's performance, they are subsequently normalized using standardization to make sure that all dimensions are always the same size. Principal Component Analysis (PCA) is used to make the number of features and the amount of computation even smaller. PCA changes the high-dimensional feature space into a lower-dimensional one by projecting the data onto a set of orthogonal principal components that capture the most variation. This method boosts classification efficiency and generalization performance by getting rid of extra and noisy features while keeping the most useful information [14].

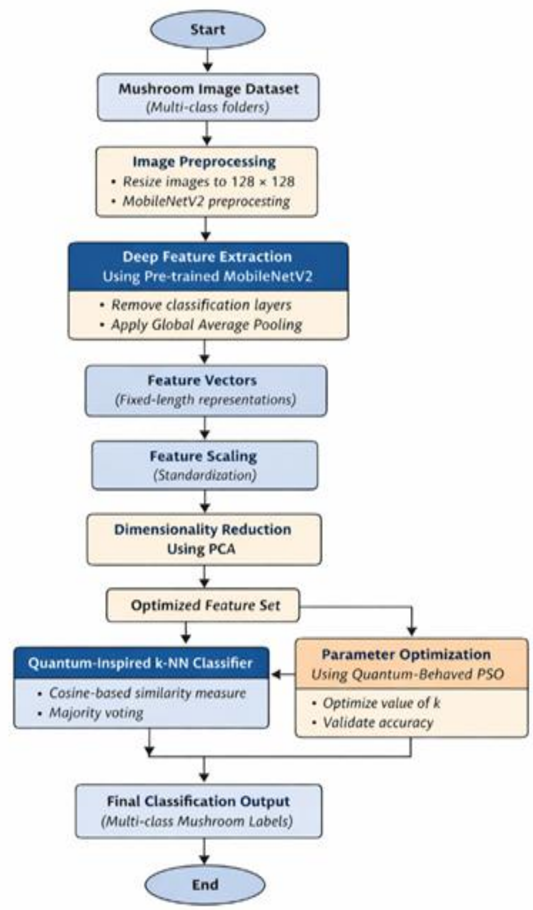

FIG.1 FLOWCHART FOR PROPOSED METHOD

D. QUANTUM-INSPIRED K-NEAREST NEIGHBOR CLASSIFICATION

The mushroom images are classified into many classes using a quantum-inspired k-nearest neighbor (Qk-NN) classifier. Unlike conventional k-NN algorithms that use Euclidean distance, the proposed method measures the relationship between feature vectors using a quantum-inspired similarity measure based on cosine similarity. By emphasizing angular proximity in high-dimensional feature spaces, this similarity formulation facilitates distinguishing between classes that are fairly similar. The classifier selects the k training examples that are most similar to the test instance with the aid of the quantum-inspired similarity measure. A majority vote is then used to determine the final class label. Using a quantum-inspired distance measure makes it easier to separate classes and makes them more stable, especially when there are a lot of features [15] [16].

E. OPTIMIZATION USING QUANTUM-BEHAVED PARTICLE SWARM OPTIMIZATION

Quantum-Behaved Particle Swarm Optimization (QPSO) is a global search method that automates the selection of the best neighborhood size k for the quantum-inspired k-nearest neighbor classifier and stops people from changing hyperparameters. Using QPSO, a population-based metaheuristic that combines quantum mechanical ideas with particle swarm optimization, particles can explore the solution space and move toward the best parameter values. To find the best neighborhood size for strong multi-class discrimination, QPSO repeatedly tests different values of k by improving the accuracy of classification on a validation subset. This method uses QPSO's better ability to explore the whole space and converge in high-dimensional parameter spaces to make classifiers work better and make it less necessary to choose parameters based on heuristics [17].

III. PERFORMANCE EVALUATION AND COMPARITIVE ANALYSIS

We carefully tested the recommended hybrid classification framework and compared its performance to that of classic deep feature-based classifiers. The performance of the quantum-inspired k-nearest neighbor model, improved using Quantum-Behaved Particle Swarm Optimization, is evaluated using various quantitative metrics.

A. EXPERIMENTAL SETUP

The same preprocessing and feature extraction steps are followed for each trial to make sure the comparison is fair. After resizing mushroom photos to 128 by 128 pixels, the MobileNetV2 preprocessing program is used to prepare them for use. Global average pooling is used to get back deep features after taking off the classification layers from a pre-trained MobileNetV2 model. Principal Component Analysis (PCA) is used to make the recovered data more uniform and lower its number of dimensions. After that, the following models are used to sort the smaller feature vectors:

- MobileNetV2 + PCA + SVM
- MobileNetV2 + PCA + Random Forest
- MobileNetV2 + PCA + K-NN
- Proposed: MobileNetV2 + PCA + Quantum k-NN optimized using QPSO

To ensure consistency, all models are assessed using the same train-test split.

B. EVALUATION METRICS

Several standard measures, including as Accuracy, Precision, F1-score, Specificity, False Positive Rate (FPR), and Cohen's Kappa, are calculated to assess the performance of the suggested mushroom image classification model. While precision assesses the accuracy of positive class predictions, accuracy quantifies the overall percentage of correct predictions. For unbalanced class distributions, the F1-score which is the harmonic mean of Precision and Recall—offers a fair evaluation. FPR shows the frequency at which negative samples are mistakenly labelled as positive, whereas specificity assesses the model's capacity to accurately identify negative cases. Lastly, Cohen's Kappa provides a more thorough assessment than accuracy alone by evaluating the agreement between true and projected labels beyond chance.[18] [19] [20] [21].

$$\text{Precision} = \frac{TP}{TP + FP} \tag{1}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{4}$$

$$\text{FPR} = \frac{FP}{FP + TN} \tag{5}$$

$$\kappa = \frac{p_o - p_e}{1 - p_e} \tag{6}$$

In Equations (1) – (6), the terms TP, FP, TN, FN, p_0 and p_e are defined as follows (22):

True Positives (TP) are instances where the model correctly predicts the mushroom species or class.

False Positives (FP) occur when a mushroom sample is incorrectly classified as a target species or class when it actually belongs to another category.

True Negatives (TN) refer to cases where mushroom samples are correctly classified as not belonging to the target species or class.

False Negatives (FN) pertain to instances where a mushroom sample belonging to the target species or class is incorrectly classified as another category.

OBSERVED AGREEMENT (p_0)
The proportion of instances where the predicted labels exactly match the true labels (i.e., the overall accuracy).

EXPECTED AGREEMENT (p_e)
The proportion of agreement expected to occur by chance alone, calculated from the marginal probabilities of the predicted and true class labels.

TABLE 1: CLASSIFICATION METRICS RESULTS

Metrics	Acc %	Precision %	F1-score %	Specificity %	FPR %	Kappa %
RF	89.75	89.80	89.75	96.58	3.42	86.33
SVM	96.25	96.27	96.25	98.75	1.25	95.00
K-NN	97.12	97.16	97.12	99.04	0.96	96.17
Proposed Model	98.75	97.78	97.75	99.25	0.75	97.00

RF – Random Forest
Acc- Accuracy

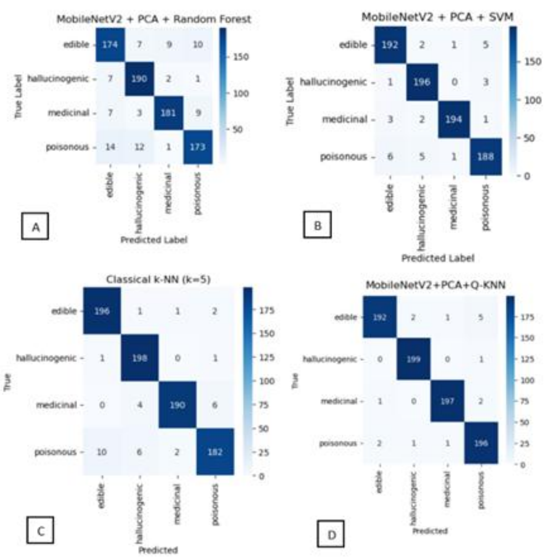

FIG. 2 SHOWS THE CONFUSION MATRIX OF ALL THE FOUR MODELS.

A) MobileNetV2 + PCA + RF
B) MobileNetV2 + PCA + SVM
C) MobileNetV2 + PCA + K-NN
D) Proposed: MobileNetV2 + PCA + Quantum k-NN optimized using QPSO

IV. CONCLUSION

For multi-class mushroom image recognition, a novel hybrid classification framework that combines quantum-inspired decision and optimization techniques with deep convolutional feature learning has been introduced. Compact yet highly informative visual descriptors may be extracted by using a lightweight pre-trained network, while computational stability and efficiency are enhanced by feature normalization and dimensionality reduction. The suggested method improves class identification without requiring a lot of manual parameters tuning by using a quantum-inspired k-nearest neighbor classifier with an optimized similarity search directed by quantum-behaved particle swarm optimization. The results show that quantum-inspired approaches can successfully supplement traditional deep learning models, opening the door to more sophisticated and scalable image categorization systems in challenging real-world situations.

V. FUTURE DIRECTIONS

Future research can concentrate on combining deep and quantum-encoded representations by investigating quantum-inspired feature fusion and incorporating attention processes to improve feature discrimination. For increased robustness, ensemble or adaptive neighborhood techniques might be added to the Qk-NN classifier. Scalability and performance can be further enhanced by substituting nonlinear dimensionality reduction techniques for PCA and testing the framework on bigger or real-time datasets.

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DECLARATIONS

The authors declare no competing financial interests or personal relationships that could have influenced this work.

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