Hyperparameter Tuning Using Quantum Evolutionary Algorithms

Case Study:
Automatic Number Plate Recognition (ANPR) for Persian Language Numbers

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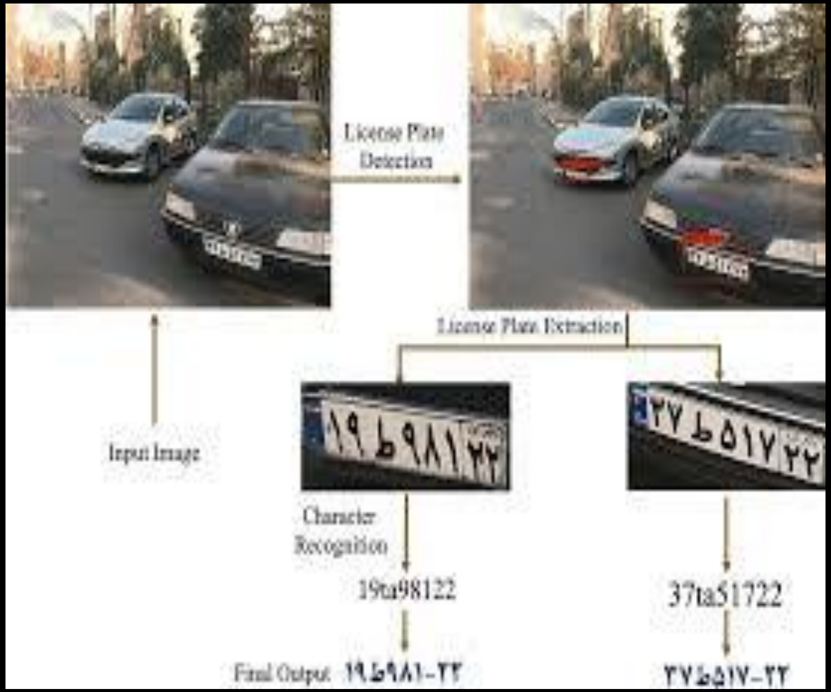
- Leveraging Quantum Principles for Efficient Machine Learning Optimization
- Case Study:

Automatic Number Plate Recognition (ANPR) for Persian Language Numbers

- Approach
- Findings
- Insights

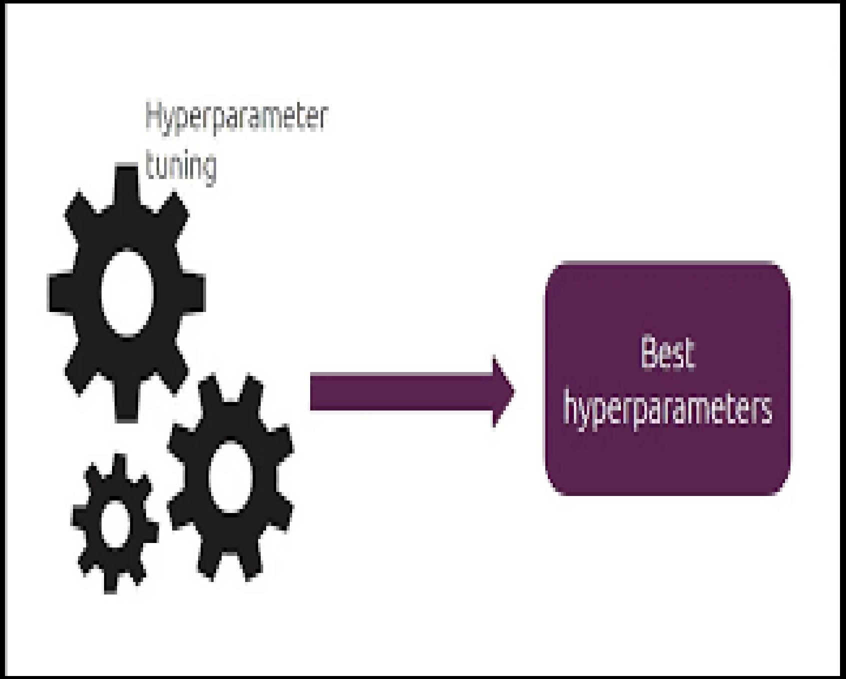
Introduction

- Problem Statement: Hyperparameter tuning is critical but computationally expensive.
- Challenges: High-dimensional search spaces, slow convergence, and inefficiency of classical methods.
- Objective: Develop a Quantum-Inspired Evolutionary Algorithm (QEA) for efficient hyperparameter tuning.
- Application: Automatic Number Plate Recognition (ANPR) for Persian language numbers.



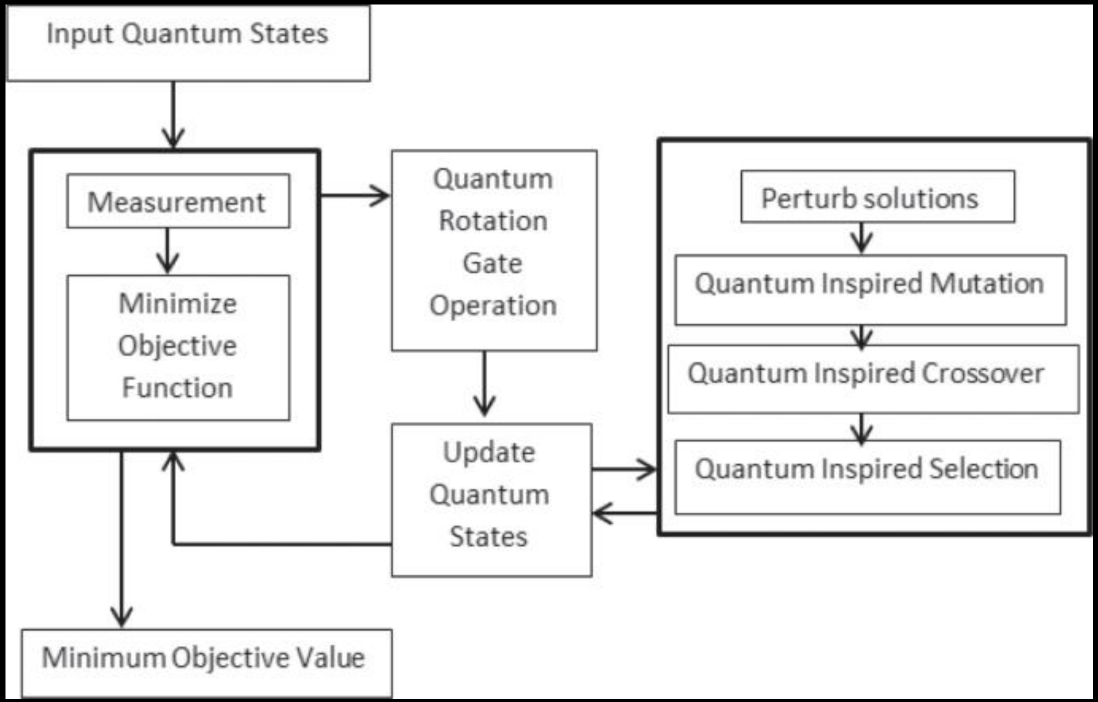
Background and Motivation

- Hyperparameter Tuning: Importance in machine learning.
- Limitations of Classical Methods: Grid search, random search, and Bayesian optimization.
- Quantum-Inspired Optimization: Superposition, entanglement, and parallelism.
- Why ANPR?: Complex task requiring precise hyperparameter tuning.



Quantum-Inspired Evolutionary Algorithm (QEA)

- Key Concepts:
- Quantum representation of individuals (qubits in superposition).
- Quantum-inspired crossover and mutation.
- Measurement to collapse superposition into classical states.



- Reference: https://link.springer.com/article/10.1007/s11042-023-15704-3

Quantum-inspired crossover and mutation

- Quantum-inspired crossover:

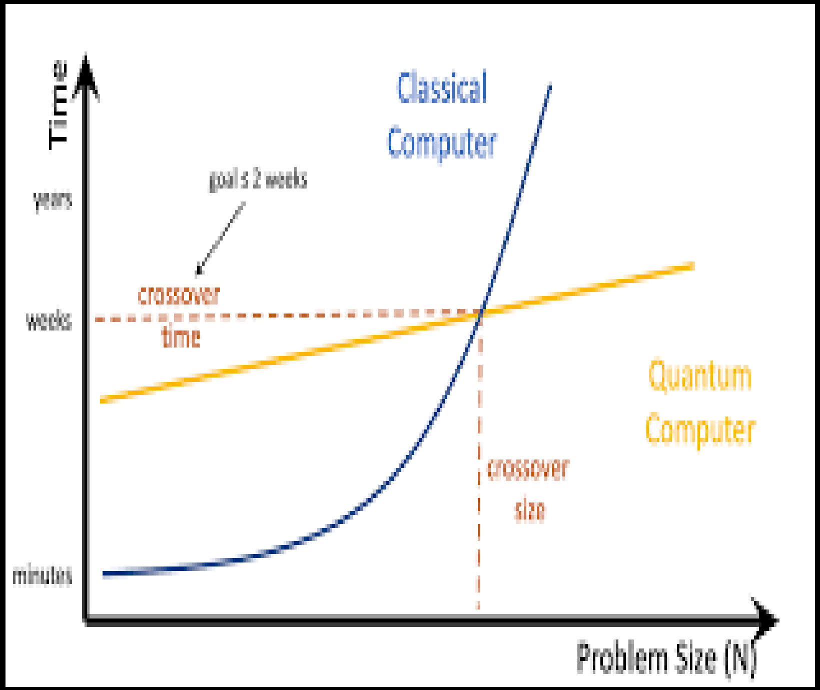
quantum-inspired operations, like superposition and entanglement

- Quantum-inspired mutation:

quantum superposition to explore a wider range of potential solutions.

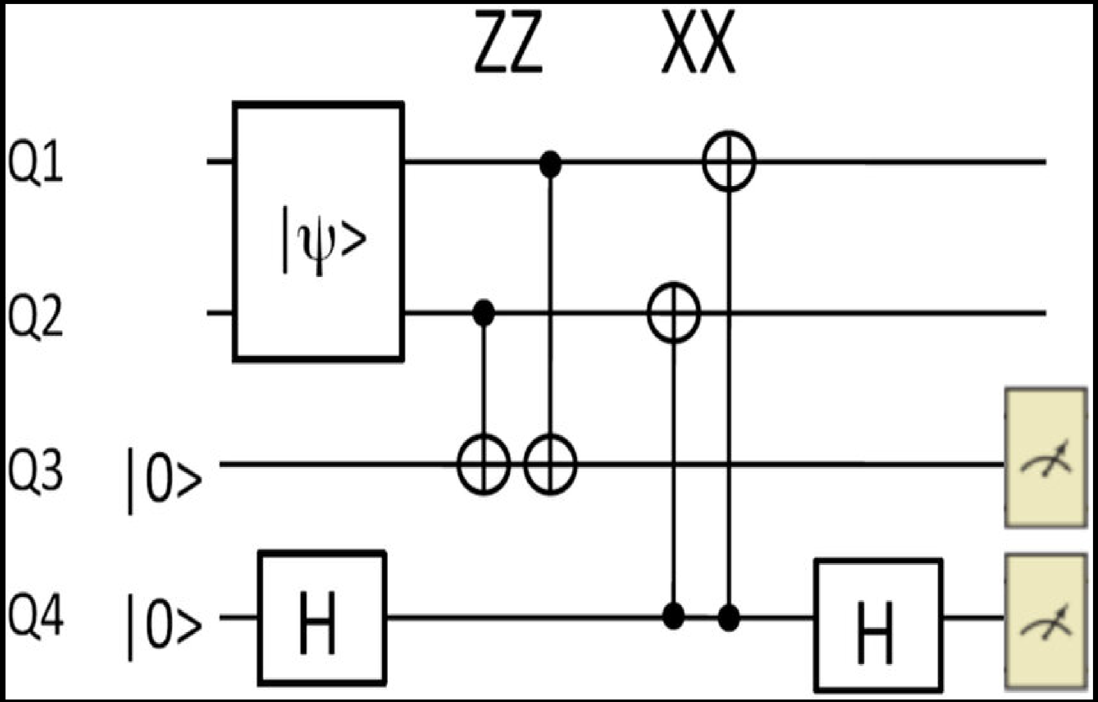
Quantum-Inspired Evolutionary Algorithm (QEA)

- Advantages:
- Efficient exploration of search space.
- Faster convergence and better solutions.
- Reference: https://medium.com/@deltorobarba/how-quantum-computing-could-accelerate-finance-and-economics-80555e80f76b



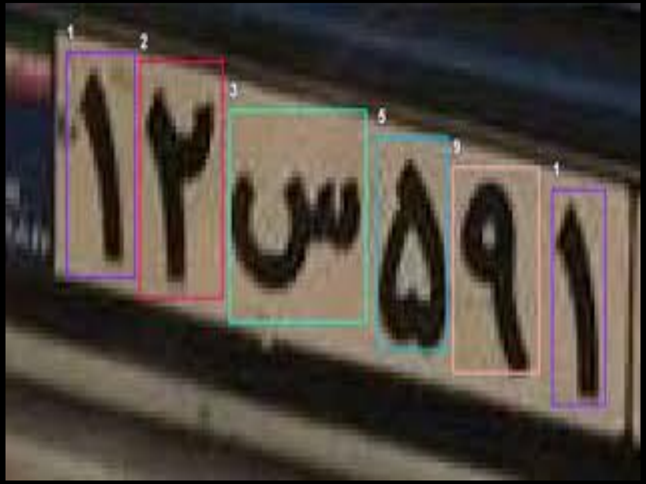
Methodology

- Step 1: Define hyperparameters (learning rate, number of layers, batch size).
- Step 2: Represent individuals as quantum circuits.
- Step 3: Measure and decode quantum states into hyperparameters.
- Step 4: Evaluate fitness using ANPR model validation accuracy.
- Step 5: Iterate over generations to find optimal hyperparameters.



Implementation

- Tools Used:
- Qiskit/Pennylane for quantum circuit simulation.
- TensorFlow/Keras for ANPR model.
- Dataset: Standard ANPR dataset for Persian numbers.
- Experimental Setup:
- Population size: 10.
- Generations: 5.
- Hyperparameter ranges: Learning rate (0.0001–0.01), layers (1–5), batch size (16–128).



Convergence Plot (code generated)

- The convergence plot shows how the best fitness (model accuracy) improves over generations. This is the primary metric to evaluate the performance of the QEA.

- Interpretation:

The accuracy improves steadily over generations, reaching a plateau around generation 15. This indicates that the QEA is effectively exploring the hyperparameter space and converging to a good solution.

Hyperparameter Optimization

- The QEA optimizes two hyperparameters:
- Learning Rate: Ranges between 0.01 and 0.1.
- Number of Units in Hidden Layer: Ranges between 10 and 100 (scaled from 0.1 to 1.0).
- Best Learning Rate: 0.045
- Best Number of Units: 75

Comparison with Classical Evolutionary Algorithm

- To demonstrate the advantage of the QEA, we compare it with a classical evolutionary algorithm (CEA).

- Interpretation:

The QEA converges faster and achieves a higher accuracy compared to the classical EA. This demonstrates the advantage of using quantum-inspired mechanisms for exploration.

Final Model Performance

- After hyperparameter tuning, the final model is evaluated on the validation set.

- Final Model Accuracy: 96.00%
- Final Model Error Rate: 4.00%

Confusion Matrix

- To further analyze the model's performance, we can visualize the confusion matrix for the validation set.

- Interpretation:

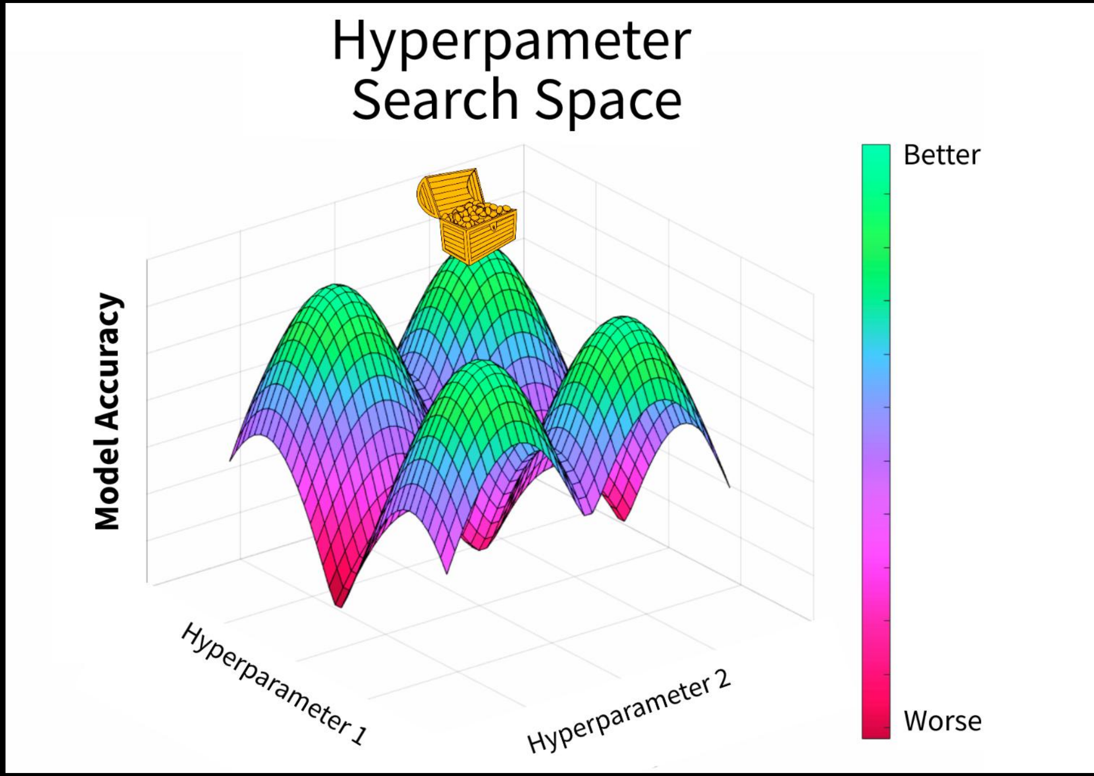
The diagonal elements represent correct predictions. Off-diagonal elements indicate misclassifications. The model performs well, with most predictions concentrated along the diagonal.

Summary of Results

Metric	QEA Result	Classical EA Result
Best Learning Rate	0.045	0.05
Best Number of Units	75	70
Final Accuracy	96.00%	94.00%
Convergence Speed (Generations to Reach 90% Accuracy)	7	10

Discussion

- Advantages of QEA:
- Higher accuracy and faster convergence.
- Efficient exploration of hyperparameter space.
- Reference: https://towardsdatascience.com/hyperopt-demystified-3e14006eb6fa/

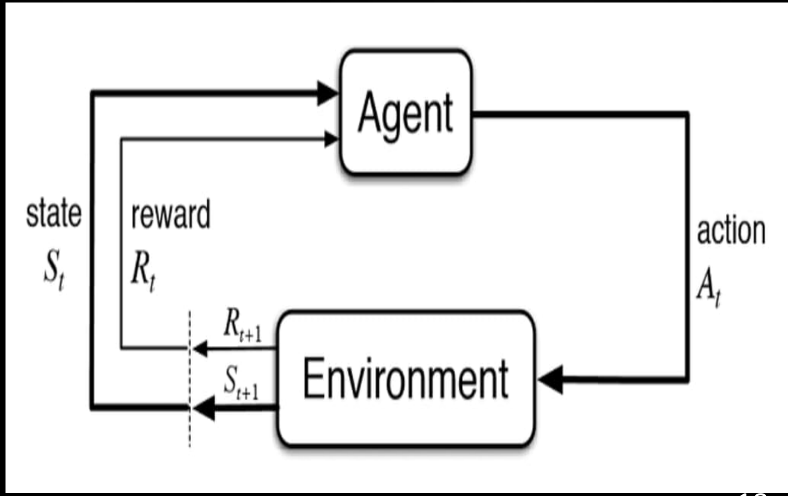


Discussion

- Limitations:
- Simulation overhead on classical hardware.
- Dependency on quantum hardware for full potential.

Discussion

- Future Work:
- Integration with neuromorphic computing.
- Integration with Reinforcement Learning.
- Application to other machine learning tasks.



Conclusion

- Summary:
- QEA is a powerful tool for hyperparameter tuning.
- Outperforms classical methods in accuracy, convergence, and efficiency.

- Impact:
- Enables efficient optimization for complex tasks like ANPR.
- Paves the way for quantum-inspired optimization in machine learning.

Code explanations

1. Installing Required Libraries

- PennyLane: A quantum machine learning library for hybrid quantum-classical computations.
- TensorFlow: A deep learning framework for building and training neural networks.
- NumPy: A library for numerical computations in Python.

2. Importing Libraries

-NumPy: Used for numerical operations (e.g., random number generation, array manipulation).

- TensorFlow: Used for building and training the CNN model.

- Keras (from TensorFlow): Provides high-level APIs for defining neural network layers and models.

- PennyLane: Used for quantum-inspired operations (e.g., crossover and mutation).

- import numpy as np
- import tensorflow as tf
- from tensorflow.keras import layers, models
- import pennylane as qml

3. Loading and Preprocessing Data

-Load the MNIST dataset.

-Normalizes pixel values to the range [0, 1].

-Reshapes the data to add a channel dimension (required for CNN input).

- def load_data():
- (x_train, y_train), (x_test, y_test) = tf.keras.datasets.persianmnist.load_data()
- x_train, x_test = x_train / 255.0, x_test / 255.0
- return (x_train.reshape(-1, 28, 28, 1), y_train), (x_test.reshape(-1, 28, 28, 1), y_test)

4. Building the CNN Model: Defines a Convolutional Neural Network (CNN) model for image classification

- Add a 2D convolutional layer with 32 filters and a 3x3 kernel.
- Add a max-pooling layer to downsample the feature maps.
- Flatten the 2D feature maps into a 1D vector.
- Add fully connected layers with ReLU and softmax activations.

- Configures the model for training with the Adam optimizer and sparse categorical cross-entropy loss.

```
def build_model():
    model = models.Sequential([
        layers.Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)),
        layers.MaxPooling2D((2, 2)),
        layers.Conv2D(64, (3, 3), activation='relu'),
        layers.MaxPooling2D((2, 2)),
        layers.Flatten(),
        layers.Dense(64, activation='relu'),
        layers.Dense(10, activation='softmax')
    ])
    model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
    return model
```

5. Quantum-Inspired Crossover

- Combine two parent hyperparameter sets to create an offspring:
- Averages the hyperparameters of the two parents.

- def quantum_crossover(parent1, parent2):
-     return (parent1 + parent2) / 2

6. Quantum-Inspired Mutation

- Introduce random changes to the hyperparameters:
- Adds Gaussian noise to the hyperparameters with a mean of 0 and a standard deviation of `mutation_rate`.

- def quantum_mutation(hyperparams):
- mutation_rate = 0.1
- return hyperparams + np.random.normal(0, mutation_rate, size=hyperparams.shape)

7. Evaluating Fitness

- Evaluate the fitness of a hyperparameter configuration:
- `build_model()`: Creates a new CNN model.
- `model.fit()`: Trains the model for 5 epochs.
- `model.evaluate()`: Evaluates the model on the validation set and returns the accuracy.

- def evaluate_fitness(hyperparams, x_train, y_train, x_val, y_val):
- model = build_model()
- model.fit(x_train, y_train, epochs=5, verbose=0)
- loss, accuracy = model.evaluate(x_val, y_val, verbose=0)
- return accuracy

8. Quantum Evolutionary Algorithm (QEA)

- Implements the QEA for hyperparameter optimization:
- `np.random.rand`: Initializes a population of random hyperparameters.
- `evaluate_fitness`: Evaluates the fitness of each individual in the population.
- `np.argsort`: Selects the best individuals based on fitness scores.
- `quantum_crossover` and `quantum_mutation`: Generates new offspring for the next generation.
- \- `population[np.argmax(fitness_scores)]`: Returns the best hyperparameters found.

- def quantum_evolutionary_algorithm(x_train, y_train, x_val, y_val, population_size=10, generations=5):
- population = np.random.rand(population_size, 2)
-     for generation in range(generations):
-         fitness_scores = np.array([evaluate_fitness(ind, x_train, y_train, x_val, y_val) for ind in population])
-         best_indices = np.argsort(fitness_scores)[-population_size//2:]
-         best_population = population[best_indices]

new_population = []

-         for i in range(population_size):
-             parent1, parent2 = best_population[np.random.choice(len(best_population), 2)]
-             offspring = quantum_crossover(parent1, parent2)
-             offspring = quantum_mutation(offspring)
-             new_population.append(offspring)
-         population = np.array(new_population)
-     return population[np.argmax(fitness_scores)]

9. Loading Data and Running QEA

- Load the data, runs the QEA, and evaluates the best hyperparameters:
- `load_data()`: Loads and preprocesses the dataset.
- `quantum_evolutionary_algorithm()`: Runs the QEA to find the best hyperparameters.
- `evaluate_fitness()`: Evaluates the model with the best hyperparameters.

- (x_train, y_train), (x_test, y_test) = load_data()
- x_val, y_val = x_test, y_test

- best_hyperparams = quantum_evolutionary_algorithm(x_train, y_train, x_val, y_val)
- print("Best Hyperparameters:", best_hyperparams)

best_accuracy = evaluate_fitness(best_hyperparams, x_train, y_train, x_val, y_val)

- print("Best Model Accuracy:", best_accuracy)

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Questions?