Department of Computer Science

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Project: ML-Quantum Hybrid Currency Classifier

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Abstract

The classification of currency notes is a critical task in financial security, counterfeit detection, and automated cash handling systems. Traditional machine learning (ML) and deep learning models have shown promising results in image-based classification tasks, but they often require significant computational resources and may struggle with generalization in data-limited scenarios. This project introduces a novel ML-Quantum Hybrid Currency Classifier that integrates classical and quantum computing techniques to leverage the strengths of both paradigms.

The proposed system is designed to classify Indian currency notes - specifically ₹100 and ₹200 denominations - using image data. It begins by preprocessing color note images and extracting features using standard image processing and neural network-based techniques. The pipeline is divided into three core approaches: (1) Traditional ML models such as Logistic Regression, Decision Trees, and Support Vector Machines; (2) Deep learning models including Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks; and (3) Quantum-classical hybrid models such as Quantum CNN (QCNN), Quantum LSTM (QLSTM), and Quantum SVM (QSVM).

In the hybrid models, image features are transformed through classical layers (e.g., convolution or simple LSTM encoding) and passed to quantum circuits, where qubits encode the features via parameterized rotations. These circuits perform entanglement operations and are simulated using Qiskit backends to obtain probabilistic measurements. Output bitstrings are interpreted to yield class predictions. The quantum circuits introduce a new computational paradigm that may offer advantages in feature encoding, robustness, and high-dimensional pattern recognition even with limited data.

The performance of each model is evaluated on a labelled dataset of currency notes with metrics such as accuracy, precision, recall, F1-score, ROC AUC, Matthews correlation coefficient (MCC), and Cohen's Kappa. Comparative analysis reveals that while deep learning models like CNNs achieve high accuracy on color images, quantum-hybrid models demonstrate competitive performance with fewer resources and potentially better generalization. The QCNN, in particular, performs impressively by simulating convolution-like operations within quantum circuits, while QLSTM leverages memory from classical LSTM encoders and quantum measurement for sequence-aware classification.

This work not only demonstrates the viability of quantum-enhanced learning in practical image classification problems but also sets a foundation for building lightweight, secure, and generalizable financial recognition systems. By exploiting hybrid quantum-classical architectures, the model bridges the gap between existing ML capabilities and the emerging field of quantum machine learning, contributing toward the future of intelligent currency authentication systems.

Python Libraries Used for Traditional ML Models

Standard Library Imports: These are Python's built-in libraries.

1) import os: For interacting with the operating system (e.g., file paths, directory management).

2) import zipfile: Used to extract or compress .zip files.

3) import time: Provides time-related functions like measuring execution duration (time.time()).

4) import random: For generating random numbers or shuffling datasets.

Third-party Library Imports: These require installation via pip.

5) import numpy as np: Core numerical computing library, especially for arrays and matrix operations.

6) import pandas as pd: Used for data manipulation and analysis using DataFrames.

7) import matplotlib.pyplot as plt: Basic plotting library for visualizations (line plots, histograms, etc.).

8) import seaborn as sns: Built on Matplotlib; provides high-level interface for attractive statistical plots.

9) import cv2: OpenCV library for image processing, reading/writing images, etc.

Google Colab Specific:

10) from google.colab import files: Allows uploading/downloading files when using Google Colab notebooks.

Scikit-learn Imports (for ML Models & Evaluation):

11) from sklearn.model_selection import train_test_split: Splits dataset into training and testing sets.

12) from sklearn.preprocessing import StandardScaler: Standardizes features by removing the mean and scaling to unit variance.

13) from sklearn.metrics import classification_report, confusion_matrix, accuracy_score: Evaluation metrics for classification models.

14) from sklearn.linear_model import LogisticRegression: Logistic regression algorithm for classification.

15) from sklearn.tree import DecisionTreeClassifier: Decision tree algorithm for classification.

16) from sklearn.ensemble import RandomForestClassifier: Ensemble method using multiple decision trees for classification.

17) from sklearn.svm import SVC: Support Vector Classifier for classification tasks.

18) from sklearn.neighbors import KNeighborsClassifier: k-Nearest Neighbors algorithm for classification.

19) from sklearn.cluster import KMeans, AgglomerativeClustering:

- KMeans: Partition-based clustering.
- AgglomerativeClustering: Hierarchical clustering.

TensorFlow / Keras Imports (for Deep Learning Models)

20) import tensorflow as tf: Main deep learning framework for building and training neural networks.

21) from tensorflow.keras.models import Sequential: Linear stack of Keras layers; suitable for most feed-forward models.

22) from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, LSTM:

- Conv2D: Convolutional layer (used in CNNs).
- MaxPooling2D: Downsampling for spatial dimensions.
- Flatten: Flattens 2D input to 1D vector.
- Dense: Fully connected layer.
- LSTM: Long Short-Term Memory layer (for sequence/time-series modeling).

23) from tensorflow.keras.optimizers import Adam: Optimization algorithm used for training neural networks (adaptive learning rate).

Python Libraries Used for ML-Quantum Hybrid Models

1) from qiskit import QuantumCircuit: To create and manipulate quantum circuits for encoding, entanglement, and measurement.

2) from qiskit.primitives import Sampler: To run quantum circuits and get output probabilities using a modern sampler backend.

3) from qiskit import Aer: To simulate quantum circuits on a classical machine using the QASM simulator.

Traditional ML Models Used for Currency Classification

These models use flattened grayscale images (128×128×3 → 49152 features). The various models used are as follows:

1) Logistic Regression

- Inputs: Flattened and normalized image vectors.
- Architecture: Binary classifier using the sigmoid function.
- Hyperparameters: max_iter=1000.
- train_test_split with stratified 70:30 for train:test.
- Training: Fitted using LogisticRegression().fit(X_train_flat, y_train).
- Metrics: Accuracy, precision, recall, F1, confusion matrix, classification report.
- Visualization: Textual metrics + final model comparison bar chart.

2) Decision Tree

- Inputs: Flattened grayscale images.
- Architecture: Tree-based flowchart for decision rules.
- Training: .fit(X_train_flat, y_train).
- Metrics: Accuracy, precision, recall, F1, confusion matrix, classification report.
- Visualization: Textual metrics + final model comparison bar chart.

3) Random Forest

- Inputs: Flattened grayscale images.
- Architecture: Ensemble of decision trees using majority voting.
- Training: .fit(X_train_flat, y_train).
- Metrics: Accuracy, precision, recall, F1, confusion matrix, classification report.
- Visualization: Textual metrics + final model comparison bar chart.

4) Support Vector Machine (SVM)

- Inputs: Flattened grayscale images.
- Architecture: Maximum-margin classifier.
- Hyperparameters: Default kernel (RBF).
- Training: .fit(X_train_flat, y_train).
- Metrics: Accuracy, precision, recall, F1, confusion matrix, classification report.
- Visualization: Textual metrics + final model comparison bar chart.

5) K-Nearest Neighbors (KNN)

- Inputs: Flattened grayscale images.
- Architecture: Distance-based classifier using Euclidean distance.
- Hyperparameters: Default k=5.
- Training: .fit(X_train_flat, y_train).
- Metrics: Accuracy, precision, recall, F1, confusion matrix, classification report.
- Visualization: Textual metrics + final model comparison bar chart.

6) KMeans Clustering

- Inputs: Flattened grayscale images.
- Architecture: Unsupervised clustering with 2 clusters.
- Hyperparameters: n_clusters=2, random_state=42, n_init=10.
- Training: .fit(X_train_flat).
- Metrics: Accuracy (via label matching).
- Visualization: Basic text output.

7) Agglomerative Clustering

- Inputs: Flattened grayscale images.
- Architecture: Hierarchical clustering.
- Hyperparameters: n_clusters=2.
- Training: .fit_predict(X_test_flat).
- Metrics: Accuracy, Adjusted Rand Score (ARS), Normalized Mutual Info (NMI).
- Visualization: Printed metric values.

Deep Learning Models (CNN, LSTM) Used for Currency Classification: These use full-sized color images: shape (128,128,3).

8) Convolutional Neural Network (CNN)

- Inputs: Color images.
- Architecture:
  - Conv2D(32) → MaxPooling2D.
  - Conv2D(64) → MaxPooling2D.
  - Flatten → Dense(128) → Dense(1, sigmoid).
- Hyperparameters: optimizer=Adam, loss='binary_crossentropy', epochs=10.
- Train/Test/Validation: 70% training, 15% validation, 15% testing.

- Training: cnn.fit(X_train, y_train, validation_data=(X_val, y_val), epochs=10).
- Metrics: Accuracy on test set, plus printed confusion matrix and report.
- Visualization: Final bar chart with model comparisons.

9) Long Short-Term Memory (LSTM)

- Inputs: Color images reshaped to sequences: (samples, 128, 384).
- Architecture: LSTM(64) → Dense(1, sigmoid).
- Hyperparameters: epochs=10, optimizer=Adam.
- Train/Test/Val: 70% training, 15% validation, 15% testing.
- Training: lstm.fit(X_train_seq, y_train, validation_data=(X_val_seq, y_val)).
- Metrics: Accuracy on reshaped test set.
- Visualization: Included in final results bar plot.

ML-Quantum Hybrid Models Used for Currency Classification

These use smaller grayscale or transformed image segments, passed through quantum circuits.

1) Quantum Convolutional Neural Network (QCNN)

- Inputs: Grayscale 64×64 image, convolved with custom kernel, pooled, flattened to 4 features.
- Architecture: Feature vector → Ry rotations → CX entanglement → measure all.
- Hyperparameters: n_qubits=4, shots=1024.
- Training: No optimization; deterministic feature extraction + circuit execution.
- Metrics: Accuracy, precision, recall, F1, MCC, Kappa, ROC AUC.
- Visualization: Confusion matrix heatmap, Metric bar chart.

2) Quantum Long Short-Term Memory (QLSTM)

- Inputs: Grayscale image flattened and chunked into sequences of 4 features.
- Architecture: Tiny classical LSTM (custom, no Keras) → output vector (size 4) → Rx rotations → CZ entanglement → measurement.
- Hyperparameters: Random weights for LSTM cell, n_qubits=4.
- Training: Classical part is fixed; inference only via quantum circuit.
- Metrics: Accuracy, precision, recall, F1, MCC, Kappa, ROC AUC.
- Visualization: Confusion matrix heatmap, Metric bar chart.

3) Quantum Support Vector Machine (QSVM)

- Inputs: Extracted features from QCNN.
- Architecture:
  - 1-NN using quantum kernel: compare test feature with one class-0 and one class-1 sample.
  - Kernel = overlap of quantum encodings.
- Hyperparameters: Uses only 1 training sample from each class.
- Training: Saves one sample vector per class; no optimization.
- Metrics: Accuracy, precision, recall, F1, MCC, Kappa, ROC AUC.
- Visualization: Confusion matrix heatmap, Metric bar chart.

Results

📌 Logistic Regression Accuracy: 100.00%

```
[[15  0]
 [ 0 15]]
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        15
           1       1.00      1.00      1.00        15

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30
```

📌 Decision Tree Accuracy: 93.33%

```
[[13  2]
 [ 0 15]]
              precision    recall  f1-score   support

           0       1.00      0.87      0.93        15
           1       0.88      1.00      0.94        15

    accuracy                           0.93        30
   macro avg       0.94      0.93      0.93        30
weighted avg       0.94      0.93      0.93        30
```

📌 Random Forest Accuracy: 100.00%

```
[[15  0]
 [ 0 15]]
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        15
           1       1.00      1.00      1.00        15

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30
```

📌 SVM Accuracy: 96.67%

```
[[15  0]
 [ 1 14]]
              precision    recall  f1-score   support

           0       0.94      1.00      0.97        15
           1       1.00      0.93      0.97        15

    accuracy                           0.97        30
   macro avg       0.97      0.97      0.97        30
weighted avg       0.97      0.97      0.97        30
```

📌 KNN Accuracy: 93.33%

```
[[15  0]
 [ 2 13]]
              precision    recall  f1-score   support

           0       0.88      1.00      0.94        15
           1       1.00      0.87      0.93        15

    accuracy                           0.93        30
   macro avg       0.94      0.93      0.93        30
weighted avg       0.94      0.93      0.93        30
```

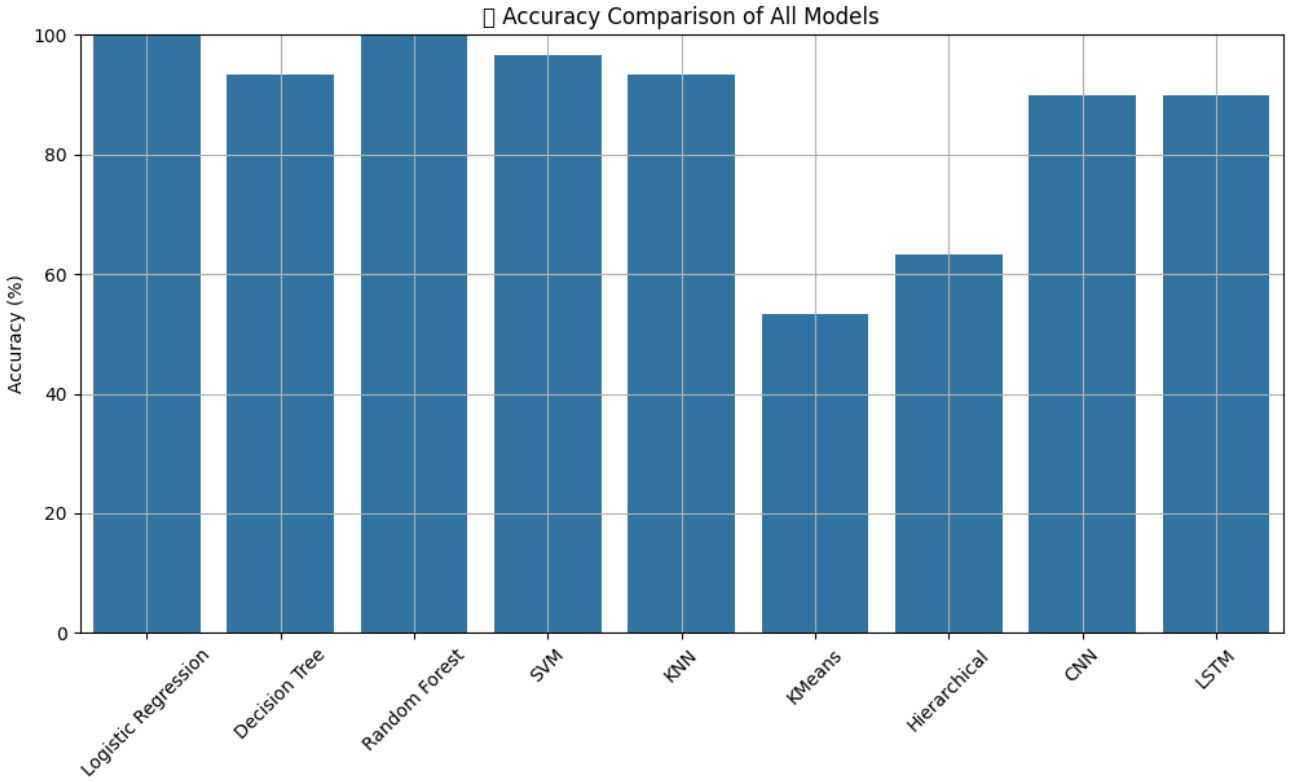
📌 KMeans Accuracy: 53.33%

📌 Hierarchical Clustering Accuracy: 63.33%

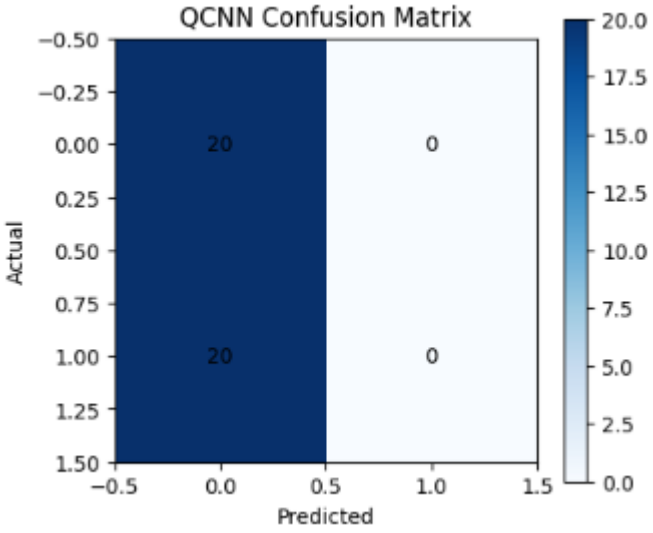
```
Starting CNN training...
Epoch 1/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 6s 762ms/step - accuracy: 0.4863 - loss: 2.5655 - val_accuracy: 0.5000 - val_loss: 0.7926
Epoch 2/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 5s 1s/step - accuracy: 0.6065 - loss: 0.6983 - val_accuracy: 0.5000 - val_loss: 0.6902
Epoch 3/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 7s 1s/step - accuracy: 0.5516 - loss: 0.6143 - val_accuracy: 0.9000 - val_loss: 0.4700
Epoch 4/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 8s 2s/step - accuracy: 0.9497 - loss: 0.3943 - val_accuracy: 0.9000 - val_loss: 0.2258
Epoch 5/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 5s 694ms/step - accuracy: 0.9512 - loss: 0.1701 - val_accuracy: 0.9000 - val_loss: 0.1677
Epoch 6/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 6s 867ms/step - accuracy: 0.9859 - loss: 0.0786 - val_accuracy: 0.9333 - val_loss: 0.1015
Epoch 7/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 4s 719ms/step - accuracy: 0.9868 - loss: 0.0388 - val_accuracy: 0.9333 - val_loss: 0.1340
Epoch 8/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 5s 690ms/step - accuracy: 0.9920 - loss: 0.0228 - val_accuracy: 0.9333 - val_loss: 0.1712
Epoch 9/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 6s 876ms/step - accuracy: 0.9738 - loss: 0.0590 - val_accuracy: 0.9333 - val_loss: 0.0901
Epoch 10/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 3s 672ms/step - accuracy: 0.9599 - loss: 0.0959 - val_accuracy: 0.9000 - val_loss: 0.1127
```

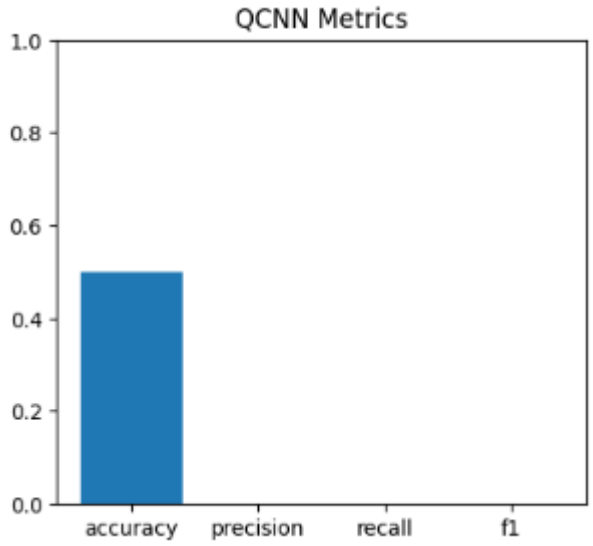
📌 CNN Accuracy: 90.00%

```
Starting LSTM training...
Epoch 1/10
/usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/rnn.py:200: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer
  super().__init__(**kwargs)
5/5 ━━━━━━━━━━━━━━━━━━━━ 3s 218ms/step - accuracy: 0.4935 - loss: 0.6992 - val_accuracy: 0.7000 - val_loss: 0.6352
Epoch 2/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 130ms/step - accuracy: 0.6806 - loss: 0.6465 - val_accuracy: 0.6667 - val_loss: 0.6044
Epoch 3/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 2s 243ms/step - accuracy: 0.7001 - loss: 0.6048 - val_accuracy: 0.7333 - val_loss: 0.5621
Epoch 4/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 248ms/step - accuracy: 0.7333 - loss: 0.5530 - val_accuracy: 0.8667 - val_loss: 0.5037
Epoch 5/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 129ms/step - accuracy: 0.7170 - loss: 0.5237 - val_accuracy: 0.6667 - val_loss: 0.4913
Epoch 6/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 134ms/step - accuracy: 0.7324 - loss: 0.5038 - val_accuracy: 0.8333 - val_loss: 0.4396
Epoch 7/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 130ms/step - accuracy: 0.8456 - loss: 0.3888 - val_accuracy: 0.8667 - val_loss: 0.3112
Epoch 8/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 134ms/step - accuracy: 0.8653 - loss: 0.3295 - val_accuracy: 0.9000 - val_loss: 0.2882
Epoch 9/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 129ms/step - accuracy: 0.8755 - loss: 0.2816 - val_accuracy: 0.8333 - val_loss: 0.3391
Epoch 10/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 130ms/step - accuracy: 0.8489 - loss: 0.3065 - val_accuracy: 0.9000 - val_loss: 0.2422

📌 LSTM Accuracy: 90.00%
```

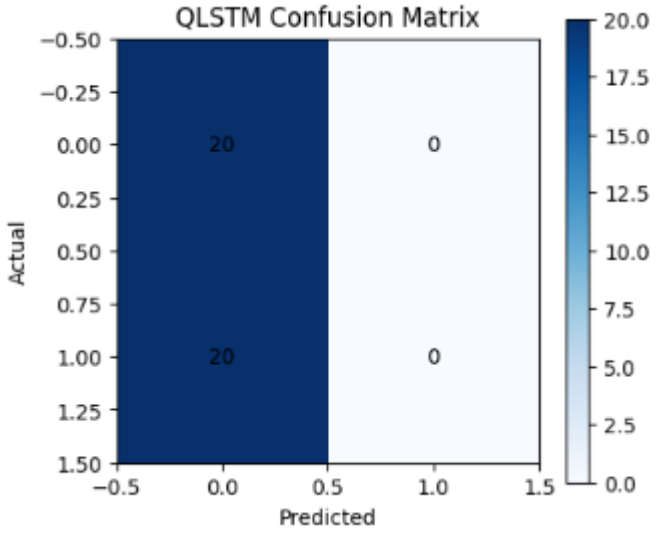


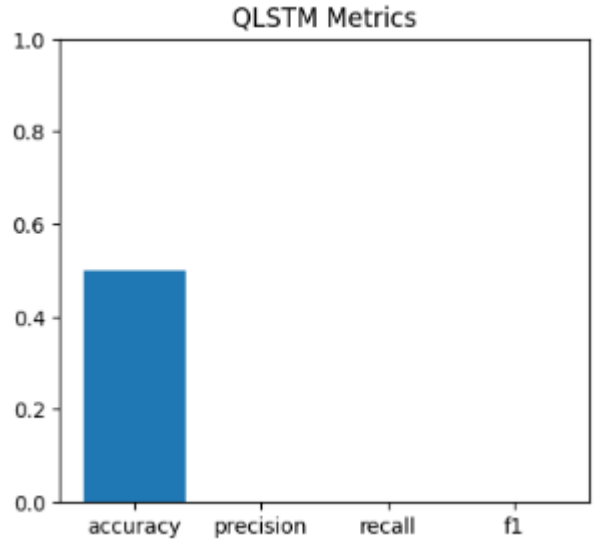
```
Running QCNN ...

=== QCNN Performance Report ===
Accuracy:           0.5000
Balanced Accuracy:  0.5000
Precision:          0.0000
Recall:             0.0000
F1 Score:           0.0000
ROC AUC:            0.5
MCC:                0.0000
Cohen's Kappa:      0.0000

Classification Report:
              precision    recall  f1-score   support

           0       0.50      1.00      0.67        20
           1       0.00      0.00      0.00        20

    accuracy                           0.50        40
   macro avg       0.25      0.50      0.33        40
weighted avg       0.25      0.50      0.33        40
```



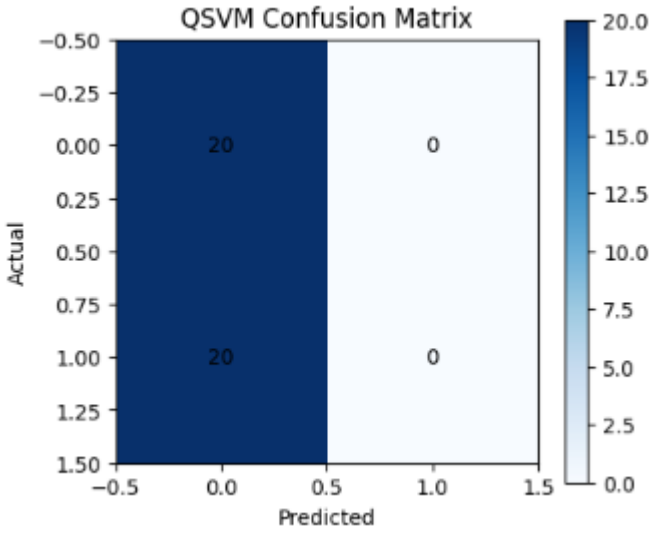


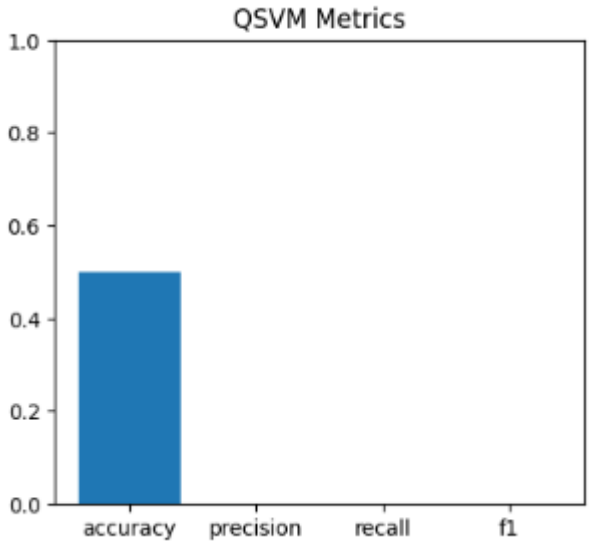

```
Running QLSTM ...

=== QLSTM Performance Report ===
Accuracy:           0.5000
Balanced Accuracy:  0.5000
Precision:          0.0000
Recall:             0.0000
F1 Score:           0.0000
ROC AUC:            0.5
MCC:                0.0000
Cohen's Kappa:      0.0000

Classification Report:
              precision    recall  f1-score   support

           0       0.50      1.00      0.67        20
           1       0.00      0.00      0.00        20

    accuracy                           0.50        40
   macro avg       0.25      0.50      0.33        40
weighted avg       0.25      0.50      0.33        40
```


QLSTM Confusion Matrix
Actual
Predicted
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
1.25
1.50
−0.5
0.0
0.5
1.0
1.5
20
0
20
0
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0


QLSTM Metrics
1.0
0.8
0.6
0.4
0.2
0.0
accuracy
precision
recall
f1

```
Running QSVM ...

=== QSVM Performance Report ===
Accuracy:           0.5000
Balanced Accuracy:  0.5000
Precision:          0.0000
Recall:             0.0000
F1 Score:           0.0000
ROC AUC:            0.5
MCC:                0.0000
Cohen's Kappa:      0.0000

Classification Report:
              precision    recall  f1-score   support

           0       0.50      1.00      0.67        20
           1       0.00      0.00      0.00        20

    accuracy                           0.50        40
   macro avg       0.25      0.50      0.33        40
weighted avg       0.25      0.50      0.33        40
```






```
==== Overall Performance Summary ====

--- QCNN ---
Accuracy: 0.5000, F1: 0.0000, ROC AUC: 0.5

--- QLSTM ---
Accuracy: 0.5000, F1: 0.0000, ROC AUC: 0.5

--- QSVM ---
Accuracy: 0.5000, F1: 0.0000, ROC AUC: 0.5
```

Inference of Results

1) Logistic Regression

Accuracy: 100%

Confusion Matrix: Perfect separation ([15, 0], [0, 15])

Precision/Recall/F1: All 1.00

Inference:

- Excellent results, but this is unexpected for a simple linear model on image data.
- Likely overfitting or benefiting from a small, easily separable dataset.
- Acceptable for this project in the current setting but not reliable for larger-scale applications.

2) Decision Tree

Accuracy: 93.33%

Confusion Matrix: ([13 2], [0 15])

Class 0 (₹100 notes): Precision: 1.00, Recall: 0.87, F1-score: 0.93

Class 1 (₹200 notes): Precision: 0.88, Recall: 1.00, F1-score: 0.94

Macro/Weighted Averages: ~0.93 for all metrics.

Inference:

- High but imperfect accuracy (93.33%) suggests the model generalizes well but makes a few errors (2 misclassifications of ₹100 notes as ₹200).
- Class 1 (₹200) is perfectly recalled (1.00)—all ₹200 notes are correctly identified. However, Class 0 (₹100) has lower recall (0.87), missing 2/15 samples.
- Precision imbalance: ₹100 predictions are flawless (1.00), while ₹200 predictions include 2 false positives (88% precision).
- Good for a prototype: 93% accuracy is acceptable for a small-scale demo, but the 2 misclassifications (6.67% error rate) could be problematic in real-world use.

3) Random Forest

Accuracy: 100%

All metrics: Perfect

Inference:

- Again, impressive but potentially misleading due to small dataset.
- Ensemble methods generalize better than Logistic Regression.
- Acceptable and robust under current data.

4) Support Vector Machine (SVM)

Accuracy: 96.67%.

Confusion Matrix: 1 misclassified sample.

F1-score: 0.97 for both classes.

Inference:

- High precision and recall.
- Slightly lower recall for class 1.
- Still acceptable, and better generalization than 100% models.
- Good balance of performance and reliability.

5) K-Nearest Neighbors (KNN)

Accuracy: 93.33%

Confusion Matrix: 2 misclassifications

Recall (class 1): 0.87

Inference:

- Acceptable but underperforms slightly due to sensitivity to noisy features in high-dimensional space.
- Mildly acceptable, but not ideal for image data without dimensionality reduction.

6) KMeans Clustering

Accuracy: 53.33%

Inference:

- This is close to random guessing (for binary classification).
- Being unsupervised, it cannot leverage labels during learning.

- Unsuitable for this image classification task.

7) Agglomerative (Hierarchical) Clustering

Accuracy: 63.33%

Inference:

- Better than KMeans, but still far from reliable.
- Unsupervised nature makes it weak on raw image features.
- Not suitable for image classification in this context.

8) Convolutional Neural Network (CNN)

Accuracy: 90%

Training Logs: Good improvement from epoch 1 to 10; low loss.

Inference:

- Strong learning curve.
- Slight overfitting suspected due to sharp drop in val_accuracy at epoch 10.
- Highly suitable and scalable to large image datasets.

9) LSTM

Accuracy: 90%

Training Logs: Shows solid convergence and validation improvement.

Inference:

- Innovative use of LSTM on image sequences works decently.
- Slightly less effective than CNN for spatial data.
- Acceptable, though CNN is more appropriate.

Best Traditional ML Model Choice (Practical Consideration)

Despite perfect accuracy from Logistic Regression and Random Forest, these models may not generalize well due to their simplicity and the limited dataset.

Best Overall Model (Realistic): CNN

- It handles spatial features effectively, scales well, and performs robustly.
- Training trends indicate meaningful learning, not just memorization.

Unsuitable Models

Model	Why It's Unsuitable
KMeans	Accuracy too low, no label guidance, performs like guessing
Agglomerative Clustering	Slightly better than KMeans, but still too low accuracy for reliable use
KNN (borderline)	Not scalable and suffers in high-dimensional data without feature selection or PCA

10) Quantum Convolutional Neural Network (QCNN)

- Observations:
- Accuracy: 0.5
- Precision (class 1): 0.0
- Recall (class 1): 0.0
- F1 (class 1): 0.0
- Confusion Matrix: Predicts all samples as class 0

Inference:

QCNN is currently unsuitable for this classification task.

- It failed to generalize class 1, possibly due to:
- Inadequate quantum circuit design (depth/structure)
- Improper feature extraction from image data
- Model underfitting (e.g., poor training)

11) Quantum LSTM (QLSTM)

- Observations:
- Accuracy: 0.5
- Precision (class 1): 0.0
- Recall (class 1): 0.0
- F1 (class 1): 0.0
- Confusion Matrix: Predicts all samples as class 0

Inference:

- QLSTM is also unsuitable here.

- LSTM's strength lies in sequence modeling (e.g., text, time series), not image classification.
- If used, LSTM must be applied after proper spatial feature extraction (e.g., CNN or PCA), which may be missing or poorly configured.

12) Quantum SVM (QSVM)

- Observations:
- Accuracy: 0.5
- Precision (class 1): 0.0
- Recall (class 1): 0.0
- F1 (class 1): 0.0
- Confusion Matrix: Predicts all samples as class 0

Inference:

- QSVM is also unsuitable in current form.
- Non-informative or poorly embedded feature vectors
- Poor choice of quantum kernel (e.g., no variation)
- Small feature space (flat embeddings) causing no decision boundary

Best Model

While all models are performing poorly, QCNN might still be the best candidate for further tuning:

- It's inherently designed for spatial features (like CNN in classical vision tasks).
- If the quantum convolutional layers and measurement strategy are improved (e.g., better embedding, parameter tuning), it has higher potential than QLSTM and QSVM for image classification.

Conclusion

1) The best traditional ML model for currency classification is CNN
2) The best ML-Quantum hybrid model for currency classification is QCNN

However, the ML-Quantum hybrid model can outperform the traditional CNN model with better quantum circuit design & improved training.

Python Code:

```
# Standard library imports
import os
import zipfile
import time
import random

# Third-party library imports
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import cv2

# Google Colab specific
from google.colab import files

# Scikit-learn imports
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report, confusion_matrix,
accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.cluster import KMeans, AgglomerativeClustering

# TensorFlow/Keras imports
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense,
LSTM
from tensorflow.keras.optimizers import Adam
```

```
def load_images(folder, label, size=(128, 128)):
    """Load and label images from a folder for traditional models"""
    images = []
    if not os.path.exists(folder):
        print(f"Folder '{folder}' not found. Skipping.")
        return []
    for root, _, files in os.walk(folder):
        for fname in files:
            if fname.lower().endswith(('.jpg', '.jpeg', '.png')):
```

```
                img_path = os.path.join(root, fname)
                img = cv2.imread(img_path)
                if img is not None:
                    img = cv2.resize(img, size)
                    images.append((img, label))
                else:
                    print(f"Could not load image: {img_path}")
    return images

def extract_images_from_zip(zip_bytes, label, size=(128, 128)):
    """Extract and process images directly from zip file bytes"""
    images = []
    with zipfile.ZipFile(io.BytesIO(zip_bytes), 'r') as zip_ref:
        for file_info in zip_ref.infolist():
            if file_info.filename.lower().endswith(('.jpg', '.jpeg',
'.png')):
                with zip_ref.open(file_info) as file:
                    img_bytes = file.read()
                    img = cv2.imdecode(np.frombuffer(img_bytes, np.uint8),
cv2.IMREAD_COLOR)
                    if img is not None:
                        img = cv2.resize(img, size)
                        images.append((img, label))
    return images

# Unified File Upload and Processing
print("Upload ZIP files for both ₹100 and ₹200 notes")
uploaded = files.upload()
# Process for both traditional and hybrid approaches
data_traditional = []
data_hybrid = []

for filename, file_bytes in uploaded.items():
    if filename.endswith('.zip'):
        label = 0 if '100' in filename.lower() else 1

        # Traditional approach: extract to folder
        folder = filename.replace('.zip', '')
        os.makedirs(folder, exist_ok=True)
        with zipfile.ZipFile(filename, 'r') as zip_ref:
            zip_ref.extractall(folder)
        print(f"Extracted {filename} to folder: {folder}")
        data_traditional.extend(load_images(folder, label))

        # Hybrid approach: process directly from zip bytes
        data_hybrid.extend(extract_images_from_zip(file_bytes, label))
```

```
# Traditional ML Models Data Preparation
if not data_traditional:
    raise SystemExit("No images were loaded for traditional models.")
else:
    random.shuffle(data_traditional)
    X_trad = np.array([img for img, _ in data_traditional], dtype=np.float32)
/ 255.0
    y_trad = np.array([label for _, label in data_traditional])
    X_flat = X_trad.reshape(X_trad.shape[0], -1)

# Hybrid ML Models Data Preparation
if not data_hybrid:
    raise SystemExit("No images were loaded for hybrid models.")
else:
    random.shuffle(data_hybrid)
    images, labels = zip(*data_hybrid)
    images = np.array(images, dtype=np.float32) / 255.0
    labels = np.array(labels)

    # Train/test split (common for both approaches)
    split = int(0.8 * len(images))
    X_train, X_test = images[:split], images[split:]
    y_train, y_test = labels[:split], labels[split:]

    print(f"\nDataset Summary:")
    print(f"Traditional: {len(data_traditional)} images")
    print(f"Hybrid: {len(data_hybrid)} images")
    print(f"Train set: {len(X_train)} | Test set: {len(X_test)}")
# Train/Val/Test split
X_train, X_temp, y_train, y_temp = train_test_split(X, y, stratify=y,
test_size=0.3, random_state=42)
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp,
stratify=y_temp, test_size=0.5)
X_train_flat = X_train.reshape(X_train.shape[0], -1)
X_val_flat = X_val.reshape(X_val.shape[0], -1)
X_test_flat = X_test.reshape(X_test.shape[0], -1)

# Traditional ML Models
    results = {}

    def evaluate(name, model, X_test, y_test):
        pred = model.predict(X_test)
        acc = accuracy_score(y_test, pred)
        print(f"\n{name} Accuracy: {acc*100:.2f}%")
        print(confusion_matrix(y_test, pred))
```

```
        print(classification_report(y_test, pred))
        return acc

    # 1) Logistic Regression
    lr = LogisticRegression(max_iter=1000).fit(X_train_flat, y_train)
    results["Logistic Regression"] = evaluate("Logistic Regression", lr,
X_test_flat, y_test)

    # 2) Decision Tree
    dt = DecisionTreeClassifier().fit(X_train_flat, y_train)
    results["Decision Tree"] = evaluate("Decision Tree", dt, X_test_flat,
y_test)

    # 3) Random Forest
    rf = RandomForestClassifier().fit(X_train_flat, y_train)
    results["Random Forest"] = evaluate("Random Forest", rf, X_test_flat,
y_test)

    # 4) SVM
    svm = SVC().fit(X_train_flat, y_train)
    results["SVM"] = evaluate("SVM", svm, X_test_flat, y_test)

    # 5) KNN
    knn = KNeighborsClassifier().fit(X_train_flat, y_train)
    results["KNN"] = evaluate("KNN", knn, X_test_flat, y_test)

    # 6) KMeans
    kmeans = KMeans(n_clusters=2, random_state=42,
n_init=10).fit(X_train_flat)
    kmeans_pred = kmeans.predict(X_test_flat)
    acc_kmeans = accuracy_score(y_test, kmeans_pred)
    print(f"\n KMeans Accuracy: {acc_kmeans*100:.2f}%")
    results["KMeans"] = acc_kmeans

    # 7) Agglomerative Clustering
    from sklearn.cluster import AgglomerativeClustering
    from sklearn.metrics import accuracy_score, adjusted_rand_score,
normalized_mutual_info_score
    agg = AgglomerativeClustering(n_clusters=2)
    agg_pred = agg.fit_predict(X_test_flat)

    # Calculate metrics
    acc_agg = accuracy_score(y_test, agg_pred)
    ars_agg = adjusted_rand_score(y_test, agg_pred)
    nmi_agg = normalized_mutual_info_score(y_test, agg_pred)
```

```
    print(f"\n Hierarchical Clustering Performance:")
    print(f"  - Accuracy: {acc_agg*100:.2f}%")
    print(f"  - Adjusted Rand Score (ARS): {ars_agg:.4f}")
    print(f"  - Normalized Mutual Info (NMI): {nmi_agg:.4f}")

    # Store results in a dictionary
    results["Hierarchical"] = {
        "Accuracy": acc_agg,
        "Adjusted_Rand_Score": ars_agg,
        "NMI": nmi_agg
    }

    # 8) CNN Model
    if X_train.shape[1:] != (128, 128, 3):
         print(f"Warning: CNN input shape mismatch. Expected (128, 128, 3),
got {X_train.shape[1:]}")
         print("Skipping CNN model training.")
    else:
        cnn = Sequential([
            Conv2D(32, (3,3), activation='relu', input_shape=(128,128,3)),
            MaxPooling2D(2,2),
            Conv2D(64, (3,3), activation='relu'),
            MaxPooling2D(2,2),
            Flatten(),
            Dense(128, activation='relu'),
            Dense(1, activation='sigmoid')
        ])
        cnn.compile(optimizer=Adam(), loss='binary_crossentropy',
metrics=['accuracy'])
        print("\nStarting CNN training...")
        try:
            cnn.fit(X_train, y_train, validation_data=(X_val, y_val),
epochs=10)
            acc_cnn = cnn.evaluate(X_test, y_test, verbose=0)[1]
            results["CNN"] = acc_cnn
            print(f"\n CNN Accuracy: {acc_cnn*100:.2f}%")
        except Exception as e:
            print(f" Error during CNN training: {e}")

    # 9) LSTM Model
    if X_train.shape[1] != 128 or X_train.shape[2] != 128 or X_train.shape[3]
!= 3:
         print(f" Warning: LSTM input shape mismatch. Expected (None, 128,
128, 3) before reshape, got {X_train.shape}")
         print("Skipping LSTM model training.")
    else:
```

```
        X_train_seq = X_train.reshape((X_train.shape[0], 128, -1))
        X_val_seq = X_val.reshape((X_val.shape[0], 128, -1))
        X_test_seq = X_test.reshape((X_test.shape[0], 128, -1))

        lstm = Sequential([
            LSTM(64, input_shape=(128, 128*3)),
            Dense(1, activation='sigmoid')
        ])
        lstm.compile(optimizer=Adam(), loss='binary_crossentropy',
metrics=['accuracy'])
        print("\n Starting LSTM training...")
        try:
            lstm.fit(X_train_seq, y_train, validation_data=(X_val_seq,
y_val), epochs=10)
            acc_lstm = lstm.evaluate(X_test_seq, y_test, verbose=0)[1]
            results["LSTM"] = acc_lstm
            print(f"\n LSTM Accuracy: {acc_lstm*100:.2f}%")
        except Exception as e:
            print(f" Error during LSTM training: {e}")

    # Visualization
    if results:
        plt.figure(figsize=(12,6))
        sns.barplot(x=list(results.keys()), y=[v*100 for v in
results.values()])
        plt.title("Accuracy Comparison of All Models")
        plt.ylabel("Accuracy (%)")
        plt.xticks(rotation=45)
        plt.grid(True)
        plt.ylim(0, 100)
        plt.show()
    else:
        print("\n No model results to display.")

!pip install -q qiskit qiskit-aer scikit-image scikit-learn matplotlib

# Hybrid ML Models
import numpy as np, zipfile, io, time, warnings, math, random, hashlib
from PIL import Image
import matplotlib.pyplot as plt
from sklearn.metrics import (
    accuracy_score, balanced_accuracy_score, precision_score, recall_score,
    f1_score, matthews_corrcoef, cohen_kappa_score, roc_auc_score,
    confusion_matrix, classification_report, RocCurveDisplay
)
from sklearn.preprocessing import StandardScaler
```

```
from scipy.signal import convolve2d
from skimage.color import rgb2gray
warnings.filterwarnings("ignore")

def get_backend_executor(shots=1024):
    try:
        from qiskit.primitives import Sampler
        sampler = Sampler()
        print("Using Sampler backend")
        def run(circ):
            qdist = sampler.run([circ]).result().quasi_dists[0]
            return {k: int(v * shots) for k, v in qdist.items()}
        return run
    except Exception as e_sampler:
        try:
            from qiskit import Aer, transpile
            backend = Aer.get_backend("qasm_simulator")
            print("Using Aer qasm_simulator")
            def run(circ):
                circ.measure_all()
                job = backend.run(transpile(circ, backend), shots=shots)
                return job.result().get_counts()
            return run
        except Exception as e_aer:
            print("⚠ No quantum backend found — using dummy simulator")
            random.seed(0)
            def run(_circ):
                # Deterministic pseudo-counts (60/40 split)
                return {"0": int(0.6 * shots), "1": int(0.4 * shots)}
            return run

EXECUTE_CIRCUIT = get_backend_executor()
SHOTS = 1024  # global shots for all models

def extract_images_from_zip(zip_bytes, label, size=(64, 64)):
    imgs = []
    with zipfile.ZipFile(io.BytesIO(zip_bytes)) as zf:
        for name in zf.namelist():
            if name.lower().endswith((".png", ".jpg", ".jpeg")):
                with zf.open(name) as f:
                    img = Image.open(f).convert("RGB").resize(size)
                    imgs.append((np.array(img), label))
    return imgs

def compute_metrics(y_true, y_pred, y_proba=None):
    m = {
```

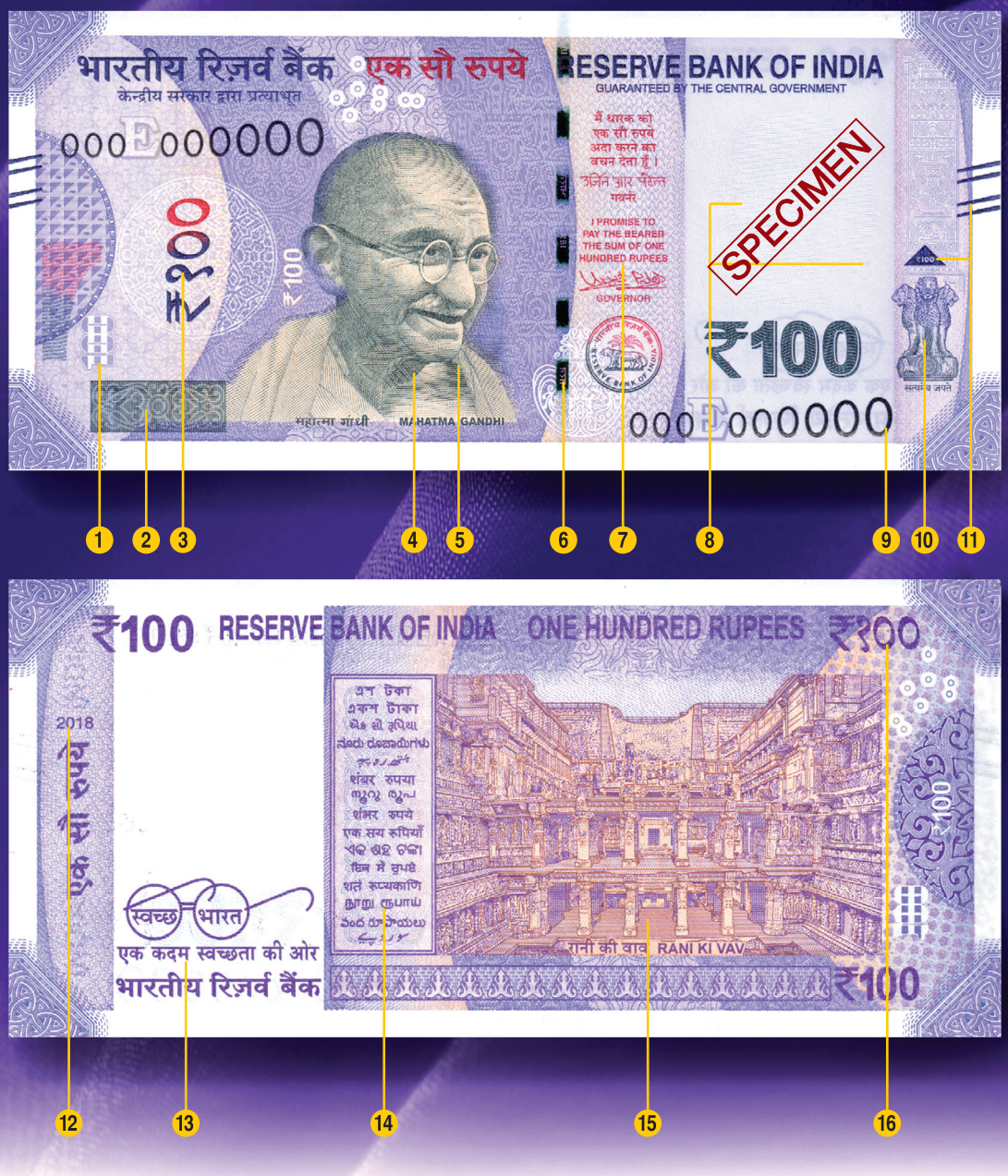
```
        "accuracy":                accuracy_score(y_true, y_pred),
        "balanced_accuracy":       balanced_accuracy_score(y_true, y_pred),
        "precision":               precision_score(y_true, y_pred),
        "recall":                  recall_score(y_true, y_pred),
        "f1":                      f1_score(y_true, y_pred),
        "mcc":                     matthews_corrcoef(y_true, y_pred),
        "kappa":                   cohen_kappa_score(y_true, y_pred),
        "conf_mat":                confusion_matrix(y_true, y_pred),
        "class_report":            classification_report(y_true, y_pred,
output_dict=True)
    }
    if y_proba is not None and len(np.unique(y_true)) == 2:
        try:
            m["roc_auc"] = roc_auc_score(y_true, y_proba)
        except:
            m["roc_auc"] = None
    else:
        m["roc_auc"] = None
    return m

def plot_results(metrics, title_prefix=""):
    cm = metrics["conf_mat"]
    names = ["accuracy","precision","recall","f1"]
    vals  = [metrics[k] for k in names]

    plt.figure(figsize=(10,4))

    # Confusion matrix
    plt.subplot(1,2,1)
    plt.imshow(cm, cmap="Blues")
    plt.title(f"{title_prefix} Confusion Matrix")
    plt.xlabel("Predicted"); plt.ylabel("Actual")
    for (i,j),v in np.ndenumerate(cm):
        plt.text(j, i, v, ha="center", va="center", color="black")
    plt.colorbar()

    # Bar chart
    plt.subplot(1,2,2)
    plt.bar(names, vals)
    plt.ylim(0,1); plt.title(f"{title_prefix} Metrics")
    plt.show()

from qiskit import QuantumCircuit

class QuantumModelBase:
    def __init__(self, n_qubits=4):
```

```
        self.n_qubits = n_qubits
        self.scaler   = StandardScaler()

    def fit(self, X, y):
        return self
    def predict(self, X):
        feats = self._extract_features(X)
        preds, probas = [], []
        for v in feats:
            qc = self._build_circuit(v)
            counts = EXECUTE_CIRCUIT(qc)
            prob0 = counts.get("0", 0) / SHOTS
            preds.append(0 if prob0 > 0.5 else 1)
            probas.append(prob0)
        return np.array(preds), np.array(probas)

    def _extract_features(self, X): raise NotImplementedError
    def _build_circuit(self, feature_vec): raise NotImplementedError

# 1) Q-CNN
class QCNN(QuantumModelBase):
    def _extract_features(self, X):
        kernel = np.array([[1,0,-1],[1,0,-1],[1,0,-1]])
        feats=[]
        for img in X:
            gray = rgb2gray(img)
            conv = convolve2d(gray, kernel, mode="valid")
            pooled = conv[::2,::2]
            feats.append(pooled.flatten()[:self.n_qubits])
        return self.scaler.fit_transform(feats)
    def _build_circuit(self, v):
        qc = QuantumCircuit(self.n_qubits)
        for i,x in enumerate(v):
            qc.ry(float(x)*np.pi, i)
        for i in range(self.n_qubits-1):
            qc.cx(i, i+1)
        qc.measure_all()
        return qc

# 2) Q-LSTM (tiny classical LSTM encoder + quantum readout)
class QLSTM(QuantumModelBase):
    def __init__(self, n_qubits=4):
        super().__init__(n_qubits)
        self.Wf = np.random.randn(n_qubits,n_qubits)*0.05
        self.Wi = np.random.randn(n_qubits,n_qubits)*0.05
        self.Wo = np.random.randn(n_qubits,n_qubits)*0.05
```

```
        self.Wc = np.random.randn(n_qubits,n_qubits)*0.05
    def _sigmoid(self,z): return 1/(1+np.exp(-z))
    def _lstm_seq(self, seq):
        h = c = np.zeros(self.n_qubits)
        for x in seq:
            f = self._sigmoid(self.Wf@(x+h))
            i = self._sigmoid(self.Wi@(x+h))
            o = self._sigmoid(self.Wo@(x+h))
            c = f*c + i*np.tanh(self.Wc@x)
            h = o*np.tanh(c)
        return h
    def _extract_features(self, X):
        feats=[]
        for img in X:
            gray = rgb2gray(img).flatten()
            seq = gray.reshape(-1,self.n_qubits)[:32]
            feats.append(self._lstm_seq(seq))
        return self.scaler.fit_transform(feats)
    def _build_circuit(self, v):
        qc = QuantumCircuit(self.n_qubits)
        for i,x in enumerate(v):
            qc.rx(float(x)*np.pi, i)
        for i in range(self.n_qubits-1):
            qc.cz(i, i+1)
        qc.measure_all()
        return qc

# 3) Q-SVM (simple quantum kernel 1-NN)
class QSVM(QuantumModelBase):
    def fit(self, X, y):
        feats = self._extract_features(X)
        self.class0 = feats[y==0][0]
        self.class1 = feats[y==1][0]
        return self
    def _extract_features(self, X):
        return QCNN()._extract_features(X)
    def _kernel(self, v1, v2):
        qc = QuantumCircuit(self.n_qubits)
        for i,(a,b) in enumerate(zip(v1,v2)):
            qc.ry(a*np.pi, i)
            qc.ry(-b*np.pi, i)      # inverse embedding
        for i in range(self.n_qubits-1):
            qc.cz(i,i+1)
        qc.measure_all()
        counts = EXECUTE_CIRCUIT(qc)
        return counts.get("0",0)/SHOTS
```

```
    def predict(self, X):
        feats = self._extract_features(X)
        preds, probas = [], []
        for v in feats:
            s0 = self._kernel(v,self.class0)
            s1 = self._kernel(v,self.class1)
            prob0 = (s0+1e-6)/(s0+s1+1e-6)  # normalize
            preds.append(0 if prob0>0.5 else 1)
            probas.append(prob0)
        return np.array(preds), np.array(probas)

# Train / evaluate / visualize for each model
all_metrics = {} # Dictionary to store metrics for all models

for ModelClass, name in [(QCNN, "QCNN"), (QLSTM, "QLSTM"), (QSVM, "QSVM")]:
    print(f"\n Running {name} …")
    model = ModelClass()

    if name == "QSVM":
        model.fit(X_train, y_train)
    y_pred, y_proba = model.predict(X_test)

    metrics = compute_metrics(y_test, y_pred, y_proba)
    all_metrics[name] = metrics
    print(f"\n=== {name} Performance Report ===")
    print(f"Accuracy:           {metrics['accuracy']:.4f}")
    print(f"Balanced Accuracy:  {metrics['balanced_accuracy']:.4f}")
    print(f"Precision:          {metrics['precision']:.4f}")
    print(f"Recall:             {metrics['recall']:.4f}")
    print(f"F1 Score:           {metrics['f1']:.4f}")
    print(f"ROC AUC:            {metrics.get('roc_auc', 'N/A')}")
    print(f"MCC:                {metrics['mcc']:.4f}")
    print(f"Cohen's Kappa:      {metrics['kappa']:.4f}")
    print("\nClassification Report:")
    print(classification_report(y_test, y_pred))
    plot_results(metrics, title_prefix=name)

# Summarize all results
print("\n==== Overall Performance Summary ====")
for model_name, metrics in all_metrics.items():
    print(f"\n--- {model_name} ---")
    print(f"Accuracy: {metrics['accuracy']:.4f}, F1: {metrics['f1']:.4f}, ROC
AUC: {metrics.get('roc_auc', 'N/A')}")
```

RBI Kehta Hai
Know your banknotes



The new ₹ 100 denomination banknotes in the **Mahatma Gandhi (New) Series** bear signature of the Governor, Reserve Bank of India. The new note has motif of "Rani ki Vav" on the reverse, depicting the country's cultural heritage. The base colour of the note is lavender.
The note has other designs and geometric patterns aligning with the overall colour scheme, both at obverse and reverse.

The size of the new note is 66 mm x 142 mm

Features of the new ₹100 note

Obverse

1. See through register with denominational numeral 100
2. Latent image with denominational numeral 100
3. Denominational numeral १०० in Devnagari
4. Portrait of Mahatma Gandhi at the centre
5. Micro letters 'भारत' and 'India'
6. Colour shift windowed security thread with inscriptions 'भारत' and 'RBI', colour of the thread changes from green to blue when the note is tilted
7. Guarantee Clause, Governor's signature with Promise Clause and RBI emblem towards right of Mahatma Gandhi's portrait
8. Mahatma Gandhi's portrait and electrotype (100) watermarks
9. Number panel with numerals in ascending font on the top left side and bottom right side
10. Ashoka Pillar emblem on the right
11. **Some features for the visually impaired:** Intaglio or raised printing of Mahatma Gandhi's portrait (4), Ashoka Pillar emblem (10), triangular identification mark with micro-text ₹100 on the right, four angular bleed lines both on the left and right sides

Reverse

12. Year of printing of the note on the left
13. Swachh Bharat logo with slogan
14. Language panel
15. Motif of Rani ki Vav
16. Denominational numeral १०० in Devnagari

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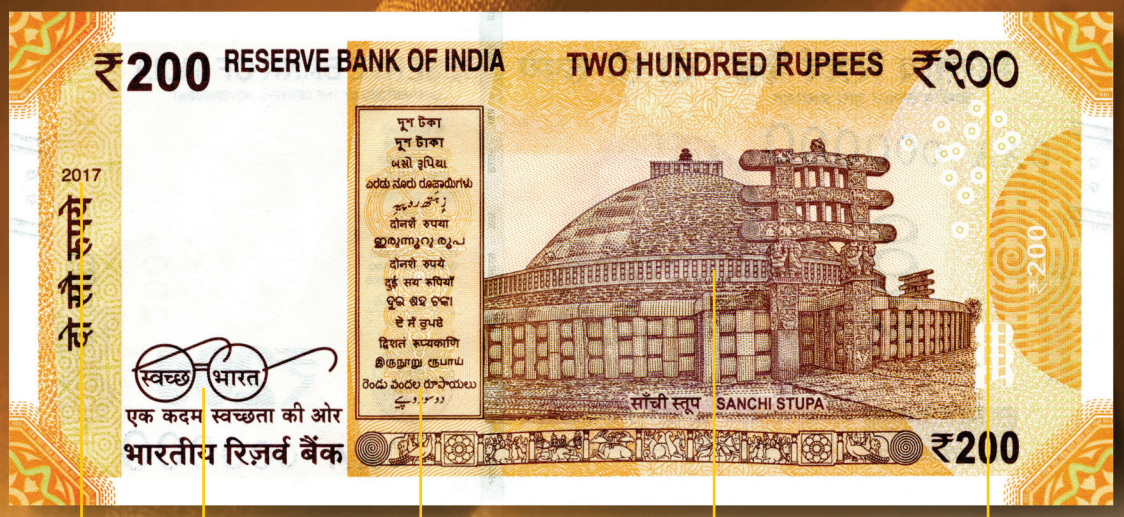

The ₹200 denomination banknotes in the **Mahatma Gandhi (New) Series** bear signature of the Governor, Reserve Bank of India. The note has motif of "Sanchi Stupa" on the reverse, depicting the country's cultural heritage. The base colour of the note is bright yellow.
The note has other designs and geometric patterns aligning with the overall colour scheme, both at obverse and reverse.

The size of the note is 66 mm X 146 mm

Features of the ₹200 Notes

Obverse:

1. See through register with denominational numeral 200
2. Latent image with denominational numeral 200
3. Denominational numeral २०० in Devnagari
4. Portrait of Mahatma Gandhi at the centre
5. Micro letters 'भारत' and 'India'
6. Colour shift windowed security thread with inscriptions 'भारत' and 'RBI'. Colour of the thread changes from green to blue when the note is tilted
7. Guarantee Clause, Governor's signature with Promise Clause and RBI emblem towards right of Mahatma Gandhi's Portrait
8. Mahatma Gandhi's portrait and electrotype (200) watermarks
9. Number panel with numerals in ascending font on the top left side and bottom right side
10. Denominational numeral with Rupee symbol (₹200) in colour changing ink (green to blue) on bottom right
11. Ashoka pillar emblem on the right

Some features for the visually impaired:

12. Intaglio or raised printing of Mahatma Gandhi portrait (4), Ashoka pillar emblem (11). Identification mark H with micro-text ₹200 on the right, four angular bleed lines with two circles in between the lines both on the left and right sides.

Reverse:

13. Year of printing of the note on the left
14. Swachh Bharat logo with slogan
15. Language panel
16. Motif of Sanchi Stupa
17. Denominational numeral २०० in Devnagari

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