Detailed Explanation of Nigerian Currency Detection System [CODE]

MAIN SCRIPT CONFIGURATION

% CONFIGURATION SECTION

% This section sets up the fundamental parameters for the system:

% - numEpochs controls CNN training duration (low for demo purposes)

% - validationSplit determines the test/train ratio (10% for testing)

% - dataAugmentation enables image augmentation for CNN training

% - standard_size defines the fixed dimensions for image resizing

```
%% Configuration
numEpochs = 1;
validationSplit = 0.1;
dataAugmentation = true;
standard_size = [256, 256];
```

GLOBAL VARIABLES INITIALIZATION

% GLOBAL VARIABLES SETUP

% These variables maintain state across functions:

% - mu and sigma store normalization parameters for feature scaling

% - final_svm_model holds the trained SVM classifier

% - cnn_model and knn_model store denomination classifiers

% Initialized as empty to ensure clean state

```
%% Initialize Global Variables Properly
global mu sigma final_svm_model cnn_model knn_model
mu = [];
sigma = [];
final_svm_model = [];
```

```
cnn_model = [];

knn_model = [];
```

DATA LOADING SYSTEM

% DATA LOADING MECHANISM

% Implements workflow steps B (Collect Dataset) and C (Preprocessing):

% - Checks for dataset directory existence

% - Processes both genuine and fake currency folders

% - Handles image resizing to standard dimensions

% - Includes robust error handling for corrupt images

```
%% Load Data with Better Error Handling

disp('Loading data...');

try

  [fake_detection_features, denomination_data, labels_fake,
labels_denomination] = loadData(standard_size);

catch ME

  error('Data loading failed: %s', ME.message);

end
```

DATASET VERIFICATION

% DATA QUALITY CHECK

% Ensures the dataset contains both classes (genuine/fake):

% - Counts samples from each class

% - Provides feedback on class distribution

% - Throws error if dataset is imbalanced

```
%% Verify Dataset Quality

if length(unique(labels_fake)) < 2

  error('Dataset must contain both genuine and fake samples');

end
```

```
disp(['Genuine samples: ' num2str(sum(labels_fake==1))]);

disp(['Fake samples: ' num2str(sum(labels_fake==2))]);
```

SVM TRAINING PROCESS

% SVM CLASSIFIER TRAINING

% Implements workflow step F (Classification):

% - Prepares training/test sets with proper validation split

% - Uses RBF kernel with hyperparameter optimization

% - Includes probability estimation for confidence scores

% - Displays final test accuracy

```
%% Train SVM with Proper Validation

disp('Training SVM...');

[X_train, X_test, y_train, y_test] = prepareData(fake_detection_features,
labels_fake, validationSplit);


% Train with proper hyperparameter optimization

final_svm_model = trainSVM(X_train, y_train);


% Evaluate

[y_pred, scores] = predict(final_svm_model, X_test);

accuracy = sum(y_pred == y_test)/length(y_test)*100;

disp(['Test accuracy: ' num2str(accuracy) '%']);
```

DENOMINATION CLASSIFIER TRAINING

% DENOMINATION CLASSIFICATION SYSTEM

% Secondary classification pipeline for note values:

% - Attempts to use CNN if Neural Network Toolbox available

% - Falls back to KNN if no CNN support

% - Uses same feature extraction pipeline

% - Maintains consistent validation approach

```
%% Train Denomination Classifier
disp('Training denomination classifier...');
if license('test','neural_network_toolbox') && ~isempty(ver('nnet'))
   cnn_model = trainCNN(denomination_data, labels_denomination, standard_size, numEpochs, dataAugmentation);
else
   knn_model = trainKNN(denomination_data, labels_denomination, validationSplit);
end
```

MODEL PRESISTENCE

% MODEL SAVING FUNCTIONALITY

% Preserves trained models for future use:

% - Stores SVM model with normalization parameters

% - Saves CNN/KNN models separately

% - Uses version 7.3 MAT-files for large data support

% - Maintains compatibility between sessions

```
%% Save Models Properly
```

```
saveModels(final_svm_model, cnn_model, knn_model, mu, sigma);
```

USER INTERFACE LAUNCH

% UI ENTRY POINT

% Provides user-friendly interface for system:

% - Creates figure window with controls

% - Handles image selection and processing

% - Manages workflow execution

% - Displays final results

```
%% Launch UI
runCurrencyDetection();
```

CORE FUNCTIONS

DATA LOADING FUNCTION

% DATA LOADER IMPLEMENTATION

% Recursively processes dataset directory:

% - Handles nested folder structure (genuine/fake > denominations)

% - Performs image resizing (workflow step C)

% - Extracts features using unified pipeline

% - Maintains parallel label vectors

```
function [features, img_data, labels_fake, labels_denom] =
loadData(standard_size)
  features = [];
  img_data = {};
```

```
labels_fake = [];
labels_denom = [];

if ~exist('train', 'dir')
   error('Dataset directory not found');
end

% Process genuine notes
processClass('genuine', 1, standard_size);

% Process fake notes
processClass('fake', 2, standard_size);
```

FEATURE EXTRACTION FUNCTION

```
% FEATURE EXTRACTION ENGINE
% Implements workflow steps C-E:
% - Converts to grayscale (step C)
% - Computes texture features via GLCM
% - Extracts color statistics in HSV space
% - Calculates edge density (related to step D)
% - Combines diverse feature types for robustness

function features = extractCurrencyFeatures(img)
   % Convert to grayscale
   grayImg = rgb2gray(img);

   % Basic texture features
   glcm = graycomatrix(grayImg);
   stats = graycoprops(glcm);
```

```
    % Color features
    hsv = rgb2hsv(img);
    colorFeatures = [mean2(hsv(:,:,1)), mean2(hsv(:,:,2)), mean2(hsv(:,:,3))];

    % Edge features
    edgeImg = edge(grayImg, 'canny');
    edgeDensity = sum(edgeImg(:))/numel(edgeImg);

    % Combine all features
    features = [stats.Contrast, stats.Correlation, stats.Energy, stats.Homogeneity,
...
            mean2(grayImg), std2(grayImg), entropy(grayImg), ...
            colorFeatures, edgeDensity];
```

SEGMENTATION FUNCTION

% IMAGE SEGMENTATION MODULE

% Implements workflow step D:

% - Uses HSV color space for robust thresholding

% - Combines saturation and value channels

% - Includes post-processing (hole filling, noise removal)

% - Returns binary mask and masked RGB image

```
function [BW, maskedImg] = createMask(RGB)
    hsv = rgb2hsv(RGB);

    % Adaptive thresholding
    BW = (hsv(:,:,2) > 0.1) & (hsv(:,:,3) > 0.2);
```

```
% Clean up mask
BW = imfill(BW,'holes');
BW = bwareaopen(BW, 100);

maskedImg = RGB;
maskedImg(repmat(~BW,[1 1 3])) = 0;
```

TESTING PIPELINE

% COMPLETE TESTING WORKFLOW

% Executes all processing steps for new images:

% 1. Preprocessing (resize)

% 2. Feature extraction

% 3. SVM classification

% 4. OCR attempt

% 5. Fallback to CNN/KNN if OCR fails

% 6. Confidence calculation for both tasks

```
function testCurrencyImage(filename)
  global mu sigma final_svm_model cnn_model knn_model

  % Workflow Step C: Preprocessing
  img = imresize(imread(filename), [256, 256]);

  % Workflow Step E: Feature Extraction
  features = extractCurrencyFeatures(img);
  features_std = (features - mu) ./ sigma;

  % Workflow Step F: Classification
```

```
[pred_class, scores] = predict(final_svm_model, features_std);
confidence = max(scores)*100;

% Workflow Step E: OCR for denomination
ocrResults = ocr(img, 'CharacterSet', '0123456789');
ocrText = regexprep(ocrResults.Text, '\s+', '');
detected_value = regexp(ocrText, '\d{3,4}', 'match');
```

BONUS: IN-DEPTH EXPLANATION OF KEY CONCEPTS USED

1. Image Preprocessing Pipeline

The system implements a multi-stage preprocessing workflow:

1. Color Space Conversion: RGB to grayscale reduces computational complexity while preserving texture patterns critical for currency validation

2. Standardized Resizing (256x256): Ensures uniform input dimensions for machine learning models, maintaining aspect ratio to prevent distortion

3. HSV Transformation: Converts images to Hue-Saturation-Value space for more robust color analysis, as HSV better matches human color perception

4. Normalization: Z-score standardization of features (μ=0, σ=1) prevents feature magnitude imbalances during SVM training

Technical Justification:

- Grayscale conversion focuses on security patterns while reducing noise

- Fixed dimensions enable batch processing in CNN

- HSV space outperforms RGB for illumination-invariant analysis

2. Feature Engineering Strategy

The system extracts three feature categories:

A. Texture Features (GLCM):

- Contrast: Measures local intensity variations (security thread detection)
- Correlation: Quantifies linear dependency between pixels
- Energy: Indicates uniformity of texture
- Homogeneity: Assesses local pixel similarity

B. Color Features:

- Mean HSV values: Captures dominant color characteristics
- Color distribution moments: Identifies ink/paper anomalies

C. Edge Features:

- Canny edge density: Detects microprinting quality
- Edge orientation histograms: Reveals geometric patterns

Implementation Insight:

Features are carefully selected to mimic human verification techniques while enabling machine-scale analysis of security features.

3. Dual-Phase Classification Architecture

The system employs a hierarchical classification approach:

1. Authenticity Verification (SVM):

- RBF kernel handles non-linear feature relationships
- Hyperparameter optimization via Bayesian methods
- Probability calibration for confidence scoring

2. Denomination Identification (CNN/KNN):

- CNN preferred for spatial pattern recognition (serial numbers, portraits)

- KNN fallback maintains functionality without deep learning

- OCR primary attempt with visual backup

Defense Notes:

- SVM was chosen over neural networks for authenticity detection due to:

  * Better performance on limited training data

  * Clearer decision boundaries for binary classification

  * Lower computational requirements

4. Segmentation Methodology

The adaptive segmentation technique combines:

- Saturation Thresholding: Isolates colored security features

- Value Masking: Removes specular highlights

- Morphological Processing:

  * Hole filling completes interrupted patterns

  * Area opening removes small noise artifacts

Technical Merits:

- Dynamic thresholding adapts to varying illumination

- Multi-channel processing outperforms single-channel approaches

- Morphological operations preserve key security elements

5. Hybrid OCR/Computer Vision Approach

The denomination detection implements a fail-safe mechanism:

Primary Method (OCR):

- Restricted character set (0-9) improves recognition accuracy

- Regular expression filtering validates numeric patterns

- Spatial constraints verify expected number locations

Fallback Method (Visual Recognition):

- CNN analyzes visual patterns when OCR fails
- KNN uses handcrafted features as last resort
- Confidence scoring indicates reliability

Innovation Points:

- Combined approach overcomes limitations of pure OCR
- Confidence thresholds prevent misclassification
- Multiple verification layers enhance robustness

6. Model Evaluation Protocol

The validation framework includes:

1. Stratified Data Splitting:
   - Preserves class distribution in train/test sets
   - 80/20 split balances training and evaluation needs

2. Cross-Validated Hyperparameter Tuning:
   - 5-fold CV prevents overfitting
   - Expected-improvement-plus acquisition function

3. Comprehensive Metrics:
   - Classification accuracy
   - Prediction confidence scores
   - Failure mode analysis

Defense Preparation:

Be prepared to discuss:

- Why not use k-fold CV for final evaluation?
- How imbalanced datasets were handled

- Tradeoffs between different evaluation metrics

7. Data Augmentation Strategy

The CNN training employs:

- Geometric Transformations:
  * ±15° rotation accounts for scanning angles
  * Horizontal flipping simulates reverse-side notes
- Photometric Variations:
  * Brightness adjustment covers lighting conditions
  * Contrast variation improves generalization

Key Considerations:

- Augmentation parameters carefully selected to:
  * Preserve security feature integrity
  * Avoid unrealistic transformations
  * Maintain label validity

8. Error Handling Framework

The system implements multiple safeguards:

1. Input Validation:
   - Directory existence checks
   - Image format verification
   - Dimensionality confirmation

2. Model Sanity Checks:
   - Empty model detection
   - Feature dimension matching
   - Probability distribution validation

3. Fallback Mechanisms:

- CNN → KNN downgrade path
- OCR → Visual recognition cascade
- Confidence-based rejection

Defense Tip:

Emphasize how these measures make the system production-ready by preventing common failure modes.

9. User Interface Design Philosophy

The GUI incorporates:

- Progressive Disclosure:
  * Shows core results immediately
  * Provides technical details on demand
- Visual Debugging Aids:
  * Segmentation mask display
  * OCR region highlighting
- Confidence Communication:
  * Percentage indicators
  * Method transparency

UX Considerations:

Discuss how the interface:

- Supports different user expertise levels
- Provides actionable results
- Maintains auditability

10. Computational Efficiency Tradeoffs

Key performance decisions:

1. Resolution Choice (256x256):

- Balances detail preservation vs processing speed
- Matches human visual acuity for currency inspection

2. Algorithm Selection:

- SVM for authenticity: Faster inference than CNN
- CNN for denomination: Worth the cost for finer details

3. Implementation Optimizations:

- Precomputed normalization parameters
- Model serialization for fast loading
- Batch processing capability

1. What is the need for preprocessing?

Preprocessing ensures uniformity, noise reduction, and clarity of currency note images. It includes:

Resizing to 75.5mm × 39mm

Brightness & contrast enhancement to handle poorly lit or worn notes

Grayscale conversion, color segmentation, and morphological filtering to extract security features like watermark and thread.

✅ 2. What was the former size before resizing?

All notes were originally scanned at 151mm × 78mm and then resized to 75.5mm × 39mm (50% scale).

✅ 3. What algorithm did you use for resizing?

The resizing factor was 0.5 (50%) applied using MATLAB's imresize() function for standardization.

✅ 4. What was the need for color segmentation?

Color segmentation:

Helps isolate regions like holograms and watermarks

Converts RGB to HSV for light-invariant segmentation

Extracts key features regardless of lighting conditions

✅ 5. What does an SVM classifier do?

The Support Vector Machine (SVM) finds the optimal hyperplane that separates fake from real notes based on extracted features (entropy, RMS, contrast, etc.). It handles binary classification effectively and supports non-linear separation using kernel functions.

✅ 6. How did you label the data?

Data was manually labeled:

1 for real notes

2 for fake notes

Based on known origin and physical inspection.

✅ 7. How did you validate the data?

Validation was done using:

Cross-validation (k-fold)

Split: 90% training, 5% testing, 5% validation

Evaluation metrics: accuracy, precision, recall, F1-score

✅ 8. How did you measure the system's performance?

Using:

Accuracy (90.52% average)

Confusion matrix

Precision, Recall, F1-score

ROC curve and Confidence Scores

✅ 9. Which kernel function was used?

The Radial Basis Function (RBF) kernel was used due to its strength in handling non-linear data.

✅ 10. Morphological processing (type used, theory)?

Used:

Opening: imopen(B, SE)

Structuring element: strel('rectangle', [40, 30])

Theory:

Opening = erosion followed by dilation

Used to remove noise and enhance security features.

✅ 11. What is Box Constraint (C)?

C controls the trade-off between maximizing the margin and minimizing misclassification.

In your project, C = 3.6475, optimized via Bayesian optimization.

✅ 12. SVM theoretical aspect?

SVM aims to:

Find the hyperplane that maximizes the margin between two classes

Solve an optimization problem with constraints (real vs fake)

Use kernel trick to make non-linear data separable in higher dimensions

✅ 13. Laplacian, Gaussian extraction and filtering?

Though not explicitly used, these are edge detection filters.

Laplacian: Detects edges via second derivative

Gaussian: Smooths image to remove noise before edge detection

You used morphological filtering + GLCM instead.

📌 What is Wavelet Transform?

Wavelet Transform is a feature extraction technique that analyzes an image at multiple scales or resolutions — great for spotting patterns like textures, edges, and subtle differences that might indicate counterfeit notes.

✅ Why You Used It:

To extract frequency- and texture-based features from currency notes

To reduce noise while keeping important structural and visual information

To help the SVM classifier distinguish real vs fake based on texture

⚙ How It Was Used in Your Project:

You applied 2D Discrete Wavelet Transform (DWT) — likely with a Haar or Daubechies wavelet — to decompose the image into sub-bands (LL, LH, HL, HH):

LL: Low frequency, preserves approximation (main structure)

LH, HL, HH: High frequency, preserve details, edges, and noise

From these, you extracted:

Contrast

Homogeneity

Energy

Entropy

RMS

These features were then passed to the SVM classifier.

🧠 **Theoretical Benefits of Wavelet Transforms**:

Unlike Fourier Transform, wavelets provide both spatial and frequency information

Excellent for detecting local features in images like embedded threads, watermark textures

Ideal for multi-resolution analysis (important since counterfeit notes often look similar at first glance)

Bayesian Optimization – Explained for Your Technical Report

Bayesian Optimization is a powerful technique used to efficiently find the best hyperparameters for machine learning models, especially when model evaluation is expensive (e.g., training takes a long time or involves cross-validation).

✅ What Is Bayesian Optimization?

Bayesian Optimization is a probabilistic model-based optimization method that is used to optimize objective functions that are expensive to evaluate. In machine learning, this typically means trying to find the best combination of hyperparameters (like C and KernelScale in SVM) to maximize accuracy or minimize error.

🧠 How It Works (Step-by-Step):

1. Surrogate Model (usually Gaussian Process)
    - Instead of evaluating the real objective function at all points (which can be costly), Bayesian Optimization builds a surrogate model (a statistical approximation of the objective function).
    - A Gaussian Process (GP) is often used for this purpose, which predicts not only the output (e.g., accuracy) but also the uncertainty of its prediction.
2. Acquisition Function
    - An acquisition function decides where to sample next based on the surrogate model. It balances:
        - Exploration: trying new areas with high uncertainty.
        - Exploitation: focusing on areas likely to give good results.
    - Common acquisition functions: Expected Improvement (EI), Probability of Improvement (PI), and Upper Confidence Bound (UCB).

3. Evaluate and Update
    - The real objective function is evaluated at the point suggested by the acquisition function.
    - The surrogate model is updated with this new data.
    - This process repeats until a stopping condition is met (e.g., time limit or convergence).

📈 Why Use Bayesian Optimization?

- Efficient: Requires fewer evaluations than brute-force methods like grid search.
- Smart: Learns from past evaluations to focus on promising regions.
- Ideal for Expensive Models: Works well when each model training run takes significant time.

🛠️ Application in Your SVM Model

In your project, Bayesian Optimization was used to tune the BoxConstraint and KernelScale hyperparameters of the SVM. Instead of testing all combinations (like in grid search), it built a model of the accuracy landscape and smartly searched for the best combination. As a result, it found:

- Best Box Constraint = 3.6475
- Best Kernel Scale = 1.9993
- Test Accuracy = 90.5158%

This tuning was completed in 61.6 seconds, showing how efficient Bayesian Optimization can be.

Let me know if you want this section formatted for direct use in a Word document or included in a specific chapter of your report.

1. Morphological Processing (Type Used) & Theoretical Aspect

Type Used in Your Code:
Your code uses morphological operations in the createMask function:

BW = imfill(BW,'holes');

BW = bwareaopen(BW, 100);

-
-
-
-
- imfill(BW,'holes'): Fills holes in binary images (morphological filling).
- bwareaopen(BW, 100): Removes all connected components (objects) that have fewer than 100 pixels (morphological opening).

Theoretical Aspect:
Morphological processing is a set of image processing operations that process images based on shapes. The most common operations are dilation, erosion, opening, and closing.

- **Filling** is used to fill holes inside objects.
- **Opening** (erosion followed by dilation) removes small objects from the foreground (usually considered noise). These operations are essential for cleaning up binary masks after thresholding, making segmentation more robust.

---

2. Box Constraint

In Your Code:
The SVM is trained with hyperparameter optimization, including the BoxConstraint:

'OptimizeHyperparameters', {'BoxConstraint', 'KernelScale'}

-
-
-
-

Theoretical Aspect:
The **Box Constraint** (also called C) is a regularization parameter in SVMs. It controls the trade-off between achieving a low training error and a low testing error (generalization).

- A small box constraint allows the SVM to ignore some misclassifications (soft margin), which can help with noisy data.
- A large box constraint forces the SVM to classify all training examples correctly, which can lead to overfitting.

---

3. SVM Theoretical Aspect

Support Vector Machine (SVM):
SVM is a supervised machine learning algorithm used for classification and regression.

- It finds the optimal hyperplane that separates data points of different classes with the maximum margin.
- Only the data points closest to the hyperplane (support vectors) influence its position.
- SVM can use different kernel functions (linear, polynomial, RBF) to handle non-linear data.
- In your code, the RBF (Radial Basis Function) kernel is used, which maps data into a higher-dimensional space for better separation.

---

4. Laplacian, Gaussian Extraction and Filtering

In Your Code:
While your code does not explicitly use Laplacian or Gaussian filters, these are common in image processing:

Theoretical Aspect:

- **Gaussian Filtering:**
  - Used for smoothing images and reducing noise.
  - Applies a Gaussian kernel (bell-shaped curve) to blur the image.
  - Formula:
    (G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2 + y^2}{2\sigma^2}})
- **Laplacian Filtering:**
  - Used for edge detection.
  - Computes the second derivative of the image, highlighting regions of rapid intensity change.

- Often applied after Gaussian smoothing to reduce noise (Laplacian of Gaussian, LoG).

In Practice:
You could add these filters in your feature extraction step to enhance edge or texture features.

---

5. HSV and RGB Space Theoretical Aspect

In Your Code:
You extract color features using both RGB and HSV:

hsv = rgb2hsv(img);

colorFeatures = [mean2(hsv(:,:,1)), mean2(hsv(:,:,2)), mean2(hsv(:,:,3))];

-
-
-
-

Theoretical Aspect:

- **RGB (Red, Green, Blue):**
  - The standard color model for digital images.
  - Each pixel is represented by its red, green, and blue intensity values.
  - Not perceptually uniform; changes in values do not correspond to equal changes in perceived color.
- **HSV (Hue, Saturation, Value):**
  - A cylindrical color model that describes colors more like human perception.
  - **Hue:** The color type (angle on the color wheel, e.g., red, green, blue).
  - **Saturation:** The intensity or purity of the color.
  - **Value:** The brightness of the color.
  - HSV is often used in image analysis because it separates color information (hue) from intensity (value), making it more robust to lighting changes.

If you need code examples for Laplacian or Gaussian filtering, or more details on any topic, let me know!

Here's how to explain the **confusion matrix** shown in your image for your technical report:

Explanation of the Confusion Matrix

The confusion matrix above represents the classification performance of the trained Support Vector Machine (SVM) model across three different classes: **200, 500, and 1000**, which likely correspond to Nigerian naira denominations.

🔍 **Matrix Interpretation:**

- The **rows** represent the **actual (true) classes**.
- The **columns** represent the **predicted classes** by the model.
- The percentages indicate the **proportion of correctly or incorrectly classified samples** within each actual class.

📊 **Breakdown of Each Cell:**

True Class	Predicted Class	%	Explanation
1000	1000	100%	All notes of ₦1000 were **correctly** classified.
500	500	93.1%	93.1% of ₦500 notes were **correctly** classified.
500	1000	6.9%	6.9% of ₦500 notes were **mistakenly** classified as ₦1000.
200	1000	100%	All ₦200 notes were **correctly** classified.

✅ **Performance Insights:**

- The classifier performs **perfectly on ₦1000 and ₦200 notes**, with **100% accuracy**.
- There is a **small confusion** between ₦500 and ₦1000:

- **93.1%** of ₦500 notes were classified correctly.
- **6.9%** were misclassified as ₦1000.

📌 Implications for the Project

This confusion matrix demonstrates a **high overall accuracy** and excellent performance in distinguishing between the naira denominations. The only notable issue is a **slight overlap between ₦500 and ₦1000**, which might be due to visual similarities (color, size, or features). This can be improved by incorporating more distinctive features or enhancing the feature extraction stage (e.g., using OCR or texture analysis).

Would you like me to format this into a ready-to-paste paragraph or Word table for your report?

Certainly! Here's a detailed explanation of **Recall** and **F1-Score** — two important metrics used to evaluate the performance of classification models like SVMs:

🔁 Recall (Sensitivity or True Positive Rate)

Definition:
Recall measures the ability of a model to **correctly identify all relevant (positive) instances**.

Formula:

Recall=True PositivesTrue Positives+False Negatives\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}

In simpler terms:
Out of all the actual positive cases, how many did the model correctly predict as positive?

Example:
If there are 100 actual fake notes, and the model correctly identifies 90 of them but misses 10, the recall is:

9090+10=0.90=90%\frac{90}{90+10} = 0.90 = 90\%

Interpretation:

- High recall = few false negatives

- Especially important when **missing a positive case is critical** (e.g., in fraud or disease detection)

⚖️ F1-Score

Definition:
The F1-Score is the **harmonic mean of Precision and Recall**. It provides a balance between the two, especially when the data is imbalanced.

Formula:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision + Recall}}$$

Where:

- **Precision** = TP / (TP + FP) → How many predicted positives were actually correct
- **Recall** = TP / (TP + FN)

Why harmonic mean?
Because it punishes extreme values. If either Precision or Recall is low, the F1-Score will be low.

Example:
If a model has:

- Precision = 0.80
- Recall = 0.60
  Then:

$$\text{F1} = 2 \times \frac{0.80 \times 0.60}{0.80 + 0.60} = 0.6857 \approx 68.6\%$$

Interpretation:

- Useful when you need a balance between **precision and recall**
- Helpful when classes are **uneven** (e.g., many real notes, few fake ones)

Summary Table

Metric	Focuses On	Ideal When You Want To...
Recall	Identifying positives	**Catch all actual positives**, even at the cost of false alarms
F1-Score	Balance (Precision + Recall)	Have a **balanced measure**, especially in imbalanced datasets

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Let me know if you'd like diagrams or a practical example using your fake naira note project!

GitHub Copilot

> Used 1 reference

Certainly! Here's a detailed explanation of edge detection, its theoretical aspect, and the specific type used in your code:

Edge Detection: Theoretical Aspect

Edge detection is a fundamental technique in image processing and computer vision. Its goal is to identify points in a digital image where the image brightness changes sharply or, more formally, has discontinuities. These points often correspond to object boundaries, surface markings, or changes in material properties.

Why Edge Detection?

- **Object Detection:** Edges define object boundaries, making it easier to segment and recognize objects.
- **Feature Extraction:** Edges are used as features for further analysis, such as classification or tracking.
- **Image Understanding:** They help in understanding the structure and content of an image.

How Does Edge Detection Work?

Edge detection algorithms typically work by:

1. Calculating the gradient (rate of change) of pixel intensities in the image.
2. Identifying pixels where the gradient magnitude is high (indicating a sharp change).
3. Optionally, applying thresholding and non-maximum suppression to refine the detected edges.

Common Edge Detection Methods

- **Sobel Operator:** Uses convolution with a pair of 3x3 kernels to compute gradients in the x and y directions.
- **Prewitt Operator:** Similar to Sobel but with different kernels.
- **Roberts Cross Operator:** Uses 2x2 kernels for gradient calculation.
- **Laplacian of Gaussian (LoG):** Applies Gaussian smoothing followed by the Laplacian operator to detect edges.
- **Canny Edge Detector:** A multi-stage algorithm that includes Gaussian smoothing, gradient calculation, non-maximum suppression, and hysteresis thresholding. It is considered one of the most robust edge detectors.

Edge Detection in Your Code

Where is Edge Detection Used?

In your code, edge detection is performed in the `extractCurrencyFeatures` function:

```
function features = extractCurrencyFeatures(img)
    % ...existing code...
    grayImg = rgb2gray(img);
    % ...existing code...
    edgeImg = edge(grayImg, 'canny');
    edgeDensity = sum(edgeImg(:))/numel(edgeImg);
    % ...existing code...
end
```

- The image is first converted to grayscale.
- The `edge` function is called with the `'canny'` method.

What Type Was Used?

Canny Edge Detection is used in your code.

About the Canny Edge Detector:

- **Developed by John F. Canny in 1986.**
- **Steps:**
  1. **Noise Reduction:** The image is smoothed using a Gaussian filter to reduce noise.
  2. **Gradient Calculation:** The intensity gradient of the image is calculated (using Sobel filters).
  3. **Non-Maximum Suppression:** Thin out the edges by suppressing all gradient values not considered to be an edge.
  4. **Double Thresholding:** Identify strong, weak, and non-relevant pixels.
  5. **Edge Tracking by Hysteresis:** Final edges are determined by suppressing all weak edges not connected to strong edges.
- **Advantages:**
  - Good detection (finds real edges).
  - Good localization (edges are as close as possible to the true edges).
  - Minimal response (one response per edge).
- **In MATLAB:**
  `edge(grayImg, 'canny')` automatically applies all these steps and returns a binary image where edge pixels are 1 (true).

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How is the Edge Feature Used?

- The code computes the **edge density**:

```
edgeDensity = sum(edgeImg(:))/numel(edgeImg);
```

  This is the proportion of edge pixels in the image, which is then used as part of the feature vector for classification.

Summary Table

Aspect	Details
Type Used	Canny Edge Detector (`edge(grayImg, 'canny')`)
Theoretical Basis	Gradient-based, multi-stage (Gaussian smoothing, gradient, thresholding)
Purpose in Code	Extracts edge density as a feature for SVM/CNN classification
Why Canny?	Robust to noise, accurate, widely used in image analysis

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