Forensic Image Classification

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Problem Statement and Motivation

- Context:
  - Digital imaging technologies (cameras, scanners, CG software) are widely accessible.
  - Images from different sources vary in their generation process, affecting forensic analysis.
- Forensic Challenges:
  - Identify whether an image originates from a camera, scanner, or CG software.
  - Establish origin, authenticity, and chain of custody for legal evidence.
- Prior Limitations:
  - Existing methods required knowing the device class (camera or scanner) beforehand.
  - CG images lack physical sensor noise, complicating unified classification.
- Proposed Solution: A unified feature-based method using sensor pattern noise to classify all three sources, independent of image content.

Solution Approach

- Core Concept:
  - Exploit differences in image generation:
  - Digital Cameras: 2D sensor arrays (CCD/CMOS); noise lacks row/column periodicity.
  - Scanners: 1D linear arrays; periodic row correlation due to sensor translation.
  - CG Images: No physical sensor, so residual noise lacks structured patterns.
- Pipeline:
  - Extract residual noise using wavelet denoising.
  - Compute 15 statistical features from noise to capture source-specific characteristics.
  - Train an SVM classifier with these features to classify images into three classes.
- Key Advantage:
  - Method is content-independent and robust to image orientation.

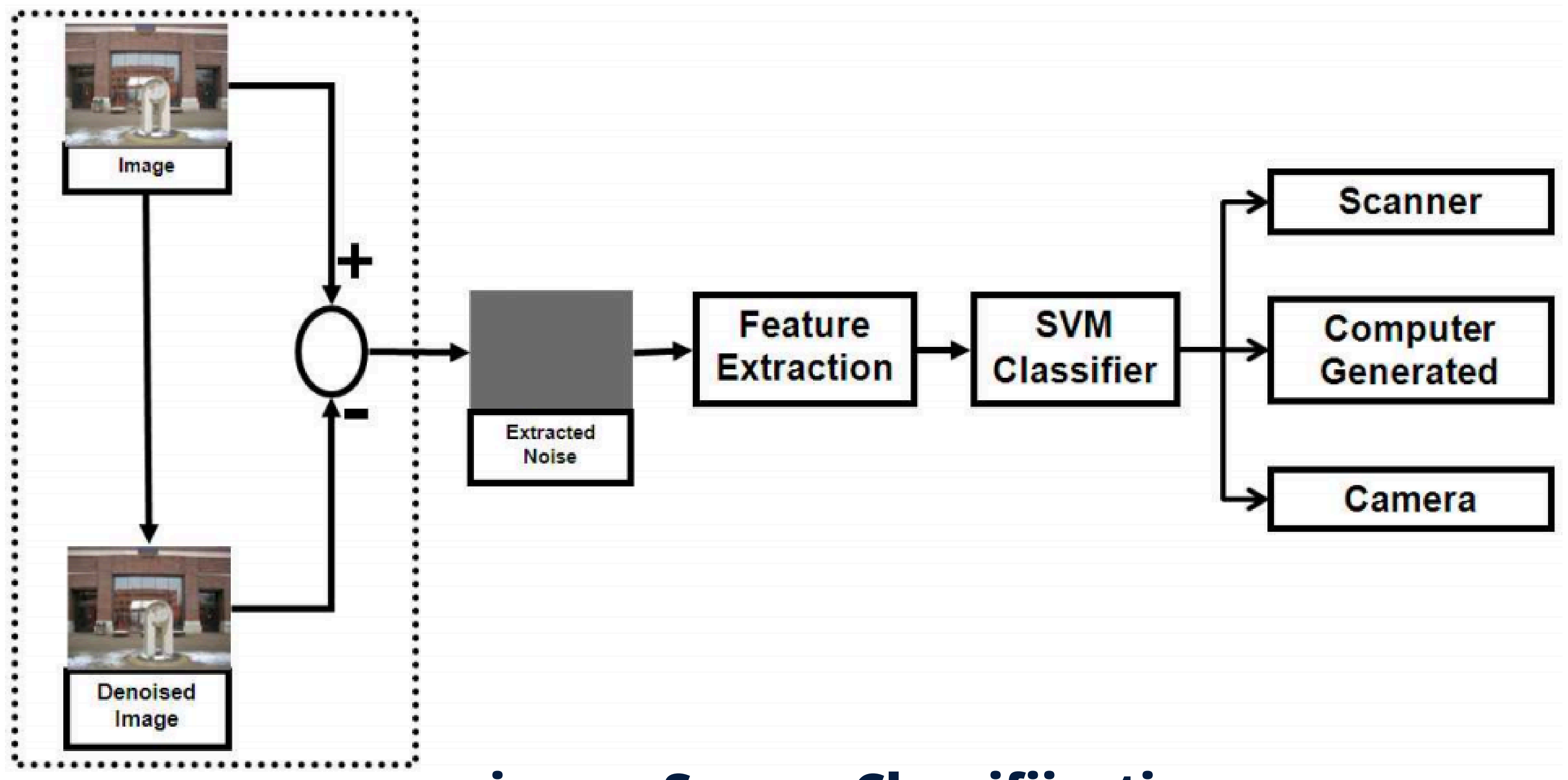


image Source Classifiication

Feature Extraction - Noise Estimation

- Mathematical Foundation:
  - Let (I) be the input image of size.
  - Apply a wavelet denoising filter to obtain.
  - Compute residual noise:

$$I_{noise} = I - I_{denoised}$$

- Implementation Details:
  - Only the green channel is used to reduce computation time.
  - Noise includes pixel non-uniformity, dark currents, dust specks, and optical interference.
- Why Noise?:
  - Cameras and scanners introduce sensor-specific noise during image acquisition.
  - CG images lack this noise, providing a basis for differentiation.

Feature Extraction - Row and Column Averages

- Feature Extraction - Row and Column Averages
- Mathematical Formulation:
  - Row average of noise:

$$\widetilde{I}^{r}_{noise}(1,j) = \frac{1}{M}\sum_{i=1}^{M} I_{noise}(i,j);\ \ 1 \le j \le N$$

  - Column average of noise:

$$\widetilde{I}^{c}_{noise}(i,1) = \frac{1}{N}\sum_{j=1}^{N} I_{noise}(i,j);\ \ 1 \le i \le M$$

- Purpose:
  - Captures spatial noise distribution.
  - Scanners exhibit periodic row correlation due to the linear sensor's mechanical translation.
  - Cameras show no such periodicity; CG images have minimal structured noise.

Feature Extraction - Correlation Features

- **Objective**: Compute correlations to capture source-specific noise patterns.
- **Correlation Calculation**:
  - Row correlation for the i-th row:

$$\rho_{\text{row}}(i) = \mathbf{C}(\bar{I}^{r}_{\text{noise}}, I_{\text{noise}}(i,:)), \quad 1 \leq i \leq M$$

  - Column correlation for the j-th column:

$$\rho_{\text{col}}(j) = \mathbf{C}(\bar{I}^{c}_{\text{noise}}, I_{\text{noise}}(:,j)), \quad 1 \leq j \leq N$$

  - Normalized correlation:

$$\mathbf{C}(X, Y) = \frac{\sum(X - \bar{X})(Y - \bar{Y})}{\sqrt{\sum(X - \bar{X})^2 \sum(Y - \bar{Y})^2}}$$

- **Expected Behavior**:
  - Scanners: High ρ_{row}; low ρ_{col}.
  - Cameras: Low ρ_{row}, ρ_{col}, no periodicity.
  - CG: Near-zero correlations.

Correlation Features

- **Features 1–8**:
  - From ρ_{row}:
    1. Mean: $\mu_{\rho_{\text{row}}} = \frac{1}{M}\sum_{i=1}^{M} \rho_{\text{row}}(i)$
    2. Standard Deviation: $\sigma_{\rho_{\text{row}}} = \sqrt{\frac{1}{M}\sum_{i=1}^{M}(\rho_{\text{row}}(i) - \mu_{\rho_{\text{row}}})^2}$
    3. Skewness: $\text{Skewness}_{\rho_{\text{row}}} = \frac{\frac{1}{M}\sum_{i=1}^{M}(\rho_{\text{row}}(i)-\mu_{\rho_{\text{row}}})^3}{\sigma_{\rho_{\text{row}}}^3}$
    4. Kurtosis: $\text{Kurtosis}_{\rho_{\text{row}}} = \frac{\frac{1}{M}\sum_{i=1}^{M}(\rho_{\text{row}}(i)-\mu_{\rho_{\text{row}}})^4}{\sigma_{\rho_{\text{row}}}^4} - 3$
  - From ρ_{col}: Mean, Standard Deviation, Skewness, Kurtosis.
- **Forensic Significance**: Scanners show high $\mu_{\rho_{\text{row}}}$, distinct skewness/kurtosis.

Feature Extraction: Noise Statistics

- **Noise Statistics (Features 9–14)**:
  - From $\bar{I}^r_{\text{noise}}$:
    9. Standard Deviation:

$$\sigma_{\bar{I}^r_{\text{noise}}} = \sqrt{\frac{1}{N}\sum_{j=1}^{N}(\bar{I}^r_{\text{noise}}(1,j) - \mu_{\bar{I}^r_{\text{noise}}})^2}$$

    10. Skewness:

$$\text{Skewness}_{\bar{I}^r_{\text{noise}}} = \frac{\frac{1}{N}\sum_{j=1}^{N}(\bar{I}^r_{\text{noise}}(1,j) - \mu_{\bar{I}^r_{\text{noise}}})^3}{\sigma^3_{\bar{I}^r_{\text{noise}}}}$$

    11. Kurtosis:

$$\text{Kurtosis}_{\bar{I}^r_{\text{noise}}} = \frac{\frac{1}{N}\sum_{j=1}^{N}(\bar{I}^r_{\text{noise}}(1,j) - \mu_{\bar{I}^r_{\text{noise}}})^4}{\sigma^4_{\bar{I}^r_{\text{noise}}}} - 3$$

  - From $\bar{I}^c_{\text{noise}}$: Standard Deviation, Skewness, Kurtosis (Features 12–14).

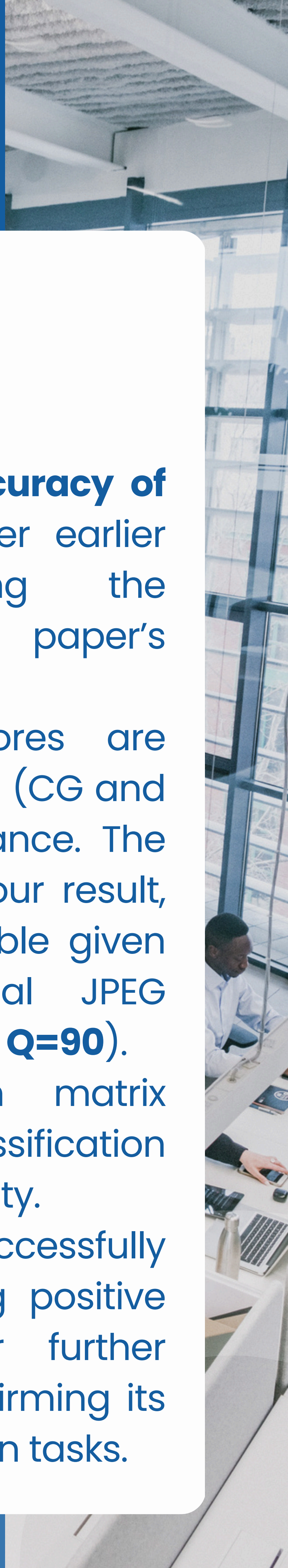
Correlation Ratio

- **Correlation Ratio (Feature 15)**:

$$\mathbf{f}_{15} = \left(1 - \frac{\frac{1}{N}\sum_{j=1}^{N} \rho_{\text{col}}(j)}{\frac{1}{M}\sum_{i=1}^{M} \rho_{\text{row}}(i)}\right) \times 100$$

  - Scanners: Large $\mathbf{f}_{15}$ (50–80) due to $\mu_{\rho_{\text{row}}} \gg \mu_{\rho_{\text{col}}}$.
  - Cameras/CG: Small $\mathbf{f}_{15}$ (0–20).
- **Total Features**: 15-dimensional vector:
  - 1–4: ρ_{row} statistics.
  - 5–8: ρ_{col} statistics.
  - 9–11: $\bar{I}^{r}_{\text{noise}}$ statistics.
  - 12–14: $\bar{I}^{c}_{\text{noise}}$ statistics.
  - 15: Correlation ratio.
- **Orientation Robustness**: $\rho_{\text{row}} > \rho_{\text{col}}$ for scanners regardless of orientation.

Key Aspects of Running the code



Theoretical Explanation of Our Approach

- Our code closely aligns with the paper's methodology for classifying CG vs. Camera images, adopting its core approach of using sensor pattern noise. We extract **15 statistical features** from the green channel's residual noise after wavelet denoising, matching the paper's feature extraction process.
- We also use an SVM classifier with an RBF kernel and perform grid search for **hyperparameters (C: [1, 10, 100], γ: [0.01, 0.001, 0.0001])**, as described in the paper.
- Additionally, we crop images to **1024×768** and use **SimpleImputer for preprocessing**, ensuring fidelity to the paper's pipeline. This alignment ensures our method leverages the proven effectiveness of noise-based forensics for image source identification.

Enhancements and Differences for Effectiveness

- While adhering to the paper's framework, our code introduces practical enhancements to improve usability and robustness. Unlike the paper, we implement a structured output system, saving cropped images, feature vectors , and a percentage-based confusion matrix in an organized directory.
- This facilitates result analysis and reproducibility.
- We also handle **potential NaNs with Simple Imputer**, ensuring all images contribute to training, even with a smaller dataset.
- We experimented with **all RGB channels**, optimizing computational efficiency while maintaining discriminative power. These adaptations make our implementation more practical and resilient for real-world applications.

Results and Impact

- Our code achieves a promising **accuracy of 81%,** a significant improvement over earlier iterations (69%), demonstrating the effectiveness of aligning with the paper's methodology.
- Our precision, recall, and F1-scores are balanced at **0.81 across both classes** (CG and Camera), reflecting robust performance. The paper reports 91.5% accuracy, and our result, though slightly lower, is commendable given dataset constraints and potential JPEG compression (paper notes **79.8% with Q=90**).
- The percentage-based confusion matrix provides clear insights into classification performance, enhancing interpretability.
- Overall, our implementation successfully applies forensic techniques, yielding positive results that pave the way for further optimization with larger datasets, affirming its potential in image source classification tasks.