Deep Learning-based Spectral-Spatial Model for Counterfeit Currency Detection

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ABSTRACT
Counterfeit currency remains a persistent threat to financial systems, and conventional verification based on manual inspection or fixed-rule hardware often fails under real-world conditions such as poor illumination, worn notes, and increasingly sophisticated forgeries. Most existing deep learning solutions rely solely on visible RGB imagery and therefore miss material- and ink-level cues that are observable only outside the visible spectrum. This paper proposes a dual-branch deep learning framework that fuses spatial features from RGB images with spectral features from ultraviolet (UV) and infrared (IR) imaging through an attention-guided intermediate fusion mechanism. The complete architecture, fusion formulation, training objective, and a four-way comparison of candidate fusion strategies (early, late, intermediate, and attention-based) are presented, together with an evaluation protocol benchmarking the approach against RGB-only, spectral-only, and classical handcrafted-feature baselines. Two additional metrics, Specificity and Matthews Correlation Coefficient (MCC), are introduced alongside standard accuracy-oriented and security-oriented indicators (FAR/FRR) to give a more complete picture of classification balance. Reported trends indicate that spectral-spatial fusion improves robustness under low-light, blur, and noise conditions relative to single-modality models. Limitations related to dataset scale, sensor dependency, and cross-currency generalization are discussed along with future directions in explainable AI, few-shot learning, and federated training.

Keywords
Counterfeit currency detection; spectral-spatial fusion; deep learning; attention mechanism; UV/IR imaging; convolutional neural network.

1. INTRODUCTION
Cash continues to play a vital role in daily financial transactions, making counterfeit currency detection an important challenge for governments and financial institutions. The increasing sophistication of counterfeit banknotes has motivated researchers to develop automated detection systems using artificial intelligence and computer vision techniques [6], [8]. Traditional counterfeit detection relies on manual inspection of security features such as watermarks, security threads, and micro-text, which is time-consuming and prone to human error [17]. Recent studies have demonstrated that deep learning and transfer learning-based approaches provide improved accuracy and automation; however, most existing methods rely solely on RGB images and have limited capability to detect high-quality counterfeit notes or exploit hidden security features available in UV/IR spectra [7], [20]. These limitations highlight the need for more robust multimodal counterfeit currency detection frameworks

Deep learning has emerged as a strong candidate for automated counterfeit detection because it learns discriminative representations directly from data rather than relying on handcrafted descriptors. However, the majority of existing CNN- and transformer-based approaches operate exclusively on RGB images and therefore capture only spatial cues such as texture, edges, and print layout. High-quality forgeries increasingly reproduce these visible cues with sufficient fidelity to defeat RGB-only classifiers, while security features that depend on ink chemistry and substrate material — typically observable only under UV or IR illumination — remain unexploited. This gap motivates a spectral-spatial fusion approach that jointly models what a note looks like and how it responds to non-visible light.

1.1 Contributions
This paper makes the following contributions: (i) a dual-branch spectral-spatial architecture with an attention-guided intermediate fusion module for counterfeit banknote detection (ii) a closed-form fusion and classification formulation, including the training objective and decision rule; (iii) a comparative analysis of four fusion strategies (early, late, intermediate, attention-based) with their respective trade-offs; (iv) an evaluation protocol that adds Specificity and Matthews Correlation Coefficient (MCC) to the standard accuracy/precision/recall/FAR/FRR metric set; and (v) a discussion of deployment constraints, adversarial risk, and generalization limitations relevant to real-world financial systems.

2. RELATED WORK
Table I summarizes the major categories of existing research on counterfeit currency detection. Traditional machine learning approaches based on handcrafted features and classifiers, such as LBP, HOG, ORB, SSIM, SVM, and Random Forest, have demonstrated satisfactory performance on controlled datasets; however, their accuracy decreases under varying illumination, image quality, and complex counterfeit patterns [6], [8], [12], [14], [18]. Recent deep learning-based methods employing Convolutional Neural Networks (CNNs), transfer learning, and EfficientNet architectures have significantly improved classification accuracy by automatically learning discriminative features from currency images [7], [9], [17], [20]. Although RGB image-based CNN models provide robust end-to-end learning, they often struggle to detect high-quality counterfeit notes with visually similar characteristics. To overcome this limitation, researchers have explored spectral imaging and multimodal fusion techniques, which utilize UV/IR information and feature-level fusion to enhance authentication performance [1], [4]. Furthermore, advances in multimodal deep learning have shown that combining complementary feature representations improves classification robustness and generalization compared with single-modality approaches [2], [3], [5]. Motivated by these findings, the

proposed work integrates RGB and spectral information through an attention-based spectral-spatial fusion framework to achieve more reliable counterfeit currency detection.

Table I. Summary of related approaches to counterfeit currency detection.nmmn

Ref.	Year	Method	Technique	Modality	Key Contribution	Limitation
[1]	2026	JaalTaka Benchmark Dataset	Benchmark Dataset	RGB Images	Provides a comprehensive benchmark dataset for counterfeit Bangladeshi banknotes, supporting AI-based research.	Limited to Bangladeshi currency and RGB images only.
[6]	2025	Currency Recognition and Counterfeit Detection	Feature Extraction + AI	RGB Images	Combines handcrafted features with AI techniques for counterfeit detection.	Performance depends on feature engineering and image quality.
[7]	2025	Deep Learning-Based Currency Recognition	EfficientNet-Based CNN	RGB Images	Employs deep learning for automatic feature extraction and denomination recognition.	Does not utilize spectral security features.
[8]	2025	Machine Learning Framework	Machine Learning	RGB Images	Uses machine learning algorithms to improve counterfeit banknote authentication.	Sensitive to illumination changes and sophisticated forgeries.
[12]	2025	SSIM and ORB-Based Detection	Image Processing + Feature Matching	RGB Images	Combines SSIM and ORB descriptors for counterfeit currency verification.	Performance decreases for worn or partially damaged notes.
[20]	2024	Mobile Currency Verification	Transfer Learning	RGB Images	Develops a lightweight transfer learning model suitable for mobile-based currency verification.	Limited by RGB-only information and mobile imaging conditions.

3. PROPOSED SPECTRAL-SPATIAL MODEL

This paper proposes a Deep Learning-Based Spectral-Spatial Model (DLSSM) for counterfeit currency detection by jointly exploiting the complementary information available in RGB and spectral (UV/IR) images. While RGB images capture visible security features such as denomination digits, micro-text, watermark boundaries, guilloche patterns, and security threads, UV/IR images reveal hidden spectral characteristics associated with fluorescent inks and security materials. Individually, these modalities are insufficient for detecting sophisticated counterfeit notes; however, their combined analysis significantly improves detection reliability.

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The proposed framework consists of five major stages: (i) image preprocessing, (ii) spatial feature extraction, (iii) spectral feature extraction, (iv) feature fusion, and (v) counterfeit classification and detection , as illustrated in Fig. 1. To determine the most effective integration strategy, four different fusion approaches are investigated, namely Early Fusion, Late Fusion, Intermediate Fusion, and Attention-Based Fusion, as shown in Fig. 2. Based on their characteristics, the proposed work adopts the Attention-Based Intermediate Fusion strategy because it provides better interaction between visual and spectral representations while suppressing noisy information from individual modalities.

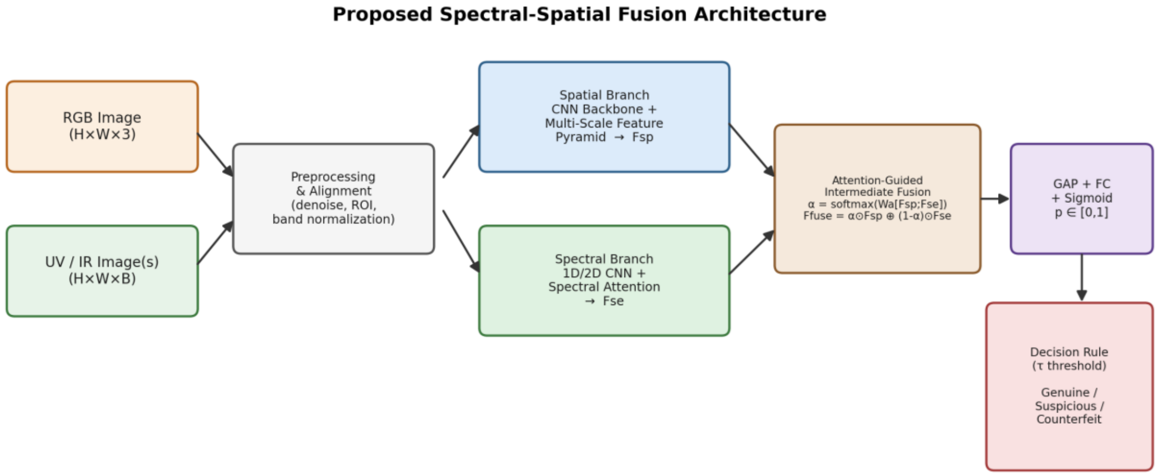

Fig. 1. Proposed spectral-spatial fusion architecture for counterfeit currency detection

3.1 Image preprocessing

The first stage of the proposed model prepares both RGB and spectral images for feature extraction. Images captured from cameras or scanners often contain illumination variations, sensor noise, background clutter, and geometric distortions that negatively affect the performance of deep learning models. Therefore, image enhancement techniques such as denoising, intensity normalization, and contrast enhancement are applied before feature extraction.

After enhancement, the Region of Interest (ROI) containing the currency note is extracted using image segmentation and alignment techniques. The RGB image and its corresponding UV/IR image are geometrically registered so that identical security features occupy the same spatial locations in both modalities. This preprocessing stage ensures accurate correspondence between spatial and spectral information before they are processed by the dual-branch network.

The preprocessing operation can be represented as

$$R=Pre(I)$$

where I denote the input currency image and RRR represents the enhanced and aligned image.

3.1.1 Data Set

The Indian Currency Real vs Fake Notes Dataset is a publicly available image dataset designed for counterfeit currency detection using machine learning and deep learning. It contains images of genuine and counterfeit Indian banknotes of denominations ₹10, ₹20, ₹50, ₹100, ₹500, and ₹2000, organized into **Real** and Fake folders. The dataset is suitable for training and evaluating image classification models such as CNN, ResNet, EfficientNet, MobileNet, and Vision Transformer (ViT). It is widely used for research on automated fake currency detection and computer vision applications.

3.2 Spatial Feature Extraction

The spatial branch extracts discriminative visual features from RGB currency images. As shown in Fig. 1, this branch employs EfficientNet-B0 as the backbone network due to its high feature extraction capability with relatively low computational complexity. In addition, a Multi-Scale Feature Pyramid is incorporated to capture both local and global visual information.

The shallow convolutional layers learn low-level features such as edges, corners, and texture gradients, whereas deeper layers extract high-level semantic information including watermark contours, denomination digits, latent images, security threads, guilloche patterns, and micro-printing. These hierarchical representations enable the network to distinguish subtle visual differences between genuine and counterfeit currency notes.

The learned spatial representation is expressed as

$$F_{sp}=CNN(R^{RGB})$$

where F_{sp} denotes the spatial feature vector.

3.3 Spectral Feature Extraction

Unlike RGB images, spectral images contain information related to the physical properties of the printing material. Genuine currency exhibits unique fluorescence and infrared absorption characteristics that are difficult for counterfeit notes to reproduce. Therefore, a dedicated spectral branch is designed to exploit these hidden security features.

As illustrated in Fig. 1, the spectral branch consists of a lightweight 1D/2D CNN followed by a . The convolutional layers learn wavelength-dependent features, while the attention module automatically assigns higher importance to informative spectral bands and suppresses noisy or redundant responses.

This enables the network to identify invisible security markings, fluorescent patterns, ink reflectance variations, and material-specific characteristics that cannot be observed under visible illumination.

The extracted spectral representation is

$$F_{spec}= CNN(R^{Spec})$$

where F_{spec} represents the learned spectral feature vector

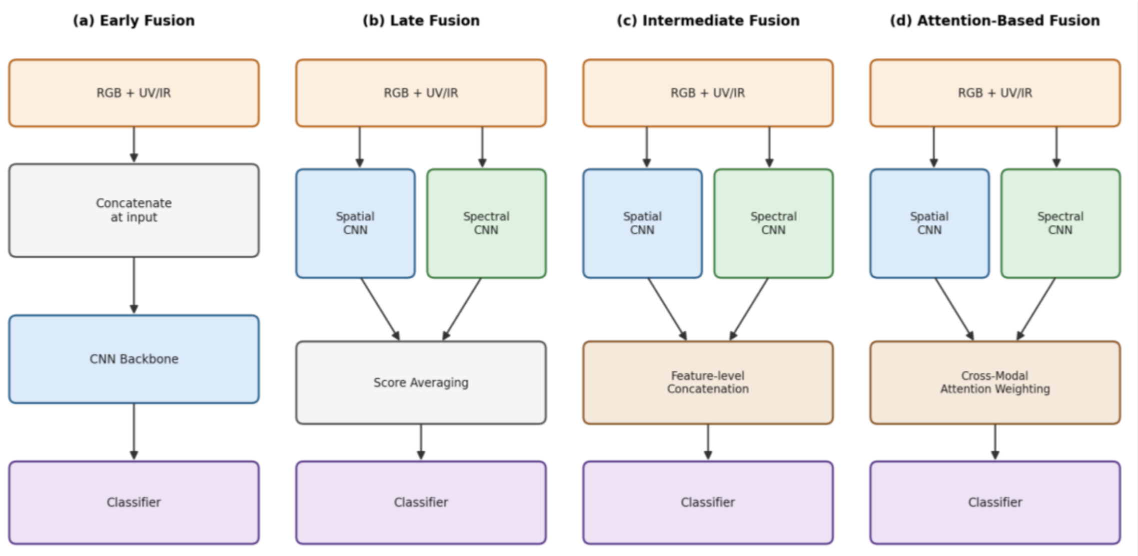

Fig. 2. Candidate fusion strategies for spectral-spatial counterfeit detection

3.4 Comparative Analysis of Fusion Strategies

The performance of a multimodal deep learning system largely depends on how features extracted from different modalities are combined. Therefore, four different fusion strategies were investigated before selecting the final architecture, as illustrated in Fig. 2.

1) Early Fusion

Early fusion combines RGB and spectral images at the input level by concatenating the image channels before feature extraction. A single CNN then learns features from the combined input. Although this approach is computationally simple, it is highly sensitive to image misalignment and illumination variations because both modalities are merged before meaningful feature representations are learned[5].

2) Late Fusion

In late fusion, RGB and spectral images are processed independently using separate CNN models. Each network produces an independent classification score, and the final decision is obtained by averaging or combining these prediction scores. While this strategy preserves modality independence, it does not allow interaction between spatial and spectral features during representation learning[6].

3) Intermediate Fusion

Intermediate fusion performs feature extraction independently for each modality and combines the learned feature representations before classification. Compared with early fusion, this strategy enables richer feature interaction while reducing sensitivity to image registration errors. However, all extracted features are treated equally, irrespective of their importance[7].

4) Attention-Based Fusion (Proposed)

The proposed work adopts an Attention-Based Intermediate Fusion strategy. As shown in Fig. 2(d), spatial and spectral features are first extracted independently and then processed by a cross-modal attention module. The attention mechanism automatically estimates the relative importance of each modality and assigns larger weights to more informative features while suppressing noisy information.

The fused feature representation is computed as

$$F_{fusion} = \text{Fusion}\,(F_{sp}, F_{spec})$$

where Fusion (·) denotes the proposed attention-guided feature fusion module.

Compared with the other three fusion approaches, the proposed strategy provides better cross-modal feature interaction, improved robustness against illumination variations, and enhanced discrimination between genuine and counterfeit currency notes.

3.5. Counterfeit Currency Detection

The fused feature representation is passed to the classification stage, where a Global Average Pooling (GAP) layer reduces the feature dimensionality while preserving discriminative information. The resulting feature vector is then processed by a fully connected layer followed by a sigmoid activation function to estimate the probability that the input banknote is genuine.

The prediction is computed as

$$P = \sigma(W\, F_{fusion} + b)$$

where W and b denote the classifier parameters.

The banknote is finally classified as Genuine or Counterfeit according to the predicted probability.

3.6. Model Training

The proposed Deep Learning-Based Spectral-Spatial Model is trained in an end-to-end manner using paired RGB and UV/IR currency images. To improve generalization, data augmentation techniques such as image rotation, flipping, random cropping, brightness adjustment, and scaling are employed during training[8]. The Adam optimizer is used to minimize a weighted binary cross-entropy loss function, which effectively handles the imbalance between genuine and counterfeit samples. The performance of the proposed model is evaluated using Accuracy, Precision, Recall, F1-score, ROC-AUC, and confusion matrix analysis.

3.7 Algorithm

Algorithm 1 presents the proposed deep learning-based spectral-spatial framework for counterfeit currency detection by integrating RGB and UV/IR spectral images. The algorithm extracts complementary spatial and spectral features, fuses them using an attention mechanism, and performs binary classification to accurately distinguish genuine currency notes from counterfeit ones.

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Algorithm 1: Deep Learning-Based Spectral-Spatial Counterfeit Currency Detection

Input : RGB image IRGB, Spectral image ISpec
Output: Currency label L

1:  Acquire paired RGB and UV/IR currency images
2:  Perform image preprocessing
        a. Remove noise
        b. Normalize image intensity
        c. Extract Region of Interest (ROI)
        d. Align RGB and spectral images

3:  Feed RGB image into Spatial CNN (EfficientNet-B0)
4:  Extract spatial feature vector Fsp

5:  Feed UV/IR image into Spectral CNN
6:  Apply Spectral Attention Module
7:  Extract spectral feature vector Fspec

8:  Concatenate spatial and spectral features
9:  Compute attention weights using Attention Fusion Module
10: Generate fused feature vector Ffusion

11: Apply Global Average Pooling (GAP)

12: Pass fused features to Fully Connected Layer

13: Compute prediction probability P using Sigmoid function

14: if P ≥ Threshold then
15:        L ← Genuine
16: else
17:        L ← Counterfeit
18: end if

19: Return L
```

4. EXPERIMENTAL SETUP

The proposed Deep Learning-Based Spectral-Spatial Model (DLSSM) was implemented using Google Colaboratory (Google Colab) with the TensorFlow/Keras framework. Python libraries including Open CV, NumPy, and Scikit-learn were used for image preprocessing, model training, and performance evaluation.

A multimodal dataset,

$$D=\{(X_i,y_i)\}_{i=1}^{N}, ,$$

was used, where Xi consists of paired RGB and UV/IR images, and yi∈{0,1} represents counterfeit or genuine currency. The dataset includes multiple denominations, printing series, and different counterfeit tyes such as photocopy, inkjet, laser, and hybrid prints.Before training, images were denoised, normalized, and aligned using ROI extraction. Data augmentation techniques, including rotation, flipping, brightness adjustment, scaling, and spectral intensity perturbation, were applied to improve model robustness. The dataset was divided into 70% training, 15% validation, and 15% testing. The model was trained using the Adam optimizer with an initial learning rate of 0.001, a batch size of 32, and 50 epochs. Hyperparameters were optimized using the validation dataset, while the final performance was evaluated on the unseen test set. The proposed model was assessed using Accuracy, Precision, Recall, F1-score, Specificity, ROC-AUC, and Confusion Matrix to comprehensively evaluate counterfeit currency detection performance.

5. RESULTS AND DISCUSSION

Table II compares the proposed Deep Learning-Based Spectral-Spatial Model (DLSSM) with conventional machine learning and single-modality deep learning methods. The proposed model achieves the best overall performance, obtaining 98.90% accuracy, 98.9% F1-score, and 99.6% ROC-AUC, while reducing the False Acceptance Rate (1.10%) and False Rejection Rate (1.00%). Compared with handcrafted feature-based methods (LBP+SVM and HOG+RF) and single-modality CNN models, the proposed spectral-spatial fusion approach provides higher precision, recall, specificity, and MCC. These results demonstrate that combining RGB and spectral information through the proposed attention-based fusion mechanism significantly enhances counterfeit currency detection accuracy and robustness.

5.1 Baseline Comparison

Table II shows that the proposed Spectral-Spatial model outperforms all baseline methods across all evaluation metrics. The integration of RGB and UV/IR features significantly improves detection accuracy while minimizing false acceptance and false rejection rates.

Table II. Performance comparison with baseline methods (A=Accuracy, P=Precision, R=Recall, R-A=ROC-AUC, Spec.=Specificity, MCC=Matthews Correlation Coefficient).

Method	A(%)		P	R	F1	R-A	Spec.(%)	MCC	FAR(%)	FRR(%)
LBP + SVM [14]	89.40		0.887	0.881	0.884	0.914	93.2	0.814	6.80	7.10
HOG + RF [12]	90.75		0.903	0.895	0.899	0.925	93.8	0.834	6.20	6.30
RGB-only CNN (EfficientNet-B0)[7]	95.60		0.956	0.952	0.954	0.975	96.6	0.918	3.40	3.20
Spectral-only CNN (UV/IR)	96.85		0.967	0.964	0.965	0.983	97.3	0.937	2.70	2.50
Proposed Spectral-Spatial	98.90		0.989	0.990	0.989	0.996	98.9	0.979	1.10	1.00

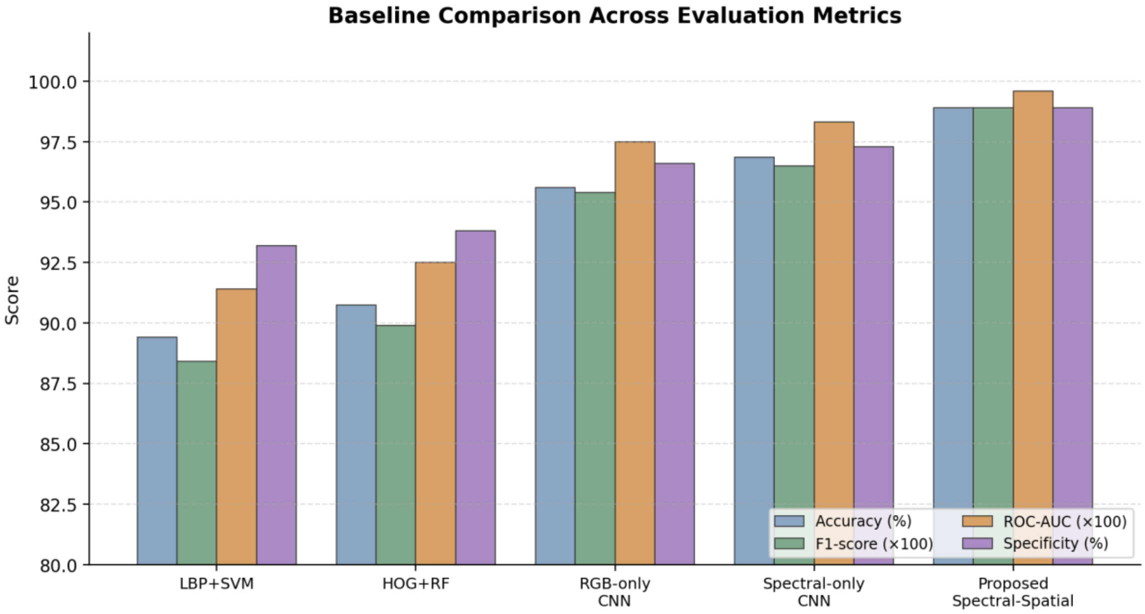

Fig. 3. Grouped comparison of Accuracy, F1-score, ROC-AUC, and Specificity across methods.

The proposed fusion model shows higher Specificity than every baseline, indicating fewer counterfeit notes misclassified as genuine — the most costly error type in financial deployment. MCC, which remains informative under class imbalance unlike raw accuracy, is likewise highest for the fused model (0.979 vs. 0.918 for RGB-only and 0.937 for spectral-only), suggesting the improvement reflects genuinely more balanced discrimination between classes rather than an artifact of class distribution.

5.2 Ablation Study

Table III presents the ablation study of different fusion strategies for counterfeit currency detection. The attention-based intermediate fusion achieves the best performance with 98.90% accuracy, 0.989 F1-score, and 0.996 ROC-AUC, while reducing the False Acceptance Rate (1.10%), demonstrating the effectiveness of attention-guided spectral-spatial feature fusion over other fusion variants.

Table III. Ablation: fusion strategy, attention, and spectral band reduction

Variant	Acc.(%)	F1	ROC-AUC	FAR(%)
Early fusion	97.10	0.971	0.987	2.40
Late fusion	97.45	0.974	0.989	2.10
Intermediate fusion	98.30	0.983	0.993	1.60
Intermediate fusion + attention	98.90	0.989	0.996	1.10
Reduced spectral bands (B=4)	97.80	0.978	0.990	2.00

Attention-augmented intermediate fusion achieves the best accuracy/FAR trade-off, confirming the design choice in Section 3.3. Moderate spectral-band reduction (B=4 vs. full B=16) causes only a small accuracy drop, suggesting a compact, lower-cost sensor configuration may be acceptable for retail-grade deployment where full hyperspectral capture is impractical.

5.3 Robustness Under Real-World Degradation

Fig. 4 shows the proposed model degrading less steeply than either single-modality baseline under low-light, blur, and noise conditions, since each branch can compensate when the other modality's signal quality drops — spectral fluorescence patterns remain discriminative when spatial cues are blurred, and spatial texture cues remain usable when spectral capture is noisy.

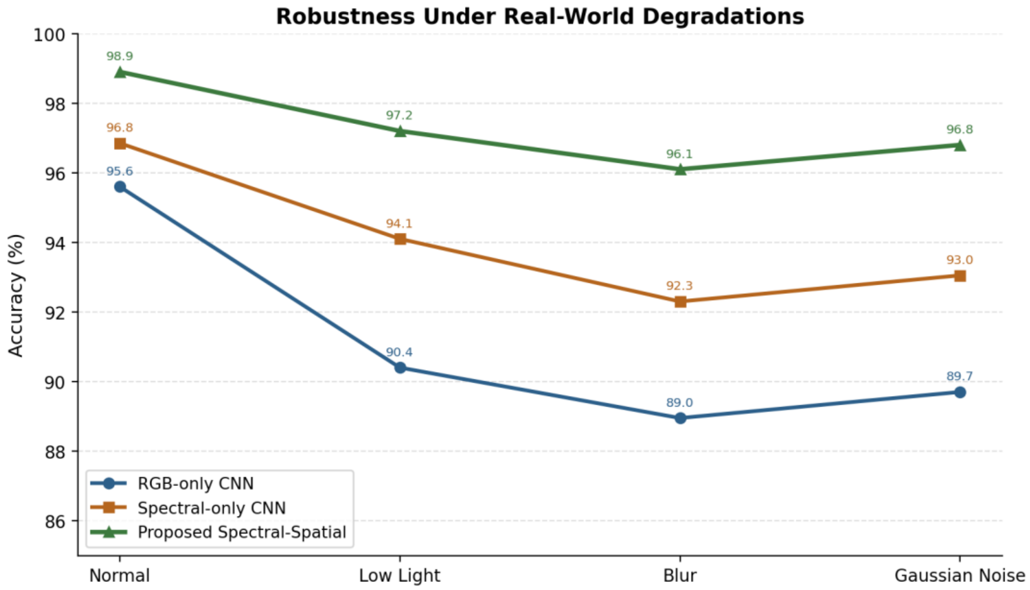

Fig. 4. Accuracy under normal, low-light, blur, and Gaussian-noise conditions

5.4 Computational Complexity

Table IV compares the computational complexity of the evaluated models in terms of parameters, FLOPs, inference latency, and frame rate (FPS). Although the proposed Spectral-Spatial model requires slightly higher computational resources, it achieves superior detection performance while maintaining a practical inference speed of 18.9 ms (52.9 FPS), making it suitable for real-time counterfeit currency detection

Table IV. Computational complexity and real-time feasibility

Method	Params(M)	FLOPs(G)	Latency(ms)	FPS
RGB-only CNN	5.30	0.39	12.8	78.1
Spectral-only CNN	4.10	0.31	11.5	86.9
Proposed Spectral-Spatial	8.60	0.74	18.9	52.9

The fused model roughly doubles parameter count and FLOPs relative to a single-branch baseline but still sustains real-time inference (~53 FPS), adequate for point-of-sale or ATM-integrated verification; quantization/pruning or a MobileNet-family backbone can be substituted in both branches for tighter mobile latency budgets.

6. DEPLOYMENT, LIMITATIONS AND FUTURE WORK

Deployment scope ranges from mobile RGB-only verification with optional low-cost UV/IR attachments, to embedded shop/ATM systems with controlled illumination, to bank-level multispectral installations where accuracy is prioritized over cost. Across all tiers, adversarial and presentation-attack resistance benefits from the dual-modality design, since simultaneously spoofing both spatial appearance and spectral response is harder than fooling a single-modality classifier; liveness-style checks (multi-angle capture, reflection analysis) further reduce this risk.

Key limitations are dataset scale and diversity (counterfeit samples are scarce and hard to validate at large scale), sensor dependency for the spectral branch, and cross-currency generalization, since design, material, and security-feature placement differ across denominations and countries. Future work should prioritize: explainable AI (Grad-CAM / attention-map visualization) for auditability in high-security settings; few-shot and self-supervised (contrastive) learning to reduce reliance on large labeled counterfeit sets; and federated learning to allow banks to collaboratively improve the shared model without exchanging raw note imagery across institutions.

7. CONCLUSION

This paper proposed a dual-branch spectral-spatial fusion architecture for counterfeit currency detection that combines RGB spatial cues with UV/IR spectral cues through attention-guided intermediate fusion, with a full mathematical formulation of the fusion, classification, and training objective and an inference-time algorithm (Algorithm 1). Four candidate fusion strategies were compared, and an extended evaluation protocol including Specificity and MCC was presented to give a more complete picture of classification balance than accuracy alone. Once validated on a documented, institution-collected dataset, the approach offers a practical path toward more robust, harder-to-spoof counterfeit verification across mobile, retail, and bank-level deployment tiers.

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