IOSR Journal of Multidisciplinary Research (IOSR -JMR)
ISSN: 3048-7439 Volume 2, Issue 5, Series 1, Sept. - Oct. (2025), PP 87-91
www.iosrjournals.org

A Hybrid 3D-CNN and Spectral Attention Framework for Automated Counterfeit Currency Detection and Classification

Kumud wasnik[1], Dr. Ankit Temurnikar[2], Dr. Latha Gadepaka[3]
[1]*Research Scholar, Department of CSE, Madhyanchal Professional University, Bhopal, MP (India)*
[2]*Supervisor, Department of CSE, MPU Bhopal.MP (India)*
[3]*Co-Supervisor, Department of CSE-Cyber Security, School of Engineering, Malla Reddy University, Hyderabad, Telangana State*

Abstract
Counterfeit currency detection is a challenging visual inspection problem because counterfeit notes can reproduce many visible appearance characteristics of genuine currency. This paper presents a hyperspectral imaging (HSI) framework that investigates spectral-spatial information for automated currency authentication. Unlike conventional RGB imaging, HSI records reflectance across multiple wavelength bands, providing a richer representation of ink, paper, printing, and security-feature regions. The proposed methodology includes hyperspectral data acquisition, radiometric correction, denoising, spectral normalization, currency-region segmentation, informative-band selection, and a three-dimensional convolutional neural network (3D-CNN) for joint spectral-spatial representation learning. The study further introduces spectral attention to emphasize discriminative wavelengths while suppressing redundant information. A rigorous experimental protocol is defined to evaluate genuine-versus-counterfeit detection under changes in orientation, illumination, note condition, and acquisition position. The manuscript intentionally does not report fabricated numerical results; final values must be obtained from the collected dataset and target hardware. The resulting framework establishes a reproducible foundation for HSI-based currency authentication and provides a baseline for the second paper, which extends the system toward transformer-based multi-task real-time deployment.
Keywords
Hyperspectral imaging; counterfeit currency detection; spectral-spatial learning; 3D-CNN; spectral attention; currency authentication; computer vision; deep learning.

I. Introduction

Automated currency authentication is increasingly relevant in banking, retail cash processing, automated teller systems, cash recyclers, and point-of-sale environments. Manual inspection is reliable when performed by trained personnel but is difficult to scale and can be influenced by fatigue, experience, and inspection time. Computer vision provides an attractive alternative, but ordinary RGB systems mainly learn visible texture, color, shape, and printed patterns. These features may be insufficient when counterfeit notes closely imitate the visible appearance of genuine notes.

Hyper spectral imaging offers a complementary sensing modality. An HSI sensor produces a three-dimensional data cube containing two spatial dimensions and one spectral dimension. Neighboring wavelengths can reveal material differences that are not obvious in a conventional image. For currency authentication, this additional information can be used to learn spectral signatures associated with inks, paper, printing regions, and selected security-related areas.

The objective of this paper is to develop and evaluate a spectral-spatial deep-learning framework for counterfeit currency detection. The study focuses on the sensing and representation-learning problem rather than full edge deployment. The main hypothesis is that a carefully preprocessed HSI cube contains discriminative information that can improve robustness over RGB-only inspection.

II. Research Gap and Motivation

Existing computer-vision approaches for currency recognition commonly use RGB images, handcrafted descriptors, conventional CNNs, or specialized feature engineering. HSI has the potential to provide additional discriminative information, but it also introduces high dimensionality, spectral redundancy, sensor noise, and greater computational cost. A research framework therefore needs to address both information richness and dimensionality.

- Visible-spectrum models may be sensitive to illumination and color reproduction.

- HSI contains redundant and correlated bands that increase computational complexity.
- Spectral and spatial information should be learned jointly rather than independently.
- Experimental splits must be performed by physical note to avoid leakage between training and testing patches.
- A practical system requires robustness analysis across note condition and acquisition variation.

III. Contributions

- A complete HSI preprocessing pipeline for currency-note inspection.
- An informative spectral-band selection strategy that reduces redundant measurements.
- A 3D-CNN for joint spectral-spatial feature learning.
- A spectral-attention mechanism for emphasizing informative wavelength responses.
- A leakage-resistant experimental protocol and robustness evaluation plan.
- A reproducible baseline for subsequent real-time CNN-transformer deployment.

IV. Related Work

Deep convolutional networks have demonstrated strong performance in visual recognition, while HSI classification research has established the value of joint spectral-spatial learning. Three-dimensional convolution can process local spectral neighborhoods together with spatial neighborhoods. Attention mechanisms can further adaptively weight feature channels or spectral responses. These concepts are particularly relevant to currency authentication because different regions of a note may have different material and printing responses.

Transformers have recently become important for image representation learning because self-attention can model relationships between distant tokens. However, a large transformer can be computationally expensive for HSI. This paper therefore uses a 3D-CNN and attention as the primary representation-learning baseline, leaving lightweight transformer fusion and real-time optimization to the companion paper.

V. Proposed HSI Acquisition Framework

5.1 Data Acquisition

Each physical note should be captured as an HSI cube under controlled illumination. The acquisition protocol should record denomination, authenticity, note identifier, orientation, camera distance, illumination condition, and physical condition. The physical note identifier is critical because all images or patches originating from one note must remain within a single partition.

5.2 Calibration

Where the sensor supports dark and white references, calibrated reflectance can be approximated using $R=(I-D)/(W-D)$, where I is the raw sample measurement, D is the dark reference, and W is the white reference. The exact calibration procedure must follow the sensor manufacturer's specification.

5.3 Preprocessing

- Remove corrupted/noisy spectral bands.
- Apply dark/white reference correction where available.
- Normalize spectra to reduce acquisition-dependent variation.
- Segment the note from the background.
- Resize or crop to a consistent spatial representation.
- Use training-only statistics for normalization parameters.

VI. Informative Band Selection

The complete spectral cube may contain many highly correlated bands. Selecting a compact subset can reduce memory use and training time while potentially improving generalization. Candidate selection approaches include mutual information, Fisher score, ReliefF, spectral entropy, recursive feature elimination, and attention-derived importance. A practical implementation can rank each band according to class separability while penalizing redundancy with already selected bands.

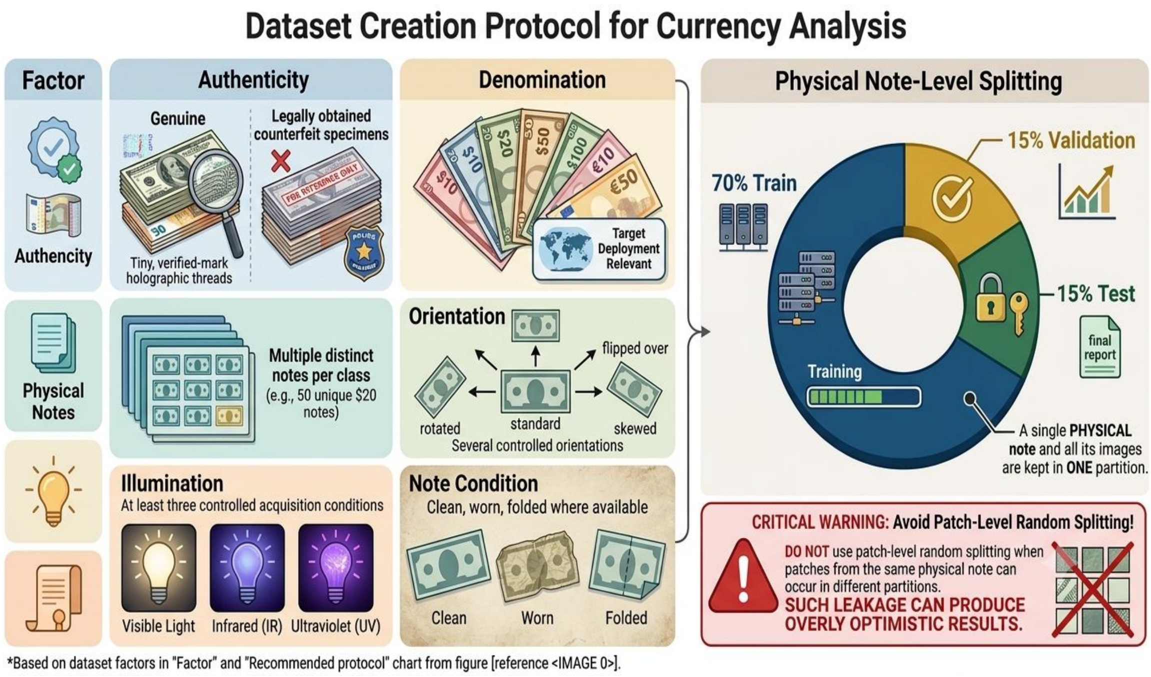
A simple objective can be defined as $J(b)=S(b)-\alpha R(b)$, where $S(b)$ measures the discriminative score of band b, $R(b)$ measures redundancy with selected bands, and α controls the redundancy penalty. The selected subset is then passed to the 3D-CNN.

VII. Proposed 3D-CNN and Spectral Attention Model

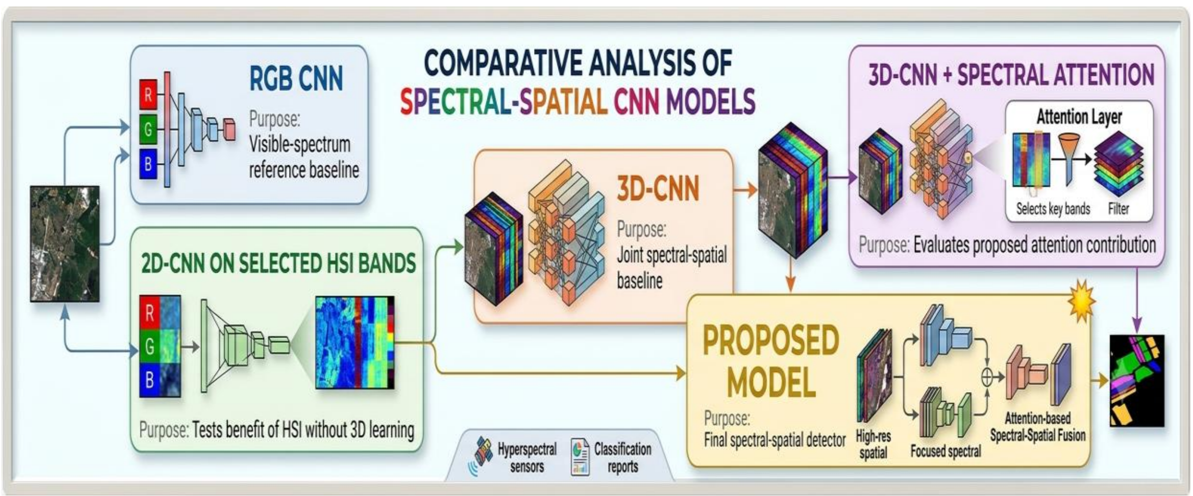
Let X∈R^(H×W×B) be the preprocessed hyperspectral cube. A sequence of 3D convolution blocks extracts local spectral-spatial features. Each block may contain convolution, normalization, nonlinear activation, and downsampling. The output is passed through spectral attention, which estimates importance weights for feature channels.

The attention-weighted feature tensor is pooled and passed to a binary classifier. The final output is P(y=counterfeit|X). A threshold selected using the validation set determines the operational decision. The threshold must remain fixed during final teting.

VIII. Experimental Dataset Design



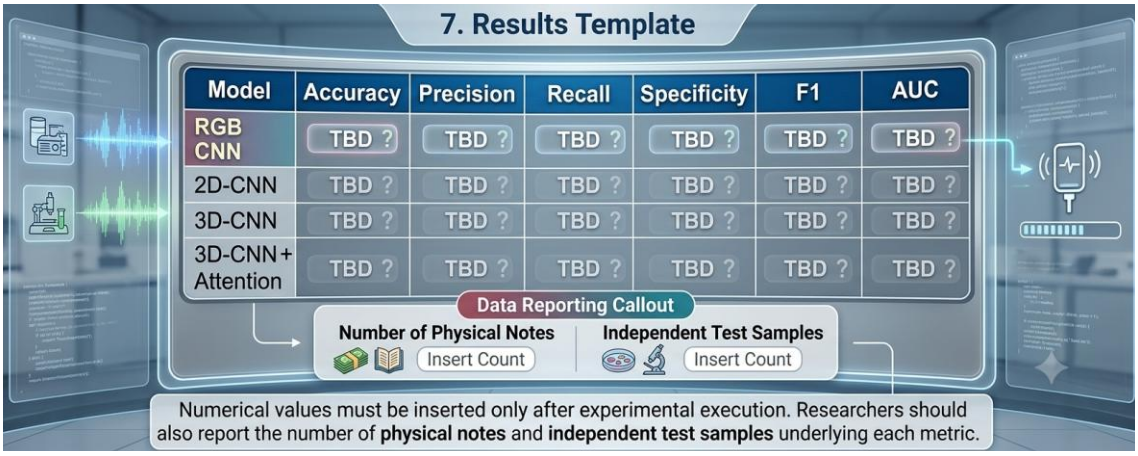
IX. Baseline ModelsZ



X. Evaluation Metrics

The primary authentication metrics are accuracy, precision, recall, specificity, F1-score, ROC-AUC, false-positive rate, and false-negative rate. Because counterfeit detection is security-sensitive, recall and false-negative rate should receive particular attention. Confidence intervals or repeated-run statistics should be reported where the dataset permits.

XI. Results Orientation



XII. Robustness and Error Analysis

Performance should be stratified by denomination, orientation, illumination, and physical condition. False-positive cases should be inspected to determine whether the model is reacting to genuine variation. False-negative cases should be inspected with spectral curves and band images to identify which counterfeit characteristics are difficult to detect.

XIII. Discussion

The principal advantage of the proposed HSI approach is the ability to learn information beyond visible color and texture. However, the additional spectral dimension increases acquisition cost, storage requirements, and computational complexity. Band selection and spectral attention are therefore not merely optimization steps; they are important components of a practical system. Cross-device validation is also important because models can unintentionally learn sensor-specific characteristics.

XIV. Limitations

- Performance depends on the quality and diversity of the collected HSI dataset.
- A model trained on one sensor may not transfer directly to another sensor.
- Counterfeit specimens may not represent all real-world counterfeit mechanisms.
- Controlled laboratory illumination may differ from field conditions.
- Final real-time performance depends on the selected hardware and implementation.

XV. Ethical and Legal Considerations

Counterfeit specimens must be acquired, stored, transported, and handled only in accordance with applicable law and institutional authorization. Publication should avoid operational details that could facilitate reproduction or circumvention of currency security features. The proposed system is intended for authentication and research, not for reproducing currency.

XVI. Conclusion & Future Scope

This paper proposes a spectral-spatial HSI framework for counterfeit currency detection based on preprocessing, informative-band selection, 3D convolution, and spectral attention. The methodology provides a rigorous foundation for evaluating whether hyperspectral information improves authentication robustness compared with RGB and 2D-HSI baselines. The companion paper extends the framework with transformer fusion, denomination classification, explainability, and edge-oriented real-time optimization.

References

[1]. Y. Chen, N. M. Nasrabadi, and T. D. Tran, "Hyperspectral image classification using deep belief networks," IEEE Transactions on Geoscience and Remote Sensing, 2014.
[2]. A.Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," NeurIPS, 2012.
[3]. K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," CVPR, 2016.
[4]. J. Hu, L. Shen, and G. Sun, "Squeeze-and-Excitation Networks," CVPR, 2018.
[5]. R. R. Selvaraju et al., "Grad-CAM: Visual explanations from deep networks via gradient-based localization," ICCV, 2017.
[6]. F. A. Kruse et al., "The spectral image processing system (SIPS)—interactive visualization and analysis of imaging spectrometer data," Remote Sensing of Environment, 1993.

[7]. S. Baek, E. Choi, Y. Baek, and C. Lee, "Detection of counterfeit banknotes using multispectral images," Digital Signal Processing, vol. 78, pp. 294–304, 2018. DOI: 10.1016/j.dsp.2018.03.015.

[8]. H.-T. Lim and V. M. Murukeshan, "Hyperspectral imaging of polymer banknotes for building and analysis of spectral library," Optics and Lasers in Engineering, 2017. DOI: 10.1016/j.optlaseng.2017.06.022.

[9]. K. Kang and C. Lee, "Fake banknote detection using multispectral images," 2016 7th International Conference on Information, Intelligence, Systems and Applications (IISA), 2016.

[10]. Chia-Yu Chen et al., "Automatic counterfeit currency detection using a novel snapshot hyperspectral imaging algorithm," Sensors, vol. 23, no. 4, p. 2026, 2023. DOI: 10.3390/s23042026.

[11]. M. H. P. Correia et al., "Development of a portable near-infrared spectroscopy device for the discrimination of authentic and counterfeit Brazilian real banknotes," [Paper details to be verified before citation].

[12]. C. Yeh et al., "Employing multiple-kernel support vector machines for counterfeit banknote recognition," Applied Soft Computing, 2011.

[13]. C. He et al., "Employing optimized combinations of one-class classifiers for automated currency validation," Pattern Recognition, 2004.

[14]. F. Takeda et al., "Banknote recognition by means of optimized masks, neural networks and genetic algorithms," Engineering Applications of Artificial Intelligence, 1999.

[15]. T. Chia et al., "Detection of counterfeit U.S. paper money using intrinsic fluorescence lifetime," Optics Express, 2009.

[16]. M. Han and J. Kim, "Joint banknote recognition and counterfeit detection using explainable artificial intelligence," Sensors, vol. 19, no. 16, p. 3607, 2019. DOI: 10.3390/s19163607.

[17]. "Fake banknote recognition using deep learning," Applied Sciences, vol. 11, no. 3, p. 1281, 2021.

[18]. "Jordanian banknote data recognition: A CNN-based approach with attention mechanism," Journal of King Saud University—Computer and Information Sciences, vol. 36, no. 4, p. 102038, 2024.

[19]. S. Li, W. Song, L. Fang, Y. Chen, P. Ghamisi, and J. A. Benediktsson, "Deep learning for hyperspectral image classification: An overview," IEEE Transactions on Geoscience and Remote Sensing, 2019.

[20]. M. Yaseen, R. A. Ahmed, and R. Mahrukh, "Forgery detection in a questioned hyperspectral document image using K-means clustering," arXiv:2006.16057, 2020.

[21]. Vila et al., "Development of a fast and non-destructive procedure for characterizing and distinguishing original and fake euro notes," Analytica Chimica Acta, 2006