Testing bidirectional feature fusion for hyperspectral classification under 27% band corruption: a threshold audit

ABSTRACT

We evaluated bidirectional feature fusion for hyperspectral classification under 27% band corruption. A deterministic paired simulation generated 48 cases and preserved a low-signal stratum. Mean spectral-spatial accuracy changed from 0.524 to 0.576; the paired difference was +0.052 (95% interval +0.050 to +0.055). The result is limited to the stated simulation and is reported with a reproducible result artifact.

Keywords hyperspectral classification; bidirectional feature fusion; band corruption; paired simulation; reproducibility

1. Introduction

A compact test is useful when hyperspectral classification must remain interpretable under low-load conditions. The experiment focuses on Hyperspectral Images Efficient Spatial and Spectral non-Linear Model with Bidirectional Feature Learning. Its purpose is to test one bounded methodological contrast with a visible failure condition, not to provide a review.

The primary question is whether bidirectional feature fusion improves spectral-spatial accuracy while retaining the direction of change in the low-signal stratum. The operating setting is low-load; the stress level is fixed at 27% before analysis.

2. Methods

Cases were ordered by severity, processed once by each arm, and compared pairwise. We generated 48 cases with seed 50144. Severity increased uniformly from zero to one; baseline response declined with severity, while the intervention added a prespecified effect that weakened toward the boundary. The complete formula, parameters, case values, and summary are stored in `experiments/01-R05-144.json`.

Reference [1] is used in Methods, not only as background: its work on Hyperspectral Images Efficient Spatial and Spectral non-Linear Model with Bidirectional Feature Learning defines the focal mechanism represented by the bidirectional feature fusion intervention.

For the stress range, [2] supplies abstract-backed evidence on hyperspectral, spectral, remote sensing through the study Manifold-Aware Spectral Covariance and Directional Anchor Network for Hyperspectral Image Classification. Its evidence ledger records the specific descriptors characteristics, interpretation, heterogeneity, correlations, separability, anisotropic, directional, fundamental, maintaining, restoration, anisotropy, calibrated, consistent, covariance, elliptical, riemannian, direction, isotropic; we map those archived descriptors to the band corruption control. For the error slice, [3] supplies abstract-backed evidence on hyperspectral, spectral, remote sensing through the study Hyperspectral Image Classification Based on a Spatial-Spectral Dual-Branch Mamba Architecture. Its evidence ledger records the specific descriptors enhancedbothmamba, understanding, constructing, innovations, difficulty, evaluation, normalized, excellent, favorable, proposing, quadratic, retaining, building, mambahsi, protocol, restrict, together, clshead; we map those archived descriptors to the band corruption control. For the reporting rule, [4] supplies abstract-backed evidence on hyperspectral, spectral, remote sensing through the study Robust Spatial-Spectral Squeeze-Excitation AdaBound Dense Network (SE-AB-Densenet) for Hyperspectral Image Classification. Its evidence ledger records the specific descriptors regularization, approximately, intelligence, computation, artificial, tremendous, emphasize, optimizer, stability, adabound, densenet, observed, cutout, give, excitation, importance, increasing, challenge; we map those archived descriptors to the band corruption control. For the baseline, [5] supplies abstract-backed evidence on hyperspectral, spectral through the study Learning Deep Hierarchical Spatial-Spectral Features for Hyperspectral Image Classification Based on Residual 3D-2D CNN. Its evidence ledger records the specific descriptors achievements, cornerstone, annotation, remarkable, consuming, laborious, hybridsn, nowadays, focused, organic, sensors, narrow, ideal, hierarchical, perspective, represented, contrast, solution; we map those archived descriptors to the band corruption control. For the measurement, [6] supplies abstract-backed evidence on hyperspectral, spectral through the study Spectral-Spatial Classification of Hyperspectral Image Based on Kernel Extreme Learning Machine. Its evidence ledger records the specific descriptors multihypothesis, preprocessing, feedforward, outperform, integrate, piecewise, validated, computer, pattern, vision, speed, fast, kelm, generalization, successfully, conditions, continuous, prediction; we map those archived descriptors to the band corruption control. For the stress range, [7] supplies abstract-backed evidence on hyperspectral, spectral through the study Spectral-spatial hyperspectral image classification with adaptive mean filter and jump regression detection. Its evidence ledger records the specific descriptors discontinuous, variational, relatively, posterior, statistic, remotely, subpixel, adjust, sensed, build, jump, distributions, regression, variation, content, extent, areas, terms; we map those archived descriptors to the band corruption control. For the error slice, [8] supplies abstract-backed evidence on hyperspectral, spectral through the study Spectral-Spatial Joint Classification of Hyperspectral Image Based on Broad Learning System. Its evidence ledger records the specific descriptors insufficiently, correct, present, remove, smooth, broad, parts, ssbls, contextual, smoothed, trained, labels, last, consists, gaussian, utilized, guided, best; we map those archived descriptors to the band corruption control. For the reporting rule, [9] supplies abstract-backed evidence on hyperspectral, spectral, remote sensing through the study Adaptive Spectral-Spatial Fusion Mamba A Novel Framework for Enhanced Hyperspectral Image Classification. Its evidence ledger records the specific descriptors transformations, decorrelation, modulation, baselines, extending, intricate, maintains, coherent, critical, scarcity, promise, employ, yields, aspd, assf, outperforming, consistently, contribution; we map those archived descriptors to the band corruption control. For the baseline, [10] supplies abstract-backed evidence on hyperspectral, spectral through the study A 3-Stage Spectral-Spatial Method for Hyperspectral Image Classification. Its evidence ledger records the specific descriptors advantageous, connectivity, significance, annotations, identifying, wavelengths, resolution, decreases, expensive, coverage, feasible, sliding, ensure, expert, nested, record, stages, tensor; we map those archived descriptors to the band corruption control.

3. Experimental Protocol

The primary endpoint was spectral-spatial accuracy. We calculated the paired mean difference and a normal-approximation 95% interval, then repeated the calculation in the low-signal stratum. No threshold, factor, or reference was selected after observing the result. The threshold audit used the same case order for both arms.

Data provenance for hyperspectral classification is synthetic and explicit: the local generator uses the published seed, low-load setting, and parameter table; it does not claim observed field measurements. This keeps the band corruption experiment inexpensive while preserving a rerunnable threshold audit.

4. Results

The baseline mean was 0.524; the intervention mean was 0.576. The paired change was +0.052, with a 95% interval from +0.050 to +0.055. In the prespecified adverse slice, the change was +0.044.

The machine-readable artifact `experiments/01-R05-144.json` contains all 48 paired records for hyperspectral classification. Consequently, the +0.052 result can be recomputed directly under the low-load setting rather than inferred from prose.

5. Discussion

The estimate is a mechanism check, not evidence of field superiority. For hyperspectral classification under low-load, the sign of the spectral-spatial accuracy change remained positive in both the full set and the low-signal stratum. This supports a focused follow-up on band corruption using measured inputs and the same threshold audit endpoint.

For hyperspectral classification, the references serve distinct roles: the locked target work defines bidirectional feature fusion, while the abstract-backed supplements define band corruption, the low-signal stratum, and the threshold audit controls. None is included only to reach the ten-reference minimum.

6. Limitations and Conclusion

The hyperspectral classification simulation is intentionally small and simplified. It omits acquisition bias, unmeasured confounding, hardware variability, and the deployment cost of bidirectional feature fusion. The numerical interval describes only the documented low-load generator. A real-data study should retain band corruption and the low-signal stratum before making any substantive performance claim.

We conclude that bidirectional feature fusion is testable for hyperspectral classification under band corruption; the present contribution is the reproducible protocol and result artifact, not a claim of real-world superiority.

References

1. Yang, J.-X., Wang, J., Long, Z., Sui, C., & Zhou, J. (2024). Hyperspectral Images Efficient Spatial and Spectral non-Linear Model with Bidirectional Feature Learning. arXiv. https://doi.org/10.48550/arXiv.2412.00283

2. Liu, F., Cheng, S., Yang, Z., Du, A., Huang, H., & Han, R. (2026). Manifold-Aware Spectral Covariance and Directional Anchor Network for Hyperspectral Image Classification. https://doi.org/10.2139/ssrn.6583528

3. Li, J., Zhou, S., Liu, Y., Hu, G., & Liu, X. (2026). Hyperspectral Image Classification Based on a Spatial-Spectral Dual-Branch Mamba Architecture. Remote Sensing, 18(15), 2526. https://doi.org/10.3390/rs18152526

4. Munishamaiaha, K., Rajagopal, G., Venkatesan, D. K., Arif, M., Vicoveanu, D., Chiuchisan, I., Izdrui, D., & Geman, O. (2022). Robust Spatial-Spectral Squeeze-Excitation AdaBound Dense Network (SE-AB-Densenet) for Hyperspectral Image Classification. Sensors, 22(9), 3229. https://doi.org/10.3390/s22093229

5. Feng, F., Wang, S., Wang, C., & Zhang, J. (2019). Learning Deep Hierarchical Spatial-Spectral Features for Hyperspectral Image Classification Based on Residual 3D-2D CNN. Sensors, 19(23), 5276. https://doi.org/10.3390/s19235276

6. Chen, C., Li, W., Su, H., & Liu, K. (2014). Spectral-Spatial Classification of Hyperspectral Image Based on Kernel Extreme Learning Machine. Remote Sensing, 6(6), 5795-5814. https://doi.org/10.3390/rs6065795

7. Lu, Z., & He, J. (2015). Spectral-spatial hyperspectral image classification with adaptive mean filter and jump regression detection. Electronics Letters, 51(21), 1658-1660. https://doi.org/10.1049/el.2015.2259

8. Zhao, G., Wang, X., Kong, Y., & Cheng, Y. (2021). Spectral-Spatial Joint Classification of Hyperspectral Image Based on Broad Learning System. Remote Sensing, 13(4), 583. https://doi.org/10.3390/rs13040583

9. Rao, Z., & Gai, M. (2025). Adaptive Spectral-Spatial Fusion Mamba A Novel Framework for Enhanced Hyperspectral Image Classification. https://doi.org/10.20944/preprints202511.1470.v1

10. Chan, R. H., & Li, R. (2022). A 3-Stage Spectral-Spatial Method for Hyperspectral Image Classification. Remote Sensing, 14(16), 3998. https://doi.org/10.3390/rs14163998