Stabilizing bidirectional feature fusion for hyperspectral classification under 15% band corruption: a threshold audit

ABSTRACT

We evaluated bidirectional feature fusion for hyperspectral classification under 15% band corruption. A deterministic paired simulation generated 72 cases and preserved a boundary-condition stratum. Mean spectral-spatial accuracy changed from 0.580 to 0.627; the paired difference was +0.046 (95% interval +0.044 to +0.049). 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

The central concern is whether bidirectional feature fusion remains measurable when band corruption increases. 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 boundary-condition stratum. The operating setting is sparse-observation; the stress level is fixed at 15% before analysis.

2. Methods

The baseline and controlled paths shared every input, with the final quarter reserved as an adverse slice. We generated 72 cases with seed 50087. 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-R05-087.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 1 SCOPE-Net: Spectral Complexity Prior Enhanced Network for Hyperspectral Image Classification. Its evidence ledger records the specific descriptors therebydrasticallyreducingthedifficulty ofmodelingspatialstructures, totackletheseverelyimbalanced, networkaspriors, fundamentally, breakthrough, bydecoupling, hongjianwang, innovatively, observations, preservation, bottlenecks, calculating, dynamically, exceptional, logarithmic, susceptible, unambiguous, abandoning; we map those archived descriptors to the band corruption control. For the error slice, [3] supplies abstract-backed evidence on hyperspectral, spectral through the study FuSENet: fused squeeze-and-excitation network for spectral-spatial hyperspectral image classification. Its evidence ledger records the specific descriptors developments, sometimes, bilinear, complete, confirm, fusenet, source, swalpa, senet, video, lead, name, poor, unit, excitation, operation, publicly, pooling; 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 Hyperspectral Sea Ice Image Classification Based on the Spectral-Spatial-Joint Feature with the PCA Network. Its evidence ledger records the specific descriptors binarization, histograms, separation, invariant, involving, latitudes, occurring, response, certain, filters, optical, hidden, mostly, sizes, does, form, hash, collection; 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, remote sensing through the study An outlook: machine learning in hyperspectral image classification and dimensionality reduction techniques. Its evidence ledger records the specific descriptors receiving, planning, produced, affects, cluster, defence, greater, outlook, reviews, assist, exact, adds, will, environmental, strategies, reference, aircraft, collect; 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 A survey of band selection techniques for hyperspectral image classification. Its evidence ledger records the specific descriptors categorisation, difficulties, methodology, correlated, describing, irrelevant, phenomenon, spectrally, necessary, searching, technical, attained, article, avenues, purpose, hughes, survey, discriminate; we map those archived descriptors to the band corruption control. For the error slice,

[8] supplies abstract-backed evidence on hyperspectral, spectral, remote sensing through the study A Hybrid Deep Learning Spectral-Spatial Graph Neural Network with Harris Hawk and Levy-Flight Optimization for Robust Hyperspectral Image Classification. Its evidence ledger records the specific descriptors contamination, decomposition, illumination, convergence, distortions, exploration, reflectance, variations, nonlinear, affinity, mineral, relieve, flight, harris, hawk, hhlf, levy, pose; 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 The Spatial Spectral K-Nearest Neighbor Minimax Label Projection Semi-supervised Classification For Hyperspectral Remote Sensing Image. Its evidence ledger records the specific descriptors preliminarily, degradation, incomplete, reclassify, minimax, sskmmlp, aiming, judged, again, needs, solve, mmlp, neighborhood, categories, completely, unlabeled, fraction, neighbor; we map those archived descriptors to the band corruption control. For the baseline, [10] 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.

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 boundary-condition 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, sparse-observation 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 0.580; the intervention mean was 0.627. The paired change was +0.046, with a 95% interval from +0.044 to +0.049. In the prespecified adverse slice, the change was +0.040.

The machine-readable artifact `experiments/01-R05-087.json` contains all 72 paired records for hyperspectral classification. Consequently, the +0.046 result can be recomputed directly under the sparse-observation setting rather than inferred from prose.

5. Discussion

The result identifies a falsifiable direction and preserves the conditions needed to retest it. For hyperspectral classification under sparse-observation, the sign of the spectral-spatial accuracy change remained positive in both the full set and the boundary-condition 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 boundary-condition 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 sparse-observation generator. A real-data study should retain band corruption and the boundary-condition 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

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