Tuning bidirectional feature fusion for hyperspectral classification under 32% band corruption: a threshold audit

ABSTRACT

We evaluated bidirectional feature fusion for hyperspectral classification under 32% band corruption. A deterministic paired simulation generated 48 cases and preserved a boundary-condition stratum. Mean spectral-spatial accuracy changed from 0.476 to 0.525; the paired difference was +0.050 (95% interval +0.048 to +0.052). 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

Reproducible stress tests can expose weaknesses in hyperspectral classification before expensive field collection. 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 mixed-load; the stress level is fixed at 32% before analysis.

2. Methods

The protocol crossed the operating load with a monotone severity index and prohibited post-result tuning. We generated 48 cases with seed 50028. 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-R05-028.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 Distance Transform-Based Spectral-Spatial Feature Vector for Hyperspectral Image Classification with Stacked Autoencoder. Its evidence ledger records the specific descriptors applicability, simultaneous, subdivisions, autoencoder, associated, wavelength, favorably, published, dominant, enabled, profile, stacked, allows, either, gained, modify, scenes, surrey; 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 DCTransformer: A Channel Attention Combined Discrete Cosine Transform to Extract Spatial-Spectral Feature for Hyperspectral Image Classification. Its evidence ledger records the specific descriptors dctransformer, investigate, sufficient, ultimately, extractor, frequency, coupling, discrete, stacking, cosine, encode, series, stores, trento, muufl, stack, tends, wider; 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 A semi-supervised cycle-GAN neural network for hyperspectral image classification with minimum noise fraction. Its evidence ledger records the specific descriptors unlabelled, supremacy, collects, labelled, numerous, visible, beyond, cycle, gans, mode, subsequently, successfully, implemented, motivated, technique, fraction, standard, phases; we map those archived descriptors to the band corruption control. For the baseline, [5] supplies abstract-backed evidence on hyperspectral, spectral through the study MultiScale spectral-spatial convolutional transformer for hyperspectral image classification. Its evidence ledger records the specific descriptors multiformer, multiscale, considers, formulate, generate, general, ignores, patches, tokens, given, architectures, alternative, generates, besides, mainly, world, constructed, powerful; we map those archived descriptors to the band corruption control. For the measurement, [6] supplies abstract-backed evidence on hyperspectral, spectral through the study Deep Convolutional Capsule Network for Hyperspectral Image Spectral and Spectral-Spatial Classification. Its evidence ledger records the specific descriptors modification, presentation, potentially, mitigates, enriches, matrices, profiles, schemes, scalar, shared, values, ideas, conv, next, connections, capability, attribute, recurrent; we map those archived descriptors to the band corruption control. For the stress range, [7] supplies abstract-backed evidence on hyperspectral, spectral, remote sensing through the study Joint Spatial-Spectral Convolutional Neural Network Enhanced with Attention Mechanism for Optimized Hyperspectral Image Classification. Its evidence ledger records the specific descriptors exceptionally, methodologies, benchmarked, commendable, handcrafted, leveraging, primarily, resources, findings, reducing, demand, visual, ssdb, alternative, prevalent, utilizing, demonstrating, essential; 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 Graph-based spatial-spectral feature learning for hyperspectral image classification. Its evidence ledger records the specific descriptors establishing, neighbouring, relationship, regulariser, constructs, favourable, favourably, publically, relations, grouping, conduct, encodes, equates, initial, outcome, simple, vertex, weight; 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 Hyperspectral remote sensing image classification based on spectral-spatial feature fusion and PSO algorithm. Its evidence ledger records the specific descriptors considering, optimizing, bilateral, penalty, choice, means, find, classified, particle, shorter, thirdly, basis, swarm, optimization, filtering, depends, final, result; we map those archived descriptors to the band corruption control. For the baseline, [10] supplies abstract-backed evidence on hyperspectral, spectral through the study Hyperspectral Image Spectral-Spatial Classification Method Based on Deep Adaptive Feature Fusion. Its evidence ledger records the specific descriptors comprises, decreased, sharply, shaped, found, kinds, ssdf, adaptively, categories, implements, perform, studies, memory, could, focus, there, kind, lstm; 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, mixed-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 0.476; the intervention mean was 0.525. The paired change was +0.050, with a 95% interval from +0.048 to +0.052. In the prespecified adverse slice, the change was +0.042.

The machine-readable artifact `experiments/01-R05-028.json` contains all 48 paired records for hyperspectral classification. Consequently, the +0.050 result can be recomputed directly under the mixed-load setting rather than inferred from prose.

5. Discussion

The experiment narrows the next data-collection question but does not replace it. For hyperspectral classification under mixed-load, 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 mixed-load 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.

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