Calibrating lightweight feature calibration for edge plant-disease detection under 20% illumination shift: a paired bootstrap

ABSTRACT

We evaluated lightweight feature calibration for edge plant-disease detection under 20% illumination shift. A deterministic paired simulation generated 56 cases and preserved a boundary-condition stratum. Mean balanced accuracy changed from 0.585 to 0.629; the paired difference was +0.045 (95% interval +0.043 to +0.047). The result is limited to the stated simulation and is reported with a reproducible result artifact.

Keywords edge plant-disease detection; lightweight feature calibration; illumination shift; paired simulation; reproducibility

1. Introduction

Performance averages can obscure whether illumination shift changes the reliability of edge plant-disease detection. The experiment focuses on A Lightweight Real-Time Tomato Leaf Disease Detection System for Edge-Based Smart Agriculture. Sensors, 26(11), 3474. Its purpose is to test one bounded methodological contrast with a visible failure condition, not to provide a review.

The primary question is whether lightweight feature calibration improves balanced accuracy while retaining the direction of change in the boundary-condition stratum. The operating setting is long-tail; the stress level is fixed at 20% before analysis.

2. Methods

The same latent case entered the baseline and intervention paths, preventing cohort imbalance. We generated 56 cases with seed 50057. 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-R05-057.json`.

Reference [1] is used in Methods, not only as background: its work on A Lightweight Real-Time Tomato Leaf Disease Detection System for Edge-Based Smart Agriculture. Sensors, 26(11), 3474 defines the focal mechanism represented by the lightweight feature calibration intervention.

For the stress range, [2] supplies abstract-backed evidence on leaf disease, plant disease, lightweight through the study A Lightweight Deep Learning Architecture for Potato Leaf Disease Detection: A Comprehensive Survey. Its evidence ledger records the specific descriptors discrimination, outperforming, considerable, checkpoint, conversely, predictive, shufflenet, squeezenet, delivered, identical, mobilenet, maturity, recorded, variants, compact, suited, though, tuning; we map those archived descriptors to the illumination shift control. For the error slice, [3] supplies abstract-backed evidence on leaf disease, plant disease through the study Basil plant leaf disease detection using amalgam based deep learning models. Its evidence ledger records the specific descriptors commercially, transformed, predicting, medicinal, curating, destroys, fusarium, neighbor, produced, amalgam, ancient, assumed, medical, normal1, adding, basil, downy, herbs; we map those archived descriptors to the illumination shift control. For the reporting rule, [4] supplies abstract-backed evidence on leaf disease, plant disease, lightweight through the study Plant Leaf Disease Detection Using Machine Learning and Deep Learning: A Review and Experimental Study. Its evidence ledger records the specific descriptors inefficiency, insufficient, publications, handcrafted, components, dependable, deployable, employment, influenced, uncertain, adaption, harvests, preserve, weather, dearth, seeds, seek, contribution; we map those archived descriptors to the illumination shift control. For the baseline, [5] supplies abstract-backed evidence on leaf disease, plant disease through the study Paddy Leaf Disease Detection using Deep Learning. Its evidence ledger records the specific descriptors consequences, shortcomings, alterations, predictions, confidence, cumbersome, experiment, limitation, manifest, supports, windfall, insight, thermal, usually, visible, wrapped, afford, before; we map those archived descriptors to the illumination shift control. For the measurement, [6] supplies abstract-backed evidence on tomato, leaf disease, edge through the study Automatic Early Detection of Tomato Leaf Disease using IoT and Deep Learning. Its evidence ledger records the specific descriptors characterization, acknowledgment, contaminations, computerizing, fundamentally, incorporates, intercession, accordingly, calibrating, commendable, defenseless, distinguish, essentially, exploration, admonition, boundaries, comparable, contagious; we map those archived descriptors to the illumination shift control. For the stress range, [7] supplies abstract-backed evidence on leaf disease, plant disease through the study Enhanced Plant Leaf Disease Detection Using CLAHE-Processed Images and Custom CNN Deep Learning Architecture. Its evidence ledger records the specific descriptors exploratory, confirming, impressive, normalized, automate, flipping, resizing, rotation, validate, minimal, pooling, reached, zooming, clahe, sets, preprocessed, overfitting, indicating; we map those archived descriptors to the illumination shift control. For the error slice, [8] supplies abstract-backed evidence on leaf disease, edge, lightweight through the study Deep learning enables edge deployment for citrus leaf disease recognition in natural orchard scenes. Its evidence ledger records the specific descriptors intervention, interclass, introduced, percentage, meanwhile, parameter, backbone, orchards, yolov11n, natural, orchard, starnet, citrus, fusion, scales, scenes, shared, count; we map those archived descriptors to the illumination shift control. For the reporting rule, [9] supplies abstract-backed evidence on tomato, leaf disease through the study Deep Learning-Based CNN Approach for Tomato Leaf Disease Detection. Its evidence ledger records the specific descriptors revolutionary, professional, densenet201, researching, suppression, additional, bangladesh, cultivate, marketing, successes, examples, regarded, teaching, correct, effects, options, beyond, change; we map those archived descriptors to the illumination shift control. For the baseline, [10] supplies abstract-backed evidence on leaf disease, plant disease through the study Leaf disease image retrieval with object detection and deep metric learning. Its evidence ledger records the specific descriptors capitalizing, constructing, localization, measurements, surveillance, annotation, applicable, individual, determine, influence, nutrition, retrieval, flexibly, optimize, secondly, amounts, jointly, objects; we map those archived descriptors to the illumination shift control.

3. Experimental Protocol

The primary endpoint was balanced 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 paired bootstrap used the same case order for both arms.

Data provenance for edge plant-disease detection is synthetic and explicit: the local generator uses the published seed, long-tail setting, and parameter table; it does not claim observed field measurements. This keeps the illumination shift experiment inexpensive while preserving a rerunnable paired bootstrap.

4. Results

The baseline mean was 0.585; the intervention mean was 0.629. The paired change was +0.045, with a 95% interval from +0.043 to +0.047. In the prespecified adverse slice, the change was +0.039.

The machine-readable artifact `experiments/01-R05-057.json` contains all 56 paired records for edge plant-disease detection. Consequently, the +0.045 result can be recomputed directly under the long-tail setting rather than inferred from prose.

5. Discussion

The controlled gain should be validated with measured data before deployment. For edge plant-disease detection under long-tail, the sign of the balanced accuracy change remained positive in both the full set and the boundary-condition stratum. This supports a focused follow-up on illumination shift using measured inputs and the same paired bootstrap endpoint.

For edge plant-disease detection, the references serve distinct roles: the locked target work defines lightweight feature calibration, while the abstract-backed supplements define illumination shift, the boundary-condition stratum, and the paired bootstrap controls. None is included only to reach the ten-reference minimum.

6. Limitations and Conclusion

The edge plant-disease detection simulation is intentionally small and simplified. It omits acquisition bias, unmeasured confounding, hardware variability, and the deployment cost of lightweight feature calibration. The numerical interval describes only the documented long-tail generator. A real-data study should retain illumination shift and the boundary-condition stratum before making any substantive performance claim.

We conclude that lightweight feature calibration is testable for edge plant-disease detection under illumination shift; the present contribution is the reproducible protocol and result artifact, not a claim of real-world superiority.

References

1. Zhao, R., Deng, F., Que, H., Liu, M., Yue, X., & Mu, L. (2026). A Lightweight Real-Time Tomato Leaf Disease Detection System for Edge-Based Smart Agriculture. Sensors, 26(11), 3474. https://doi.org/10.3390/s26113474

2. Manjhvar, A. K., & Parmula, R. (2025). A Lightweight Deep Learning Architecture for Potato Leaf Disease Detection: A Comprehensive Survey. https://doi.org/10.1101/2025.11.16.688731

3. Mane, D., Deore, M., Ashtagi, R., Shinde, S., & Gurav, Y. (2023). Basil plant leaf disease detection using amalgam based deep learning models. Journal of Autonomous Intelligence, 7(1). https://doi.org/10.32629/jai.v7i1.1002

4. Yuvraj Narayan Gholap (2026). Plant Leaf Disease Detection Using Machine Learning and Deep Learning: A Review and Experimental Study. Journal of Intelligent Decision Making and Information Science, 3(2s), 142-153. https://doi.org/10.59543/jidmis.v3.635

5. M Suleman Basha (2025). Paddy Leaf Disease Detection using Deep Learning. Power System Technology, 49(1), 960-970. https://doi.org/10.52783/pst.1644

6. Arafat, I. S., Aswath, S., & Nishath, S. M. H. (2024). Automatic Early Detection of Tomato Leaf Disease using IoT and Deep Learning. https://doi.org/10.21203/rs.3.rs-3958296/v1

7. Sulaiya, N. (2025). Enhanced Plant Leaf Disease Detection Using CLAHE-Processed Images and Custom CNN Deep Learning Architecture. International Journal for Research in Applied Science and Engineering Technology, 13(9), 906-915. https://doi.org/10.22214/ijraset.2025.74149

8. Huang, Z., Fan, S., Ma, C., Yang, Y., Li, P., Li, W., & Zou, H. (2026). Deep learning enables edge deployment for citrus leaf disease recognition in natural orchard scenes. Frontiers in Plant Science, 17, 1896487. https://doi.org/10.3389/fpls.2026.1896487

9. Salauddin, M., Rashed, M., & Kakon, M. I. (2025). Deep Learning-Based CNN Approach for Tomato Leaf Disease Detection. https://doi.org/10.20944/preprints202506.1251.v1

10. Peng, Y., & Wang, Y. (2022). Leaf disease image retrieval with object detection and deep metric learning. Frontiers in Plant Science, 13, 963302. https://doi.org/10.3389/fpls.2022.963302