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MANGOSENSE: AN IOT-ENABLED ELECTRONIC NOSE AND TEMPORAL CONVOLUTIONAL NETWORK FOR MULTI-VARIETY MANGO RIPENESS CLASSIFICATION

Asep Denih*, Siska Andriani, M Caesar Arifan Pradana
Department of Computer Science, Faculty of Mathematics and Natural Sciences, Universitas Pakuan, Bogor, Indonesia
* Corresponding author: asep.denih@unpak.ac.id

ABSTRACT

Accurate mango-ripeness assessment is important for postharvest handling, yet visual and tactile inspection is subjective and difficult to standardize across cultivars. This paper presents MangoSense, a laboratory prototype integrating a ten-channel GeNose-19 metal-oxide-semiconductor sensor array, a Temporal Convolutional Network (TCN), ESP32-based chamber control, MQTT communication, and a Django monitoring dashboard. Arumanis, Budiraja, and Indramayu mangoes were measured at unripe, half-ripe, and ripe stages using 27 primary files and 27 training-only synthetic files. File-level partitioning was completed before sliding-window extraction to reduce data leakage. Internal evaluation produced 98.1% accuracy, 98.13% macro F1-score, and 0.981 macro AUC, compared with 87.5% accuracy for an RBF-SVM baseline. The connected layer recorded 287 ms mean latency, 99.2% successful transmission, and 1.4 s web response. The results support temporal gas-sensor analysis for connected, non-destructive mango screening, although the small physical sample set and controlled conditions limit generalization.

KEYWORD

Electronic nose; mango ripeness; temporal convolutional network; metal-oxide-semiconductor sensor; Internet of Things; non-destructive assessment.

INTRODUCTION

Mango (Mangifera indica L.) is a climacteric fruit whose respiration, ethylene production, and volatile profile change rapidly during ripening (Pathak, 2024). Commercial grading commonly relies on peel appearance, firmness, and human perception of aroma. These indicators are useful but operator-dependent, cultivar-sensitive, and difficult to connect to continuous monitoring. Electronic noses offer a non-destructive alternative by combining cross-sensitive gas sensors with pattern-recognition models. Recent studies have demonstrated artificial olfactory sensing for fruit-ripeness assessment (Zhao et al., 2024), mango classification using conventional machine learning (Worasawate et al., 2022), and broader applications of electronic noses in food-quality evaluation (Vanaraj et al., 2025).

Gas-sensor responses are dynamic: adsorption, reaction, and recovery produce transient trajectories that may be partly lost when classification depends only on summary statistics. TCNs use causal, dilated convolutions and residual connections to capture temporal dependencies efficiently; multi-scale TCNs have also shown promise for gas classification (Ma et al., 2024). MangoSense addresses the practical gap between sensing, temporal modelling, controlled chamber operation, and remote monitoring. Its contributions are a standardized acquisition protocol for three Indonesian mango varieties, cultivar-specific TCN models, file-level data separation, and end-to-end integration of ESP32 control, MQTT telemetry, automated CSV processing, inference, and web visualization.

MATERIAL AND METHODOLOGY

Each fruit sample was placed in an approximately 3 L sealed acrylic chamber connected to a ten-channel GeNose-19 MOS sensor array, as shown in Figure 1. An ESP32, DHT22, pumps, relays, and a local LCD controlled the measurement cycle. Each acquisition comprised 60 s flushing, 120s sensing, and 60s purging. Channels S1-S10 were sampled at 1 Hz at approximately 28°C and 60-70% relative humidity. The dataset contained Arumanis, Budiraja, and Indramayu mangoes at unripe, half-ripe, and ripe stages: 27 primary files (three per variety-stage combination) and 27 statistically generated synthetic files.

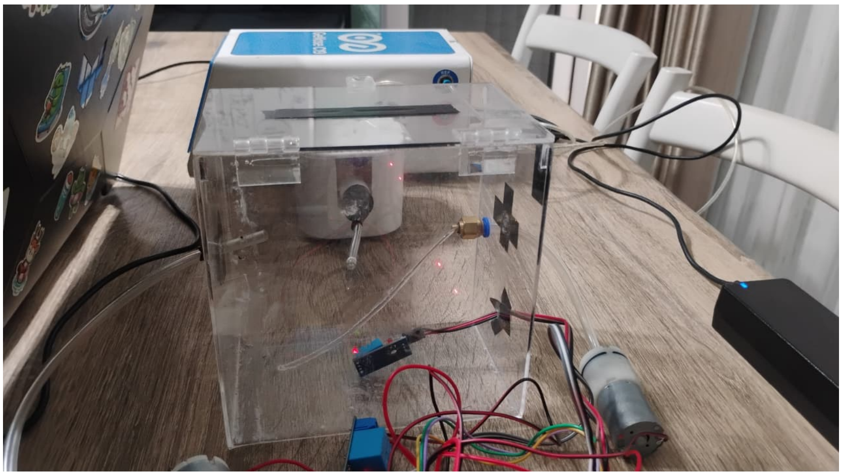

Figure 1: MangoSense laboratory chamber and electronic-nose hardware.

For each channel, the relative resistance change was calculated against the flushing baseline and normalized to the range [0,1]. Each 120 s sensing sequence was divided into 30-step windows with a stride of 5, producing 19 windows per file. Primary files were assigned at file level to training, validation, and testing before window extraction. Synthetic files and Gaussian-noise augmentation (standard deviation 0.015) were restricted to training; validation and testing used primary files only. This design reduces leakage between overlapping windows, although augmentation cannot replace independent biological samples (Iglesias et al., 2023).

The classifier used five residual temporal blocks with dilation rates 1, 2, 4, 8, and 16; kernel size 3; and 64 filters per block. Global-average pooling was followed by dense layers of 64 and 32 units and a three-class Softmax output. Three models were trained independently, one per mango variety, using Adam (learning rate 0.001), batch size 32, and early stopping with patience 10. An RBF-SVM trained on per-channel mean, standard deviation, and maximum features served as the baseline. A software watcher validated new GeNose-19 CSV files, applied preprocessing, selected the cultivar model, stored the prediction, and updated the Django dashboard. MQTT supported device and environmental telemetry, consistent with connected electronic-nose architectures (Pérez-Solano & Ruiz-Canales, 2025).

RESULT AND DISCUSSION

The internal TCN evaluation achieved 98.1% accuracy, 98.25% macro precision, 98.18% macro recall, 98.13% macro F1-score, and 0.981 macro AUC. The RBF-SVM obtained 87.5% accuracy and 87.1% macro F1-score. The TCN therefore improved accuracy by 10.6 percentage points and macro F1-score by 11.03 percentage points within the same experimental pipeline. Class-level AUC was 0.991 for unripe, 0.967 for half-ripe, and 0.984 for ripe fruit. The lower value for the intermediate stage is plausible because volatile profiles near adjacent ripeness stages may overlap. Reported cultivar accuracy was 100.0% for Arumanis, 98.1% for Budiraja, and 96.2% for Indramayu.

The connected implementation recorded 287 ms mean latency, 412 ms maximum latency, 99.2% successful transmission, and 1.4 s web response, as shown in Table 1. These values met the prototype criteria of no more than 500 ms latency, at least 95% successful transmission, and less than 2 s web response. Together, the classification and communication results show that temporal inference can be incorporated into an operational monitoring workflow rather than remaining an offline model.

The performance must nevertheless be interpreted as prototype validation. Only 27 primary files were available, half of the development files were synthetic, and measurements were obtained under controlled chamber conditions. Window count does not increase the number of independent fruits. Long-term MOS drift, seasonal and orchard variation, open-air interference, calibration transfer, and an independent harvest batch were not evaluated, as shown in Figure 2. Moreover, cultivar-specific models require the variety to be selected before inference. These limitations prevent a field-readiness claim despite the strong internal metrics.

Table 1: Summary of internal prototype performance.

Metric	TCN / System	Comparator / Criterion
Accuracy	98.1%	RBF-SVM: 87.5%
Macro F1-score	98.13%	RBF-SVM: 87.1%
Macro AUC	0.981	-
Mean / maximum latency	287 / 412 ms	Criterion: ≤500 ms
Successful transmission	99.2%	Criterion: ≥95%
Web response	1.4 s	Criterion: <2 s

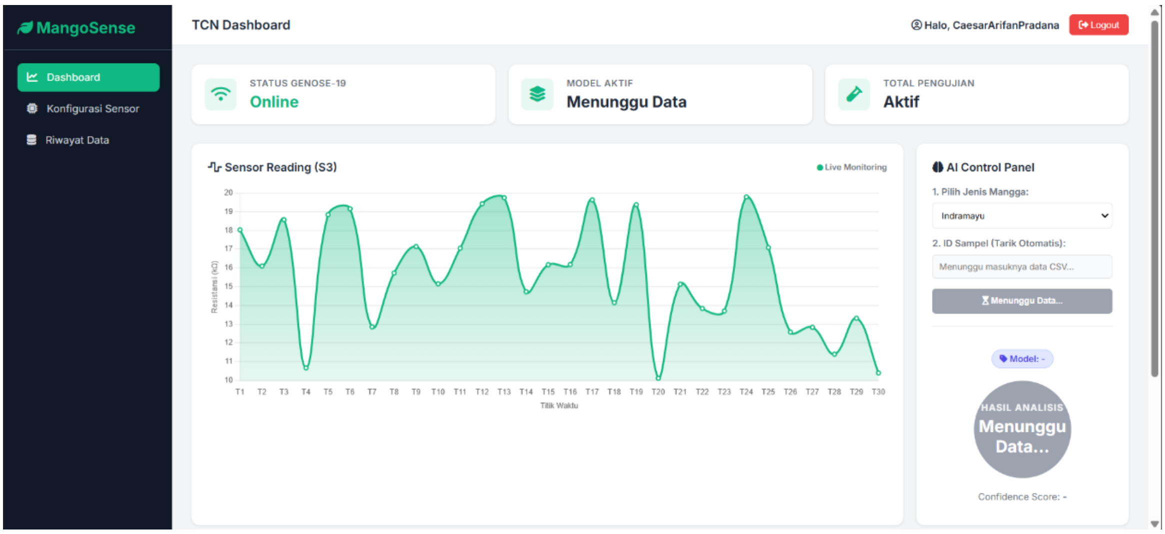

Figure 2: MangoSense web dashboard for sensor monitoring and classification.

CONCLUSION

MangoSense combines ten-channel MOS sensing, cultivar-specific TCN classification, ESP32 chamber control, MQTT telemetry, automated inference, and a Django dashboard. Under the supplied laboratory evaluation, the TCN outperformed an RBF-SVM baseline and the connected layer met its latency, transmission, and response targets. The prototype demonstrates the feasibility of connected, non-destructive mango-ripeness screening. Future work should collect substantially more physical fruit across independent harvests, reserve an untouched external test batch, report confidence intervals, quantify sensor drift, evaluate unified multi-variety modelling, and test lightweight edge inference under open-air conditions.

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