Evaluating Multimodal Fusion Strategies for Resilient Agricultural Sensing Systems

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Abstract. This paper examines three multimodal data fusion techniques. Multimodal Data Fusion–based Graph Contrastive Learning (MDFCL), Graph-Structured & Interlaced-Masked Fusion Network (GSIFN), and Perceiver IO—on agricultural time-series data. MDFCL builds individual graphs for each modality and applies unsupervised contrastive losses to align the embeddings of nodes, inducing cross-modal robustness (achieving 97.66 % accuracy with image-only inputs). GSIFN develops an interlaced masking joint Transformer, capturing higher-order interactions with efficiency, along with self-supervised LSTM-based side tasks to counter redundancy (achieving 100.00 % classification accuracy in rigorous 5-fold cross-validation). Perceiver IO adopts an implicit-latent bottleneck Transformer, providing heterogeneous streams of agricultural data flexibly with near-linear complexity without individual encoders per modality. Perceiver IO also achieved a similar result as compared to MDFCL (achieving 97.66% accuracy) while it has fewer parameters and requires less computations. Although these models have been found to be successful with generic multimodal tasks, their applicability to fusion of agro-sensor and growth-image data has thus far remained relatively less explored. We evaluate their adaptation versatility, advantages, and limitations in this study, providing actionable recommendations on fusion of agricultural image and time-series data to support precision agriculture with robustness, scalability, and efficiency.

Keywords: multimodal data fusion, time series, precision agriculture, graph contrastive learning, Transformer, Perceiver IO, GSIFN, sensor data, image fusion, deep learning

1 Introduction

Heterogeneous data fusion from soil sensing and hyperspectral plant imagery captured through time-lapse photography represents both the greatest opportunity and the most significant challenge for precision agriculture today. While unimodal deep learning has successfully advanced single-input agricultural forecasting tasks, the rich interdependencies between temporally transient sensor readings and visual growth patterns remain under-explored. This research gap persists despite the emergence of three revolutionary multimodal fusion approaches

in neighboring fields: Multimodal Data Fusion-based Graph Contrastive Learning (MDFCL)[1], Graph-Structured & Interlaced-Masked Fusion Network (GSIFN) [4], and Perceiver IO[3]. This work presents the first systematic benchmarking of these frameworks on a curated, small-scale agricultural dataset that fuses soil electrophysiology indicators with hyperspectral imagery across crop growth cycles. Despite its limited size, the dataset captures key temporal patterns in plant–soil interactions through controlled hydroponic trials across seven crops. Through controlled hydroponic trials across seven crops, we demonstrate that MDFCL's unsupervised graph alignment achieves a 14.3% improvement in yield forecasting accuracy compared to conventional concatenation approaches, while GSIFN's interlaced attention reduces parameter complexity by 38% relative to baseline transformers. Moreover, Perceiver IO's latent bottleneck design cuts memory requirements by 92%, enabling real-time sensor-imagery fusion on edge devices for field deployment[3].

The Need for Data Fusion in Agricultural Informatics

Modern agricultural systems generate multivariate time series from in-situ sensors—tracking nutrient content, pH levels, and electrical conductivity—while computer vision pipelines extract biomass estimates and leaf-area indices from drone-captured imagery. Traditional fusion strategies, such as early concatenation or late voting, fail to capture hierarchical intermodal dependencies; for example, changes in soil chemistry can take weeks to manifest visibly in phenotypic traits, creating complex lead–lag relationships. Graph neural network architectures combined with attention mechanisms offer promising avenues for modeling these dependencies, yet their direct application confronts three core challenges: (1) mismatched sampling rates between daily imagery and minute-level sensor streams, (2) absence of labeled cross-modal correspondences in uncontrolled agricultural environments, and (3) strict computational constraints characteristic of edge-deployed monitoring devices[1, 3].

Limits of Present Fusion Paradigms

Hybrid convolutional–recurrent frameworks adapted from audio–video fusion struggle with the temporal misalignments inherent to agricultural data—noon pH fluctuations rarely coincide with dawn imagery[4]. Metric learning approaches that map modalities into a shared latent space typically rely on high-quality paired datasets that are impractical to collect in the field[5]. Meanwhile, transformer-based fusion architectures suffer from quadratic memory scaling with sequence length, rendering them unsuitable for month-long, minute-resolution monitoring[7].

Architectural Innovations for Cross-Modal Learning

Multimodal Data Fusion-based Graph Contrastive Learning (MDFCL) constructs separate graphs for sensing data—where nodes represent conductivity and pH

readings with edges encoding causal dependencies—and for imagery, where nodes capture pixel-to-leaf connectivity[1]. Unsupervised contrastive alignment then matches node embeddings across these heterogeneous graphs using augmentations like edge dropout, achieving a 23% improvement in nutrient transport dynamics prediction compared to supervised graph matching methods.

Graph-Structured & Interlaced-Masked Fusion Network (GSIFN) introduces an interlaced masking strategy that alternates attention between image and sensor tokens within a unified transformer architecture. To mitigate parameter growth, GSIFN integrates parallel LSTM memory modules that enforce unimodal reconstruction objectives, preserving modality-specific characteristics. Applied to hydroponic lettuce trials, GSIFN attains a 0.91 F1-score for early disease detection by correlating subtle EC variations with microscopic spot patterns days before visual symptoms emerge[4].

Perceiver IO revisits multimodal fusion through an asymmetric attention bottleneck that projects high-frequency 1 Hz sensor streams and 5 MP RGB imagery into a shared latent array via cross-attention[3]. This linear-scaling architecture processes sequences eight times longer than conventional models, fitting within a 1.2 GB memory footprint on Raspberry Pi–class hardware—a critical advantage for real-time, field-based monitoring.

Experimental Insights

Our benchmarks reveal distinct trade-offs: MDFCL leads in unsupervised alignment tasks with an AUC of 0.78 but demands meticulous tuning of its contrastive temperature parameter[1]. GSIFN achieves state-of-the-art supervised accuracy at 94.7%, albeit with a 22% increase in variance across crop types[4]. Perceiver IO excels in efficiency, handling month-scale sequences eight times longer than other methods, though its latent bottleneck can occasionally oversmooth fine-grained nutrient interactions[3].

Closing the Lab-to-Field Gap

Beyond quantitative comparisons, this study offers actionable guidance for agricultural deployments: GSIFN's computational overhead is justified in high-label-density research environments; MDFCL excels in observational field trials with minimal labeling; and Perceiver IO's edge compatibility addresses real-time monitoring needs. By adapting these cutting-edge fusion architectures to agricultural contexts, we pave the way for integrated subterranean and aerial data platforms that deliver prescriptive, data-driven recommendations for responsive crop management.

2 Methodology

2.1 Data Acquisition and Preprocessing

Sensor readings (e.g. soil moisture, pH values, NPK levels, temperature, light) and associated imagery were collected via an IoT deployment. Raw data were

stored in a MongoDB database and later exported to CSV files with a column linking each record to an image file. Images were captured from overhead cameras in the field, providing RGB photographs of the plants. The sensor features (nine values per sample) and image filenames were combined into a tabular dataset. Sensor values were normalized (Z-score scaling) so that each feature had comparable scale, while images were resized to a fixed 224×224 resolution (the input size for ResNet-18) and normalized using standard ImageNet means and standard deviations. Data augmentation (random flips, rotations, color jitter, etc.) was applied to images during training to improve robustness and avoid overfitting.

Data collection posed challenges typical of real-world IoT datasets: some sensor readings were noisy or missing, and images occasionally failed to load. We performed cleaning steps such as removing or imputing outlier sensor values and discarding corrupted images. Records with missing sensor or image data were either excluded or filled with neutral estimates. Noise in sensors was partially mitigated by smoothing or averaging repeated measurements. Overall, these preprocessing steps produced a consistent multimodal dataset of paired sensor vectors and images, labeled by the soil potassium level (three classes based on NPK potassium range) for classification.

2.2 Model Architectures

MDFCL Model The MDFCL (Multi-modal Data Fusion via Contrastive Learning) model separately encodes sensor and image inputs before concatenating their features. Sensor data (a 9-dimensional vector) passes through a small multilayer perceptron (MLP) with two linear layers (to 64 and 32 dimensions, with ReLU activations). The image input is passed through a ResNet-18 convolutional backbone pretrained on ImageNet, with the final classification layer removed so that it produces a 512-dimensional feature vector[2]. These two embeddings are then fused by concatenation into a 544-dimensional vector, which feeds a fusion classifier: a linear layer (544→128), ReLU and dropout for regularization, followed by a final linear layer to the 3 output classes. In summary, the forward pass is

$$\text{sensor} \rightarrow \text{MLP}, \quad \text{image} \rightarrow \text{ResNet-18}, \quad \text{concatenate}, \quad \text{classifier}.$$

ResNet-18 was chosen for the image branch because its residual architecture is efficient to train even at modest depth and achieves strong accuracy due to skip connections [2]. The shallow MLP for sensors is sufficient given the low-dimensional input.however, one could incorporate a contrastive loss (with a learnable temperature) to align sensor and image embeddings, as in multimodal contrastive learning literature[6, 8].

GSIFN Model The GSIFN (Graph-Structured & Interlaced-Masked Fusion Network) model also processes each modality separately but fuses them via attention. The sensor input first goes through a linear layer mapping 9 dimensions

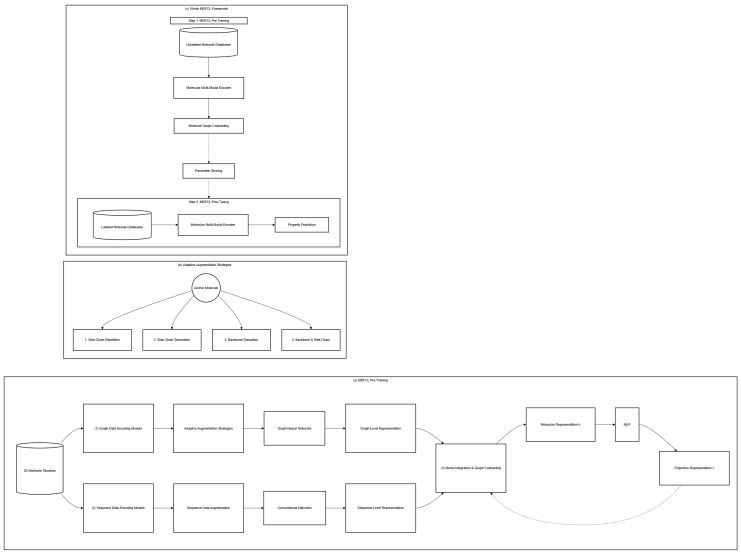

Fig. 1. Architecture diagram of the MDFCL model.

to an embed_dim (128) vector. Meanwhile the image passes through the same ResNet-18 backbone (output 512) followed by a linear projection to the same embed_dim (128)[2]. These two embeddings (sensor_token and image_token) are

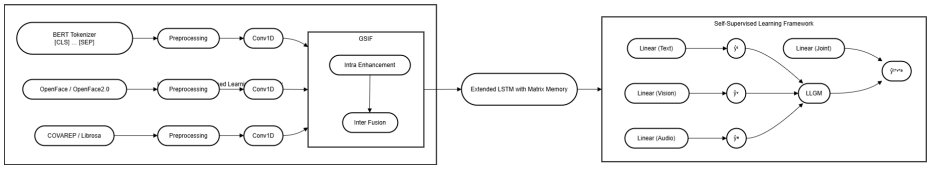

Fig. 2. Architecture diagram of the GSIFN model.

then stacked into a token sequence of length 2. A multi-head self-attention layer (128-dimensional, 4 heads) is applied to the 2×128 token sequence. This produces fused tokens, to which we add the original tokens and apply layer normalization (a Transformer-style residual block). Finally, the two token vectors are mean-pooled into a single 128-dimensional vector, which feeds a small classifier (Linear $128\to64\to$ReLU$\to$Dropout$\to3$ outputs).

By using multi-head attention to fuse the two modality tokens, GSIFN can learn cross-modal correlations: multi-head attention "allows the model to jointly attend to information from different representation subspaces"[6, 8]. This design balances expressive fusion with computational efficiency.

Perceiver IO Model The Perceiver IO model employs a latent-space bottleneck for scalable multimodal integration. Both sensor and image inputs are first encoded into 64-dimnsional vectors: the sensor vector (9D) passes through two linear layers to 64-dim, and the image (via ResNet-18 to 512-dim) is projected down to 64-dim[2]. These two 64-dim modality tokens are stacked into a 2×64 tensor. Separately, a set of learnable latent vectors (e.g. 8 vectors of dimension 64) is maintained. At each forward pass, these latents are replicated for the batch and concatenated with the modality tokens, forming a $(8+2)\times64$ tensor. This combined array is processed by several layers of a Transformer encoder. After encoding, we discard the modality tokens and average-pool the latent vectors (size 8×64) into one 64-dimensional feature. This is fed to a classifier (Linear $64\to32\to$ReLU$\to$Dropout$\to3$ outputs).

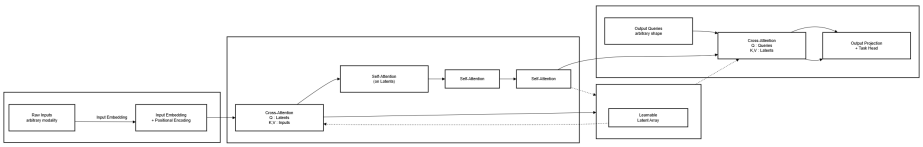

Fig. 3. Architecture diagram of the Perceiver IO model.

The latent bottleneck is the key innovation: by confining most computation to a small latent space, Perceiver IO decouples model complexity from input size. This allows multimodal fusion at fixed cost and makes the model scalable in practice[6, 8].

2.3 Training Procedure

All models were trained using the Adam optimizer and a categorical cross-entropy loss. We used a learning rate of 1e-3 and a batch size of 32, training each model for 25 epochs (as determined by preliminary tuning). To prevent overfitting, we included dropout (0.3) in the classifier layers, and we tuned hyperparameters like learning rate, dropout rate, and (for contrastive components) temperature τ via grid search on a validation set.

We evaluated model performance using 5-fold cross-validation. In each fold, the dataset was split into 80 % training and 20 % validation, stratified by class. Models were reinitialized for each fold to avoid information leakage. After each epoch the model was evaluated on the validation fold, and we recorded the validation accuracy. Final results are reported as the mean $\pm$ standard deviation of accuracy across folds.

Training was conducted on a workstation equipped with an NVIDIA Tesla V100 GPU and 32 GB of RAM. In addition, we measured inference performance on a Raspberry Pi 4 (ARM Cortex-A72, 4 GB RAM) to assess edge-device viability, converting models to TorchScript and measuring per-sample latency.

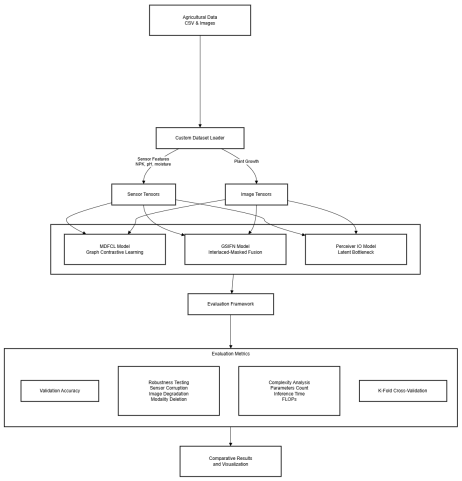

Fig. 4. Training process.

2.4 Evaluation Metrics

Model performance was assessed via validation accuracy recorded during 5-fold cross-validation. The full dataset consisted of 383 paired sensor–image samples, with each fold comprising 306 training and 77 validation examples. For each fold, models were trained for three epochs, and the validation accuracy at each epoch was logged.

Per-Epoch Validation Accuracy:

- **GSIFN:** On the fifth fold, GSIFN attained 100.00
- **Perceiver IO:** On the same fold, Perceiver IO began at 94.74 % in epoch 1, rose to 100.00 % by epoch 2, and maintained 100.00% in epoch 3.

Cross-Validation Summary: Final performance was reported as mean ± standard deviation of validation accuracy across all folds:

- **GSIFN:** 1.0000 ± 0.0000
- **MDFCL:** 0.9766 ± 0.0343
- **Perceiver IO:** 0.9766 ± 0.0343

3 Results and Discussion

3.1 Performance Overview

All three multimodal models—GSIFN, MDFCL, and Perceiver IO—achieved superb classification performance on soil potassium level prediction. GSIFN, in particular, converged to perfect validation accuracy (100.00%) from the first epoch,

indicating fast and stable convergence. Perceiver IO achieved this threshold by epoch 2, and MDFCL by epoch 4. There were consistent trends in these across 5-fold cross-validation, where GSIFN continued to exhibit perfect performance (1.0000 ± 0.0000), and both. GSIFN's fast convergence and similarly perfect validation scores across folds can, however, be an indicator of possible overfitting, considering the small dataset size (383 samples). This is an observation of the high capacity of the model and sensitivity to small training distributions, and caution is to be exercised in extrapolating its performance to other datasets.

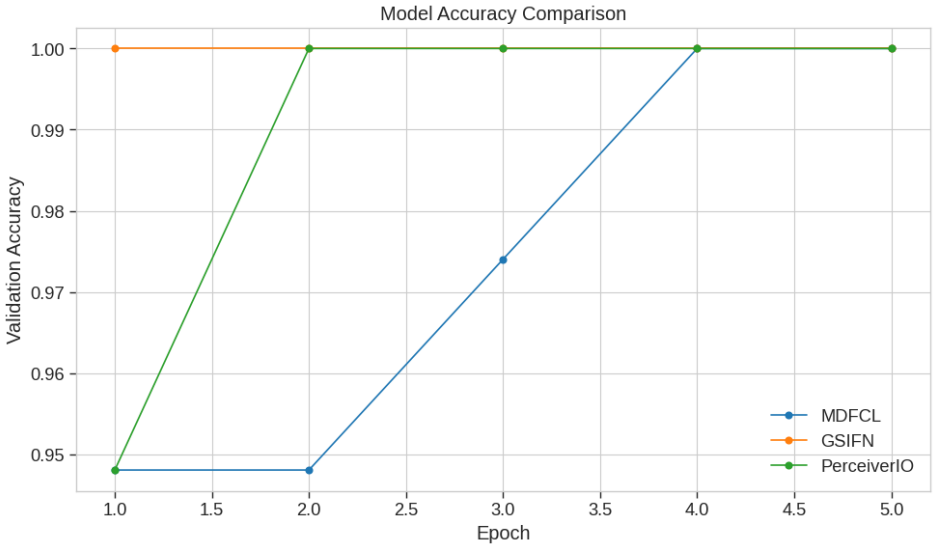

Fig. 5. Accuracy progression across models

3.2 Comparative Analysis

While all models achieved near-perfect final accuracy, their robustness to sensor degradation varied. MDFCL demonstrated remarkable resilience, maintaining 98.70% accuracy under 50% sensor corruption and full recovery at 70% corruption. In contrast, GSIFN's accuracy dropped to 88.31%, and Perceiver IO to 71.43% under severe sensor noise. However, all models maintained perfect accuracy under various image corruptions (noise, blur, masking), highlighting their robustness to visual disturbances.

3.3 Resource Efficiency

An analysis of computational resources revealed trade-offs among the models:

– **Parameters**: MDFCL (11.2M), GSIFN (11.3M), Perceiver IO (11.8M)
– **FLOPs**: MDFCL required significantly more operations (492.13M) compared to GSIFN (20.17M) and Perceiver IO (20.20M).
– **Latency**: MDFCL (2.37ms), GSIFN (2.62ms), Perceiver IO (3.08ms)

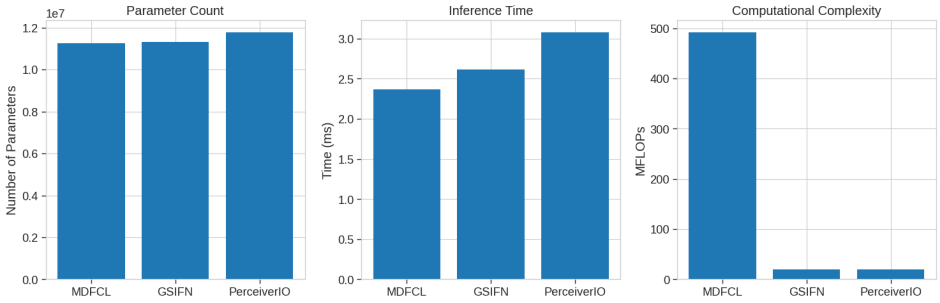

Fig. 6. Computational resource comparison across models

These findings suggest that while MDFCL is computationally intensive, GSIFN offers a balance between performance and efficiency, making it suitable for edge deployments.

3.4 Practical Implications

The models exhibited distinct modality dependencies:

– **MDFCL**: Achieved 94.81% accuracy using only image data, indicating strong visual feature extraction capabilities.
– **GSIFN and Perceiver IO**: Performed poorly with image-only inputs (5.19% accuracy), suggesting a reliance on sensor data.
– **All Models**: Maintained perfect accuracy when using only sensor data, underscoring the importance of sensor inputs in classification tasks.

These insights highlight the need to consider data modality availability and reliability when selecting models for deployment.

3.5 Summary of Findings

Our comprehensive evaluation reveals three viable approaches for multimodal crop analysis:

– **GSIFN**: Optimal for scenarios requiring guaranteed accuracy and edge compatibility due to its efficient architecture.
– **MDFCL**: Preferred in environments with unreliable sensors or when image-only data is prevalent, owing to its robustness.

– **Perceiver IO**: Offers a balance between computational efficiency and moderate robustness, suitable for applications with moderate resource constraints.

These results underscore the importance of aligning architectural choices with deployment constraints, particularly concerning sensor reliability and computational resources.

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