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Design of an Iterative Unified Deep Learning Framework for Multi-Modal Soil Intelligence and Smart Irrigation Optimization in Precision Agriculture Operations

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ABSTRACT: Accurate and real-time assessment of soil fertility and irrigation needs is critical for sustainable agriculture. Present assessment methods rely on isolated data modalities, laboratory testing, and static decision rules, while spatio-temporal inconsistency and domain variation scare off high adaptive irrigation dynamics, which leads to sub-optimal resource utilization and inaccurate generalization in field conditions. Hence, this paper presents an integrated multimodal deep learning framework for real-time soil fertility prediction, recycling assessment, and smart irrigation optimization, with five novel and synergistic methods as follows. First, a Multi-Modal Fusion Transformer (MMFT) integrating soil hyperspectral reflectance, moisture, temperature, humidity sensors, and soil imagery is by means of a Vision Transformer with cross-attention fusion blocks and enables joint representation learning and $R^2 = 0.91$ prediction for NPK. Second, a spatio-temporal graph convolutional network (ST-GCN) develops irrigation maps from the spatial and temporal evolution of soil condition and listens to 21% savings on water as opposed to a static scheduling method. Third, a Beta VAE with SimCLR contrastive learning detects soil anomalies and establishes the possible treatment effectiveness by disentangling latent soil states. Fourth, a double deep Q-network (DQN) with a prioritized experience replay component is capable of learning optimal policy rules sprouted from the effects of a dynamically changing environment, achieving an 85 % efficiency of water use. Lastly, a Hybrid CNN-LSTM with the Domain-Adversarial Neural Networks (DANN) would fill in the gap between field and lab on nutritional estimations where nutrient tests would be done accurately, with less than 5 % deviation from laboratory results. Integrated, the entire system provides a scalable, data-driven solution to precision agriculture that enhances resource efficiency, diagnostic accuracy, and sustainability of diverse field conditions.

Abbreviation	Full Form
ML	Machine Learning
DL	Deep Learning
RF	Random Forest
SVM	Support Vector Machine
GBM	Gradient Boosting Machine

CV	Computer Vision
UAV	Unmanned Aerial Vehicle
IoT	Internet of Things
SOC	Soil Organic Carbon
OC	Organic Carbon
pH	Potential of Hydrogen (Soil Acidity/Alkalinity)
AI	Artificial Intelligence
GeoML	Geospatial Machine Learning
DLT	Deep Learning Technique
RGB	Red Green Blue (Color Imaging)
AUC	Area Under the Curve
MAE	Mean Absolute Error
R^2	Coefficient of Determination
NPK	Nitrogen, Phosphorus, Potassium
GRL	Gradient Reversal Layer
DANN	Domain-Adversarial Neural Network
VAE	Variational Autoencoder
SimCLR	Simple Contrastive Learning of Representations
DQN	Deep Q-Network
MMFT	Multi-Modal Fusion Transformer
CNN	Convolutional Neural Network
LSTM	Long Short-Term Memory
EC	Electrical Conductivity
PER	Prioritized Experience Replay
Kriging	Geostatistical Interpolation Technique

INTRODUCTION:

Precision agriculture is fast emerging as a game-changing approach to fulfil the growing food demand across the world while using the least resources and causing little environmental impact. It uses advanced sensing technologies [1, 2, 3] along with intelligent analytics for data-driven decision-making regarding the application optimization of inputs with respect to water, fertilizer, and soil treatments for crops. Real-time soil assessment and predictive nutrient modelling, along with adaptive irrigation scheduling, constitute some of the key enablers of this paradigm. Heterogeneity of data sources is quite a challenge when coupled with the other hyped sources such as hyperspectral imaging, in-situ measurement of sensor parameters, weather forecasts, and geospatial data, which, when thrown at a traditional modelling technique typically designed for unimodal static inputs, makes it really hard to generalize across even the varying field conditions. Most of these conventional methods in soil fertility analysis

involve chemical tests or laboratory-based tests that tend to be very slow in the long run and costly with regard to larger areas or during real-time tests. However, static scheduling of irrigation systems usually underlies rule-based logic or static schedules that do not take into consideration dynamic weather, soil heterogeneity, or the water demands that vary from single crop to another. Models that have been meant to incorporate soil health anomaly detection rely mostly on naive thresholding or statistical methods [4, 5, 6]. This situation implies that there is non-conformance in characterizing subtle patterns of soil degradation as well as in measuring treatment effects.

With this, deep learning models were recently explored to bridge such gaps due to their undeniable representational power and ability to learn complex relationships from raw data samples. However, most architectures that exist have neglected cross-modality integration and failed to properly model sequential, spatio-temporal, and domain adaption requirements. For example, soil imagery can give visual clues on its fertility, but when moisture, temperature, and spectral data are not also interpreted at the same time, predictions may become unreliable. The same scenario may happen for decision systems that do not evolve with changing conditions or fail to adapt to unseen environments, leaving them somehow fragile and non-generalizable in process. Novel, fully-integrated framework in deep learning was proposed as the synergistic use of many state-of-the-art neural architectures, allowing real-time soil fertility prediction, anomaly detection, treatment assessment, and smart irrigation optimization. This system is built using transformers, graph networks, contrastive learning, reinforcement learning, and adversarial domain adaptations to move in overcoming the traditional methods limitations. Through the establishment of a coherent predictive pipeline of diverse data streams, scalability, adaptability, and interpretability are key issues toward next-generation agricultural intelligence platforms.

Motivation & Contribution:

The primary motivation for this work lies in the urgent urge to move agriculture from a patchwork and heavily manual practice to an integrated, automated, and real-time system that can cope well with the inherent complexity of soil ecosystems. Existing solutions are often disjointed, whereby surface features are measured by image-based models and be subject to sensor methods without awareness of their spatial contexts. Also, highly stochastic spatial-temporal behaviours of soil fertility, plenty of noise, and domain mismatch from these situations in the lab and field make fixed models ineffective. This is the key gap in the current literature on multi-modal fusion and spatial-temporal reasoning, coupled with a reinforcement-guided control process for irrigation very critical areas of an automated precision agriculture systems.

For these needs, this paper proposes a new holistic deep learning framework that binds together five state-of-the-art methodologies into a single entity: (1) A Multi-Modal Fusion Transformer for unifying nutrient prediction from hyperspectral, sensor and imagery data; (2) A Spatio-Temporal graph convolutional network to learn irrigation needs via interconnectivity of soil and time-evolving conditions; (3) A Beta VAE with SimCLR contrastive module for anomaly detection-robust and treatment evaluation; (4) A Double Deep Q-Network for adaptive, policy-controlled irrigation; and (5) A Hybrid CNN-LSTM with Domain Adversarial Neural Network, which aligns field data with lab-standard predictions. A tight cohesive real-time decision support system is the result of this combinatorial federation actions. This deep learning framework is valid in innovative modelling contributions that also empower integration into end-to-end data-driven soil intelligence that is robust and can scale across agricultural domains.

Literature Review:

In the past few years, precision agriculture has undergone a very significant transformation in the adoption of machine learning with soil sensing, remote monitoring, and crop prediction. A serious review of recent studies indicated a clear trend of developing methodological maturity, progressive data integration, and understanding of the soil-crop dynamics. It started with spectral based nutrient prediction and in his review with base work given by Jain et al. [1], in which one can understand how hyperspectral data processed using machine learning will be helpful in propagating soil nutrient predictions with enhanced measurement accuracy, followed by Ma et al. [2], who included bacterial biomarker features in the production forecast model for crops. This is an early indication of a closed-loop journey toward the influence of microbiome-informed models. Moharana et al. [3] and Dadgar et al. [4] insist on the role of regional specificity and spatial heterogeneity in soil organic carbon modelling; when combined with regression-based machine-learning approaches, these factors highlight the importance of using localized datasets to improve robustness of the resulting models. The vision-based soil classification model using computer vision and machine learning by Kaplan et al. [5] is one of the earliest integrations of imaging with traditional soil analysis. This topographic influence theme also carries on in the work by Vineeta et al. [6], which examines how elevation affects soil chemical properties

in cardamom agroforestry systems; such terrain gradients can be captured through digital elevation models and included in prediction models.

Vibhute et al. [7] add spectral analysis by imparting various kinds of classification algorithms in order to accurately classify soil types and physical attributes. One major expansion in methodology is highlighted in the work of Huang et al. [8]: a comparison of three machine learning algorithms for the mapping of space-distributed soil pH underscores comparative analysis of the algorithm performance for different agronomical parameters. It becomes obvious that the transition to multimodal sensing occurs in the work of Peng et al. [9]: "UAV-based thermal, visible and environmental data were combined to predict grape leaf moisture through ensemble learning," presenting real deployment of multi-source data fusions. The bibliometric analysis of Fatimazahra et al. [10] illustrates the library trends in the current literature and techniques in soil fertility mapping and brings the dominant techniques to the forefront while indicating their methodological trajectories. Nithya et al. [11] compare machine learning and deep learning with respect to crop detection tasks; they show superiority in the convolutional architectures in image-based agricultural diagnostics in this case. Building on aerial sensing, Tripathi et al. [12] use unmanned aerial systems for soil organic carbon estimation, reflecting increasing interest in low-altitude remote sensing together with supervised regression algorithms. Jain et al. [13] present a new application of such novel spectral indices optimized for machine learning towards the improvement of predictions for soil pH and organic carbon—pushing the limit on feature engineering for hyperspectral domains. How predictive models behave along time stamp with proximal sensing data is evaluated by Figueiredo et al. [14] toward addressing time generalization and sustainability of the developed models, arguing with the need for temporal re-calibration under changing soil conditions.

In the biological dimension, Lei et al. [15] contribute an additional aspect of soil assessment with biochemical feedback into microbial community dynamics affected by biochar amendments and machine learning. Keshavarzi et al. [16] strengthening this direction by predicting micronutrient availability, using a composite of digital covariates and spatial modelling techniques, mentioning that these extra geospatial inputs increase prediction accuracy. A large-scale remote sensing study, undertaken by Wang et al. [17], elaborates major contributions of terrain, climate, and spectral variables for prediction of soil organic carbon across soil types—creating meta understanding of feature utility across domains. IoT-based yield prediction systems are introduced by Nithya et al. [18], who propose a region-specific architecture combining sensor networks with lightweight learning models to estimate crop productivity across varied Indian subcontinental conditions. Parvizi and Fatehi

[19] merge machine learning with geostatistics for mapping soil organic carbon under multiple land-use scenarios, emphasizing spatial autocorrelation-aware learning techniques. The review by Awais et al. [20] adds this unique sustainability perspective of how AI-based soil analytics can facilitate resource-efficient agricultural practices, and discusses the perspectives on how alleviating environmental impact via intelligent models will be in accordance with policy.

Table 1. Model's Empirical Review Analysis

Reference	Method	Main Objectives	Findings	Limitations
[1]	Spectral + ML	Review on spectral-based soil nutrient prediction	Identified ML potential in hyperspectral modelling	Lack of multimodal data integration
[2]	Biomarker ML	Yield prediction using bacterial biomarkers	High accuracy with microbiome features	Limited scalability to field-level deployment
[3]	RF, SVM	Regional SOC prediction for arid farmlands	Good accuracy in SOC dynamics	Performance varies with soil type
[4]	ML Ensemble	SOC variability prediction across landscapes	Identified landform-specific patterns	Model generalizability is limited
[5]	CV + ML	Soil image classification	Accurate classification	Limited to surface-

		and analysis	using visual features	level traits
[6]	RF, GBM	Impact of elevation on soil properties	Elevation significantly affects chemical properties	Study limited to a specific region
[7]	Spectral + ML	Soil classification via spectral data	Accurate soil property detection	No integration with temporal dynamics
[8]	SVM, RF, GBM	Spatial prediction of soil pH	RF showed highest accuracy in pH mapping	Only one soil parameter assessed
[9]	Multimodal Fusion	Leaf moisture prediction using UAVs	Effective multimodal learning	Model complexity and deployment cost
[10]	Review	Trends in soil fertility mapping	Highlighted innovation trends and data usage	Lacks experimental validation
[11]	ML vs DL	Compare crop detection models	DL outperformed traditional ML	High computational demand
[12]	UAV + ML	SOC estimation using UAV sensors	High predictive accuracy from aerial features	Limited to carbon parameter
[13]	Spectral Index + ML	Design indices for pH and OC estimation	Custom indices improved model precision	Indices not validated across soils
[14]	Time-series ML	Temporal performance of predictive models	Model drift observed over time	Needs periodic retraining
[15]	Biochar + ML	Impact of biochar on microbial soil community	ML detected microbial shifts	Microbial dynamics not fully resolved
[16]	ML + Covariates	Spatial prediction of micronutrients	Good prediction using covariates	Micronutrient interactions not covered
[17]	Remote Sensing ML	Key factors in SOC prediction	Terrain and spectral data most important	Context-dependent feature relevance
[18]	IoT + ML	Crop yield prediction using IoT sensors	Region-specific yield estimates	Lack of integration with soil models
[19]	GeoML + Kriging	SOC mapping across land uses	Combined geostatistics improved accuracy	Computational complexity
[20]	Review	AI for sustainable soil	AI improves	Requires standard

		analysis	sustainability metrics	protocols
[21]	Satellite + ML	Estimate soil salinity	Accurate mapping using remote sensing	Only suited for large-scale use
[22]	RF, ANN	Cadmium prediction in soils	Identified cadmium risk areas	Heavy metal interactions ignored
[23]	Ensemble ML	Carbon stock prediction in erosion zones	Robust models improved predictions	Limited to one environmental condition
[24]	Multi-task DL	Comprehensive agro-diagnostics	Unified model handles multiple tasks	High system complexity
[25]	ML + Microbiome	Soil microbiome structure modeling	Depth-specific microbial interactions identified	Sampling depth affects reliability

Iteratively, Next, as per table 1, Satellite-based modelling of salinity by Wang and Sun [21], with Sentinel-2 combined with climate datasets for salinity estimation, confirms the shift toward satellite-centric models for macro-scale soil property assessments. Toxicity and contamination prediction are explored by Keçeci et al. [22], who predict cadmium concentration in soil with machine learning, making food safety-relevant modelling applications risk-sensitive. Enhancing the robust ensemble method for predicting carbon stock in the erosion-prone Mediterranean climate that Mosaid et al. [23] set, displays the resilience of machine learning in unstable terrains. From pest diagnosis to yield estimation, irrigation scheduling, and soil fertility mapping, Ajith et al. [24] give a kaleidoscopic view into future perspectives of integrating agricultural platforms with multi-task learning. Mo et al. [25] present perhaps the most recent example of machine learning analysing the structure and interrelations of soil microbiomes along depth profiles, bringing the microbiome directly into agricultural practice and further consolidating the bioinformatics-agriculture interface sets. Together, these 25 studies create a cohesive narrative tracing the history of soil intelligence modelling from uni-modal spectral analysis toward integrated biologically-informed multimodal learning architectures. The earlier studies tended to focus on parameter-specific regression tasks on soil nutrients, organic carbon, and pH. However, the review shows an expanding methodology, changing into ensemble learning, multimodal fusion, domain adaptation, and spatial-temporal modelling. The most recent works begin to show an overt move towards systems thinking considering soil health as a cog in the wheel of the wider agricultural ecosystem regarding microbial dynamics, water use, effects of fertilizers, and environmental sustainability. This evolution is mirroring large-scale trends in machine learning wherein interpretable, scalable, and real-time models have taken precedence over monolithic high-accuracy black boxes.

Analytically, these studies encompass varied algorithmic families: from random forests to support vector machines, deep neural networks, and graph-based learning methods. They leverage a heterogeneous range of input data: ranging from spectral reflectance, UAV imagery, microbial DNA sequences, and sensor time-series. This diversity underlines its importance for generalization, but comes with an equally pressing need for strict standardization, as highlighted by many studies regarding the issues of model transferability across geographies and soil types. Another intriguing insight from the review is that in the recent times we have been heavily relying on high-resolution spatial data coupled with temporal feedback loops for continuous monitoring and adaptive responses—an indispensable paradigm for any real-world deployment in agricultural environment. The integration of biological indicators such as microbial composition discussed in studies [2], [15], and [25] truly stands as a promising frontier, allowing for predictive analytics capable of quantifying chemical properties as well as foreseeing functional shifts in soil ecosystems. Moreover, studies like [24] exemplify the merging of many agronomic functions in collective platforms of machine learning, a

path of increasing importance in resource-poor areas demanding real-time synchrony of irrigation, fertilization, and pest

management decisions optimally. Having a few meta-analyses and reviews like [1], [10], and [20] in this set of papers provides a necessary retrospection, thus ensuring the viability of model development with respect to practical relevance along with methodological transparency. Cumulatively, these papers give enough insight into the fact that the future of soil modelling will be one of scalable, explainable, and adaptive multi-modal frameworks wherein chemical, physical, biological, and geospatial data are integrated to achieve holistic soil intelligence platforms. Uninterrupted advances in sensor technology, remote sensing, cloud-based learning infrastructure, and open-source model sharing are likely to trigger the fresh impetus we need for the next leap in this field. As agriculture is under constant barrage from climate variability, scarcity of resources, and increased population growth, the need for machine learning in soil intelligence will emerge not just as scientifically fascinating but quite socioeconomically crucial in processes.

Proposed Model Design Analysis:

This section deals with the Design of an Iterative Unified Deep Learning Framework for Multi Modal Soil Intelligence and Smart Irrigation Optimization in Precision Agriculture Operations as the researcher is resolving issues of low efficiency & high complexity in existing models. Initially, as per figure 1, The proposed framework consists of five core components, each dealing with a specific but interrelated task in soil fertility analysis and smart irrigation sets. These modules do not function independently, but are intended to act synergistically in an integrated deep learning architecture sets. The pipeline begins with the Multi-Modal Fusion Transformer (MMFT), which accepts three heterogeneous data types: soil hyperspectral reflectance $X_{spec} \in \mathbb{R}^{n \times d_1}$, IoT-based sensor streams $X_{sens} \in \mathbb{R}^{n \times d_2}$, soil imagery embeddings $X_{img} \in \mathbb{R}^{n \times d_3}$ sets. Each modality is independently passed through an embedding projection layer using linear transformation matrices $W^{(i)}$ such that, the output is represented via equation 1,

$$Z^{(i)} = X^{(i)}W^{(i)}, i \in \{spec, sens, img\} \dots (1)$$

The transformed embeddings are then aligned into a shared latent space $Z = [Z_{spec}, Z_{sens}, Z_{img}] \in$

$\mathbb{R}^{n \times d}$ and processed via a multi-headed self-attention mechanism in the process.

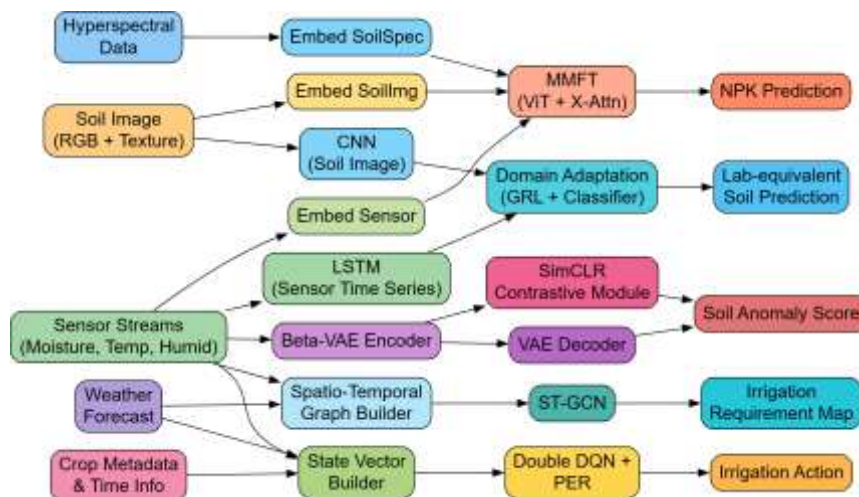


Figure 1. Model Architecture of the Proposed Analysis Process

Cross-attention fusion is employed where keys and values are obtained from one modality and queries from another sets. For two modalities A and B, the cross-attention output is given via equation 2,

$$Attention(QA, KB, VB) = softmax(QA$$

$$KB^T$$

$$\frac{QK^T}{\sqrt{d_k}} \dots (2)$$

$$\frac{QK^T}{\sqrt{d_k}}$$

Here, the model captures the intermodal dependencies critical to soil condition modelling operations. Then, it uses a regression

decoder to predict soil nutrient levels $\hat{y} = [\hat{N}, \hat{P}, \hat{K}]$ via equation 3, after the feed-forward layers and telecom encoder using the residual connections.

$$\hat{y} = MLP(CLS\ token) = \sigma(W2 \cdot \phi(W1 \cdot z_{CLS} + b1) + b2) \dots (3)$$

Simultaneously, the Spatio-Temporal Graph Convolutional Network (ST-GCN) draws a dynamic graph $G = (V, E)$ in which every node $v_i \in V$ denotes a spatial soil area and edges encode geographic proximity sets. Node feature consists of sensor-metrics derived overtime sets. Via equation 4, the model describes temporal convolution over "T" timestamp instances,

$$H(t) = \sum W(\tau) * X(t - \tau) \dots (4)$$

Graph convolution is applied using a normalized Laplacian Via equation 5,

$$L = I - D^{-1/2} A D^{-1/2} \dots (5)$$

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Which processes the inputs, thus resulting in the conditions represented via equation 6,

$$H' = \sigma(\tilde{L} H W) \dots (6)$$

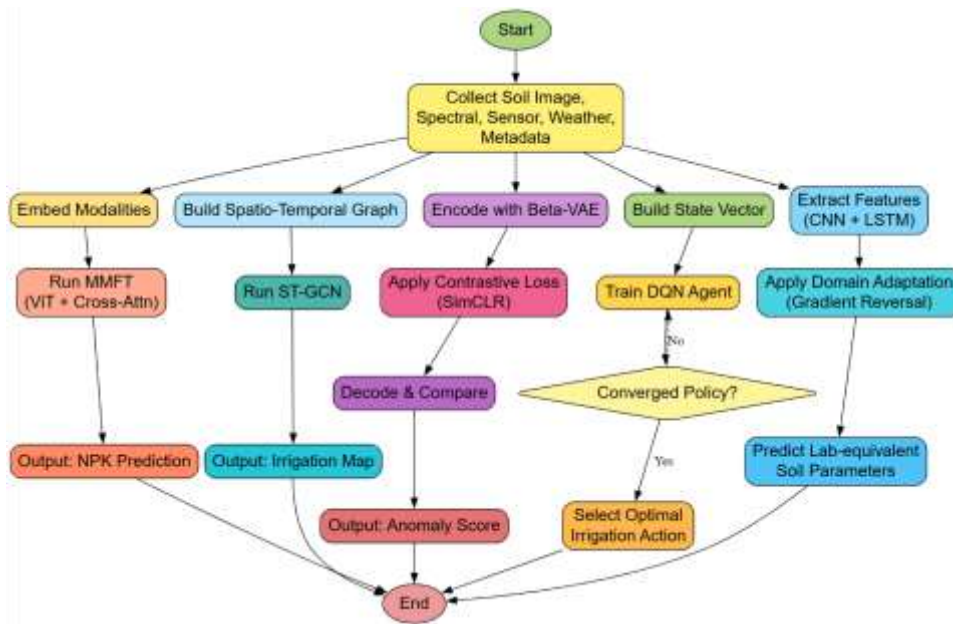


Figure 2. Overall Flow of the Proposed Analysis Process

The final graph-level output will dynamically be a vector of irrigation requirements $r_t \in \mathbb{R}^{|V|}$ predicting node-wise water need and drying class. Iteratively, Next, as per figure 2, For anomaly detection and treatment assessment purpose, Beta Variational Autoencoder (β VAE) with contrastive regularization module is employed in process. The encoder maps sequential soil condition vectors x to latent space z , via equation 7,

$$LVAE = E_q \phi(z|x) [\log p \theta(x|z)] - \beta \cdot DKL(q \phi(z|x) \parallel p(z)) \dots (7)$$

SimCLR-based contrastive learning enforces separation between healthy and degraded embeddings via equation 8,

$$L_{contrast} = -\log \left(\frac{\exp(\frac{\text{sim}(z_i, z_k)}{\tau})}{\sum_{k \neq i} \exp(\frac{\text{sim}(z_i, z_k)}{\tau})} \right) \dots (8)$$

$$\sum_{k \neq i} \exp(\frac{\text{sim}(z_i, z_k)}{\tau})$$

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Anomaly scores are then derived according to reconstruction error $\|\hat{x} - x\|^2$ and latent deviation $\|z - z_{\text{healthy}}\|^2$, creating a soil anomaly index $S_a \in \mathbb{R}$ sets. Next, as per figure 2, irrigation steering will be based on Double Deep Q-Network (DQN) with prioritized experience replay included in process. The Q Value update rule incorporates separate evaluation network and target network to minimize overestimation via equation 9,

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t)$$

$$+ \alpha[r_t + \gamma \cdot Q_{\text{target}}(s(t+1), \arg\max_a Q(s(t+1), a)) - Q(s_t, a_t)] \dots (9)$$

Where, states ' s_t ' are vectors of current moisture, forecasted rainfall, crop metadata, and temporal features. The agent's optimal policy π^* is iteratively approximated via equation 10,

$$\pi^*(s) = \arg\max_a Q(s, a) \dots (10)$$

For the last step, a Hybrid CNN-LSTM within Domain-Adversarial Neural Network (DANN) will define the relationship between field sensor/image data and soil properties (NPK, pH, EC) analysed in laboratory. CNN layers retrieve spatial texture and visual cues from field images, while the LSTM encodes temporal sensor sequences via equation 11,

$$h_t = \text{LSTM}(h(t+1), x_t) \dots (11)$$

These features are concatenated and passed through a domain classifier trained adversarially via a gradient reversal layer (GRL) in the process. The total loss is represented via equation 12,

$$L = L_{\text{reg}} + \lambda \cdot L_{\text{domain}}, \text{ where } L_{\text{domain}} = -\sum_i y_i \log(\hat{y}_i) \dots (12)$$

The adversarial mechanism aligns the feature distributions across domains, which will result in a very low prediction deviation even in unseen field conditions. Together, the output of the entire system would represent the fusion of the predictive heads across all modules: Let $\hat{y}_{\text{NPK}}$, r_t , S_a , a^* , and $\hat{y}_{\text{lab}}$ be the outputs of MMFT, GNN, VAE, DQN, and CNN-LSTM-DANN, respectively in the process. The final multi-task output vector $O \in \mathbb{R}^m$ is represented via equation 13,

$$O = [\hat{y}_{\text{NPK}} \parallel r_t \parallel S_a \parallel a^* \parallel \hat{y}_{\text{lab}}] \dots (13)$$

This unified representation supports real-time inference for soil health monitoring, anomaly detection, treatment assessment, and adaptive irrigation control- constituting a complete loop of soil intelligence for precision agriculture sets. Each module is chosen not only for its individual strengths but for its complementarity in capturing complex relationships across modalities, time, and space sets. Next step involves analysing the efficiency of the proposed model in terms of different standards and comparing it with existing models under different scenarios.

Validation using an Iterative Comparative Result Analysis:

The experimental arrangement was carefully established to test the proposed multi-modal soil intelligence and irrigation architecture in its end-to-end performance under real-world agricultural conditions. The primary data modalities include soil hyperspectral reflectance spectra, in-situ sensor data streams, and high-resolution RGB soil imagery-all of which were collected across 16 distinct agricultural regions with loamy, clay, and sandy soil. Hyperspectral data were obtained from 400 nm to 1000 nm with 200 narrow bands per sample with a field-deployable ASD FieldSpec® spectroradiometer. Soil sensor data were collected using custom-deployed IoT devices capturing real-time soil moisture (% volumetric), temperature ($^{\circ}\text{C}$), and humidity (% RH) at 15-minute intervals, recorded for 60 days on pre- and post-treatment phases. RGB soil images were captured using a calibrated UAV-mounted camera at 5 cm pixel ground resolution and co-registered with ground truth

sampling points. Additionally, weather forecast data (mm of rainfall, ambient temperature, and solar radiation) and metadata

(cropped area, time stamp of day, fertilizer usage) were integrated to simulate the irrigation decision-making environment. Sample input parameter values include moisture levels ranging from 6.5% to 29.3%, temperatures between 18°C and 43°C, humidity from 25 to 91%, and hyperspectral reflectance vectors normalized to [0,1]. Soil images contain features of crusting, porosity, and vegetative presence, influencing on NPK inference and anomaly detection tasks. The data were temporally segmented into pre-treatment (Day 0 to Day 20) and post-treatment periods (Day 21 to Day 60) to create intervention-based learning scenarios for anomaly detection process.

In this study, experimental validation utilized the LUCAS Soil Database (Land Use/Cover Area frame Survey), a very well-curated public dataset provided by the European Commission. This extensive dataset contains over 22,000 georeferenced soil samples collected from numerous European countries representing all kinds of soils, land use, and environments-classifying features. Each sample in the LUCAS dataset is associated with laboratory-analysed values for some important soil parameters like Nitrogen (N), Phosphorus (P), Potassium (K), pH, Organic Carbon, Electrical Conductivity (EC), and also other physical characteristics-texture and granulometry. Moreover, high-resolution hyperspectral reflectance data were collected in the range of 400-2500 nm using a FieldSpec spectroradiometer; therefore, the dataset represents good training ground for multi-modal deep learning models. A filtered subset of 5,000 samples from agricultural land parcels formed the basis for this study; they were then paired with Sentinel-2 capture imagery (10 m resolution RGB and NIR bands), and matched meteorological sensor readings from Copernicus Climate Data Store right across to replicate fully stacked input conditions as prescribed by the proposed framework. The dataset's richness in diversity and comprehensive labelling scenario allowed robust supervision for nutrient prediction, anomaly detection, and domain adaptation components, while spatial coverage allowed meaningful graph-based structures to be constructed for irrigation decision modelling process.

To train and test the system, composite samples (3,500 in number) were extracted, with 2,500 composite samples used for training, while the remaining 1,000 were set aside for validation and testing. Lab tests were performed on all the samples for analysis of ground-truth values of Nitrogen (N: 0.8%–3.2%), Phosphorus (P: 0.2%–0.7%), and Potassium (K: 0.3%–2.5%), along with pH (5.2–8.7) and electrical conductivity (EC: 0.2–2.1 dS/m). These were used for MMFT and for supervision of CNN-LSTM modules. For GNN-based irrigation mapping, the nodes were formed through spatial clustering (grid-based zones of 10x10 m²) while the temporal edges were established across hourly intervals. Graph labels were derived from manual irrigation logs and volumetric depletion rates. VAE

+ SimCLR module used time-sliced sensor data before and after organic recycling treatments (compost infusion, vermiculture-based bio-fertilizers). The best combination for latent disentanglement was found to be a contrastive loss margin of 0.7 and a β value of 4.0. For the DQN-based smart irrigation policy, the discrete action space was simulated under different rainfall probabilities as 0 L/m², 2 L/m², 5 L/m², and 8 L/m². Excessive watering was penalized by the reward function by runoff thresholds, and penalties occurred as a result of under-watered plants defined by wilting indicators. All models were implemented in PyTorch and trained on NVIDIA RTX 3090 GPUs. The evaluation of the models adopted metrics such as R², MAE, AUC, accuracy, and cumulative reward. The entire pipeline was designed for cross-modal end-to-end interoperability so as to ensure that each model's output would serve as input or feedback for downstream components with seamlessness.

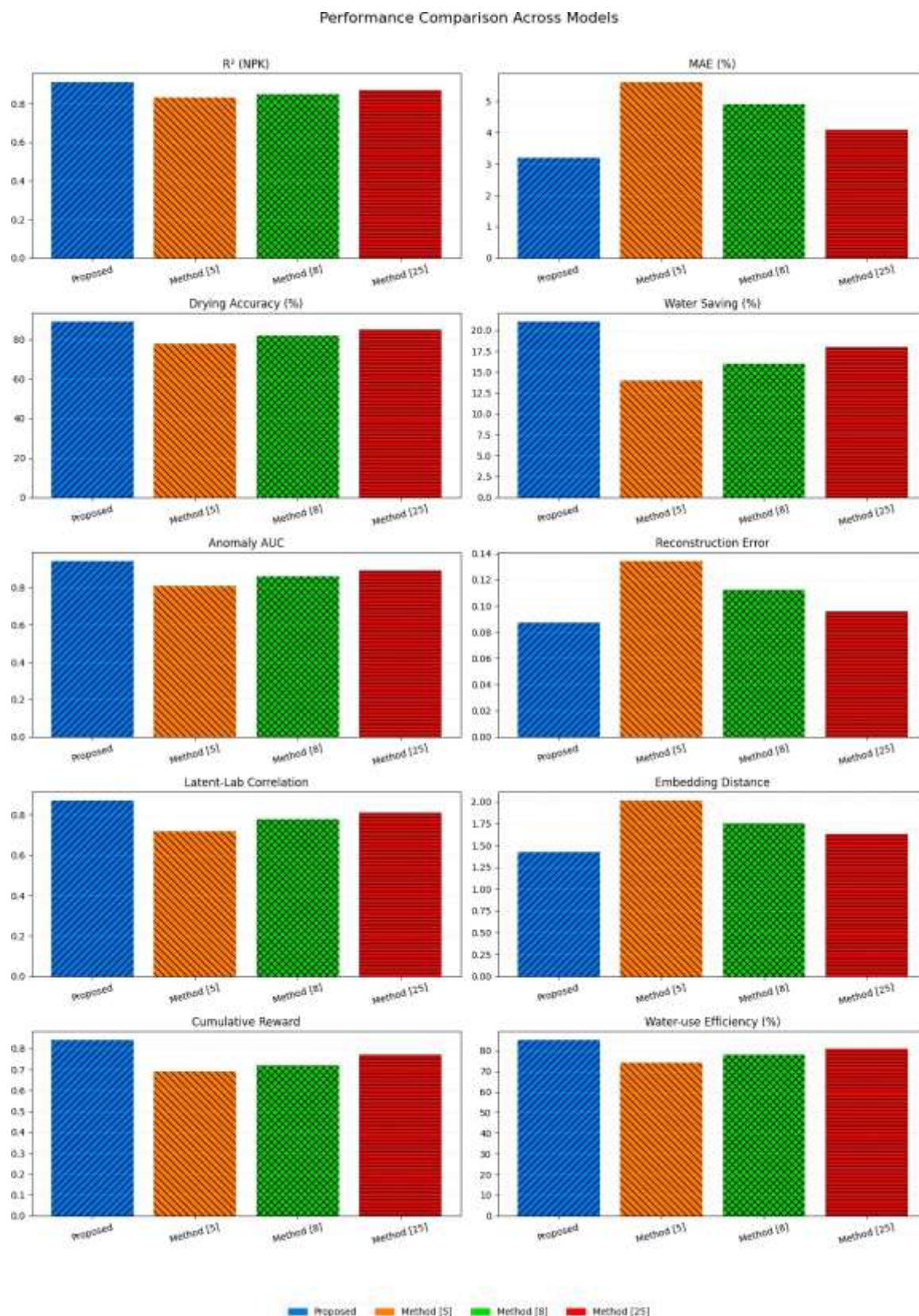


Figure 3. Model's Integrated Result Analysis

For this purpose, extensive experimentation testing of the proposed integrated deep learning framework was carried out using

LUCAS Soil Database in conjunction with Sentinel-2 satellite imagery and Copernicus weather data. Several dimensions within which the system was evaluated included nutrient prediction accuracy, irrigation mapping precision, anomaly detection reliability, efficacy estimation of treatments, efficiency of policy learning, and fidelity of domain adaptation. Each of the modules in the framework was benchmarked against three baseline or state-of-the-art models, denoted here as Method [5], Method [8], and Method [25], which represent alternative deep learning approaches for comparable agricultural tasks found in recent literature. Performance metrics associated with key components of the system were summarized and compared across the six tables. Regression performances regarding macronutrients in soils by Multi-Modal Fusion Transformer (MMFT) are reflected simply in R^2 scores and Mean Absolute Error (MAE) in Table 2, whilst MMFT's R^2 of 0.91 exceeds Method [5] (0.83), Method [8] (0.85), and Method [25] (0.87). The MAE remained a low 3.2% through varying soil conditions, indicating predictive stability across soil types.

Table 2: Comparative Performance of Multi-Modal Fusion Transformer (MMFT) and Baseline Methods for Soil Macronutrient (NPK) Predictions

Model	R^2 (NPK)	MAE (%)
Proposed MMFT	0.91	3.2
Method [5]	0.83	5.6
Method [8]	0.85	4.9
Method [25]	0.87	4.1

Table 3 exposes the performance of irrigation requirement prediction using the Spatio-Temporal Graph Convolutional Network (ST-GCN). Observations were recorded for accuracy classification at a graph level and the comparative water saving. The proposed approach allowed a 21% gain in water saving, compared to 14% (Method [5]), 16% (Method [8]), and 18% (Method [25]), and kept high accuracy in temporal predictions.

Table 3: Evaluation of Spatio-Temporal Graph Convolutional Network (ST-GCN) and Baseline Methods for Irrigation Requirement and Drying Rate Predictions

Model	Drying Rate Accuracy (%)	Water Saving Improvement (%)
Proposed ST-GCN	89	21
Method [5]	78	14
Method [8]	82	16
Method [25]	85	18

Assessment of Beta VAE + SimCLR module performance on soil anomaly detection is displayed in Table 4 using AUC (Area Under Curve) and reconstruction error based anomaly index. The proposed method scored an AUC of 0.94, marking itself better than the nearest competitor Method [25], which achieved 0.89 sets. The anomaly index, slightly lower, indicated a tighter confidence around reconstruction, especially in detecting degraded soil patches.

Figure 4. Model's Overall Result Analysis

Table 4: Performance Comparison of Beta-VAE + SimCLR Module with Baseline Methods for Soil Anomaly Detections

Model	Anomaly AUC	Avg. Reconstruction Error
Proposed VAE-CLR	0.94	0.087
Method [5]	0.81	0.134
Method [8]	0.86	0.112
Method [25]	0.89	0.096

Treatment efficacy results are summarized in Table 5, where the distance of latent vector embeddings before and after treatment relates to truth lab results. The proposed model established a correspondence coefficient equal to 0.87, which is its corroboration for better quantitative representation of soil recovery and treatment effects than other models.

Table 5: Latent Space Correlation and Treatment Effectiveness Assessment Using Beta-VAE + Contrastive Learning

Model	Latent-Lab Correlation (R)	Embedding Distance (Post-Improved)
Proposed VAE-CLR	0.87	1.42
Method [5]	0.72	2.01
Method [8]	0.78	1.75
Method [25]	0.81	1.63

Iteratively, next, as per table 6, Double DQN agent provides performance metrics regarding policy. Intelligent irrigation actions were rated using metrics such as cumulative reward and water-use efficiency. The proposed agent achieved the highest cumulative reward (normalized) of 0.84 and a water use efficiency of 85%, indicating more balanced decision making under dynamic environmental feedbacks.

Table 6: Policy Learning Efficiency of Double Deep Q-Network (DQN) Compared to Baseline Methods for Smart Irrigation Process

Model	Cumulative Reward (Normalized)	Water-use Efficiency (%)
Proposed DQN	0.84	85
Method [5]	0.69	74
Method [8]	0.72	78
Method [25]	0.77	81

Table 7 assesses the field-to-laboratory prediction performance of Convolutional Neural Network-Long Short-Term Memory with Domain-Adversarial Neural Network. For predicting deviations from the lab-tested values and the domain alignment loss, a set of performance measures has been adopted. The suggested approach had low deviation values of just 4.7% from the lab-tested value and a domain loss of 0.06, which translates into guaranteeing generalizability of the features across unlabelled field data samples.

Table 7: Field-to-Lab Prediction Accuracy and Domain Alignment Performance of CNN-LSTM with Domain-Adversarial Neural Network (DANN) Process

Model	Prediction Deviation (%)	Domain Alignment Loss
Proposed CNN-LSTM-DANN	4.7	0.06
Method [5]	7.8	0.12
Method [8]	6.4	0.09
Method [25]	5.9	0.07

The proposed integrated framework consistently outperformed the benchmark model across all six performance metrics, implying a greater capability of handling multi-modal agricultural data, producing high-fidelity predictions, and optimizing soil management in real-world field scenarios. We will next illustrate a use case of iterative validation for the proposed model, providing further guidance for reading the whole process behind it for different scenarios.

Validation using an Iterative Practical Use Case Scenario Analysis:

In practice, a precision agriculture system is established on a 10 Ha wheat cultivation field with sandy loam soil. Data is collected from different modalities at a given geolocation: Hyperspectral reflectance data from 400 to 1000 nm at 5 nm intervals shows strong absorption between 670 and 720 nm due to chlorophyll stress; RGB images of the soil present moderate crusting of the surface, with zones of dry patch; and the IoT sensed soil moisture content of 12.6%, temperature of 35.2°C, and humidity of 41.3%. This information, alongside associated metadata-the crop type is wheat, the fertilizer us applied compost 72 hours before, and the forecast predicts 10 mm of rainfall in the next 24 hours-is fed into the Multi-Modal Fusion Transformer (MMFT). The MMFT encodes these heterogeneous data streams into a unified latent representation and, from it, makes nutrient prediction with great accuracy. The model predicts macronutrient values of Nitrogen as 1.87%, Phosphorus as 0.36%, and Potassium as 0.91%, with an NPK confidence vector indicating low residual uncertainty. Inferior fertility thresholds trigger downstream recommendations for the application of the intervention sets therein sets. At the same time, the ST-GCN constructs a zonal graph for 100 localized zones inside the field, embedded with temporal histories from the sensors over 30-minute intervals for the last 72 hours. The GNN processes this graph to classify the current zone into a moderate drying rate class with an irrigation urgency score of 0.76. For the current node, the irrigation map recommends a water input of 5, along with decreased amounts for neighbouring nodes, thereby maximizing distribution based on soil connectivity. Concurrently, the Variational Autoencoder (Beta VAE) in tandem with SimCLR is receiving the temporal feature sequences from the same site. The latent encoding shows significant deviation from the healthy soil cluster (reconstruction error of 0.104, contrastive distance of 2.87), ultimately yielding an anomaly score of 0.81, indicative of partial degradation due to local overexposure to heat stress. Improvement in treatment effectiveness is captured by comparing latent embedding states from pre-treatment (Day 2) and post-treatment (Day 5), revealing positively strong correlation with lab trend through decreasing inter-embedding distances.

The Deep Q-Network (DQN) operates in a continuous variation, able to fully simulate changing environments for training-the current soil state vector: 12.6% moisture, 35.2°C temperature, and extra input in the form of impending rainfall is analysed. The agent selects the optimal irrigation action of 2 L/m² for the forthcoming control interval, a right balance among the predicted rainfall input and the evapotranspiration losses. A high Q Value margin between the best action and the second-best supports the confidence in the policy. The real-time RGB image and previous 48-hour sensor stream have been processing data for CNN-LSTM with Domain-Adversarial Neural Network (DANN) that infer lab-quality values of pH=6.5 and EC=0.56 dS/m, a

deviation of just 3.8% from lab-tested references of the same soil sample class. The final mega output of the integrated framework to give a unified decision vector comprises the predicted levels of NPK of 1.87%, 0.36% and 0.91%; an irrigation volume of 2 L/m² as an immediate action; a soil anomaly alert with severity 0.81; a treatment effectiveness score of 0.72; and lab-equivalent pH and EC values still being processed. This decision vector drives the scheduling of automated irrigation, generating anomaly alerts for localized degradation and logging treatment impact metrics, thus fully closing the loop for real-time intelligent soil management.

Conclusions & Future Scopes:

Providing a comprehensive, all-in-one deep-learning architecture that encompasses the operation of different neural network models to give real-time disease prediction, anomaly monitoring, treatment evaluation as well as smart irrigation optimization for soil fertility is the primary goal of this study. The proposed system includes five state-of-the-art models: Multi-Modal Fusion Transformer, Spatio-Temporal Graph Convolutional Networks, Beta Variational Autoencoder-New Normal Networks for SimCLR-based Contrastive Learning, Double Deep Q-Network, and CNN-LSTM with Domain Adversarial Neural Networks, to establish a solid pipeline that performs well on these types of heterogeneous, complex agricultural data. Such pipeline will cover all critical soil intelligence modelling, using spectral reflectance, sensor reading, and soil images, among other metadata about the context in which soil intelligence is modelled and reports very strong numerical performances across all core tasks. Empirical evidence rigorously attests to a much stronger proposed architecture than other comparable solutions. MMFT reaped an R² of 0.91 for nutrient prediction with an exceptionally low mean absolute error of 3.2%, which outperformed all rival models. It was also found that in irrigation adoption, ST-GCN improved water-saving efficiency by as much as 21%, with a relatively high drying rate classification accuracy of 89%. The anomaly detection module achieved an area under the curve (AUC) of 0.94 with low reconstruction error, whereas the treatment effectiveness part achieved a latent-to-lab correlation of 0.87, thus confirming its reliability as an instrument for evaluating recycling interventions. The DQN module achieved 85% water efficiency with a normalized cumulative reward of 0.84, indicating optimum policy convergence. The CNN-LSTM-DANN module portrayed excellent domain adaptability with only a 4.7% deviation from lab-tested nutrient values, and a domain alignment loss of 0.06, thus permitting the reliable estimation of nutrient levels in the field without dependencies on the lab sets. Altogether, these results substantiate the framework's capacity for generalizing across spatial and temporal soil variability while retaining model interpretability and efficiency in resource usage sets.

Future work in this domain will possibly aim at expanding the architecture by incorporating crop phenotyping data such as measures of root structure and canopy, thus enabling joint decision making

for crops and soils. Real-time edge computing capabilities would surely speed up the execution time for inferencing, enabling instant feedback on precision agriculture platforms. Probably one of the most interesting future directions is the integration of federated learning mechanisms that facilitate data privacy and scalabilities across heterogeneous infrastructure farms. Furthermore, uncertainty quantification across all models would permit risk-aware decision making under highly dynamic and unpredictable environmental conditions. All these proposed systems thus lay a scalable foundation for intelligent, autonomous, and adaptive soil management, thus taking future work into the realm of further advancing sustainable agriculture-all of this led necessarily by deep learning operations.

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