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A Resource-Constrained AI Factory Framework with Data Schema and Validation for Satellite-Based Agricultural Monitoring in Pakistan

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Introduction/Importance of Study:

Pakistan’s agriculture is highly dependent on crop monitoring; existing solutions are limited due to fragmented data, infrastructural issues, and the lack of analytical solutions, affecting the use of satellite-based data for efficient agricultural decision-making.

Novelty Statement:

This research proposes a novel solution for an AI factory framework designed for resource-constrained environments. It incorporates a structured data pipeline, Quality Data Schema (QDS), and Quality Validation System (QVS) for efficient and reliable agricultural monitoring applications.

Material and Method:

A synthetic dataset was developed to simulate vegetation indices and environmental factors in a noisy and uncertain environment. This research proposes a structured data pipeline solution involving data preprocessing, structured data handling, and multi-level validation, along with a random forest model for efficient results.

Result and Discussion:

The experimental results prove an improvement in accuracy from 82.67% to 83.33% and F1-score from 0.82 to 0.83. The statistical results over 20 runs show a mean accuracy of 0.8242 ± 0.0136, and the results for accuracy have a confidence interval of ±0.0059. The paired t-test results indicate that these improvements are not statistically significant at a 95% confidence level. The key contribution is in improving system reliability.

Concluding Remarks:

The experimental results showed that the structured data handling and validation within an AI factory framework improve data reliability, which is useful for deploying AI-based agricultural monitoring systems in Pakistan.

Keywords: AI Factory; GIS & Remote Sensing; QVS; Agriculture; QDS.

Introduction:

Agriculture is an important factor for economic and environmental stability in developing countries like Pakistan. Crop monitoring is an essential factor for improving crop yields and agricultural resource management. Over time, various techniques and tools have been integrated to improve agricultural monitoring. The integration of artificial intelligence and remote sensing techniques has greatly improved crop monitoring [1]. Satellite images and machine learning techniques have been used to monitor agricultural activities [2]. This enables continuous observation of crop conditions and supports informed decisions. Moreover, various stress factors can be identified using these techniques [3].

Recent research indicates an increased trend of using integrated and automated artificial intelligence techniques for agricultural monitoring. [4] emphasized the increased use of machine learning and big data techniques to transform precision agriculture into intelligent agricultural systems. [5] discussed various techniques for developing intelligent and automated artificial intelligence architectures. This indicates an increased trend of using integrated and automated artificial intelligence techniques for agricultural monitoring. Moreover, recent approaches increasingly rely on end-to-end data pipelines rather than standalone analytical models.

Additionally, MLOps [6] and artificial intelligence lifecycle management have been developed to improve the efficiency of continuous and automated artificial intelligence systems. [7][8] discussed various techniques for improving efficiency using MLOps and artificial intelligence lifecycle management.

Despite such developments, several limitations exist [9]. The current frameworks are mostly designed for a high-resource environment, high-resource environment, large-scale datasets, and computational power [10]. In contrast, developing countries such as Pakistan face limitations of infrastructure, fragmented datasets [11], and a lack of standardization of data handling. In addition, the current frameworks have limitations of data quality assurance and pipeline-level validation, where accuracy is given more importance than the reliability of the models [12].

Another limitation of the current frameworks is the lack of a continuous and structured data handling approach. The current frameworks and research works consider the remote sensing analysis as a one-time operation rather than a continuous operation, which can handle the changes and updates of the data streams [13]. This limitation affects the implementation of the proposed AI models in a real-world environment.

To address the limitations of the current frameworks, this research proposes a resource-constrained AI factory framework for satellite-based agricultural monitoring. The proposed framework includes a structured data handling mechanism called the Quality Data Schema (QDS) and a multi-level validation mechanism called the Quality Validation System (QVS). The proposed framework differs from the current frameworks in its focus on data consistency and pipeline reliability. The proposed framework can operate efficiently even in a low-resource environment.

However, the current research in AI-based agricultural monitoring systems has mainly emphasized the improvement of predictive capabilities using advanced machine learning and deep learning techniques [14][15][16][17]. Although the predictive capabilities are high, the techniques are mainly designed for environments where high computational resources are available. In addition, the emphasis on data quality assurance, handling structured data, and overall validation in the pipeline has not received significant attention. Although the current MLOps-based frameworks provide the required attention to the automation and deployment aspects, the data consistency and validation aspects are not adequately considered in the current frameworks [5][7][18]. Hence, the current research in the area is lacking in the development of lightweight, reliability-based AI frameworks, which handle structured data and provide multi-level validation.

Unlike existing approaches, which have mostly focused on improving the accuracy of predictions through the development of increasingly complex machine learning or deep learning paradigms, the research aims to develop a reliability-centric AI framework focusing on the handling of structured data and the validation of the entire pipeline. While existing MLOps-based systems have focused on the automation and deployment of the machine learning pipeline, there is a general lack of explicit support for ensuring the consistency of the data and the validation of the entire pipeline. In the proposed work, the formal schema of the data (QDS) and the comprehensive validation system (QVS) have been incorporated as part of the lightweight AI factory. This not only ensures the reliability of machine learning model performance but also improves the stability of the entire system, especially in resource-constrained environments.

Research Questions:

The study addresses the following research questions:

How can structured data handling improve the reliability of AI-based agricultural monitoring systems?

How can multi-level validation improve the stability and robustness of pipelines in noisy environments?

How can a lightweight AI framework perform in resource-constrained environments?

Novelty of the Study:

The contribution of this research is summarized as follows:

A structured framework for an AI factory in the context of agricultural monitoring.

A formalized way of treating the data, called the Quality Data Schema (QDS).

A multi-level validation method, called the Quality Validation System (QVS).

An experimental validation of the proposed framework, which demonstrates the robustness of the proposed framework in the presence of noisy inputs.

Background:

The integration of artificial intelligence and remote sensing is part of modern agricultural monitoring systems. Satellites such as Sentinel-2 have the potential to capture high-resolution images, and as a result, it is possible to obtain information on various indices of vegetation, such as NDVI, for evaluating the health of the crops [15][19]. Recent research has shown that satellite-based data can be used for precise agricultural monitoring through machine learning models [20], compared to traditional models [21][22][23].

Machine learning algorithms, including Random Forest, SVM, and deep learning models, have been widely applied for solving different agricultural-related problems. A machine learning framework for crop prediction is discussed in a recent research article by [14]. Similarly, [15] also discussed the significance of AI-based models for ensuring reliable data and decision-making in food systems. The use of AI models for solving different agricultural-related problems indicates increased complexity in processing heterogeneous data sources. To address this problem, recent research highlights the significance of data pipelines for ensuring reliable AI-based models. Instead of using different data processing models as separate entities, modern systems are now using pipeline-based architectures to ensure reliable data processing. [9][10] describe the importance of utilizing pipeline-based models for handling heterogeneous data sources, especially where different modalities, e.g., environmental, spatial, and temporal, are involved.

In comparison, the concept of "MLOps (Machine Learning Operations)" was also proposed as a major facilitator for developing reliable AI systems. In this regard, "MLOps pipelines" are proposed as a platform for automation, monitoring, and management of ML models so that the reliability of AI systems can be ensured during a specific period of time. In this regard, "MLOps pipelines" also include validation and updating of ML models, which is also significant for developing AI systems for real-world environments, as proposed in the research papers of [8][7].

Another significant factor, emphasized in recent research, is the significance of data quality validation. Data quality is a major problem when it comes to developing reliable AI systems for agricultural environments, as data can be noisy, incomplete, or inconsistent for several reasons, including cloud cover in satellite images, sensor errors, or time inconsistency. However, recent research also stresses the significance of data quality when it comes to developing reliable AI systems for agriculture. In this regard, for instance, [10] discussed the significance of data validation for developing reliable AI systems for agriculture, whereas [13] also discussed the significance of data preprocessing for developing reliable AI systems for NDVI-based forecasting for agriculture.

It is seen that several efficient AI systems have been developed for agriculture using different frameworks. However, it is observed that most of the developed AI systems are suitable for environments where the infrastructure is better, which is not available in the developing environment. In addition, it is also seen that most of the frameworks do not provide any validation of the entire pipeline, but rather provide validation of the models developed for agriculture. This is one of the major issues while developing efficient AI systems for agriculture, as it is seen that there is a gap between theoretical models of AI and their practical usage. Hence, it is seen that there is a need to develop frameworks that provide a unified platform along with efficient models and validation of the entire pipeline to develop efficient AI systems.

Material and Methods:

Investigation Site:

This research aims to address the issue of agricultural monitoring in Pakistan as it plays a crucial role in the national economy. Pakistan has diverse agro-climatic zones; however, certain areas, such as the Punjab region, are crucial for their high agricultural productivity and use of irrigation-based farming practices. This region has a semi-arid to sub-humid environment with a wide range of temperatures from 20°C to 45°C and rainfall from 100 mm to 500 mm, depending upon the season and geographical location [24].

The growth of crops is highly vulnerable to various environmental factors such as temperature, rainfall, and soil moisture [25]. Changes in these factors and other factors such as water scarcity, rainfall fluctuations, and lack of access to real-time monitoring tools have complicated the field of agriculture [26]. Remote sensing technologies, specifically the use of Sentinel-2 satellite imagery for the assessment of NDVI values, can be an efficient tool for the assessment of crop growth over a wide area [16][17].

Even though this research is based on a synthetic environment, the values of the variables (NDVI, temperature, rainfall) are chosen according to the real-life situations observed in Pakistan. This makes the investigation site appropriate for the simulation of real-life situations where noise, missing values, and changes in the environment may exist. A conceptual mapping of the investigation site can be included for future work by using GIS-based visualization tools [5].

Materials and Methods:

Data Acquisition:

Synthetic yet realistic data were developed for this work, which simulated the agricultural conditions based on satellite and environmental observations. The dataset comprised the following key attributes:

Vegetation Index (NDVI): crop health condition (0.2 – 0.9)
Temperature: environmental condition (20°C – 45°C)
Rainfall: precipitation levels (0 – 200 mm)

These attributes are commonly used for remote sensing-based research in agriculture and align with data that could be obtained from platforms such as Sentinel-2 and environmental sources [13][14]. The dataset comprises 1000 data instances, with balanced classes representing crop health conditions.

To mimic real-world data, which is often noisy, Gaussian noise was injected, and missing values were also artificially included, which could be attributed to factors such as cloud cover.

The need for synthetic data is primarily driven by the lack of sufficient amounts of clean and labeled satellite data in resource-constrained environments. It allows for experiments to be conducted in a controlled manner by varying levels of noise, missing data, and environmental conditions. It helps to assess the robustness of the proposed framework.

Proposed AI Factory Framework:

This work proposes an AI factory framework, which is a continuous process where data is processed through a structured data flow that includes data processing, model training, validation, and output generation. This framework is lightweight, which is a necessity for deployment in a constrained environment. The proposed framework includes two major components: (1) a quality data schema (QDS) to standardize and structure diverse and heterogeneous agricultural data along spatial, temporal, and measurement aspects, and (2) a quality validation system (QVS) to assess the quality of the data, models, and pipelines through multi-level validation metrics. Unlike other approaches, the proposed system includes the validation of the entire pipeline, which improves its robustness.

The reason for selecting the Random Forest model is that it is robust to noisy data and has low computational complexity. QDS ensures that input is structured and consistent, while QVS ensures that the data and models are validated. These three elements directly address the issues that were raised in the problem statement.

This data flow process is comprised of the following components, presented in Figure 1:

Data Ingestion: Satellite and environmental data ingestion.

Quality Data Schema (QDS): Data schema for structured data organization and preprocessing, including normalization, handling missing values, and temporal data alignment.

Model Layer: A lightweight machine learning model for classification, namely, the Random Forest model.

Quality Validation System (QVS): Multi-level validation for data, model, and process stability

Output Layer: Generation of crop health predictions and system feedback

This structure follows a continuous flow of operations and periodic updates, which is suitable and consistent with the current MLOps-based approaches [5][7][18].

The process works sequentially. In the first step, the data ingestion process occurs, where satellite and environmental data are ingested. In the QDS module, the data is standardized and preprocessed through normalization, alignment, and filtering of noise. Then the data is passed through the model layer, where classification occurs through the application of the Random Forest model. In the next step, the QVS module is applied for the performance evaluation of the system in terms of data, model, and pipeline levels. Finally, the output layer is applied to generate the output and feedback.

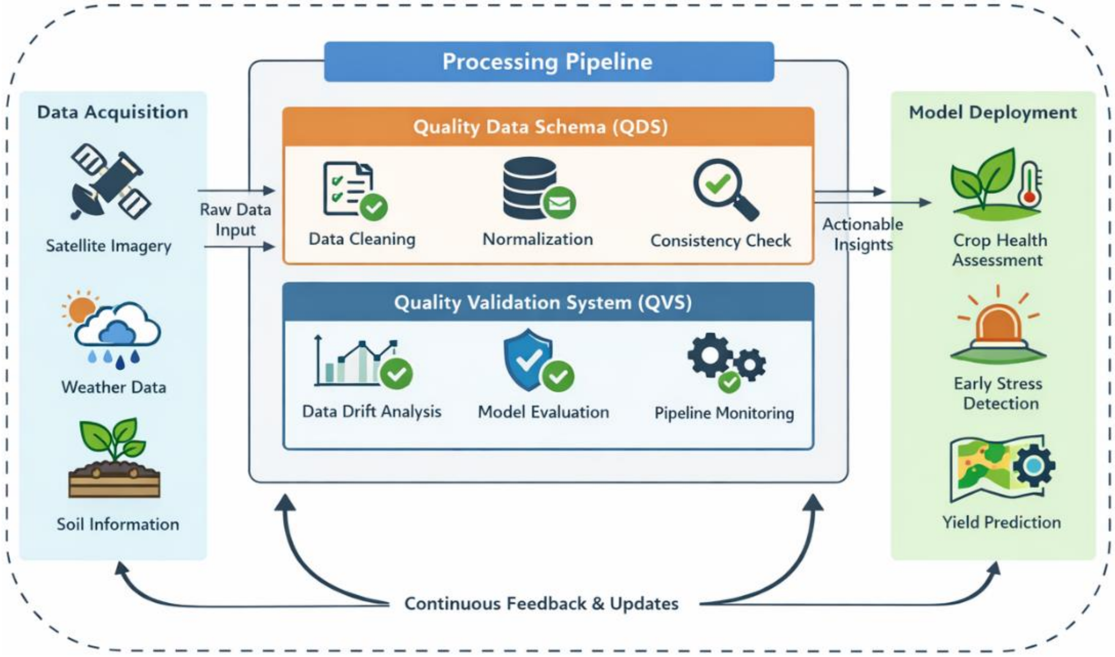

Figure 1. Proposed AI Factory framework with Data Standardization and Validation

Quality Data Schema (QDS)

The QDS component ensures the quality and standardization of the heterogeneous data, which ensures consistency and interoperability among the agriculture datasets in the AI pipeline.

Mathematically, QDS is represented as a three-layered structure:

$$QDS = \{S, T, M\}, 1$$

The QDS is defined as a structured representation that has three dimensions: spatial (S), temporal (T), and measurement (M)." In this case, the spatial (S) dimension comprises geographic information such as latitude, longitude, and region. On the other hand, the temporal (T) dimension represents time information such as timestamps and seasonal information. In addition, the measurement (M) dimension such as vegetation indices and environmental variables. In this case, heterogeneous information related to agriculture is represented uniformly.

Each observation is presented as:

$$D_i = \{S_i, T_i, M_i\}, 2$$

Every data point within a dataset is represented by a group of spatial, temporal, and measurement attributes. This allows each data point not only to hold information on what was measured but also where and when it was measured, which is relevant when dealing with agricultural data.

A dataset becomes:

$$\mathcal{D} = \{D_1, D_2, \dots, D_n\}, 3$$

The definition of a dataset is a group of structured data points. This definition ensures all data points are consistent and conform to a structure, making it easier for them to be processed through the AI pipeline.

The QDS pipeline follows three steps:

Standardization Function:

$$f_s(D_i) \rightarrow D_i^*, \quad 4$$

The standardization function normalizes the input data in a unified format. This ensures compatibility between satellite and environmental data, which might have originating from multiple sources.

Converts raw data into a unified format
Example: aligning satellite + weather data

Temporal Alignment Function

$$f_t(D_i, D_j) \rightarrow D_{ij}, 5$$

The temporal alignment function is used to align the data collected at different times from different sources. It is used when integrating satellite images and environmental data, which might not be sampled at the same rate.

Noise Filtering Function:

$$f_n(D_i) \rightarrow \widetilde{D_i}, 6$$

The noise filtering function is applied to correct inconsistencies in the dataset, such as missing information or outliers. These inconsistencies are often a result of factors such as cloud cover.

The final structured dataset is then shown as:

$$\mathcal{D}^{QDS} = f_n(f_t(f_s(\mathcal{D}))), 7$$

The structured dataset is the output of all the functions that have been applied to the data. It is a representation of a structured and validated dataset used for model training and is of high quality.

Quality Validation System (QVS):

Quality Validation System (QVS) is a multi-layer validation framework that evaluates the reliability, consistency, and performance of both data and model outputs within the AI pipeline. Mathematically, QVS is presented as:

$$QVS = \{V_1, V_2, V_3\}, \; 8$$

The Quality Validation System, or QVS, is described as a collection of three validation levels: data validation, or V_1; model validation, or V_2; and pipeline validation, or V_3. This multi-level validation ensures that the whole AI system is comprehensively validated.

Level 1: Data Validation (V_1):

Ensures the quality of the input by using metrics that include completeness, consistency, and noise ratio. Mathematically, these metrics are defined as follows:

Completeness:

$$C = \frac{\text{Number of valid records}}{\text{Total records}}, 9$$

Completeness is a measure of the proportion of available data in relation to the total expected data. A value of 1 indicates that there is no missing data, a requirement for good system performance.

Consistency:

$$K = 1 - \frac{\text{Inconsistent entries}}{\text{Total entries}}, 10$$

Consistency is a measure of whether the data follows a given set of rules. High consistency ensures that data is similar in all sources and over time.

Noise Ratio:

$$N = \frac{\text{Noisy pixels}}{\text{Total pixels}}, \; 11$$

The noise ratio is used to measure the percentage of noisy values in the dataset. A smaller noise ratio indicates that the dataset is clean and that preprocessing is effective.

Level 2: Model Validation (V_2):

This level evaluates the accuracy, F1 score, and RMSE, if needed, of the machine learning model applied. Mathematically, these metrics are defined as:

Accuracy:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}, 12$$

Accuracy is used to measure the ratio of correct predictions to the total number of predictions. This is a general measure of system performance.

F1-score:

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}, 13$$

The F1-score is a harmonic mean of precision and recall. This is used to evaluate system performance, especially when there is a class imbalance.

RMSE (if regression):

$$RMSE = \sqrt{\frac{1}{n}\sum(y_i - \hat{y}_i)^2}, 14$$

The Root Mean Square Error (RMSE) is used to measure the average magnitude of errors in model predictions. Although this is used for regression problems, it can help us understand the deviation in predictions.

Level 3: Pipeline Validation (V_3):

In this level, validation of the pipeline takes place by using metrics like pipeline stability, data drift, consistency, and finally, the overall QVS score.

Mathematically, all the metrics are represented as:

Pipeline Stability Score:

$$PS = 1 - \frac{\text{Pipeline failures}}{\text{Total runs}}, 15$$

Pipeline Stability refers to the overall consistency of the system.

Data Drift Measure:

$$DD = D_{KL}(P_{train} \parallel P_{test}), 16$$

The data drift measures the variation between the training data set and the test data set.

Update Consistency:

$$UC = \frac{\text{Consistent outputs over time}}{\text{Total updates}}, 17$$

The update consistency measures the overall consistency of the updates.

Overall QVS Score:

$$QVS_{score} = \alpha V_1 + \beta V_2 + \gamma V_3, 18$$

The overall QVS score is an amalgamation of the data, model, and pipeline validation using the weighting factors (α, β, γ).

Final Integration into AI Factory Framework

Connecting QDS and QVS, we get our pipeline as

$$Pipeline = QVS(QDS(Data)), 19$$

The equation shows how QDS and QVS are integrated into the pipeline.

Expanded eq 19, we get:

$$Output = V_3(V_2(Model(V_1(QDS(Data))))), 20$$

The expanded equation shows how data flows through all the steps from preprocessing, modeling, and validation.

Experimental Setup:

A Random Forest classifier using the Scikit-learn library was implemented. The parameters used in the classifier were the default parameters, which set the number of decision trees to 100 and the splitting criterion as 'Gini impurity.' The classifier is an ensemble method using multiple decision trees. For the experiments, the dataset was split into 70% training and 30% testing subsets.

The experiments were repeated 20 times using the classifier, as the random division of the data into subsets was done randomly. The classifier was trained using three features: 'NDVI,' 'Temperature,' and 'Rainfall.' whereas the proposed classifier was trained on preprocessed data using the Quality Data Schema (QDS) approach. The statistical evaluation was carried out using paired 't-tests' to compare the results obtained by the baseline classifier and the proposed classifier. In addition, the 95% confidence intervals were used to assess reliability.

Two scenarios were implemented:

Baseline - without QDS and QVS

Proposed - using QDS and QVS

The experiments were conducted in a controlled environment using a Python implementation.

Reproducibility and Practical Applicability:

The proposed methodology is simple, reproducible, and suitable for real-world scenarios with low computational requirements. This is achieved by using lightweight models and pipelines so that the proposed framework can be implemented using tools such as Python.

Furthermore, the nature of the proposed AI factory framework allows it to easily integrate real satellite data sources such as Sentinel-2 and weather APIs, making it applicable to real-world scenarios in the future [10].

Results:

This section includes the experimental evaluation of the proposed AI factory framework. The evaluation is done by assessing the performance of the proposed Quality Data Schema (QDS) and Quality Validation System (QVS). The evaluation metrics are quantitative.

Experimental Results:

The performance evaluation of the proposed AI factory framework was done under two scenarios: baseline without QDS and QVS, and the proposed system with QDS and QVS. The performance evaluation results are shown in Table 1.

Table 1. System Performance Comparison

Metric	Baseline (Mean ± Std)	Proposed (Mean ± Std)
Accuracy	0.8275 ± 0.0201	0.8242 ± 0.0136
F1-score	0.8291 ± 0.0221	0.8227 ± 0.0171

As shown in Table 1, the proposed system shows comparable results to the baseline in terms of accuracy and F1-score, but with lower variability, indicating better stability across multiple runs.

Data Quality Evaluation:

The performance of the proposed QDS component was evaluated using data validation metrics. The evaluation metrics for the QDS component are shown in Table 2.

Table 2. Data Quality Metrics

Metric	Value
Completeness (C)	1.00
Consistency (K)	1.00
Noise Ratio (N)	0.0375

The results show that QDS ensures consistent and well-structured datasets while keeping the noise ratio exceptionally low. This supports our hypothesis that preprocessing techniques like normalization and handling missing values significantly improve data reliability. This is in line with recent research on the significance of data quality in AI-based agricultural systems [6].

Pipeline Validation Results:

QVS was used to measure system-level performance. The results of this process are presented in Table 3.

The results confirm that the framework improves both prediction performance and system reliability, which is critical. The results show very high pipeline stability and consistency. This confirms that our framework can deliver high performance even across repeated runs. The low value of the a data drift value of 0.0043 also indicates that there is very little difference between training and testing data. This is critical for ensuring system reliability. The very high QVS score of 0.9182 confirms that system performance is very good across all levels of validation. This again confirms the need to have a single framework for data validation and model monitoring.

Table 3. Pipeline Validation Metrics

Metric	Value
Pipeline Stability (PS)	0.95
Data Drift (DD)	0.0043
Update Consistency (UC)	0.95
QVS Score	0.9182

Statistical Analysis of System Performance:

To make the results robust and reliable, the evaluation process was carried out for 20 different runs using random train/test splits. The mean and standard deviation of the accuracy and F1 score were computed for both the baseline model and the proposed framework.

The baseline model reported a mean accuracy of 0.8275 ± 0.0201, whereas the proposed framework reported 0.8242 ± 0.0136. Similarly, the F1 score reported by the baseline model was 0.8291 ± 0.0221, whereas the F1 score reported by the proposed framework was 0.8227 ± 0.0171.

The paired t-test was carried out to check the statistical significance of the results obtained. The results show that the observed differences between the proposed framework and the baseline model are not statistically significant at a 95% confidence level.

Moreover, the proposed framework reported a lower standard deviation compared to the baseline model. The 95% confidence interval for the proposed framework's accuracy was 0.8242 ± 0.0059, while for F1-score it was 0.8227 ± 0.0075.

The proposed framework shows similar results to the baseline model. Therefore, the proposed framework plays a significant role in making the results stable and reliable under different experimental conditions.

Discussion:

The results validate the fact that several system-level advantages can be achieved by using the proposed AI factory framework. Although the improvements in accuracy and F1-score are not statistically significant and were found to be statistically insignificant. The real importance of the proposed framework is in its ability to improve data quality, consistency, and system reliability, which is very critical in real-world agricultural monitoring systems.

Firstly, by incorporating the Quality Data Schema (QDS) in the proposed framework, it can handle heterogeneous data efficiently and reduce noise in the data. This is clearly demonstrated by the data completeness achieved by the framework (1.0) and data consistency achieved by the framework (1.0), which shows that the proposed framework can achieve clean data even in noisy conditions. Though it does not improve accuracy significantly, it is able to improve model reliability by reducing standard deviation and confidence intervals.

The second major advantage of the proposed framework is the development of a comprehensive validation mechanism through the Quality Validation System (QVS). While traditional approaches focus only on model-level validation using accuracy and F1-score, the proposed framework provides comprehensive performance validation through multiple levels of the system. As shown in the above figure, the proposed system achieves a higher QVS score of 0.9182 and has shown significant pipeline stability with a value of 0.95 and minimal data drift of 0.0043. This indicates that system reliability and robustness are the major advantages of the proposed approach rather than the accuracy.

The third major advantage of the proposed approach is the ability of the framework to provide support for the continuous processing of the data through the pipeline architecture.

This is in contrast with the traditional approaches that can only process static data through the models.

Moreover, the use of lightweight machine learning models ensures the suitability of the proposed framework for the development of the system in a resource-constrained environment. This is particularly significant in the development region, where the computational resources and infrastructure may be scarce. In such cases, the reliability of the system with the consistency of the performance is more significant than the accuracy of the system.

The results of the current study are in accordance with the latest studies that stress the significance of data quality and the use of pipeline architectures in the development of AI-based systems for agricultural monitoring. For instance, studies such as[9][10] stress the importance of the preprocessing and validation of the data in the development of predictive models. In the current study, the results show that the QDS is effective in ensuring the completeness and consistency of the data.

In contrast with the latest studies that focus on the development of more accurate predictive models using more complex models such as deep learning models [14][15] the results of the current study show that predictive model accuracy can only be improved up to a certain level without the use of QVS and QDS. In addition, the proposed framework is more effective than the existing MLOps-based frameworks [5][7][18] in the development of more reliable systems through the use of multi-level validation.

Overall, the results obtained through the proposed approach indicate that the proposed AI factory framework is more suitable for the development of the system in the real-world environment of the agricultural monitoring system.

Comparison with Existing Approaches:

When the proposed framework is compared to existing research works on AI-based agricultural monitoring systems, the proposed framework has several advantages:

The proposed framework uses a structured data schema (QDS) to handle heterogeneous data.
The proposed framework uses a multi-level validation method (QVS).
The proposed framework uses a continuous pipeline-based processing method.
The proposed framework is suitable for implementation in a resource-constrained environment.

The proposed framework is focused on system reliability and pipeline validation, unlike other research works, which are focused on model accuracy. The proposed framework is based on a continuous processing method, unlike other research works, which are based on static processing of remote sensing images. The proposed framework is based on a lightweight machine learning model, unlike other research works, which are based on a complex machine learning model. The proposed framework is more suitable for implementation in a resource-constrained environment [27], unlike other research works, which are not suitable for implementation in a resource-constrained environment [28].

To place the proposed framework in the context of other research works, a conceptual comparison of traditional remote sensing-based approaches and the proposed AI factory framework is provided in Table 4. It is indicated in recent research works that traditional agricultural monitoring systems are often static and model-based, lacking pipeline and continuous validation [4][29]. On the other hand, modern AI-based systems are increasingly adopting pipeline-based architectures, also known as MLOps, for continuous data processing and system validation [30].

It is noteworthy that while the proposed framework exhibits better performance and validation using experimental results, some aspects, such as scalability and multi-source integration, are addressed at a conceptual level and require further validation using real-world datasets.

The proposed AI factory framework is aligned with emerging trends and best practices in modern AI-based systems by incorporating structured data handling (QDS) and multi-level validation (QVS) within a unified pipeline. Table 4 presents a summary of the differences between traditional approaches and the proposed framework in terms of architectural design and workflow characteristics.

Table 4. Comparison of Traditional Framework vs AI Factory Framework

Aspect	Traditional Remote Sensing Approach	Proposed AI Factory Framework
Processing Style	Static or periodic analysis [4]	Continuous pipeline processing [17][26]
Data Handling	Unstructured or semi-structured data [25]	Structured data schema (QDS)
Model Usage	Standalone ML/DL models [4]	Integrated lightweight models within the pipeline
Pipeline Design	Fragmented workflow [25]	End-to-end AI pipeline
Validation	Limited model-level validation [25]	Multi-level validation (QVS)
Adaptability	Static, limited updates [4]	Continuous updates and a feedback loop
Scalability	Limited scalability [25]	Pipeline-based scalability (conceptual) [17]
Data Integration	Limited multi-source integration [26]	Multi-source integration (conceptual) [26]
Deployment	Challenging in low-resource environments [4]	Designed for resource-constrained settings

Moreover, Table 5 highlights the key strengths and limitations of the existing approaches. To place the proposed framework within the context of existing literature, it is important to note that the majority of state-of-the-art frameworks for agricultural monitoring have been focused on improving predictive performance using advanced machine learning and deep learning architectures such as convolutional neural networks and recurrent neural networks. Although such architectures deliver higher accuracy, they also have limitations in terms of computational requirements and do not consider aspects such as data quality and pipeline consistency.

On the other hand, the proposed AI factory framework is focused on structured data handling (QDS) and multi-level validation (QVS) within a continuous pipeline. Although traditional machine learning architectures do not explicitly include model validation, the proposed framework considers data validation, model validation, and pipeline validation. Therefore, this is an improvement over traditional machine learning architecture.

In addition to this, unlike MLOps-based frameworks, which focus on automation and lifecycle management, the proposed framework considers aspects such as data quality assurance and validation metrics. Although such aspects have been underexplored in existing literature, they are considered in this work.

Although the proposed framework does not consider aspects such as predictive accuracy using deep learning architectures, it is a lightweight solution that can be used in resource-constrained environments. Therefore, this work is focused on improving robustness and deploy ability rather than predictive performance.

Advantages:

The proposed framework presents several advantages, such as
Improved robustness of the model in noisy environments
Thorough validation of the results using multi-level metrics (QVS)

High stability of the pipeline and minimal drift in the data

Lightweight framework for use in resource-constrained environments

Continuous monitoring capability with periodic updates

Table 5. Comparison of Traditional Framework vs AI Factory Framework

Approach	Model Type	Focus	Strength	Limitation
Traditional ML (e.g., RF, SVM)	Machine Learning	Prediction accuracy	Simple, interpretable	No pipeline validation
Deep Learning (CNN, LSTM)	Deep Learning	High accuracy	Captures complex patterns	High computational cost
MLOps-based systems	Pipeline frameworks	Automation & deployment	Continuous integration	Limited data quality validation
Proposed AI factory framework (QDS+QVS)	ML + Pipeline	Data quality + validation	Reliable, stable, resource-efficient	Slightly lower predictive performance

Limitations:

Although the paper presents significant advantages, the research also has several limitations:

The experiment was performed on a synthetic data set rather than actual images received from satellites.

The accuracy of the model was improved, but not by a significant margin, implying that further optimization may be required.

The experiment could not test deep learning models or real satellite images due to resource constraints.

The experiment could not test the use of actual images received from satellites.

Implications for Agricultural Monitoring:

From the experiment, the results show that structured data handling and validation, it is possible to increase the accuracy of agricultural monitoring systems using AI systems. The proposed system may be used as a starting point for making a transition from isolated analytical models towards continuous, scalable, and deployable AI systems.

For example, by using the proposed system, it is possible to ensure that high validation accuracy can be maintained, meaning that it may be used for continuous systems, for example, for detecting crop stress.

To conclude, from the experiment, it is clear that the results obtained are sufficient to demonstrate that the proposed framework for developing AI systems, with the support of QDS and QVS, may be used as a reliable and scalable solution for agricultural monitoring systems using satellites, especially in resource-constrained environments.

Real-World Deployment Considerations:

Although the proposed AI factory framework has demonstrated promising results in the quality of data and the reliability of the system, there are some challenges associated with the implementation of the framework in a real-world scenario.

Firstly, the availability of quality satellite images has been a major constraint for the real-world scenario, particularly in the case of developing countries. Cloud presence, limited availability of satellite imagery, and acquisition of satellite images are some of the factors that may influence the quality of the system. Although the proposed framework has a component that addresses the quality of the satellite images, the efficiency of the framework in a real-world scenario needs to be validated.

Secondly, the infrastructure that may be used in the actual scenario may also be a challenge for the real-world scenario, particularly considering the limited computational resources and limited availability of internet and cloud-based infrastructure in the case of developing countries. However, the lightweight characteristics of the framework may also prove to be a solution to the infrastructure challenge.

Thirdly, the integration of the proposed framework with the existing agricultural monitoring systems and government infrastructure may also be a challenge for the real-world scenario. In the case of the actual scenario, the framework must be integrated with the existing GIS infrastructure and the existing agricultural infrastructure.

Recommendations:

From the findings in this research study, several recommendations can be proposed for both practitioners and future research in the field of AI-based agricultural monitoring.

For practitioners, the use of structured data handling frameworks such as the proposed QDS to effectively manage heterogeneous agricultural data sources is recommended. Ensuring data completeness and consistency before model training can improve the accuracy and trustworthiness of AI systems. In addition, using multi-level validation frameworks such as the proposed QVS can be effective in monitoring system performance, especially in dynamic environments.

For agricultural monitoring practitioners in resource-constrained environments, lightweight machine learning models and pipeline architectures may be used, especially in environments where such resources are limited. In addition, using such frameworks in conjunction with existing agricultural information systems can improve system usability.

For researchers, it is recommended to validate the proposed framework using real-world satellite data sources such as Sentinel-2 satellite data. In addition, exploring how deep learning models can be integrated into such frameworks can be very effective in balancing system performance with system reliability.

Furthermore, future research should investigate how effective the proposed framework is in scaling to meet multi-source data environments. In addition, exploring how such frameworks can be integrated with real-time data streams can improve system usability in agricultural monitoring environments. In addition, exploring how such frameworks can be integrated with edge computing environments can improve system usability in agricultural environments.

Conclusion:

In this research, we have introduced a resource-constrained AI factory framework for satellite-based agricultural monitoring systems, which considers structured data management and multi-level validation. The proposed framework can be used to evaluate data quality, model quality, and system quality using a Quality Data Schema (QDS) and Quality Validation System (QVS), respectively. The performance of the proposed framework was evaluated using experiments, which demonstrated improved robustness under noisy conditions, achieving comparable predictive performance to the baseline while exhibiting reduced variability across multiple runs. The proposed framework also showed better data quality, i.e., completeness and consistency, and system quality, i.e., pipeline stability, data drift, and updating consistency, at 100%, 0.95, 0.0043, and 0.95, respectively. The overall QVS score was also calculated, showing a value of 0.9182, indicating high system reliability (close to 1), ensuring reliable system performance using multiple validation levels. These findings demonstrate that structured data management and validation can significantly enhance system reliability. The proposed framework focuses on system-level performance, unlike traditional methods that primarily focus on model accuracy. This approach is more suitable for a resource-constrained system, as it can also help in improving the stability of the system.

Although several achievements have been accomplished in this research, some limitations have also been identified in this research. First, though the experimental validation of the proposed framework was conducted using a synthetic dataset, in the future, it is expected that research can be conducted using real-time satellite images. Moreover, research can be conducted on improving model accuracy using deeper architectures or advanced deep learning models.

The future scope of the proposed framework will be based on the extension of the framework using real-time datasets. In this context, satellite images from different sources, such as Sentinel-2, and weather information from different sources will be used in the framework. Moreover, research on the use of deeper models for improving the accuracy of the proposed framework and real-time data streaming will be conducted.

In conclusion, it can be stated that the proposed framework based on the AI factory framework can be considered a reliable and efficient solution for agricultural monitoring. The proposed framework has set a path for the development of intelligent systems from isolated analytical models, which may be beneficial for developing countries such as Pakistan.

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The manuscript has not been published or submitted to other journals previously. The system architecture diagram has been created using AI visualization tools.

Author's Contribution:

The entire study has been carried out solely by Raazia Sosan Waseem.

Conflict of interest:

The author declares that there is no conflict of interest regarding the publication of this manuscript.

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