IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 12, December 2024

DOI: 10.17148/IJARCCE.2024.131270

Cloud-Based AI Models for Precision Agriculture Development

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Abstract: Precision agriculture is considered one of the key solutions to satisfy world food demand by 2050. To achieve precision at the smallest farming unit, data collected, processed, and analysed to produce fit-for-use knowledge must be visible, sharable, and accessible among all stakeholders. Cloud computing technology on the foreshore has penetrated all segments of everyday life, not sparing the agriculture segment, making visible the nondirectional flow of information in real time. Cloud computing generally provides scalable infrastructure, powerful storage, data-sharing facilities, low operational costs, and powerful analytics, metering AI/ML model development and inference more affordable and enabling artificial intelligence and machine learning development and inference at regional scales. Its challenges include single-point failure, low-quality service, latency, and resource dependency. Conclusively, precision agriculture at the farm and field levels can also benefit from clustering agriculture stakeholders' data on the cloud and making the data accessible to eminent researchers and agriculture domains using various algorithms to develop AI/ML models. The planned architecture helps shed light on the logical flow of information from the sensor to decision representation. It includes key functional modules, components required for data ingestion, integration towards data lakes, model training nested in the cloud, deployment in different environments for inference, and governing data with respect to modelling, privacy, and security of stakeholders' data in the cloud.

To satisfy world food demand by 2050, precision agriculture is considered one of the key solutions. Precision requires collecting, processing, and analysing data to produce fit-for-use knowledge that is visible, sharable, and accessible among all stakeholders. Cloud-computing technology on the foreshore has penetrated all segments of everyday life, not sparing agriculture, and enabling a non-directional flow of real-time information. Cloud computing generally provides scalable infrastructure, powerful storage, data-sharing facilities, low operational costs, and powerful analytics, making artificial intelligence and machine learning development and inference at regional scales more affordable. The technology's challenges include single-point failure, low-quality service, latency, and resource dependency. Precision agriculture at the farm and field levels can benefit from clustering agriculture stakeholders' data on the cloud and making the data accessible to eminent researchers and agriculture domains.

Keywords: Precision Agriculture, Cloud Computing In Agriculture, Smart Farming Systems, Agricultural Data Analytics, IoT Sensors In Farming, Real-Time Farm Data, Agricultural Data Sharing, Scalable Cloud Infrastructure, AI And ML In Agriculture, Farm-Level Decision Support, Data Ingestion Pipelines, Agricultural Data Lakes, Model Training And Inference, Edge–Cloud Agriculture Architectures, Food Security 2050, Stakeholder Data Accessibility, Agricultural Data Governance, Privacy And Security In Agri-Data, Latency And Reliability Challenges, Digital Agriculture Ecosystems.

I.INTRODUCTION

Agricultural sciences continue to advance steadily, yet it is neither possible for research to solve all problems in all regions, nor for extension services to provide support for every farmer. Consequently, many farmers follow more traditional approaches, giving rise to the exploration of the farmer's data ecosystem, which uses cloud-based artificial intelligence to facilitate decision making in precision agriculture.

The important thing is that strategic planning by governments, institutes, research centres, and companies leads to a dynamic ecosystem of the data cloud that becomes widely available, where farmers' data become part of the process with real benefits to real users. Lack of access to cloud-based artificial intelligence solutions means that farmers with small plots of land remain disconnected from the technological revolution. The concentration of creation, availability, and deployment of the models in

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a cloud is key to enabling smallholders to take advantage of these services. Large private companies usually develop models that support their internal decision-making processes and favour their operations in the production chain. Cloud services available to farmers not only increase farmers' production but also help in environmental preservation and sustainability, enable efficient management of natural resources, and improve farmers' quality of life.

1.1. Overview of Cloud Computing in Agriculture

Cloud computing encompasses a collection of methods for delivering on-demand computing resources (e.g., processing power, data storage), as well as providing more abstract online tools (e.g., databases, visualization software) over the Internet, freely or for a fee. In general, cloud services can be grouped into Infrastructure-as-a-Service (IaaS), Platform-as-a-Service (PaaS), and Software-as-a-Service (SaaS). IaaS focuses on renting virtualized physical resources (minimal hardware). PaaS offers a platform through which resources are accessed (coordination of various hardware pieces, higher level access for testing/debugging). SaaS delivers software externally via a subscription model. Cloud deployment models can be private (dedicated to a single organization), public (accessible to all, on a multi-tenancy basis, free or fee-based), community (infrastructure shared among specific organizations), or hybrid (combination thereof).

Cloud-based data ecosystems have great potential for precision agriculture and the agrifood domain in general. Cloud offers a PaaS approach for sharing AI models and making them available as tools for farm-level decision support based on novel data sources (e.g., satellite weather data) integrated with established data sources (e.g., farm machinery data). The nature of growing seasons and geographical concentrations of farms allows the sharing of data and model training among multiple users, enabling scaling not only of model training, but also of the process of compiling and making data suitable for model training. Cloud enables offloading of analytics and reduces the need for sophisticated on-farm computational resources. Data generated in agriculture are used widely throughout the industry and by many players (crop growers, food processors and retailers, governments, NGOs); cloud is key to achieving the required level of collaboration.

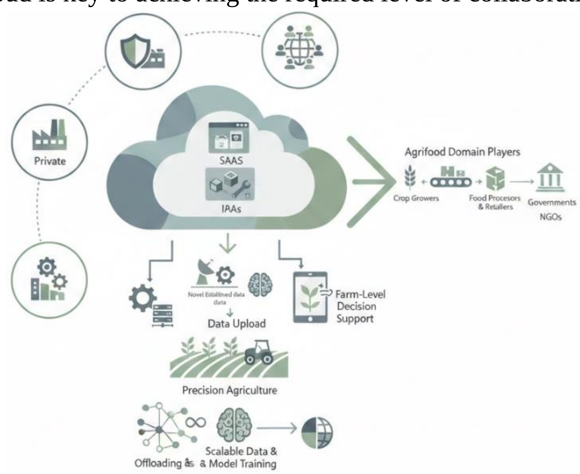

Fig 1: Scaling Precision Agriculture: Cloud-Based Architectures for Collaborative Agrifood Data Ecosystems

2. THE ROLE OF CLOUD COMPUTING IN PRECISION AGRICULTURE

The widespread adoption of the Internet of Things (IoT) enables the collection of unprecedented amounts of information from farms worldwide. Such massive and diverse data can advance precision agriculture using machine-learning models deployed in the cloud, where automatic and intelligent data analytics can support decision-making at a farm level. Despite the model training being carried out in the cloud, data and models are required at the edge or on-farm for making predictions. Cloud computing enables the automated deployment of trained models to the decision-support solutions of individual farms. Cloud architectures make use of data, sensory, model, and artificial intelligence (AI) ecosystems composed of public, private, and industry clouds.

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Cloud-based systems are important enablers of precision agriculture because they allow users to share, scale, and analyze data. Enabling users' access to and sharing of specialised data at lower prices can advance the development of domain-specific models. Such information-sharing can enhance farms' resilience to shocks through better planning and increase farmers' bargaining power by reducing asymmetries in information. Serving data languages lay the foundation for continuous data ingestion along with data lakes, advanced analytics, and other services. Advanced analytics applied to the continuing influx of data allow stakeholders to make informed decisions quickly and efficiently.

Equation 1) F1 score

Definition :

$$F1 = \frac{2 \times PREC \times TPR}{PREC + TPR}$$

Derivation (harmonic mean of Precision and Recall)

1. Harmonic mean of two positive numbers a, b is:

$$H(a,b) = \frac{2ab}{a+b}$$

2. Substitute $a = PREC, b = TPR$:

$$F1 = \frac{2 \cdot PREC \cdot TPR}{PREC + TPR}$$

2.1. Key Advantages and Challenges of Cloud Technology in Agricultural Practices

As a paradigm capable of revolutionizing the digital agricultural landscape, cloud technology offers several advantages, including increased collaboration; a pay-per-use economic model; virtually unlimited resources that drive continuous innovation; the ability to host advanced analytics algorithms or tools; and natural resilience in case of failure. However, some of these benefits are yet to be fully realized in agricultural practices, and other difficulties remain challenges for farmers. Compared to systems deployed on the farm edge, agriculture-oriented cloud solutions must cope with higher latency, data management issues that reduce response speed and reliability, and data-centric bottlenecks, as they rely heavily on the ability to share and join data from different sources. Spurred by their growing data intensity and by the consolidating data ecosystem, they present their own regulatory concerns, beside complying with standard security and privacy issues. Such hurdles should thus not preclude the adoption of cloud solutions for more data-intensive agricultural applications that support farmers by using data from other farms or organizations.

With the necessary conditions met, such solutions may indeed alleviate local burdens for the farm by hosting algorithms—especially AI-based ones—that require extensive computational resources for training. Continuous training or sweeping updates enable deployment of small models on the edge and burdening of the cloud facility with nondeterministic requests in a reactive approach, while update-aware constant training strengthens generalization capability. Latency-style data connectivity allows the use of cloud models running TCO-level multicasting training (involving a common source for all farms and sharing of user-specific data), and models running a GFS-like distributed training alleviate edge resources when deployed on multiple farms. Edge-to-cloud task-oriented data exchange can submit data for late learning and obtain cloud data analytics results.

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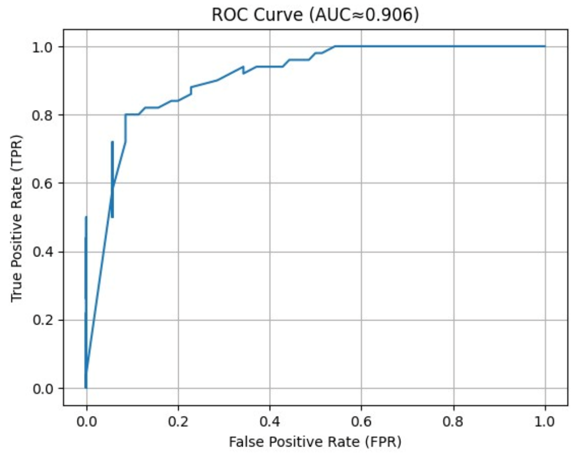

3. ARCHITECTURE OF CLOUD-BASED AI MODELS FOR AGRICULTURE

Cloud-based AI models comprise four functional layers—the application layer, model layer, cloud layer, and edge layer—interconnected by unidirectional and bidirectional data flows. Input data originate from cloud databases; sensor data flow through preprocessing and model-training/logging modules to cloud storage; trained models move to the cloud and edge for deployment; data from the cloud and edge-resident models arrive at visualization and decision-support dashboards. End-users have access to a model repository.

The application layer consists of decision-support applications designed to offer improved advice to farmers and agriculture stakeholders. The model layer encompasses the files and processes required to train application-and-domain-specific AI models. Data used to train the models are processed by a collection of modules for data preparation, cleaning, transformation, filtering and augmentation. Trained models are kept in cloud storage for internal retrieval and/or execution and/or for end-user retrieval. Data from edges fly into cloud models, and predicted data from cloud-resident models enter the application-dashboard visualization layer. Respond Data from modules in the application layer are routed to edge AI models for training. A metadata-management adjudicator allows inclusion of new datasets into the training pipeline even when these datasets are not ready for the ETL process.

Metric	Value
TPR (Recall)	0.8
TNR (Specificity)	0.9
Precision	0.851063829787234
F1	0.8247422680412372
FPR	0.1

3.1. Data Ingestion and Integration

Data generated by the Internet of Things (IoT) are pivotal for AI models in agriculture. These data originate from various sensors and devices including satellites, Unmanned Aerial Systems (UAS), drones, sensors stationed in the field, remote devices mounted on agricultural machinery, and crop models. Data source distinctions involve spatial and temporal resolution, spectral bands, data types (raster or vector), and data volume and need to be considered when designing deep-learning models. The models often process terabytes and even petabytes of data.

Several types of data need to be collected during the entire life cycle of an agricultural project. These data types can be categorized based on different characteristics and provide information that can be exploited by numerous models in the

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literature. To enable use of these data from different sources, standard formats for storage and metadata need to be defined. Once data are generated, cleaned, and stored in an interoperable format, they can be processed and exploited using monitoring and decision-support systems. Data should be made available to all services that produce advanced AI models. AI model training is computationally intensive and therefore requires substantial resources, including computing time, data volume, specific libraries, and suitable graphics processing-unit resources for the chosen algorithm.

Fig 2: From IoT Streams to Actionable Intelligence: Interoperability Frameworks for High-Dimensional AI in Agriculture

3.2. Model Training and Deployment in the Cloud

Ensuring sound training and accuracy of the models is key before they can be deployed. Dedicated workflows guarantee reproducibility and version control and thereby minimize the risk of faulty predictions. Continuous integration pipelines automatically trigger re-training of the models whenever newer training data streams in. The trained models are accessible through Application Programming Interfaces (APIs) and can either be executed as Serverless functions (with no dedicated hosting) or deployed onto a dedicated server. Edge computing components can preprocess raw data as well as host parts of the model for low-latency predictions. Streamlined architectures deploy the prediction models in the cloud after executing the training phase in order to save resources.

Cloud training pipelines are designed specifically for model families that incur high retraining costs, especially deep learning models with long training execution times. By integrating synchronously with the data ingestion pipeline and being regularized with testing datasets, these training workflows guarantee sound re-training of the deployed models without requiring manual intervention. The pipelines initialize all training data either from the latest available checkpoint or through cross-validation on previously deployed model versions. Adopting an edge-to-cloud strategy for data execution further optimizes cloud resources and minimizes latency of the model predictions. Such architectures avoid always-on cloud infrastructure by placing the model in dedicated hosting only during the prediction phase, using edge compute resources for all processing and hosting during the other operational phases.

4. DATA GOVERNANCE, PRIVACY, AND SECURITY

Solutions hosted in cloud environments for agriculture must consider data governance aspects such as ownership, sharing, privacy, and security. In particular, the impact of data governance on cloud service adoption cannot be disregarded. For instance, even if a farmer wishes to gain from cloud computing, ownership and governance issues may obstruct any possibility of actually putting the huge datasets to good use. It is therefore necessary to clearly delineate restrictions and expectations in order for agricultural data to be useful to all parties. Relevant topics being investigated by several researchers include the regulation of data access in the case when the data owner is a farmer who has outsourced data storage to a third party; the possibility of data anonymization and the effect of greenhouse laws; the position of data controllers and data processors; regulation under GDPR; and reliable accountability mechanisms.

Privacy and security provide an additional layer of complexity by introducing a range of issues that can be tackled either independently or from a data-sharing perspective. The former focusses on the mandatory cloud infrastructure-based security

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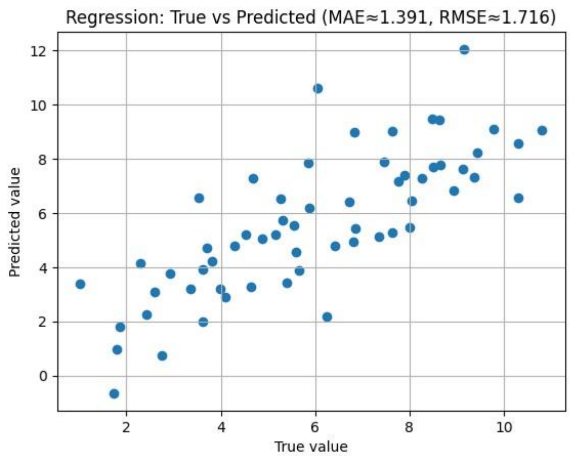
aspects, such as Confidentiality, Availability, Integrity, Authentication, and Non-repudiation. The latter, on the other hand, based on creating conditions for successful information sharing, investigates risks related to data privacy and the sharing of private data with trusted third parties, ensuring that sensitive private data are not leaked during the process. All in all, such advanced solutions provide the tools for privacy-preserving cloud security against any malicious attack, thus paving the way for a future where farmers can safely share big data with cloud-based architectures while being assured of their data owners' approaches.



Equation 2) True Positive Rate (TPR) / Sensitivity / Recall

Definition :

$$TPR = \frac{TP}{TP + FN}$$

Derivation (from "rate among actual positives")

1. "Actual positives" are all cases where the ground truth is 1. Count = $TP + FN$.

2. Correctly detected positives among them = TP.

3. So the fraction (rate) is:

$$TPR = \frac{\text{correct positives}}{\text{all actual positives}} = \frac{TP}{TP + FN}$$

4.1. Ensuring Data Integrity and Compliance in Agricultural Cloud Solutions

Integrity is paramount for providing trustworthy services over any data platform; if data quality cannot be graded or controlled, models' predictions are meaningless or dangerous. Cloud service providers must implement integrity-checking mechanisms during data ingestion and whenever data is modified, establishing rules for validating incoming data, controlling thresholds and ranges, and monitoring data flow throughout the whole system to detect outliers or suspicious data. Since stored data are usually not accessible to end users, the assessment of data quality should be performed through a series of checks collecting information through various channels, e.g. real-time device integrity control, periodic trustworthiness estimation, trends and incontestable metadata.

When wearable devices are used in the farming process, farm management systems must control data integrity to avoid contributing to the detection of low-quality data. Additionally, the operation of these devices is usually easily replicated by the people in charge of these systems. Therefore, farms must implement proper auditing processes that guarantee credibility

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on their statements. Since they are part of the supply chain, their statements cannot be considered fully reliable; instead, their trustworthiness must be periodically evaluated through auditing processes. When data used for explaining models are not produced within the farm, the systems become more vulnerable to data manipulation by suppliers or clients. Standards and other regulations can help mitigate this risk, as organizations not behaving in accordance with the rules can be penalized.
Compliance with existing regulations must always be considered when developing and deploying cloud applications and services. Depending on the information's sensitivity, the transparency and privacy requirements may vary and could be even included as a service in modern cloud computing platforms. Integrating specific infrastructures and services in the cloud technology stack allows the compliance assessment of applications or services with the underlying privacy rules during runtime. In such cases, the technology offers an added value; information about compliance can be included in the data cloud, warning data consumers about possible risks when using some data.

5. ALGORITHMS AND MODEL FAMILIES SUITABLE FOR AGRICULTURE

The artificial intelligence techniques suitable for agricultural applications can be organised into the following main groups: rule-based expert systems, supervised and unsupervised machine learning models, evolutionary algorithms, artificial neural networks and their deep learning implementation, natural language processing models, and computer vision models. These techniques can solve many different problems within agronomy and the global agri-food system.
Computer vision models are particularly important for monitoring wild and cultivated plants. These approaches rely mostly on images collected by drones or mobile robots (ground and aerial). Tasks commonly addressed include detecting living beings (plants, animals and invasive species), segmenting plants or their parts (leaf, flower, fruit), estimating phenotypic traits (height, density), predicting biomass or yield, and performing long-term crop monitoring (phenotyping). A large number of datasets and models for these tasks are publicly available, which is convenient for the scientific community but can also lead to a lack of adequate validation during the development of particular implementations. Evaluation is normally conducted by computing appropriate metrics (for image detection and semantic segmentation), using public repositories of test images or developing ad hoc trials.

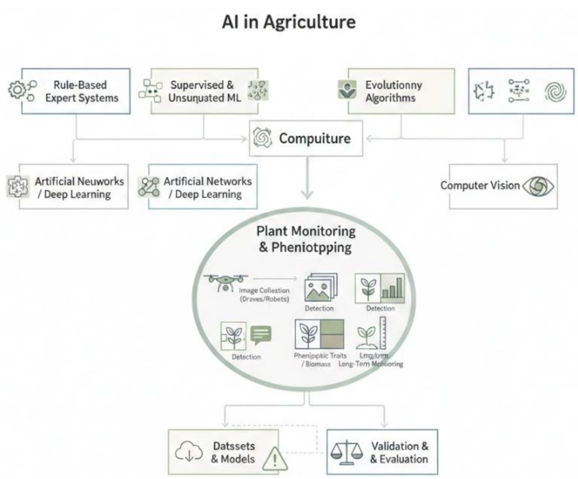

Fig 3: Synthesizing Artificial Intelligence Paradigms in Agronomy: A Systematic Framework for Computer Vision Deployment and Validation in Global Agri-Food Systems

5.1. Computer Vision for Crop Monitoring

The use of Computer Vision in agriculture and agribusiness has been growing rapidly. Acquiring images, extracting information from them, and making predictions has shown enormous applicability in many sectors. For crops, the main image sources are aerial, taken from UAVs, satellites, or airplanes, and ground acquired with smartphones, cameras, or mobile robots. The tasks associated with this kind of data are multiple, ranging from crop and disease detection to segmentation and phenotyping. In addition to exploring how computer vision can support crop monitoring, this section lists some important datasets in the field and reflects on key evaluation criteria to be adopted. Depending on the application, they may include accuracy (ACC), precision, recall, F1 score, receiver operating characteristics-area under the curve (ROC-AUC), mean absolute error (MAE), root mean square error (RMSE), Intersection over Union (IoU), calibration, or robustness to realistic conditions. When aiming at delivering a decision support system instead of a standalone algorithm, such aspects need to be further considered, as planned evaluations will affect model design.

With respect to crop monitoring, several papers can serve as illustrations of how it can be done and some of them are so comprehensive that they even serve as reviews in their topics, presenting a complete panorama of the applications realized until their date of publication. Most works in the area, however, tackle only very specific subquestions such as detecting the presence or spatial distribution of a given disease. When seeking to use computer vision applied to agriculture, one aspect that must be addressed is the lack of an appropriate dataset, as in Detect & Close, where the absence of an available dataset to tackle the problem posed made the authors create a new one to be used in the automation of Ug99 pathogen detection.

5.2. Precision Irrigation and Resource Management

As one of the fastest-growing sectors in the global economy, agriculture faces immense pressure to provide nutritious food for an ever-growing population. Precision agriculture can help ensure productivity and sustainability, emphasizing water and fertiliser efficiency, among other factors. Resources should be applied precisely where needed, in quantities sufficient to satisfy the needs of the crop, while wasting as little as possible in the process. External resources have a cost, so it is not only wasteful but also economically unwise to apply more than needed. Deep Learning models that consume data from various sources can help provide guidance in this extensive decision space.

Surface mining and patches of reduced transpiration such as those caused by diseases or pests create a non-homogeneous evaporative demand. Ensuring that water loss from the soil surface matches the plant's uptake capacity and therefore preventing waterlogging becomes necessary when some areas have a higher evaporative demand than others. Meanwhile, for rainfed crops, supplying water is important during periods when plants require resources for flowering and head formation and the rainfall forecast suggests that no precipitation will occur. Resources should be applied precisely where needed, in quantities sufficient to satisfy the needs of the crop, while wasting as little as possible in the process.

6. EVALUATION METRICS AND VALIDATION METHODOLOGIES

Cloud-based model supporting precision agriculture development, optimization, and advisory relies on the quality of the underlying algorithms, which are implemented and trained in a federated way. Establishing an evaluation plan with a description of the metrics used to assess quality and generalization capabilities is therefore crucial. Measuring the performance of algorithms addressing real-world problems requires working with a ground-truth dataset, specifically designed for the task under consideration, and eventually associated with a statistical setting. Although not exhaustive and limited to the most relevant families of algorithms related to precision-agriculture applications, the definition of an evaluation plan can facilitate the deployment of algorithms.

The performance assessment of AI algorithms typically involves a calibration dataset on which hyperparameters are fine-tuned and a test set, distinct from the training procedure, exploited to evaluate the model quality. Validation methods often go beyond the common training-test split, following the concept of generalization capability testing. Supported by a sound experimental design, the analysis is usually based on the agreement of replication of an experiment performed by different researchers or labs. In this context, generalization refers to the ability of a model to accurately predict unknown samples, reflected through a decrease in performance results when switching from the training to the calibration set. To assure a broad spectrum of analysis, the following metrics have been consolidated in the examination of AI algorithms, taking into account different tasks and types of data.

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Equation 3) True Negative Rate (TNR) / Specificity

Definition :

$$TNR = \frac{TN}{TN + FP}$$

Derivation (from "rate among actual negatives")

1. "Actual negatives" are all cases where truth is 0. Count = $TN + FP$.
2. Correctly detected negatives among them = TN.
3. Therefore:

$$TNR = \frac{TN}{TN + FP}$$

6.1. Assessing Performance: Metrics and Methods for Evaluating Agricultural AI Models

Evaluating algorithmic performance entails more than just the model accuracy. The analysis should usually incorporate different metrics to measure diverse aspects of the model behavior. The conventional machine-learning validation procedure rests on creating two complementary data subsets: the training set (used for modeling) and the test set (used to assess prediction performance). The performance is generally assessed based on the distribution of prediction errors over the test set. If such a testing process is performed multiple times, the estimates of any performance metric can be validated through nonparametric bootstrap or cross-validation techniques. However, such a strategy (test set) usually fails to quantitatively verify generalization properties of the underlying model.

In classifications tasks, it might also be interesting to evaluate the model quality through a confusion matrix, showing the number of true and false negatives and positives. Familiar metrics calculated from the confusion matrix are the true positive rate (TPR, sensitivity) defined as TPR = TP / (TP + FN), the true negative rate (TNR, specificity) defined as TNR = TN / (TN + FP), precision defined as PREC = TP / (TP + FP), recall (i.e. TPR) and the F1 score defined as F1 = 2 × PREC × TPR / (PREC + TPR). An ROC curve showing the trade-offs between TPR and the false-positive rate (FPR) defined as FPR = FP / (FP + TN) for different thresholds can also be plotted, and the area under the ROC curve (AUC) computed. The calibration of the predicted probabilities can be also assessed through reliability diagrams.

For regression tasks, the most common performance metric is the mean absolute error (MAE) defined as MAE = 1/N × Σ|yi − ȳi|, along with the root mean square error (RMSE) defined as RMSE = sqrt(1/N × Σ(yi − ȳi)2), where yi and ȳi represent the true and predicted values, respectively, and N is the number of data samples. For spatial tasks such as segmentation or detection, the intersection over union (IoU) is the recommended metric. Finally, the robustness of the model can be assessed through adversarial tests, in which inputs are modified by means that lead to wrong predictions; noise perturbations in the image domain are commonly adopted for such experiments.

y_true	y_pred	error	|error|
1.789611332007281	0.9833437802513765	0.8062675517559046	0.8062675517559046
2.753952606722345	0.7506634237980592	2.003289182924286	2.003289182924286
3.8114206545886855	4.218411718474282	-0.4069910638855969	0.4069910638855969
2.9324547838990345	3.7551658413046	-0.8227110574055656	0.8227110574055656
2.5973742216729763	3.098304521698058	-0.5009303000250815	0.5009303000250815

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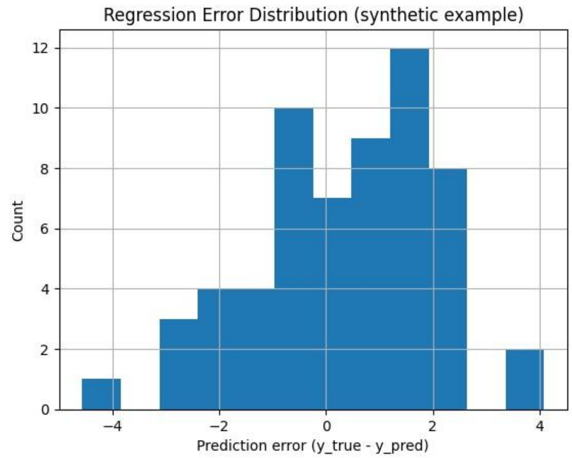

7. CONCLUSION

Cloud Computing is a relevant, widely explored, and understood technology that offers many advanced features and tools, gives fertile ground for agile and scalable software systems and enables full exploration of Artificial Intelligence and Machine Learning algorithms. Precision Agriculture improves productivity and sustainability by using AI and Machine Learning algorithms at different farm levels. The deployed models must be carefully trained and adapted to the local context, be transparently available to the user, and integrated into a decision support platform. A cloud-based architecture for developers and researchers is proposed. It formalises the necessary components located in the cloud, edge, and on the end-user devices. The solution also includes the Data Ingestion and Integration component, responsible for managing the acquisition and preparation for training. Proper Amazon AWS Cloud support features for Decision Support Applications, as Data Governance, Privacy and Security and Machine Learning Operations Pipeline, among others, are incorporated.

Precision Agriculture refers to the application of intelligent solutions for the improvement of decision-making at the field, farm, regional, or sectoral level, aiming to increase productivity, sustainability, and profitability while reducing energy and agrochemical usage. Intelligent solutions encompass algorithms from the field of Artificial Intelligence, particularly Machine Learning, that extract patterns from data generated during the daily activities within farms and agrifood systems. The successful application of these intelligent solutions requires the broad availability of high-quality, diverse data and ensures that users have the necessary knowledge and training for their proper use. Cloud Computing provides a convenient environment for deploying, sharing, and using these solutions.

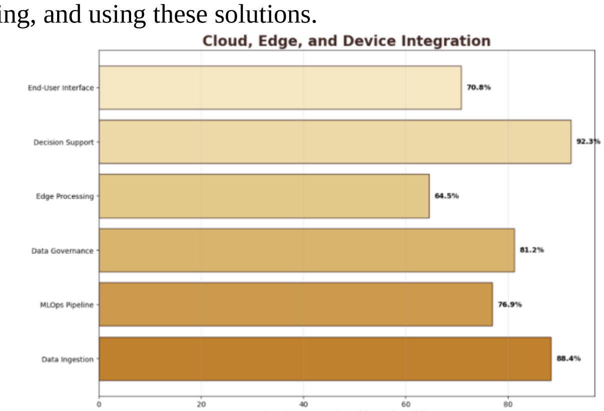

Fig 4: Cloud, Edge, and Device Integration

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7.1. Future Directions and Innovations in Cloud Computing for Agriculture

Guidelines, drivers, and innovative concepts for the application of cloud technology enable amazing support for any developer building solutions for agriculture and provide measurable advantages allowing more accurate results with lower costs. It is estimated that more than 70% of future agricultural production methodologies will be using methods developed for Precision Agriculture.

Cloud computing offers possibilities to revolutionize the management training of AI models by reducing costs, accelerating the production of more efficient solutions, and, in many cases, enabling manufacturers of model algorithms to deliver state-of-the-art models as a service. This makes their use accessible to any company, consultancy, or farm willing to pay for it only at the time of execution, making the business more cost-efficient to current use. Models are delivered as MLaaS in the form of application programming interfaces (APIs) available and documented for the market. Maintaining and training these models becomes a regulated service, through continuous training, to ensure that they remain state-of-the-art. The data captured in the execution of the models are continuously fed into preparation for the next training cycle. Vertical companies in API services are taking the place of data lakes that have bloomed but hardly met expectations, especially because the requested and paid services usually require the integration of several deep-learning models for each execution request.

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International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.102 ⁂ Peer-reviewed & Refereed journal ⁂ Vol. 13, Issue 12, December 2024
DOI: 10.17148/IJARCCE.2024.131270

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