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DESIGN OF A MICROSERVICE-BASED ARCHITECTURE FOR FARM MANAGEMENT INFORMATION SYSTEMS WITH IOT DATA INTEGRATION AND YIELD PREDICTION

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Abstract. *In the context of agricultural digitalization, integrating data from multiple sources and leveraging modern technologies have become essential for supporting operational decision-making. This paper proposes a Farm Management Information System (FMIS) designed using a microservice-based architecture and supported by cloud computing and Internet of Things (IoT) technologies. This solution enables the collection and integration of heterogeneous data, including operational records, weather observations, and measurements from soil and plant sensors, through dedicated services and API interfaces. The architecture ensures modularity, interoperability, and incremental extensibility of functionalities. The main components for data ingestion, storage, and analysis are presented, together with decision-support mechanisms based on rules and predictive models. The prediction module employs machine learning algorithms based on decision trees, namely Random Forest and XGBoost, which are well suited for structured agricultural datasets. The approach is illustrated in the context of maize cultivation.*

Keywords: FMIS, microservices, IoT data integration, machine learning, yield prediction

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1. Introduction

Agricultural production is increasingly supported by digital technologies that facilitate the collection, processing, and interpretation of operational data. The growing adoption of Internet of Things (IoT) devices, artificial intelligence techniques, and integrated management platforms has enabled farmers to monitor field activities more effectively, optimize resource consumption, and improve decision-making processes through timely access to relevant information [1, 2].

Despite these advancements, small and medium-sized farms continue to face important challenges in adopting digital solutions. High implementation and

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maintenance costs, limited access to technological infrastructure, insufficient digital skills, and a lack of awareness regarding the benefits of such systems remain key barriers. Recent studies emphasize the need for targeted strategies and supportive policies to facilitate the adoption of digital technologies among smaller agricultural producers [3].

To overcome these limitations, this study introduces a Farm Management Information System (FMIS) developed around a microservice-based architectural model and enhanced through cloud and IoT technologies. The proposed solution promotes modularity and independent service deployment, allowing agricultural functionalities to evolve without affecting the entire platform. In addition, the integration of sensor-generated information and machine learning techniques enables continuous analysis of field conditions and supports evidence-based operational decisions.

The proposed FMIS is designed primarily for small and medium-sized farms, while remaining applicable to larger agricultural operations. It integrates functionalities for production and inventory management, environmental data acquisition through sensors, weather data processing, and yield prediction, contributing to a comprehensive decision-support environment.

To contextualize the proposed approach, maize cultivation is considered as a representative use case, given its importance in Romanian and European agriculture and its suitability for digital monitoring and optimization. The maize lifecycle comprises multiple phenological stages, each associated with distinct operational and environmental requirements. Integrating these stages within an FMIS enables continuous monitoring, automated recommendations, and proactive, data-driven interventions.

The remainder of this paper is structured as follows. Section 2 outlines the proposed FMIS architecture, emphasizing the integration of microservices, cloud technologies, and IoT components. Section 3 presents the data organization model and the information processing workflow used for collecting, validating, and integrating agricultural data. Section 4 summarizes the main contributions of the proposed approach and discusses future development directions.

2. Architecture of the Proposed FMIS Platform

The proposed Farm Management Information System adopts a distributed architecture that combines microservice design principles with cloud and IoT technologies. This architectural choice was motivated by the need to efficiently manage heterogeneous information sources, continuous sensor-generated data streams, and multiple functional modules while preserving scalability and ease of future expansion. Compared with monolithic software solutions, the proposed approach offers improved maintainability, flexibility, and long-term adaptability [7].

The architecture is closely integrated with IoT and cloud technologies, supporting a multi-layered deployment model that spans from field-level devices to centralized services. At the lowest level, the perception layer includes sensors and actuators deployed in the field, responsible for collecting environmental and operational data [6]. These data are transmitted through a network layer to an intermediate middleware layer, where they are aggregated, filtered, and prepared for further processing. The upper layer consists of cloud-based services that provide data analysis, optimization, and decision support functionalities.

From a structural perspective, the FMIS platform follows a layered design, comprising a perception layer for data acquisition, a middleware layer for data management and pre-processing, and an application layer that hosts the microservices responsible for core system functionalities.

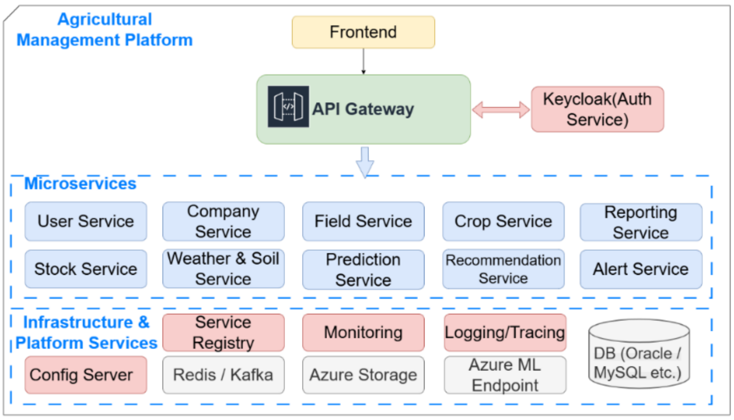

Figure 2. Cloud-enabled FMIS architecture built on microservice principles

The overall architecture of the FMIS is depicted in Figure. 1, illustrating the main system components, including the user interface, authentication and authorization module, API gateway, functional microservices, and the supporting infrastructure for monitoring, configuration, and data storage.

Secure and scalable access control is ensured through a dedicated authentication and authorization component, implemented as a centralized Identity Provider using Keycloak. This module manages user identities and enforces access policies across the system. Data exchanges between devices and cloud components are secured using standard encryption protocols (TLS/SSL), while personal data handling complies with GDPR and other applicable regulations.

The system leverages components from the Spring Cloud ecosystem to support service discovery, centralized configuration, and system observability. Service registration is handled through a registry mechanism (e.g., Eureka), while configuration management is provided by a centralized configuration server. Monitoring and performance tracking are achieved using tools such as Prometheus and Grafana, complemented by distributed tracing services for improved system visibility [7].

3. Agricultural Data Management and Processing

3.1. Domain-Oriented Data Model

The agricultural management system is structured as a set of microservices, each responsible for a specific data domain, including user management, field information, crop data, resource inventories, and environmental parameters (soil and weather). This design follows microservice principles, where each component operates independently, with clearly defined responsibilities and lightweight communication mechanisms [10].

A simplified representation of the database schema is shown in Figure. 2, highlighting the core entities involved in crop monitoring, environmental sensing, and yield prediction. The Field Service manages agricultural plots through attributes such as area, soil type, and geographic location, while the Crop Service associates seasonal crop data with specific fields, including crop type and key phenological dates.

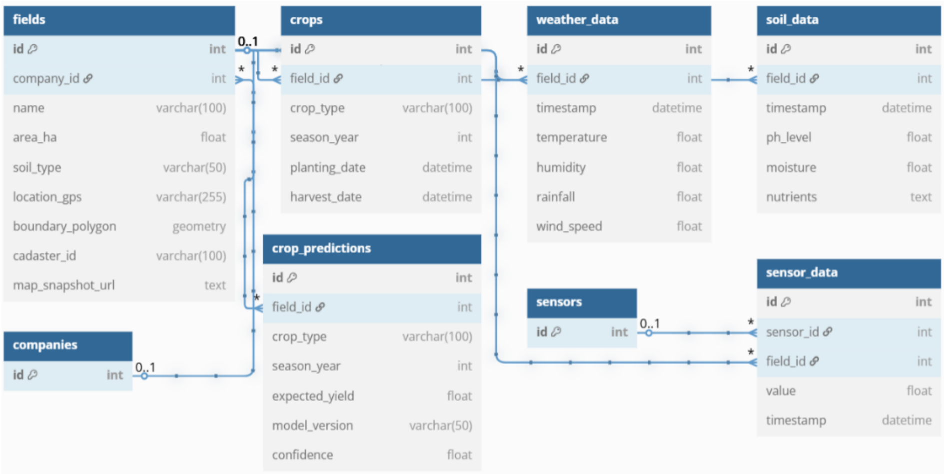

Figure 3. Conceptual database model supporting FMIS services

Environmental data are acquired via the Sensor & Data Collection Service, which records time-stamped measurements, while the Weather & Soil Service aggregates both local sensor data and external sources into a unified representation of environmental conditions [10].

The Prediction Service combines historical and real-time data to estimate crop yield, storing outputs such as expected yield and confidence levels. These results support downstream recommendations and alerts, enabling data-driven agricultural decisions. This segmentation provides a solid foundation for efficient data processing and supports the decision-making workflows described in the following sections [11].

3.4 Sensor Data Acquisition and Processing Pipeline

Raw data are acquired directly from the field through networks of soil and climate sensors deployed across the farm. In the experimental setup, parameters such as soil moisture, temperature, precipitation, and light intensity are monitored at regular intervals (15–60 minutes), enabling near real-time observation of field conditions. Sensor nodes transmit data collected to a central gateway via Wi-Fi, chosen for its ease of deployment and compatibility with existing infrastructure in small to medium-sized farms. The gateway aggregates the data and forwards them to a buffer database within the FMIS, ensuring secure transmission through an internet connection [11]. To improve robustness in environments with unstable connectivity, local buffering is implemented at gateway or edge level, preventing data loss during temporary network interruptions.

An automated scheduling mechanism periodically retrieves newly collected data from the buffer database and performs initial processing steps, including filtering, validation, and standardization of heterogeneous sensor inputs [11]. The processed data are then forwarded to the Weather & Soil microservice, which updates the central database with the latest environmental indicators and maintains a consistent view of field conditions, such as soil moisture, temperature, and cumulative precipitation.

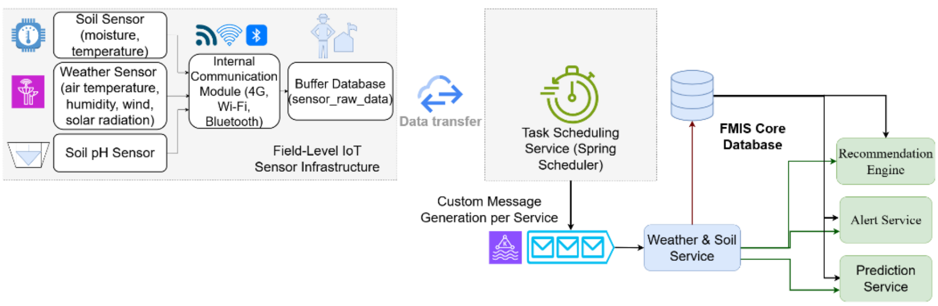

Figure 4. End-to-end workflow for sensor data acquisition and integration

Once integrated, these data are used by higher-level services responsible for prediction, recommendation, and alert generation. The Prediction service combines historical and real-time data to estimate crop evolution and yield using machine learning models. Based on environmental time series, the system can infer irrigation needs, assess potential risks, and support production forecasting, as also highlighted in recent IoT-based agricultural studies [12].

The Recommendation service builds upon both current measurements and predictive outputs, together with agronomic rules, to generate actionable guidance for farmers. These include suggestions regarding irrigation and fertilization timing, adjustments to operational plans, and crop selection decisions based on environmental conditions and field history [12].

In parallel, the Alert service continuously monitors incoming data and prediction results to detect critical situations requiring immediate attention. When predefined thresholds are exceeded (e.g., low soil moisture or risk of frost), alerts are automatically generated and delivered to users via application notifications or messaging channels. Similar event-driven mechanisms are widely used in agricultural IoT systems for real-time monitoring and intervention [13].

The internal processing flow of the Weather & Soil microservice, described in Figure 4. further refines this pipeline. A scheduling component periodically triggers data ingestion from the buffer database, after which raw records are stored to ensure traceability. The data then undergoes validation (to detect anomalies or missing values), normalization (e.g., time alignment and unit conversion), and mapping into structured entities. Finally, the processed data persists in dedicated repositories, enabling efficient access for downstream services.

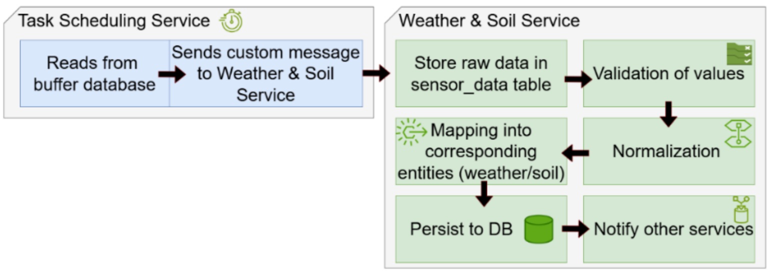

Figure 5. Internal workflow of the Weather & Soil service for environmental data management

4. Conclusions

The proposed FMIS demonstrates how microservice architectures, cloud platforms, and IoT technologies can be combined to support modern agricultural management. Through its modular design, the platform facilitates the integration of additional services, sensing devices, and analytical capabilities while maintaining scalability and operational flexibility. The unified management of agronomic and environmental information provides a consistent basis for decision support and more efficient resource utilization.

An important advantage of the proposed solution resides in the use of open and technologies such as Spring Cloud and Keycloak, which ensure portability, interoperability, and adaptability to different crop types and farm sizes. These characteristics place FMIS as a practical and sustainable management solution for a large range of agricultural environments.

This research contributes a unified architectural model that combines IoT-enabled data acquisition, cloud-native services, and predictive analytics within a single management platform. By supporting real-time monitoring and decision support, the proposed FMIS addresses practical challenges related to data fragmentation, limited technological infrastructure, and the growing demand for accessible digital solutions in agriculture.

Future work will be directed to extend the FMIS with new functionalities, such as early pest detection using drone imagery and real time machine vision techniques, as well as AI techniques improving predictive capabilities through the customization of powerful machine learning models, algorithms and enhanced datasets, following the trend visible in recent specialty studies [14].

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