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PLATFORM IMPLEMENTATION FOR MONITORING AND DETECTING FAILURES IN AGRICULTURE MACHINERY

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In the dynamic landscape of modern agriculture, ensuring the reliability and efficiency of machinery is a critical challenge. This article proposes an innovative platform for monitoring and detecting failures in agricultural machinery, harnessing the power of Internet of Things (IoT) technology and cloud computing. The system in AWS cloud receives data from vehicles in real-time and can predict potential failures in engine, transmission, electric and hydraulic systems using machine learning algorithm LSTM. An article provides detailed description of the proposed remote monitoring method, describes the structure of the remote monitoring system and the organization of data transmission, pre-processing, analysis and visualization. Architecturally, the platform adopts a microservices framework, ensuring scalability, high performance, security, and reliability. Algorithms of data processing in the system are described and the main features and benefits of using the monitoring solution are presented. The system's predictive performance is assessed by processing real telemetry and maintenance data collected over 12 months from farms located in United States. The collected data was sent to platform using Java-based simulator and prediction results were evaluated using the Mean Absolute Percentage Error and Coefficient of Determination metrics, demonstrating the high accuracy of the implemented prediction model.

Keywords – Agriculture vehicles, GIS, LSTM, Predictive Maintenance, RUL, IoT

Problem Statement

The wear and tear of technical equipment, which reaches 70-80 %, is a significant problem in Ukraine's agricultural sector. Many farmers in the country still rely on outdated equipment and methods, which limits productivity and efficiency (Semernia, 2018). Worn-out equipment requires frequent repairs or replacements, but farmers often lack the funds to purchase new equipment or provide maintenance for the existing one. When machinery breaks down or does not function properly, it harms agricultural operations, causing delays in sowing, harvesting, and transportation of crops, which negatively affects yields and overall productivity.

Repair and maintenance of agricultural vehicles are expensive, and farmers need substantial funds to restore them to working condition, ultimately impacting the cost of crop production. Equipment wear and tear is also a safety issue. Older machinery may not meet current safety standards, putting farmers at risk of injury or accidents while operating it. This is a major concern for farmers who rely on their equipment for their livelihood. Additionally, worn-out equipment contributes to the problem of low productivity in the sector, as farmers have to use old and less efficient machinery, which reduces the amount of harvested crops. Agricultural vehicles are essential for farmers to transport their products to market. When these vehicles break down, it complicates the sale of goods and reduces farmers' profits or increases food prices. Overall, the wear and tear of technical equipment is a serious issue that limits productivity and efficiency in Ukraine's agricultural sector, reducing its global competitiveness and contributing to higher food prices worldwide.

The increase in food prices has a significant impact on global hunger, as it makes it more difficult for people living in poverty to secure enough food to meet their basic needs. According to research by the Global Network Against Food Crises, rising prices lead to hunger in many regions worldwide. Currently, nearly 30 million people suffer from hunger specifically due to the increased cost of food (Global Network Against Food Crises, 2022).

Many studies have found that repair and maintenance costs depend on differences in tractor operation, lack of spare parts, operator skills, crop and weather conditions, maintenance policies, and other factors. However, all studies observe a pattern: as equipment ages, repair and maintenance costs increase, while timely detection of malfunctions reduces repair expenses (Al-Suhaibani & Wahby, 2015). At present, the development and research of methods and models for monitoring and detecting malfunctions in agricultural machinery remain a relevant scientific challenge.

Analysis of Recent Studies and Publications

In industrial use of machinery and equipment, maintenance and repairs are carried out according to one of three strategies: reactive maintenance, preventive maintenance, or predictive maintenance (Carbonell, 2016; O'Grady & O'Hare, 2017).

In the case of reactive maintenance, machines and equipment are operated until a defect or malfunction occurs, which is then repaired. This maintenance strategy is not planned, and components are used for as long as possible, which reduces spare parts costs but makes machines more vulnerable to downtime when a failure occurs. Similarly, the cost of repairing equipment after failure may be higher than the value of the product obtained from its operation before the failure. Furthermore, when parts start to vibrate, overheat, and break, additional damage to the equipment may occur, leading to further costly repairs. When organizations use a reactive maintenance strategy, they often deal with fixing the consequences of malfunctions rather than addressing their root causes.

Spinelli, Eliasson, and Magagnotti (2019) in their work proposed the preventive maintenance strategy, where equipment is replaced before a defect occurs. The usage interval is typically determined based on operating hours, experience, or manufacturer-defined maintenance intervals. Thus, machinery or its components may be replaced before reaching the end of their service life, increasing costs compared to reactive maintenance. On the other hand, preventive maintenance reduces unplanned downtime, as maintenance work can be scheduled before a defect occurs. This type of maintenance is based on theoretical failure frequency rather than the actual performance of specific equipment, meaning that failures may occur before the next scheduled maintenance or that maintenance may be performed unnecessarily if no failure would have occurred. Jekayinfa et al. (2005) developed an analytical model and conducted computer simulations to calculate the optimal preventive maintenance interval, aiming to reduce maintenance costs and maximize production profits for a group of small industrial enterprises. The study concluded that reducing repair costs through careful operation and proper maintenance could significantly lower tractor maintenance expenses. However, even with high-quality maintenance, unpredictable failure costs accounted for about 41 %. Dankyarana and Umar (2020) found that high tractor repair costs could be explained by the high cost of imported spare parts, improper tractor use, and negligence in preventive maintenance. These studies do not guarantee the avoidance of unexpected tractor failures during peak seasonal operations, such as sowing or harvesting. Such failures can critically impact farming operations since tractor repairs may take a long time due to spare parts delivery times, which in turn reduces the volume of harvested agricultural crops and increases their production costs.

According to the predictive maintenance strategy, repairs are planned based on the condition of the machine or its components. Typically, the machine's condition is monitored and analyzed using sensor data installed on the vehicle, while some approaches also use data from enterprise resource planning (ERP) systems to predict downtime. Predictive maintenance allows for efficient scheduling of maintenance while reducing spare parts costs. Unlike preventive maintenance, predictive maintenance is more complex to implement but is cheaper to use and requires less maintenance time since it occurs only when necessary –

when a failure is predicted. Predictive maintenance is currently an insufficiently researched topic. The main drawbacks of existing solutions (Xiao et al., 2020; Li et al., 2019) include the low number of predicted failures, the use of artificially generated data instead of real historical data for training the neural network, which does not support the use of synthesized data.. Additionally, these solutions consider only sensor data from the tractor but do not take into account the environmental conditions in which the tractor operates (such as air temperature, humidity, terrain, soil types, etc.), the tractor's operating time, its age, and other factors. On-device data analysis proposed by Xiao et al. (2020 adds extra load to the device, making it more resource-intensive, increasing its cost, and complicating its management.

Formulation of the Article's Objective

To address the problem of monitoring and detecting failures in agricultural machinery, the Internet of Things (IoT) technology can be applied. IoT enables the creation of networks between devices, people, and applications on the internet, forming ecosystems with higher productivity, better energy efficiency, and increased profitability. Devices help recognize the state of objects, allowing them to anticipate human needs based on collected contextual information. These smart devices not only gather information from their surroundings but are also capable of making decisions without human intervention.

By leveraging IoT, it is possible to implement an information-analytical platform that will allow farmers to:

1. Store telemetry data from agricultural vehicles with geolocation and environmental conditions.
2. Analyze the collected data, detect existing failures, predict potential failures, and receive alerts about them.
3. Better plan maintenance, upgrades, and tractor replacements, reducing the cost of growing agricultural crops.

Additionally, this platform will assist researchers and developers in implementing their own information-analytical platform for remote monitoring or improving existing systems.

The main challenges that need to be addressed when developing this platform include:

1. Real-time transmission of data collected from the CAN bus and aggregated by the device to the cloud application for further analysis.
2. Real-time processing of large data streams.
3. Handling data that was not transmitted on time due to the IoT device's lack of network connectivity.
4. Storing large volumes of geospatial data in the cloud application.
5. Analyzing stored data in the cloud application to detect existing failures.
6. Developing a predictive model for potential failures and notifying farmers about them.
7. Creating an architectural and informational model for processing data in information-analytical systems for monitoring and detecting failures in agricultural machinery, considering the characteristics of an ideal fault diagnosis system (Venkatasubramanian et al., 2003).

Main Results

Scaling and load optimization are essential aspects of a system for monitoring and detecting failures in agricultural machinery for several key reasons. First, given the large volume of data and traffic generated by agricultural objects depending on the season in which operations are performed, scaling enables efficient real-time data processing and ensures prompt response to events and failures. The second reason lies in the dynamic nature of the agricultural environment, where objects rapidly change their position and condition. Load optimization allows the system to effectively adapt to these changes by distributing computing resources based on current needs. Additionally, considering the need for real-time execution in some monitoring and failure detection tasks, scaling and load optimization ensure compliance with system response time requirements. Finally, load optimization enables efficient utilization of computing resources, reducing infrastructure costs while maintaining high system performance. To achieve these quality attributes, it is advisable to use a microservices architecture when developing a system for monitoring and detecting failures in agricultural machinery.

However, relying solely on a microservice architecture does not guarantee the achievement of all necessary quality attributes, as infrastructure is another critical factor. Deploying a monitoring and fault detection system for agricultural machinery using cloud computing offers numerous advantages that help optimize its performance and ensure efficient resource utilization. Firstly, cloud computing enables efficient resource management and cost optimization for system deployment. It eliminates the need for significant investments in acquiring and maintaining dedicated hardware and infrastructure.Secondly, cloud computing provides substantial benefits in terms of system flexibility and scalability. It allows the system to scale easily based on demand. Since the volume of telemetry data from tractors may vary depending on operating conditions and the number of active machines, the flexibility of cloud computing ensures that the system's infrastructure can be adjusted dynamically without significant time and resource costs.

Fig. 1 illustrates the deployment, scaling, and load optimization model for the monitoring and fault detection system for agricultural machinery, which is based on a microservice architecture deployed using cloud computing.

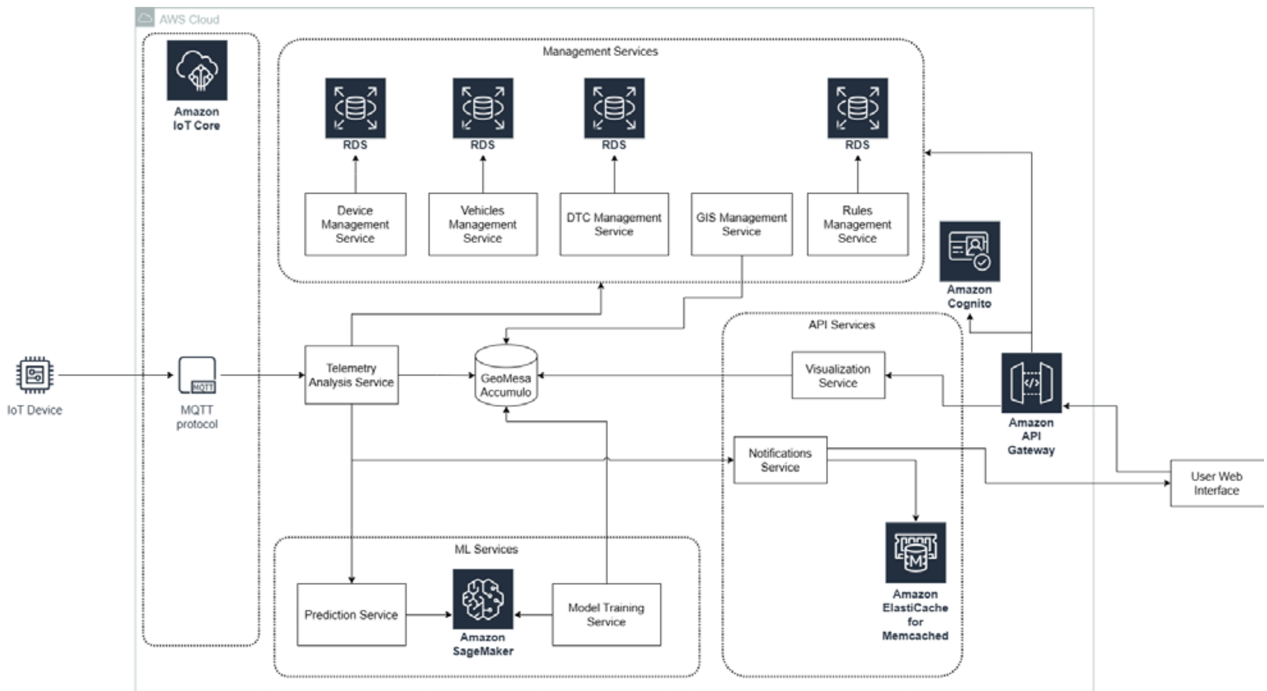

Fig. 1. Architecture of the system for monitoring and detecting failures

Based on our previous research (Shykhmat & Veres, 2023), the AWS IoT Core service, integrated with an MQTT bridge, was selected as a key component of the system for monitoring and detecting faults in agricultural machinery. This service provides the infrastructure for collecting data from IoT devices installed in vehicles.

The Telemetry Analysis Service retrieves data from the MQTT bridge, validates the received data, enriches it with information about the device, agricultural machinery, and decoded error codes, and analyzes it using predefined rules to detect existing faults as well as artificial intelligence to predict potential failures. This service is implemented using Apache Spark. The processed data is stored in the GeoMesa Accumulo database, which is designed for executing a wide range of geospatial queries and analytical tasks in distributed computing environments and that was selected in (Shykhmat & Veres, 2023).

The Device Management Service allows adding and retrieving information about IoT devices integrated into the system. When an IoT device connects to the network for the first time, it must be registered. Unlike traditional devices, IoT devices lack a full-fledged, independent interface for navigation during onboarding. The process includes credential verification, authentication protocol determination, and device ID assignment. Additionally, this service enables device configuration and maintenance.

The Vehicles Management Service allows adding and retrieving information about agricultural machinery that the system monitors. This includes specific vehicle details - brand, model, year of manufacture, start-of-operation date, serial number, etc., as well as general model information, which applies uniformly to all instances of a given model.

The GIS Management Service enables storing and retrieving information about the environmental conditions in which the machinery operates, such as terrain and weather conditions.

The DTC Management Service functions as a dictionary that translates error codes into human-readable formats. Since error codes vary across different machinery models, it is essential to translate error codes for each supported model of agricultural equipment.

The Rules Management Service is an expert system containing predefined rules for specific agricultural machinery models, which can be used to diagnose existing failures. These rules follow a simple IF-THEN structure, allowing for quick identification of already occurring faults.

The Prediction Service utilizes artificial intelligence algorithms to predict potential failures using a machine learning model trained on historical data. The deployment of the machine learning model is powered by SageMaker.

The Model Training Service is also built using SageMaker. This service trains the model by analyzing all historical data stored in the GeoMesa Accumulo database.

The Visualization Service integrates with the GeoMesa Accumulo database to provide a convenient REST API for retrieving data needed by the user interface.

The Notifications Service is used to send alerts about detected or predicted faults to all relevant stakeholders. These notifications can be delivered through the web interface (via WebSocket protocol).

The User Web Interface is essential for both system administration (registering devices, adding new supported machinery models, managing error code dictionaries, and defining analysis rules) and for farmers. Through this interface, farmers can access all current information about their machinery, including overall equipment status, potential failures, history of diagnosed faults, machinery location, and operating conditions. The user interface's main page (Figure 2) allows farmers to monitor the current state of their agricultural operations, including identified and predicted failures, equipment status, details about machinery with detected or predicted failures, and failure statistics over recent days. The data is displayed for the selected farm (which the user has access to).

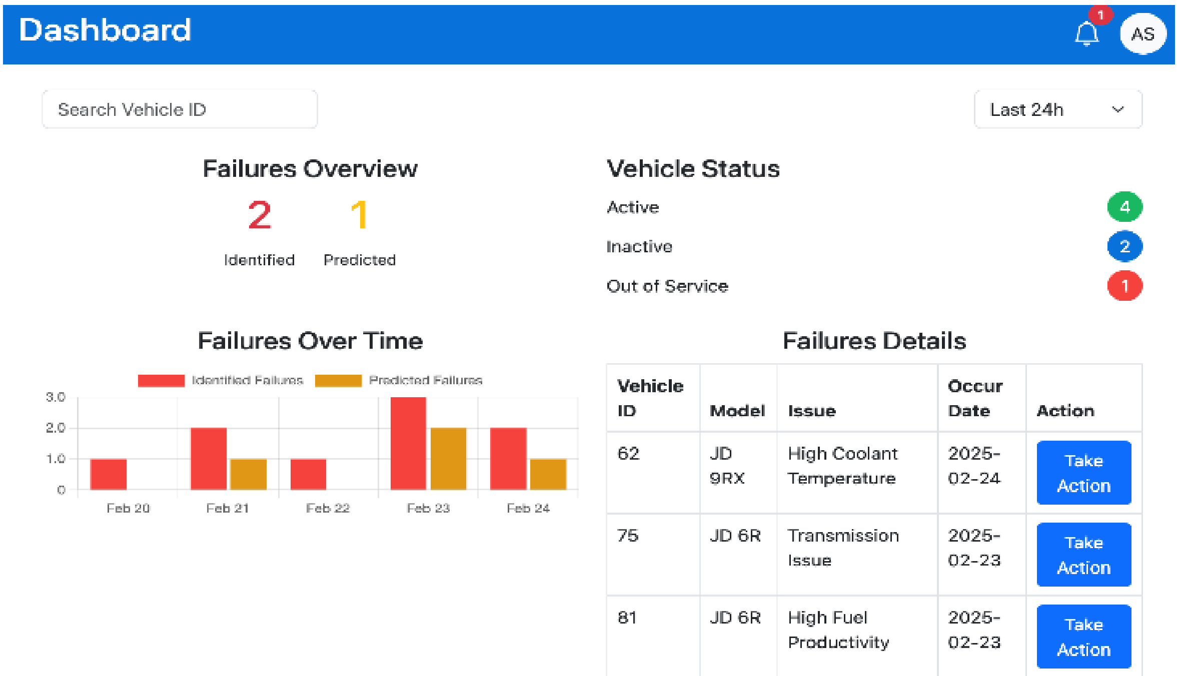

Fig. 2. Main dashboard

The user interface provides functionality for selecting the farm whose statistics the user wants to view. Users can only choose farms they have access to, as granted in AWS Cognito. Figure 3 shows the field selection panel.

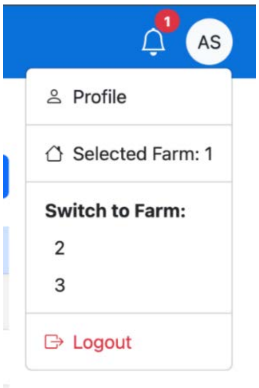

Fig. 3. Farm selection panel

When clicking on the notification icon, alerts appear on the screen, as shown in Figure 4.

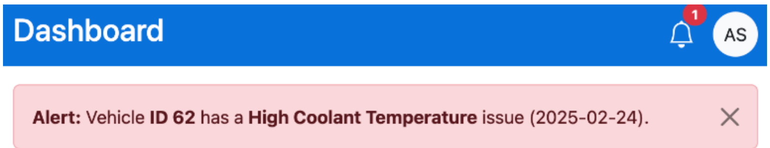

Fig. 4. Vehicle failure alert

The telemetry page (Figure 5) allows farmers to view all telemetry data sent from vehicles operating on the selected farm. This page also displays statistics on telemetry transmission frequency over the last 12 hours/day/week/month and provides filtering options using the Vehicle ID.

Fig. 5. Telemetry view page

Figure 6 illustrates the vehicle management page for agricultural machinery. From this page, users can update vehicle information, change the status to "Under Maintenance" or "OK," view the maintenance history, telemetry data, and delete a vehicle.

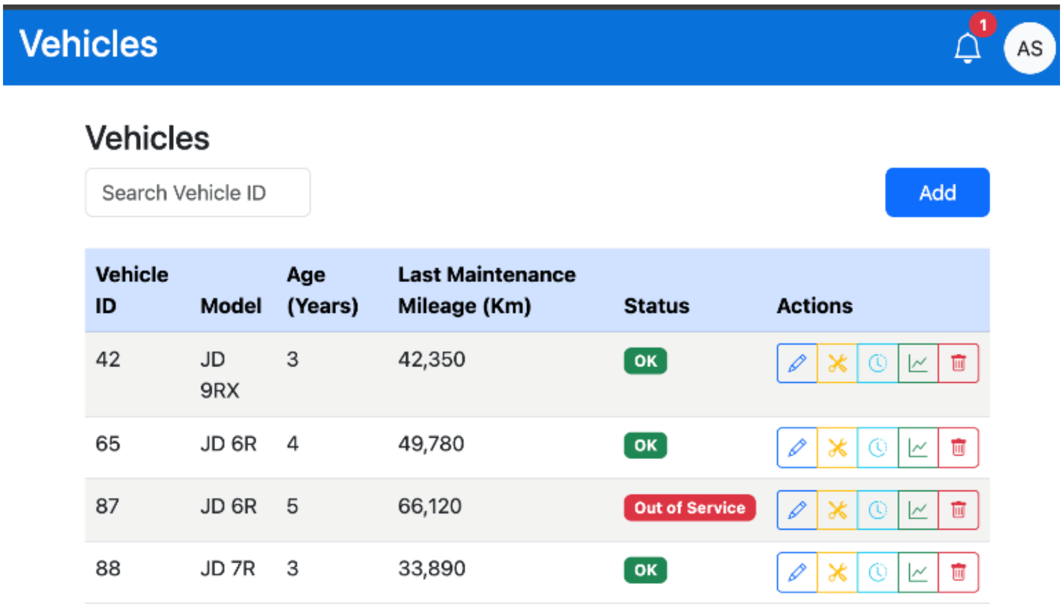

Fig. 6. Vehicles management page

Figure 7 presents the maintenance history page for a se lected vehicle. This page displays the maintenance date, detected issues, work performed, replaced parts (if any), the technician responsible for the maintenance, and the associated costs.

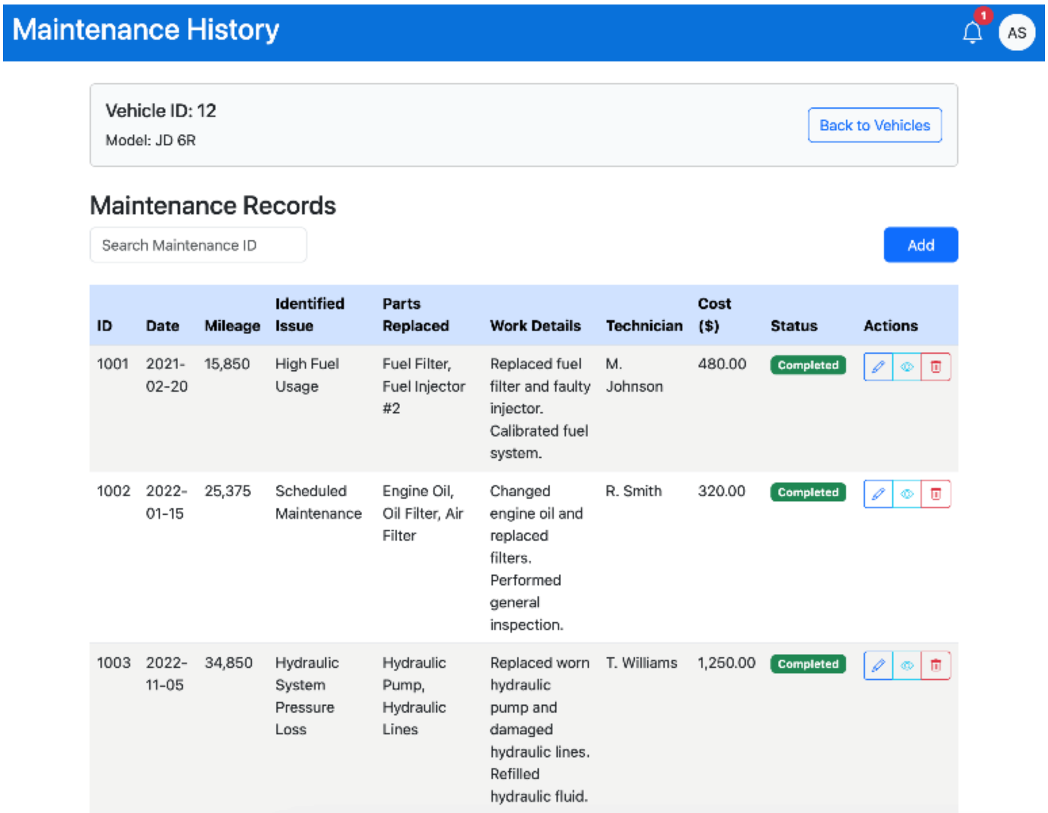

Fig. 7. Maintenance history page

The functionality described above is available to agricultural enterprise representatives. However, there are additional features accessible only to platform administrators, such as device management, modifying Diagnostic Trouble Codes, managing GIS data, and managing error detection rules for existing failures.

The algorithm for processing telemetry data includes receiving the data, validating the data, retrieving device data from the Device Management Service, retrieving vehicle data from the Vehicles Management Service, retrieving GIS data from the GIS Management Service, decoding DTCs using the DTC Management Service, retrieving historical data from the past 24 hours from GeoMesa, detecting existing faults using the Rules Management Service, predicting potential faults using the Prediction Service, and saving the processed data to GeoMesa. If faults are detected or predicted, the Notification Service is called to alert farmers. Figure 8 represents telemetry processing algorithm.

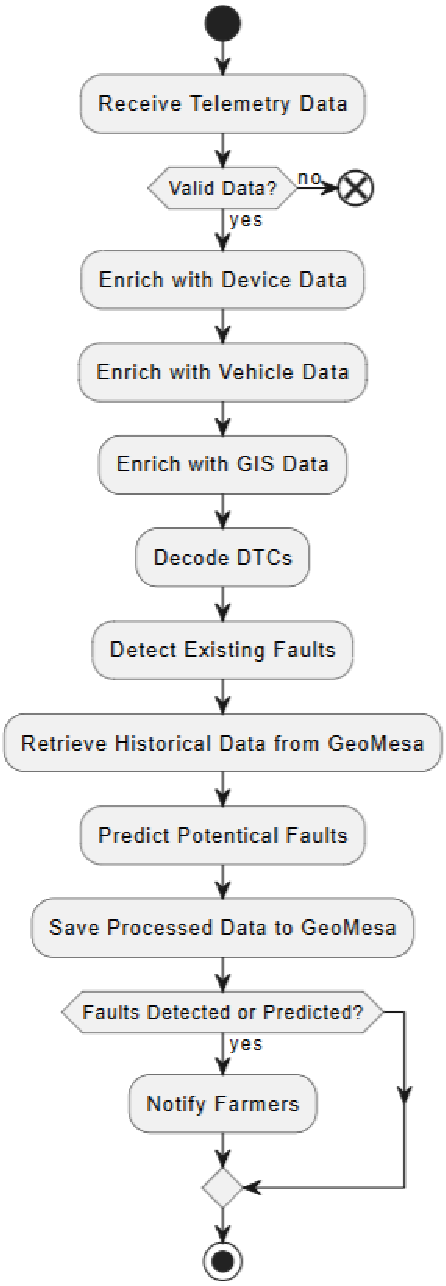

Fig. 8. Telemetry Processing Algorithm

The faults prediction is done using separate RUL prediction LSTM model per each vehicle model component, described in our previous research (Shykhmat & Veres, 2024). Currently it is possible to predict failures of engine, electric system, hydraulic system, and transmission components.

Results

For testing the the system for monitoring and detecting failures, telemetry data and maintenance records for the year 2023 were collected from 50 tractors of 5 different models. These tractors were operated on 2 different fields of the same farm. 10 of these tractors had documented malfunctions that occurred within the last 12 months. Instead of developing a physical device to integrate with the tractor's CAN bus to collect telemetry and send it to the information system, a simulator was created. This simulator, developed using the Java programming language, used real telemetry data accumulated by the farm over the last 12 months and sent it to the system, thus mimicking the behavior of a device installed on a tractor working in the field. This approach allowed testing in a controlled environment without the need to develop hardware or physically intervene in the machinery. Figure 9 illustrates the integration scheme of the device simulator installed on a local computer with the system for monitoring and detecting failures in the AWS cloud provider.

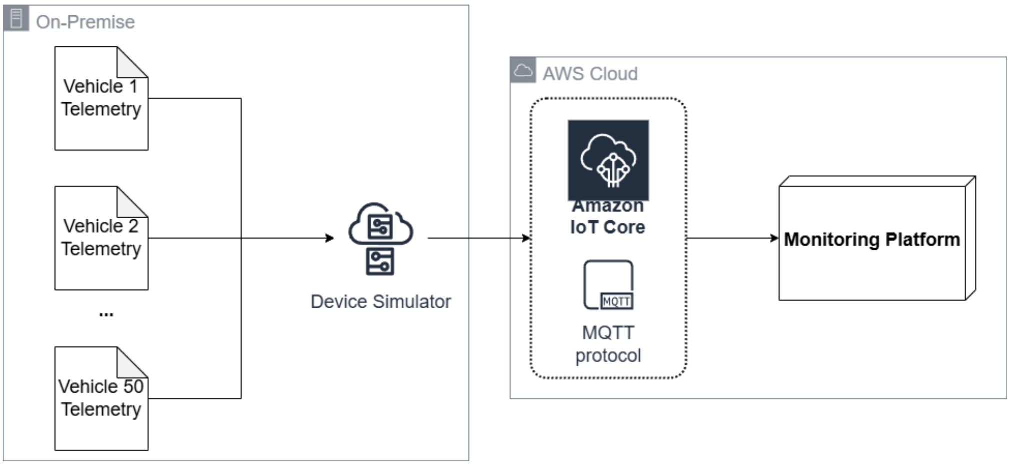

Fig. 9. Simulator integration with the system for monitoring and detecting failures

The average processing time for a single telemetry message was 1127 ms. When transmitting data simultaneously from all 50 tractors, the delay did not exceed 3215 ms. The accuracy of the predictions was evaluated using MAPE and R^2. As shown in the results presented in Table 1, the models demonstrated high accuracy for all tractor components. The average MAPE for models incorporating GIS-integrated features decreased by 28.48 %, while the R^2 increased by 5.78 %, compared to models that exclude GIS data. These results support the hypothesis that integrating GIS factors, such as weather and terrain characteristics, improves the accuracy of predictive maintenance models.

Table 1

Components RUL Prediction Performance

Model	Component	MAPE GIS	MAPE No GIS	R^2 GIS	R^2 no GIS
1	2	3	4	5	6
1	Engine	3,20	4,57	0,91	0,85
	Electric System	2,70	3,72	0,93	0,88
	Hydraulic System	2,60	3,63	0,94	0,88
	Transmission	3,10	4,42	0,90	0,84
2	Engine	2,80	3,87	0,92	0,87
	Electric System	3,20	4,54	0,89	0,84
	Hydraulic System	2,90	4,06	0,90	0,85
	Transmission	2,90	4,14	0,91	0,86
3	Engine	3,10	4,42	0,89	0,84
	Electric System	2,90	3,99	0,90	0,86
	Hydraulic System	2,80	3,92	0,92	0,87
	Transmission	3,00	4,25	0,89	0,84

Continuation of Table 1

1	2	3	4	5	6
4	Engine	2,90	4,01	0,91	0,86
	Electric System	3,00	4,21	0,90	0,85
	Hydraulic System	2,70	3,72	0,93	0,88
	Transmission	2,80	3,85	0,92	0,87
5	Engine	2,70	3,71	0,94	0,88
	Electric System	2,90	4,05	0,90	0,84
	Hydraulic System	2,90	4,04	0,91	0,87
	Transmission	2,70	3,77	0,94	0,90

Thus, the system demonstrated its effectiveness in predicting malfunctions and preventing emergency shutdowns, which are particularly critical during seasonal work, as they render the equipment unusable until repairs are completed, leading to a decrease in the amount of work that farmers can perform and, ultimately, a reduction in the harvested crop. However, additional research is needed to predict malfunctions in other tractor components.

Conclusion

Predictive maintenance is currently an insufficiently researched topic. The platform for monitoring and detecting failures in agriculture machinery has been developed, to fill gaps in this area. Unlike existing systems, this platform with the AWS cloud deployment capabilities ensures achievement of scaling, performance, security, and reliability quality attributes by using microservices architecture.

Failure prediction methods have been enhanced by integrating preprocessed and normalized geospatial data into LSTM-based models, incorporating weather and terrain attributes into the input vector, achieving higher prediction accuracy. The implemented RUL prediction models achieved an average MAPE of 2.89 and an R^2 of 0.91, representing improvements of 28.48 % and 5.78 %, respectively, compared to models that do not incorporate GIS data. This confirms the high prediction accuracy of the proposed models. Experimental evidence is provided for the first time demonstrating that integrating geospatial data into LSTM-based agriculture vehicles failure prediction models enhances accuracy over telemetry-only systems.

An implemented web interface allows farmers, and their representatives continuously monitor their machinery fleet and plan maintenance, upgrades, and tractor replacements, that can potentially reduce the cost of growing agricultural crops.

This research can speed up the development of new predictive models and IoT systems, which can collect real-time telemetry from agricultural vehicles operating in the field. It is worthwhile exploring models' creation to predict RUL of other vehicle components.

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ІНФОРМАЦІЙНА СИСТЕМА МОНІТОРИНГУ ТА ВИЯВЛЕННЯ НЕСПРАВНОСТЕЙ У СІЛЬСЬКОГОСПОДАРСЬКІЙ ТЕХНІЦІ

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У динамічному середовищі сучасного сільського господарства, забезпечення надійності та ефективності техніки є важливим викликом. Дана стаття пропонує інноваційну платформу для моніторингу та виявлення несправностей сільськогосподарської техніки, що використовує переваги технологій Інтернету Речей та хмарних обчислень. Інформаційна система, що розгорнута у хмарі AWS, отримує дані від транспортних засобів у реальному часі та може передбачати потенційні несправності в двигуні, трансмісії, електричних і гідравлічних системах за допомогою алгоритму машинного навчання LSTM. У статті детально описано запропонований метод віддаленого моніторингу, структура системи віддаленого моніторингу та організація передачі даних, попередньої обробки, аналізу та візуалізації. Платформа використовує мікросервісну архітектуру, що забезпечує масштабованість, високу продуктивність, безпеку та надійність. Описано алгоритми опрацювання даних у системі, представлені основні характеристики та переваги використання рішення для моніторингу. Коректність прогнозування оцінено на основі опрацювання реальних телеметричних та технічних даних, зібраних протягом 12 місяців з ферм, розташованих у Сполучених Штатах. Зібрані дані передавалися на платформу за допомогою Java-симулятора, а результати прогнозування оцінювалися за допомогою метрик середньої абсолютної відносної помилки та коефіцієнта детермінації, що підтвердило високу точність реалізованої моделі прогнозування.

Ключові слова - Сільськогосподарські транспортні засоби, ГІС, LSTM, Прогнозне обслуговування, RUL, IoT