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GEOSPATIAL AND WAVELET-BASED FEATURE FUSION FOR RUL FORECASTING IN AGRICULTURE MACHINERY

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***Abstract*: This study extends previous research on Remaining Useful Life (RUL) prediction for agricultural vehicles by utilizing an enriched dataset to overcome earlier limitations in forecasting RUL for electric and hydraulic system components. Influential features have been identified through Pearson correlation and Random Forest feature importance analysis. Discrete Wavelet Transform (DWT) has been applied to extract additional approximation and detail coefficients, enhancing the feature set. Prediction algorithms—LSTM, FCNN, and SVM—have been evaluated using Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and Coefficient of Determination (R^2) metrics. Results indicate that LSTM models demonstrate superior performance, particularly those incorporating DWT-extracted features and geospatial factors such as weather and terrain conditions. The findings suggest that the developed RUL prediction models can be integrated into future Internet of Things (IoT) systems for remote monitoring and predictive maintenance of agricultural machinery.**

***Index Terms*: Agriculture vehicles, GIS, RNN. LSTM, FCNN, SVM, Predictive Maintenance, RUL, DWT**

I. INTRODUCTION

To enhance efficiency and meet the demands of a growing population, modern agriculture increasingly depends on various machinery, including tractors, harvesters, and other vehicles [1,2]. These machines play a vital role during seasonal operations such as planting and harvesting, where any malfunction can disrupt workflows and cause significant economic losses [3]. To help farmers proactively address issues, optimize maintenance schedules, and extend machinery lifespan, predictive maintenance with Remaining Useful Life (RUL) estimation is employed.

In our previous study [4], we introduced an approach for RUL prediction by integrating telemetry data from agricultural vehicles, maintenance records, and Geographic Information System (GIS) data—such as weather and terrain conditions—to train a Long Short-Term Memory (LSTM) model. Our results demonstrated that models incorporating GIS data achieved higher accuracy compared to those without it. However, RUL prediction performance for electrical and hydraulic components did not meet expectations due to insufficient data. Additionally, that study focused solely on evaluating the LSTM algorithm for RUL prediction.

This study extends our earlier work [4] with three main objectives. First, we examine the influence of GIS data on other machine learning algorithms, including Fully Connected Neural Networks (FCNN) and Support Vector Machines (SVM). By comparing each model's performance with and without GIS data, we aim to assess how these variables affect RUL prediction accuracy across different computational approaches. Second, we seek to enhance RUL prediction for electrical and hydraulic systems by addressing the data limitations identified previously. To achieve this, the LSTM model will be reconstructed and re-evaluated using an expanded dataset. Third, we apply Discrete Wavelet Transform (DWT) to telemetry features to extract temporal and frequency-domain characteristics, investigating whether these wavelet-based features further improve prediction accuracy.

This research offers practical insights for agricultural operations adopting predictive maintenance systems tailored to their equipment's unique characteristics. Our findings on the comparative performance of different algorithms across machinery components contribute to more resilient, efficient, and cost-effective farming practices.

II. LITERATURE REVIEW AND PROBLEM STATEMENT

RUL prediction is not a new challenge, and several established methods have been developed to address it. A review of the literature shows that Recurrent Neural Networks (RNNs) are highly suitable for analyzing time-series telemetry data to predict potential equipment failures, as they perform well with sequential data [5]. Temporal dependencies are crucial for accurate RUL estimation, and RNNs capture these dependencies by feeding the output of one step into the next. This is achieved through hidden layers that retain information about previous inputs. Long Short-Term Memory (LSTM) networks are an advanced form of RNNs that overcome the limitations of traditional RNNs, particularly in handling long-term dependencies. LSTM networks use three gates, nput, output, and forget, which act like switches that can be turned on (1) or off (0) [6]. This mechanism enables LSTMs to retain only relevant information over extended periods while discarding unnecessary details. Consequently, LSTMs are well-suited for predicting the RUL of agricultural machinery, as they can process large datasets combining telemetry data, maintenance records, and GIS information.

FCNN presents another approach used in predictive maintenance. These networks process input data sequentially through an input layer, hidden layers, and an output layer, without feedback loops. Unlike RNNs, FCNNs do not retain memory of past data, and their connections have distinct weights that are not shared across layers [7]. Despite this limitation, FCNNs can still effectively analyze sensor data, maintenance histories, and geographic context information.

Both neural network types discussed above are forms of deep learning models that can automatically detect patterns without explicit supervision. However, traditional supervised learning algorithms are also applied to RUL prediction, with SVMs being a notable example. As noted in [8], SVMs perform well for RUL estimation due to their ability to handle high-dimensional data efficiently. Their capacity to determine optimal separating boundaries, known as hyperplanes, makes them particularly effective for binary classification tasks—such as distinguishing between machinery operating normally and machinery nearing failure.

The prediction of agricultural vehicle RUL remains an underexplored research area, with relatively few studies dedicated to it. Recent works [9-11] indicate a growing interest in applying advanced machine learning techniques to predict equipment lifespan. However, most of these studies rely solely on onboard sensor data, overlooking environmental and operational conditions that significantly affect machinery longevity. Moreover, there is a lack of research evaluating RUL prediction algorithms using consistent datasets and standardized performance metrics. The integration of geospatial data into RUL prediction for agricultural machinery also remains largely unexplored. As highlighted in our previous work [3], accurately predicting RUL for electrical and hydraulic systems in agricultural vehicles is still a challenging problem that demands further investigation.

The study in [12] proposes an enhanced prediction approach utilizing the Discrete Wavelet Transform (DWT) and demonstrates that LSTM, RNN, and Back Propagation (BP) models achieve higher accuracy when DWT-extracted features are applied to wind power prediction. Similar improvements were observed in RUL prediction for lithium batteries, as shown in [13]. However, it remains uncertain whether these algorithms will exhibit comparable performance in agricultural machinery RUL prediction, particularly when telemetry data is combined with GIS information.

III. SCOPE OF WORK AND OBJECTIVES

In this study, we aim to assess the performance of LSTM, FCNN, and SVM algorithms for predicting the RUL of agricultural vehicles. Our objective is to determine how GIS data and DWT-extracted features influence prediction accuracy. To achieve this, four groups of models will be implemented, and their performance metrics are compared: a dataset without GIS and DWT-extracted features, a dataset with GIS but without DWT-extracted features, a dataset without GIS but with DWT-extracted features, and a dataset including both GIS and DWT-extracted features. These comparisons will help identify the most suitable algorithm for agricultural vehicle RUL prediction.

Furthermore, this research emphasizes the integration of telemetry, maintenance, and geospatial data to create a comprehensive dataset, addressing the specific challenge of predicting failures in electrical and hydraulic systems of agricultural machinery. The results are expected to support the development of more robust predictive maintenance models, improving remote health monitoring of agricultural vehicles and enabling optimized operations while reducing maintenance costs.

IV. MATERIALS AND METHODS

The proposed RUL prediction workflow follows the same procedure as in our previous study [3]. It starts with data collection, including telemetry, maintenance records, weather conditions, and terrain information, followed by dataset integration and preprocessing. Subsequently, predictive models are developed for each vehicle component using machine learning techniques such as LSTM, FCNN, or SVM. The final step involves applying these models to generate RUL predictions. In our prior research [3], the dataset was insufficient for accurately predicting the RUL of electric and hydraulic components. To address this limitation, a new dataset was obtained from a US-based cereal farming operation, comprising telemetry and maintenance records. The dataset includes records collected in 2023 from 50 tractors across 5 different tractor models, operating on 2 farms located in distinct regions. Relevant features, that were extracted from maintenance records, are presented in Table 1.

The telemetry dataset includes several features. Timestamp represents the exact date and time when the telemetry data was recorded. Tractor ID is a unique identifier for each tractor in the fleet. Mileage indicates the total distance traveled by the tractor from the beginning of its operational life in kilometers. Engine RPM shows how fast the engine is spinning. Fuel Productivity refers to the rate of fuel consumption in liters per hour. Engine Load represents the current engine load as a percentage of maximum capacity. Current Speed indicates the current speed of the tractor in kilometers per hour. Power Take Off Load refers to the amount of power being transferred through the Power Take Off (PTO) system to operate attached implements, measured in kilowatts. Transmission Load shows the current stress on the transmission system as a percentage. Lub Oil Temperature is the temperature of the engine’s lubricating oil in degrees Celsius. Coolant Temperature represents the temperature of the engine cooling system in degrees Celsius. Battery Voltage indicates the main battery voltage level in volts. Alternator Output Voltage is the voltage output from the alternator in volts. Alternator Current represents the current output from the alternator in amperes. Battery Current shows the battery charge or discharge current in amperes. Starter Motor Current indicates the current draw during engine start in amperes. ECU Voltage represents the voltage at the Electronic Control Unit in volts. Power Consumption Total refers to the total electrical load on the system in watts. Battery Temperature is the temperature of the main battery in degrees Celsius. Alternator Temperature represents the operating temperature of the alternator in degrees Celsius. Battery State of Charge indicates the estimated battery charge level as a percentage. Battery State of Health represents the estimated battery condition as a percentage. Generator RPM shows the rotational speed of the generator or alternator. Circuit Load Distribution represents the load distribution across electrical circuits as a percentage. Charging System Status refers to the status codes for the charging system. Electrical Fault Codes are the diagnostic trouble codes for electrical systems. Hydraulic Oil Pressure indicates the main system pressure in bar or PSI. Hydraulic Oil Temperature shows the oil temperature in degrees Celsius. Hydraulic Oil Level represents the fluid level in the reservoir as a percentage. Hydraulic Pump Speed indicates the rotational speed of the main pump in revolutions per minute. Hydraulic Flow Rate refers to the system flow rate in liters per minute. Hydraulic Filter Differential Pressure represents the pressure difference across the hydraulic filter in bar. Hydraulic Actuator Position indicates the position of hydraulic cylinders as a percentage. Hydraulic Valve Position represents the position of control valves as a percentage. Hydraulic System Leakage refers to the calculated leak rate in liters per minute. PTO Hydraulic Pressure indicates the Power Take-Off hydraulic pressure in bar. Steering Hydraulic Pressure shows the steering system pressure in bar. Implement Hydraulic Pressure represents the implement circuit pressure in bar. Hydraulic Pump Efficiency indicates the calculated pump efficiency as a percentage. Hydraulic Cooler Efficiency represents the heat exchanger effectiveness as a percentage. Hydraulic System Load refers to the load on the hydraulic system as a percentage. Hydraulic Fault Codes are the diagnostic trouble codes for hydraulic systems.

Geospatial information including weather and terrain data for regions in provided datasets was manually collected. For this purpose, VisualCrossing (https://www.visualcrossing.com) solution was used to obtain weather records, and ArcGIS (https://www.arcgis.com/) solution was used to identify terrain characteristics. This process was done for each field's geographical boundaries in obtained dataset. Table 2 represents extracted weather data features, and Table 3 – extracted terrain data features.

The dataset preparation workflow began with preprocessing and integrating the collected data to support predictive maintenance analysis. Integration started by joining telemetry and maintenance records using the TractorID field. This combined dataset was then enriched with corresponding weather and terrain records using the Region and Timestamp fieldsю telemetry data were recorded every minute, while weather information was collected daily, resulting in uniform weather parameters across all same-day telemetry records within each region.

Table 1

Maintenance Data Features

Name	Description
Timestamp	The exact date and time when the maintenance entry was recorded
TractorID	A unique identifier for each tractor in the fleet
Model	The specific make and model of the tractor.
Region	The geographical area where the tractor is operating
Age	The number of years since the tractor was manufactured or put into service
Mileage	The total distance traveled by the tractor from the beginning of its operational life till the maintenance date (km)
ComponentFailure	Indicates which specific part or system of the tractor failed

Table 2

Weather Data Features

Name	Description
Year	The calendar year during which the weather data was recorded
Month	The calendar month during which the weather data was recorded
Day	The calendar day during which the weather data was recorded
AvgTemperature	The average temperature that day (C)
MinTemperature	The minimum temperature that day (C)
MaxTemperature	The maximum temperature that day (C)
Precipitation	The total amount of precipitation that day (mm)
Wind	The average wind speed (Km/h)
Region	The geographical area for which data is collected

Table 3

Terrain Data Features

Name	Description
MeanElevation	The average elevation of the terrain (m)
MinElevation	The minimum elevation of the terrain (m)
MaxElevation	The maximum elevation of the terrain (m)
StdElevation	The standard deviation of elevation of the terrain (m)
MeanSlope	The average slope within the region (degrees)
MinSlope	The minimum slope within the region (degrees)
MaxSlope	The maximum slope within the region (degrees)
StdSlope	The standard deviation of slope within the terrain (degrees)
Region	The geographical area for which data is collected

Next, highly correlated features were identified, as they could negatively impact model performance. Pearson correlation analysis was applied to the integrated 54-feature dataset to detect potential feature redundancies. The following features, with correlation coefficients near -1 or 1, were considered highly correlated and removed: ECU Voltage, Circuit Load Distribution, Charging System Status, Electrical Fault Codes, Hydraulic Actuator Position, Hydraulic Valve Position, Hydraulic System Leakage, PTO Hydraulic Pressure, Steering Hydraulic Pressure, Implement Hydraulic Pressure, Hydraulic Pump Efficiency, Hydraulic Cooler Efficiency, Hydraulic Fault Codes, MinTemperature, MaxTemperature, MinElevation, MaxElevation, StdElevation, MinSlope, MaxSlope, StdSlope. A total of 21 features were removed, leaving 33 features for further modeling.

The combined dataset was further enhanced by calculating RUL values for each component based on maintenance history analysis. These values represented the intervals between consecutive failures in the maintenance records. Consequently, four new fields were added: EngineRUL, ElectricSystemRUL, HydraulicSystemRUL, and TransmissionRUL. With five tractor models and four components under study, the main dataset was partitioned into 20 distinct subsets, each focusing on a specific component-tractor model combination while excluding irrelevant features associated with other components or models. Random Forest was then employed to identify the most influential features for predicting each specific component's RUL.

After that, for each subset of the dataset, DWT was applied specifically to the telemetry features within that subset to extract additional features, namely the approximation and detail coefficients. The transformation was implemented using the Daubechies wavelet of order 2 (db2). Compared to higher-order Daubechies wavelets (db4, db6, etc.), db2 is less sensitive to noise and less prone to excessive approximation, making it more stable for practical telemetry data processing tasks where signals may contain a significant level of noise. In addition, db2 provides a better trade-off between signal reconstruction accuracy and computational complexity, which is important when working with large datasets. Daubechies wavelet shows higher classification accuracy, comparing to Haar wavelet [14]. The approximation coefficients a_{j+1}[k] and detail coefficients $d_{j+1}[k]$ are calculated using formulas:

$$a_{j+1}[\mathrm{k}] = \sum_n a_j[n] * h[n-2k]\,. \tag{1}$$

$$d_{j+1}[\mathrm{k}] = \sum_n a_j[n] * g[n-2k]\,. \tag{2}$$

Here, $h[n]$ and $g[n]$ represent the low-pass and high-pass filter coefficients of the db2 wavelet and defined as

$$h[0] = \frac{1+\sqrt{3}}{4\sqrt{2}}, h[1] = \frac{3+\sqrt{3}}{4\sqrt{2}}, h[2] = \frac{3-\sqrt{3}}{4\sqrt{2}}, h[3] = \frac{1-\sqrt{3}}{4\sqrt{2}} \tag{3}$$

$$g[0] = \frac{1-\sqrt{3}}{4\sqrt{2}}, g[1] = -\frac{3-\sqrt{3}}{4\sqrt{2}}, g[2] = \frac{3+\sqrt{3}}{4\sqrt{2}} \tag{4}$$

$$g[3] = -\frac{1+\sqrt{3}}{4\sqrt{2}} \tag{5}$$

Using these coefficients, several additional features were calculated – energy of the detail coefficients E_j, mean of the approximation coefficients at the final level μ_a, and variance of the approximation coefficients σ_a^2. The calculation formulas related to these additional features are:

$$E_j = \sum_k |d_j[k]|^2, \tag{6}$$

$$\mu_a = \frac{1}{N}\sum_k a_J[k], \tag{7}$$

$$\sigma_a^2 = \frac{1}{N}\sum_k (a_J[k] - \mu_a)^2, \tag{8}$$

The final enriched component-tractor model specific subsets were formed by combining these DWT-derived features stated in formulas (4)-(8) with the original telemetry, maintenance history and GIS records.

After dataset integration and preprocessing, prediction models using LSTM, FCNN and SVM were implemented.

To evaluate the model's accuracy, Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE) and Coefficient of Determination (R-squared) metrics were used. These metrics were calculated using the following input values: x_i – actual RUL values, y_i – predicted RUL values, and n – total number of samples.

MAE is a metric that measures the average magnitude of errors in prediction, as an absolute difference between predicted and actual values:

$$MAE = \frac{\sum_{i=1}^{n} |x_i - y_i|}{n}. \tag{9}$$

MAPE expresses the forecast error as a percentage of the actual values, and is calculated using the formula:

$$MAPE = \frac{\sum_{i=1}^{n} \left|\frac{x_i - y_i}{x_i}\right|}{n} * 100. \tag{10}$$

RMSE measures the square root of the average squared differences between actual and predicted values:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (x_i - y_i)^2}{n}}. \tag{11}$$

R-squared gives a measure that represents how close the data is to the fitted regression line, and is calculated using the formula:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2}. \tag{12}$$

where $\bar{x}$ is the mean of the actual RUL values that is calculated using the formula:

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n}. \tag{13}$$

For MAE, MAPE and RMSE lower values indicate better model performance. R^2 values range from 0 to 1, where 1 means perfect prediction, and 0 means the model explains no variance in the data.

V. RESULTS

A total of eighty models were developed for each RUL prediction algorithm and used for training and testing. Each model corresponded to a specific combination of component and tractor model. The first 20 models included only telemetry and maintenance history records, without applying DWT. The next 20 models also used only telemetry and maintenance history records, but with DWT applied. The following 20 models incorporated telemetry, maintenance history, and GIS data, without applying DWT. The final 20 models used the complete dataset, including GIS data, with DWT applied. This setup allowed for a thorough analysis of the effects of geospatial data and DWT-derived features on the predictive accuracy of the models.

Tables 4–7 present the performance results of each prediction algorithm across the four components: Table 4 for Engine, Table 5 for Electric System, Table 6 for Hydraulic System, and Table 7 for Transmission. The reported values—MAE, MAPE, RMSE, and R^2—represent the averages observed across all tractor models.

All algorithms show lower MAE, MAPE and RMSE and higher R^2 for RUL prediction with the help of GIS data and DWT extracted features. Average MAE for models across all algorithms that use complete dataset was reduced by 29,37%, MAPE by 28,4% and RMSE 29,23%. R^2 was increased by 5,92%. Models that are enriched with only one additional type of data – GIS or DWT derived features, also overperform models that leverage only telemetry and maintenance history data. This supports the hypothesis that integrating GIS factors, such as weather and terrain characteristics, and applying DWT to extract additional approximation and detail coefficients enhances the accuracy of predictive maintenance models.

The LSTM network demonstrated the best overall performance among the RUL prediction algorithms. FCNN performed slightly worse than LSTM, although for the Transmission component, FCNN achieved the highest accuracy. SVM consistently showed the lowest performance.

Table 4

Algorithms Performance Comparison for Engine RUL prediction

Metric	LSTM	FCNN	SVM
MAE GIS NO DWT	8,25	8,84	9,58
MAE NO GIS NO DWT	10,76	11,31	12,48
MAE GIS DWT	7,52	8,03	8,71
MAE NO GIS DWT	9,60	10,09	11,21
MAPE GIS NO DWT	2,54	2,72	2,95
MAPE NO GIS NO DWT	3,12	3,28	3,62
MAPE GIS DWT	2,21	2,36	2,56
MAPE NO GIS DWT	2,76	2,91	3,23
RMSE GIS NO DWT	11,47	12,39	13,42
RMSE NO GIS NO DWT	15,18	15,91	17,53
RMSE GIS DWT	10,47	11,29	12,20
RMSE NO GIS DWT	13,62	14,11	15,91
R^2 GIS NO DWT	0,9253	0,9109	0,8757
R^2 NO GIS NO DWT	0,8857	0,8704	0,8452
R^2 GIS DWT	0,9357	0,9207	0,8883
R^2 NO GIS DWT	0,9029	0,8876	0,8627

Table 5

Algorithms Performance Comparison for Electric System RUL prediction

Metric	LSTM	FCNN	SVM
MAE GIS NO DWT	8,45	8,71	9,68
MAE NO GIS NO DWT	10,96	11,55	12,34
MAE GIS DWT	7,82	8,03	8,84
MAE NO GIS DWT	9,80	10,62	11,09
MAPE GIS NO DWT	2,6	2,68	2,98
MAPE NO GIS NO DWT	3,18	3,35	3,58
MAPE GIS DWT	2,30	2,36	2,60
MAPE NO GIS DWT	2,82	3,06	3,19
RMSE GIS NO DWT	11,71	12,24	13,42
RMSE NO GIS NO DWT	15,57	15,99	17,16
RMSE GIS DWT	11,08	11,14	12,37
RMSE NO GIS DWT	13,66	14,88	15,68
R^2 GIS NO DWT	0,9201	0,9155	0,8808
R^2 NO GIS NO DWT	0,8807	0,8754	0,8506
R^2 GIS DWT	0,9297	0,9306	0,8944
R^2 NO GIS DWT	0,8940	0,8925	0,8633

Table 6

Algorithms Performance Comparison for Hydraulic System RUL prediction

Metric	LSTM	FCNN	SVM
MAE GIS NO DWT	8,12	8,61	9,42
MAE NO GIS NO DWT	10,86	11,10	12,58
MAE GIS DWT	7,44	7,96	8,61
MAE NO GIS DWT	9,78	9,97	11,15
MAPE GIS NO DWT	2,5	2,65	2,9
MAPE NO GIS NO DWT	3,15	3,22	3,65
MAPE GIS DWT	2,19	2,34	2,53
MAPE NO GIS DWT	2,82	2,87	3,21
RMSE GIS NO DWT	11,28	12,15	13,02
RMSE NO GIS NO DWT	15,39	15,33	17,81
RMSE GIS DWT	10,52	11,30	11,93
RMSE NO GIS DWT	13,73	13,95	15,51
R^2 GIS NO DWT	0,9284	0,9153	0,868 7
R^2 NO GIS NO DWT	0,8904	0,8751	0,840
R^2 GIS DWT	0,9498	0,9242	0,890
R^2 NO GIS DWT	0,9014	0,8856	0,852

Additionally, the RUL prediction performance for Electric and Hydraulic System components was consistent with that observed for Engine and Transmission. This indicates that the telemetry and maintenance datasets used in this study provide sufficient information to accurately predict RUL for these components, improving upon the limitations of the dataset in our previous research [3].

Table 7

Algorithms Performance Comparison for Transmission RUL prediction

Metric	LSTM	FCNN	SVM
MAE GIS NO DWT	9,03	8,93	9,91
MAE NO GIS NO DWT	11,45	11,20	12,48
MAE GIS DWT	8,19	8,05	9,00
MAE NO GIS DWT	10,55	10,39	11,15
MAPE GIS NO DWT	2,78	2,75	3,05
MAPE NO GIS NO DWT	3,32	3,25	3,62
MAPE GIS DWT	2,41	2,37	2,65
MAPE NO GIS DWT	3,04	2,99	3,21
RMSE GIS NO DWT	12,60	12,34	13,86
RMSE NO GIS NO DWT	15,97	15,72	17,23
RMSE GIS DWT	11,48	11,28	12,78
RMSE NO GIS DWT	14,88	14,61	15,52
R^2 GIS NO DWT	0,9259	0,9151	0,875
R^2 NO GIS NO DWT	0,8659	0,8758	0,845
R^2 GIS DWT	0,9405	0,9274	0,886
R^2 NO GIS DWT	0,8774	0,8857	0,864

These results offer valuable insights for future predictive maintenance applications, particularly regarding the integration of RUL prediction models with Internet of Things (IoT) platforms for remote monitoring of agricultural machinery.

VI. CONCLUSION

Our previous study highlighted the importance of incorporating GIS data into agricultural vehicle RUL prediction models using the LSTM algorithm. However, high prediction accuracy was not achieved for the Electric and Hydraulic systems [3].

In this study we advanced our prior research by obtaining a new dataset, enriching it with additional approximation and detail coefficients extracted using DWT, and evaluating not only LSTM, but also FCNN and SVM algorithms. The results highlight that predictive models can be significantly improved, by integrating telemetry, maintenance history, weather, terrain, and DWT-extracted features. Pearson correlation and Random Forest helped to identify what features should be used prediction models for each component. This allowed to create models for previously underexplored Electric and Hydraulic systems. It was identified that average MAE for models across all algorithms that use complete dataset was reduced by 29,37%, MAPE by 28,4% and RMSE 29,23%. R^2 was increased by 5,92%.

Future research should focus on developing prediction models for additional vehicle components and integrating these models into IoT frameworks for real-time monitoring. Such systems would enable predictive maintenance alerts, helping farmers prevent failures, optimize maintenance schedules, and reduce operational costs.

VII. CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

VIII. DECLARATION ON GENERATIVE AI

During the preparation of this work, the author(s) used ChatGPT, Grammarly in order to: Grammar and spelling check, Paraphrase and reword. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the publication’s content.

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