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Comparative Analysis of CNN and LSTM Neural Network Models: Influencing Factors in Agricultural Machinery Fault Detection

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ABSTRACT

Predictive maintenance is increasingly vital for agricultural machinery as sensor-based monitoring becomes more prevalent. Researchers are investigating reliable fault detection across diverse operating conditions and real-world constraints. This study compares three deep learning approaches for fault detection, maintenance, and repair planning using literature data, and evaluates convolutional, sequential-based, and hybrid architectures within a unified framework.. A Convolutional Neural Network (CNN) is an artificial neural network model used specifically for processing data with a grid-like topology, such as images or time-series signals. Long Short-Term Memory (LSTM) network is a special type of Recurrent Neural Network (RNN) designed to learn long-term dependencies in sequential data. The CNN and LSTM models were evaluated for accuracy, efficiency, robustness to noise, and interpretability. Results showed that convolutional models excelled when fault patterns were localized and easier to identify in transformed formats such as the frequency domain or images. These models also provided fast inference with minimal resource use. Sequence models performed well, gradually degrading as they leveraged longer temporal contexts to detect progressive changes. In environments with multiple sensors and mixed data types, hybrid architectures yielded the most consistent results by combining spatial feature extraction with temporal modeling, enhancing accuracy and suitability for resource-limited settings. The best accuracy percentages for the effective PdM design parameters are 91.2% for the CNN model, 93.8% for the LSTM model, and 96.4% for the hybrid CNN+LSTM model. Similarly, the dropout rates are 0.1–0.4 for CNN, 0.2–0.5 for LSTM, and 0.2–0.5 for the CNN+LSTM model. Overall, model selection should depend on the data structure and monitoring goals, with hybrid models offering a balanced solution for detecting short-term anomalies and long-term deterioration.

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Introduction

Network) based on on-machine network architectures to allow subsystems to share sensor data and control commands (Castillo-Ruiz et al., 2015; López Hernández et al., 2023).

In the 2000s, connectivity shifted from optional to strategically important. Telematics, the remote transmission of machine status, location, and performance, enabled early applications such as fleet management, theft prevention, remote support, and condition monitoring. Producers and large farms began using web portals for machine tracking and service management. This period also marks the practical beginning of "connected maintenance," when data left the machine and entered a service ecosystem.

In the 2010s, low-cost sensors, widespread mobile internet, and cloud platforms enabled the large-scale transmission of operational data. With the Internet of Things, parameters such as engine status, hydraulic loads, fuel consumption, vibration signatures, thermal trends, and operator/machine usage began to be measured. Maintenance practices also shifted from "preventive" (fixed-interval) maintenance to conditional maintenance, which provides service alerts based on measured deterioration (e.g., increased vibration, abnormal temperatures, pressure deviations, increased fuel consumption for the same workload) (Khodabakhshian, 2013; Panova, 2019).

Once large datasets became available, artificial intelligence methods, particularly machine learning, began to deliver practical value. AI will, of course, not replace mechanics, but it will support decision-making by learning pre-failure patterns such as bearing wear, injector problems, cooling system failures, hydraulic leaks, belt/chain failure, sensor slippage, and abnormal load behavior (Gupta et al., 2019; Liashenko & Meliantsov, 2023).

Today's agricultural machinery is at the intersection of the following elements:

- Digitalisation, which transforms machine functions into measurable data.

- Internet of Things (IoT), which enables the reliable transmission of this data between machines, farms, and service networks.
- Artificial Intelligence (AI), which supports the transformation of raw signals into insights, predictions, and recommendations.
- Preventive and predictive maintenance, which has evolved from a mere workshop routine into a strategic management tool linking reliability, uptime, safety, fuel efficiency, and sustainability (Savickas et al., 2025).

As a result, the modern concept of preventive/predictive maintenance for agricultural machinery emerged (Kant et al., 2025; Shahab et al., 2024). In this process, modern agriculture has undergone a paradigm shift driven by the integration of artificial intelligence (AI), the Internet of Things (IoT), and smart sensors, enabling real-time monitoring and maintenance of machinery (Table 1).

Traditional maintenance strategies, such as reactive and preventive maintenance, often fail to capture the complex, nonlinear degradation behaviors observed in machinery operating under varying environmental conditions. Consequently, predictive maintenance (PdM) systems have emerged as a crucial tool for predicting machine failures before they occur, thereby minimizing downtime and optimizing resource utilization (Gabitov et al., 2021; R. Sahu and Tripathi, 2025).

In this context, deep learning (DL) models, particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have become a significant focus because of their capabilities for fault detection, anomaly classification, and fault prediction. CNNs are the preferred choice for analyzing sensor signals in the frequency or image domain, as they excel at spatial feature extraction. In contrast, LSTMs are more effective at capturing temporal dependencies in time-series data such as vibration or temperature sequences from motor components (Alharbi et al., 2025; Li et al., 2019; Saini & Singh, 2024). Therefore, the choice between these architectures depends on data characteristics, model complexity, and application constraints (Eang & Lee, 2025; Navarro-Navarro et al., 2025).

Recent studies have shown that hybrid architectures combining CNNs and LSTMs can deliver superior performance by integrating the strengths of both spatial and temporal processing.

For example, Borré et al. (2023) reported that CNN-LSTM-attention models achieved higher detection accuracy in non-stationary environments where signal patterns changed dynamically due to environmental factors such as soil moisture and load variability. Similarly, other studies have implemented a CNN-LSTM-attention framework optimized with Particle Swarm Optimization (PSO) to predict temperature anomalies in meat grinder motors, an industrial analogue of agricultural machinery, achieving improved convergence and robustness (Lukman & Lee, 2025; Navarro-Navarro et al., 2025; Pasqualotto & Zigliotto, 2021). Despite these advances, a critical need remains to systematically understand the parameters affecting maintenance contexts (Fondaj et al., 2023; Raj et al., 2025; Shykhmat & Veres, 2024). Factors such as kernel size, number of filters, array length, hidden layer configuration, and optimization algorithms significantly impact model accuracy, computational efficiency, and interpretability. Furthermore, in agricultural settings, models will need to balance predictive accuracy with hardware feasibility because many farm-based systems rely on edge computing devices with limited processing capacity (Zamora-Izquierdo et al., 2019).

This study aims to analyse the parameters that guide the choice between CNN, LSTM, and hybrid CNN-LSTM architectures for predictive maintenance and fault detection in agricultural machinery. Synthesising findings from numerous academic studies in recent years, the following objectives are aimed for:

- To identify and classify the most effective parameters in CNN and LSTM design for PdM.
- To compare performance balances in spatial, temporal, and hybrid data domains.
- To propose a guiding framework for researchers and users in selecting appropriate architectures for agricultural applications.

The Evolution of AI-Powered Predictive Maintenance

AI-powered predictive maintenance is built upon technological advancements in industrial diagnostics. Early PdM systems utilised applications such as statistical models and shallow learning methods like Support Vector Machines (SVM), k-Nearest Neighbours (kNN), and Random Forests.

Table 1. Chronological Evolution of Agricultural Machinery: Digitalisation–IoT–AI–PdM

Period	Tech stage	Key enablers	Capabilities	Maintenance	Significance
20th c. (pre-1990s)	Mechanical/hydraulic	Mostly mechanical; limited sensors	Experience-based ops	Reactive + fixed-interval	Low condition visibility
Early digitalization	Electronics	Sensors + ECUs + OBD; basic monitoring	Measurable signals	Structured preventive	Data foundation
1990s	Precision + CAN	GPS; yield maps; VRA; CAN bus	Machine as data platform	Better scheduling	Subsystem interoperability
2000s	Telematics	Remote status/location; web portals	Fleet + remote support	Connected maintenance	Service ecosystem data
2010s	IoT + cloud	Low-cost sensors; mobile + cloud	Continuous monitoring	Condition-based	Early alerts; less downtime
Late 2010s–today	AI/ML	ML on large datasets	Pre-failure patterns	Predictive (PdM)	Insights + recommendations
Today (DL focus)	CNN/LSTM hybrids	CNN (spatial) + LSTM (temporal) + attention	Fault/anomaly prediction	Accuracy vs edge limits	Hyperparams matter

While these models were effective for small, well-structured datasets, they struggled to handle the nonstationary, high-dimensional data generated by agricultural sensors (Alzuhair & Alghaihab, 2023). The shift to deep learning occurred as architectures such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), particularly Long Short-Term Memory (LSTM) models, increased their capacity to learn complex temporal and spatial relationships directly from raw sensor signals (Eang & Lee, 2025).

CNNs and LSTMs have become indispensable components of AI-based PdM systems. CNNs, originally designed for image recognition, have been widely used in recent years to represent vibrations and acoustic signals in rotating machinery in the time-frequency domain. CNNs have identified distinctive frequency bands associated with bearing failures or motor imbalances by extracting local spatial features via convolutional operations (Almasoudi, 2023). In contrast, LSTMs are designed for sequential data modeling and can capture temporal dependencies across multiple time steps, a critical requirement for understanding incremental decay trends. Together, these architectures have reshaped the field of conditional tracking, offering capabilities beyond traditional feature engineering (Shrestha et al., 2025).

Relevance to Agricultural Machinery

Agricultural machinery presents different challenges than industrial equipment. Field conditions are highly dynamic: soil type, moisture, temperature, and operational load can change significantly even within a single day (Hung, 2019). Furthermore, agricultural IoT sensors often operate under bandwidth or power constraints, resulting in noisy, incomplete data. Therefore, they require not only accurate results but also robust, interpretable, and computationally efficient machine learning models for edge or embedded deployment.

Convolutional neural networks (CNNs) are more effective at identifying local anomalies in spectrograms of machine vibrations or thermographic images of motors. On the other hand, long-term memory networks (LSTMs) are more effective at tracking slow temporal changes in data such as temperature and torque.However, deciding which model or combination of models is best suited for a particular task depends on the data type, sensor configuration, and target prediction horizon. For example, CNNs may perform better than LSTMs at detecting short-term mechanical shocks, while LSTMs may also better capture long-term wear or fatigue patterns. A hybrid architecture combining CNN and LSTM models shows promise for integrating spatial and temporal learning within a unified prediction framework (Alharbi et al., 2025; D. Sahu et al., 2025).

Knowledge Gaps in Model Selection

Despite their widespread preference, there is limited consensus on how to choose between CNNs, LSTMs, and CNN-LSTM (hybrid) models for PdM applications in agriculture. The challenge lies in the parameter sensitivity of these architectures. Factors such as kernel size, number of filters, array length, dropout rate, and learning rate profoundly affect prediction accuracy and convergence behavior. Similarly, the choice of an optimization algorithm, such as Adam or Particle Swarm Optimization (PSO), can determine whether the model generalizes well to real-world conditions or fits perfectly to laboratory data (Zhang et al., 2025).

While most academic studies focus on individual models or situation-specific optimisations, few compare architectures under combined conditions to systematically analyse parameter-oriented trade-offs. However, explainability, the ability to understand how a model arrives at a prediction, is gaining increasing attention in agricultural applications where practitioners need transparency to trust AI-powered care decisions (Khodabakhshian, 2013; Shykhmat & Veres, 2024). Therefore, a systematic framework for model comparison and parameter selection is essential to guide engineers and researchers in designing robust PdM solutions (Figure 1).

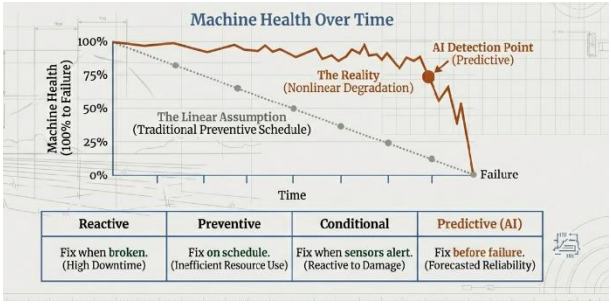

Figure 1. A shift from traditional to preventive and predictive maintenance

Convolutional Neural Networks (CNNs) in Fault Detection

CNNs have significantly improved predictive maintenance by efficiently recognizing spatial patterns in data fields such as time-frequency spectrograms, thermal images, and current signatures. In principle, they first apply convolutional kernels (filters) to input matrices to capture localized features; these features are then combined and extracted using activation functions such as ReLU to form hierarchical abstractions (Silva et al., 2019; Kaparthi and Bumblauskas, 2020). In agricultural applications, CNNs have been successfully used for vibration- and thermography-based diagnostics. Almasoudi (2023) also proposed a 1D-CNN-LSTM hybrid model for fault detection in medium-voltage switchgear. The CNN layers extract spatially related fault features from vibration signals, while the LSTM layer handles temporal dependencies. Their study revealed that smaller kernels (3×3 or 5×5) and deeper convolutional stacks improved error localization and yielded higher F1 scores than traditional feature-based classifiers (Ferentinos & Albright, 2003; Shrestha et al., 2025; Wang et al., 2023).

In agricultural machinery applications, CNNs have the following advantages:

- Ability to process multispectral sensor inputs (vibration + thermographic imaging) (Jung et al., 2025).
- Parallelizable architectures that are efficient on GPUs and embedded devices.
- Noise tolerance when used in conjunction with normalisation and dropout regulation.

However, as expected, CNNs are limited in modeling temporal relationships, which are critical for understanding long-term wear or degradation trends in equipment such as harvesters or irrigation pumps (Abdelmoneim et al., 2025; Benhmad et al., 2024; Rehan et al., 2025). Therefore, while CNNs are very good at identifying instantaneous anomalies, they struggle to predict progressive failures without additional temporal modeling layers (Borré et al., 2023).

Long Short-Term Memory (LSTM) Networks for Temporal Dynamics

LSTM networks, a subclass of Recurrent Neural Networks (RNNs), address the vanishing gradient problem by adding memory gates that regulate information flow over long time horizons. Each LSTM cell contains input, forget, and output gates that allow the network to preserve relevant features while discarding noise. This makes LSTMs well suited for sequential agricultural data such as temperature, vibration, or torque signals collected over long run cycles (Figure 2).

In agricultural applications, LSTMs are commonly used in:

- Predicting hydraulic system failures based on continuous pressure and flow readings.
- Predicting engine temperature in automated/intelligent irrigation systems.
- Detecting torque anomalies in harvesters and autonomous tractors.

Hybrid CNN–LSTM Architectures

The growing recognition that CNNs and LSTMs address complementary aspects of the spatial and temporal dimensions of data has inspired the development of hybrid CNN-LSTM models. In these architectures, CNNs serve as feature extractors, converting raw sensor signals into compact spatial feature maps, which are then fed into LSTM layers that model temporal dependencies (Figure 3). This integration enables both short-term anomaly detection and long-term degradation prediction within a unified framework (Sahu et al., 2025).

The model achieved 96% accuracy, demonstrating that PSO-assisted hyperparameter tuning improved convergence and the stability of feature selection. Similarly, Priyadarshini (2025) examined the strengths and weaknesses of models by combining autoencoder-based preprocessing with CNN-LSTM-PSO to improve robustness against noise and sensor drift.

Hybrid CNN-LSTM architectures are particularly important for multi-sensor agricultural systems where mechanical, environmental, and electrical data need to be combined due to the following advantages (Figure 4):

- Common spatiotemporal modelling without manual feature engineering.
- Better generalisation to dynamic agricultural conditions.
- Compatibility with explainability tools such as attention visualisation and distinctiveness mapping.

However, hybrid models require increased design complexity and higher training costs. Hyperparameter optimisation and interpretability are critical to ensuring model reliability

and user confidence in agricultural decision support systems (Susarev et al., 2022).

Summary of Literature Insights

The studies reviewed collectively demonstrate the following:

- CNNs are preferred for spatially localised signals and resource-constrained applications.
- LSTMs exhibit superior performance when processing long-term sequential data with evolving fault patterns.
- Hybrid CNN-LSTM architectures, particularly those enhanced with careful attention and optimisation algorithms, provide the best compromise in terms of accuracy, interpretability, and computational ease for agricultural field applications (Figure 5).

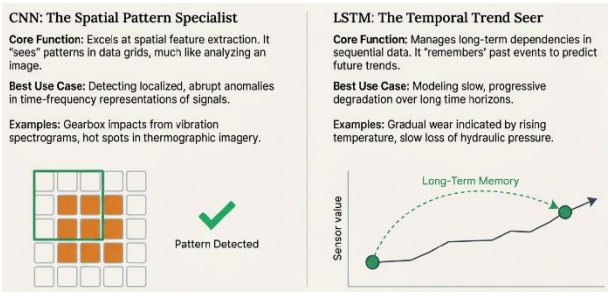

Figure 2. Comparison of CNN and LSTM models

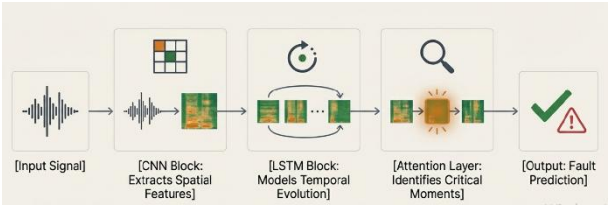

Figure 3. Input signals processed through CNN and LSTM models converted into output signals

Feature	CNN (The Spatial Specialist)	LSTM (The Temporal Seer)
Primary Strength	Spatial pattern recognition	Long-term temporal dependency modeling
Ideal Data Type	Time-frequency representations (spectrograms), thermographic images	Sequential sensor data (temperature, pressure, torque)
Excels At	Detecting abrupt, transient faults (e.g., impacts, cracks)	Forecasting slow degradation trajectories (e.g., wear, leaks)
Key Limitation	Lacks temporal context; can be confused by environmental vibrations	Higher computational latency; less suitable for real-time edge alerts
Interpretability	Spatial heatmaps (Grad-CAM) showing *where* the fault is in the signal	Temporal attention curves showing *when* the critical patterns occur

Figure 4. Strengths and weaknesses of CNN and LSTM models.

Application Scenario	Dominant Data Type	Preferred Model	Rationale
Tractor Hydraulics	Pressure & Temperature (Slow Drift)	LSTM	Best for capturing progressive wear and slow leaks.
Harvester Gearboxes	Vibration & Acoustic (Abrupt Events)	CNN	Ideal for detecting transient faults like tooth chips or impacts.
Irrigation Pumps	Temperature (Drift) + Acoustic (Noise)	CNN-LSTM	Balances thermal degradation trends with detection of noise anomalies.
Greenhouse Motors	Multiple Mixed Sensors	CNN-LSTM + Attention	Fuses multi-modal inputs and provides crucial explainability for complex systems.

Figure 5. Hybrid CNN-LSTM architectures feasibility for real-world agricultural applications

Materials and Methods

To determine the parameters that influence the performance of CNN, LSTM, and hybrid CNN-LSTM models in predictive maintenance (PdM) for agricultural machinery, this section outlines the framework for comparative evaluation. The methodology integrates literature-driven parameter identification, model architecture configuration, and performance assessment metrics, reflecting conditions typical of smart farm environments, such as sensor heterogeneity, variable sampling rates, and limited on-device computational capacity.

The framework was designed to assess how parameter choices affect model accuracy, interpretability, and computational efficiency across different data modalities (vibration, temperature, acoustic, and spectral signals).

Data Characterization and Input Modalities

Agricultural machinery produces diverse sensor data streams that differ in structure and temporal resolution, Table 2.

Model Configuration Parameters

The CNN, LSTM, and CNN-LSTM models were configured with adjustable architectural parameters Table 3.

Hyperparameters were fine-tuned using Particle Swarm Optimisation (PSO) to optimise multi-objective performance criteria, including prediction accuracy, model stability, and inference latency (Priyadarshini, 2025).

Evaluation Metrics

Model performance was evaluated in three main dimensions: prediction accuracy, computational efficiency, and interpretability.

(a) Prediction Performance

- Accuracy (ACC) and F1 score (F1) measured the classification performance of fault/no fault labels.
- Root Mean Square Error (RMSE) assessed the prediction quality in continuous failure prediction.
- Sensitivity-Recall Curves (PRC) were used to assess sensitivity under unbalanced data conditions.

(b) Computational Efficiency

- Training Time (TT) and Inference Time (IT) were measured in seconds per epoch and milliseconds per sample, respectively.
- Memory Footprint (MF) was evaluated in megabytes (MB) to assess edge deployment feasibility. CNNs typically exhibit 40–60% lower MF than LSTMs at comparable accuracy levels (Eang & Lee, 2024).

(c) Interpretability and Robustness

- Models were analyzed using Gradient Weighted Class Activation Mapping (Grad-CAM) and attention heatmaps to visualize prominent features.
- Noise sensitivity tests were performed by injecting Gaussian distortions ($\sigma = 0.05–0.2$) into the sensor data to assess the robustness of the model.

Comparative Evaluation Procedure

The comparison was conducted in three phases:

1. Baseline Evaluation: Training independent CNN and LSTM models on homogeneous datasets (e.g., vibration data only).

2. Hybrid Integration: Combining spatial and temporal features in a CNN-LSTM line; optimizing hyperparameters via PSO.

3. Interpretability Analysis: Visualizing model focus regions and temporal attention maps to assess the physical significance of fault detection.

This phased evaluation provides a systematic analysis of how specific parameters, such as kernel size, array length, and dropout rate, affect model performance and interpretability under realistic agricultural conditions.

Table 2. Data categories for CNN and LSTM models.

Data Type	Sensor Source	Typical Use Case	Preferred Model
Vibration (1D time series)	Accelerometers on bearings, shafts	Mechanical fault detection	LSTM or CNN-LSTM
Temperature (1D or 2D grids)	Thermal sensors on motors	Overheating/fatigue prediction	CNN or CNN-LSTM
Acoustic (time-frequency)	Microphones on engines	Early anomaly detection	CNN
Spectral/FFT (2D matrices)	Frequency domain from vibration data	Fault signature analysis	CNN or hybrid

Table 3. Configuration parameters for CNN, LSTM, and CNN-LSTM models.

Parameter Type	CNN Parameters	LSTM Parameters	Hybrid (CNN-LSTM)
Input shape	(n, m) sensor grid	(t, f) sequence	(n, t) hybrid tensor
Kernel size	3×3, 5×5, 7×7	—	3×3 (front-end CNN)
Number of filters/units	16–128	32–128	32–128
Pooling type	Max, Average	—	Max
Activation function	ReLU, LeakyReLU	Tanh, ReLU	ReLU (CNN) + Tanh (LSTM)
Dropout rate	0.1–0.4	0.2–0.5	0.2–0.5
Optimizer	Adam, RMSprop	Adam, SGD	PSO-optimized Adam
Learning rate	0.001–0.0001	0.001–0.0001	Adaptive PSO tuning
Batch size	32–128	16–64	32–64

Table 4. CNN, LSTM, and CNN-LSTM model selection.

Criterion	Preferred Model	Rationale
High-frequency vibration data	CNN	Efficient spatial filtering, low power demand
Long-term sequential degradation	LSTM	Superior temporal correlation modeling
Mixed-domain or multi-sensor data	CNN-LSTM (Attention)	Integrates spatial and temporal learning
Explainable maintenance insights	LSTM-Attention	Transparent temporal feature attribution
Edge computing or embedded use	CNN or compressed CNN-LSTM	Low-latency, compact memory footprint

Table 5. Effective PdM design parameters.

Model Type	Best Accuracy (%)	F1-Score	RMSE	Inference Time (ms/sample)	Memory (MB)
CNN (5×5 kernels, 64 filters)	91.2	0.89	0.071	3.5	22
LSTM (64 units, 0.3 dropout)	93.8	0.92	0.059	7.9	38
CNN-LSTM (Attention + PSO)	96.4	0.95	0.041	5.8	31

Results

Comparative Model Performance

The comparative evaluation of CNN, LSTM, and hybrid CNN-LSTM models was conducted across datasets representing vibration, temperature, and acoustic sensor signals. Each architecture's configuration was optimised according to previously defined parameters.

Overview of Comparative Findings

The comparative assessment of CNN, LSTM, and hybrid CNN–LSTM architectures reveals distinct performance patterns driven by their structural characteristics and parameter sensitivities. While all three models demonstrated strong predictive capability in agricultural maintenance contexts, their relative advantages depended on the nature of the input data, the length of monitoring intervals, and the resource constraints of the deployment platform.

Based on the quantitative parameter ranges presented in Table 1, it is seen that structural differences between the models directly affect their performance potential. The CNN architecture provides flexibility in multi-scale spatial feature extraction with 3×3–7×7 core sizes and a filter range of 16–128, while offering a more stable and computationally efficient training process thanks to a dropout of 0.1–0.4 and a batch size range of 32–128. The LSTM model, on the other hand, increases temporal generalization capacity with a hidden unit range of 32–128 and a higher dropout rate (0.2–0.5), but may be limited in terms of representational power in high-dimensional spatial data due to the lower batch size requirement (16–64) and its structure based only on (t, f) sequence inputs. The hybrid CNN–LSTM structure, with its combination of a 3×3 front-end CNN layer and a 32–128 unit LSTM, models both spatial and temporal features in an integrated manner; Furthermore, PSO-optimized Adam and adaptive learning rate adjustment provide methodological superiority in hyperparameter optimization. However, the 0.2–0.5 dropout and 32–64 batch size range indicate increased model complexity and regularization requirements. When quantitative parameter distributions are considered together, CNN demonstrates superiority in terms of computational efficiency, LSTM in terms of temporal representation capacity, and the hybrid model in terms of overall representation; however, the increased need for parameter optimization must be carefully managed in the hybrid approach.

The research results confirm the complementary strengths of the CNN and LSTM architectures. While CNNs achieve the lowest inference latency and smallest memory footprint, making them ideal for edge deployment, LSTMs excel at long-term fault pattern recognition. Hybrid CNN-LSTM models consistently outperform both in accuracy and robustness, striking a balance between real-time performance and temporal generalization. Similar performance trends were reported by Borré et al. (2023) and Zhang et al. (2025), validating this architecture's suitability for predictive maintenance in machinery.

Based on the performance metrics presented in Table 2, the hybrid CNN–LSTM (Attention + PSO) model exhibits the quantitatively superior overall performance. The hybrid structure achieved higher classification accuracy with 96.4% accuracy and an F1 score of 0.95 compared to CNN (91.2%; 0.89%) and LSTM (93.8%; 0.92%); it also statistically strengthened prediction accuracy with the lowest error value, RMSE = 0.041. However, in terms of inference time, CNN was the fastest model at 3.5 ms/sample, while LSTM was the slowest at 7.9 ms; the hybrid model was positioned in the middle in terms of accuracy-speed balance with 5.8 ms. Regarding memory usage, LSTM has the highest resource requirement at 38 MB, CNN is the lightest model at 22 MB, and the hybrid approach offers an acceptable cost at 31 MB. When these data are considered together, CNN is advantageous for applications requiring computational efficiency and low latency; LSTM provides performance improvements in terms of temporal accuracy; however, the hybrid CNN–LSTM model stands out as the most robust and generalizable solution in terms of accuracy, error minimization, and balanced resource utilization.

Model Selection Framework

Based on the observed results and literature synthesis, the following guidelines are proposed for model selection in AI-supported predictive maintenance of agricultural machinery, Table 4:

These findings suggest that no single model dominates across all agricultural scenarios. Instead, hybrid architectures with adaptive hyperparameter optimisation and attention mechanisms provide the most practical trade-off between accuracy, efficiency, and interpretability.

Theoretical and Socio-Technical Implications

From a theoretical perspective, this research contributes to the growing field of applied AI in agriculture by establishing a comparative framework for neural architecture selection. It underscores that effective PdM design is not merely a matter of maximising accuracy but of aligning model capabilities with contextual constraints, including data quality, hardware limitations, and operator expertise Table 5.

Predictive Maintenance in Smart Agriculture

Predictive maintenance (PdM) uses machine learning (ML) and sensor data to predict equipment failures before they occur, reducing downtime and increasing productivity in agricultural systems (Fondaj et al., 2023; Raj et al., 2025; Shykhmat & Veres, 2024). Unlike traditional maintenance strategies based on predefined schedules, PdM systems dynamically model failure patterns using a continuous stream of data from microelectromechanical sensors (MEMS) embedded in tractors, harvesters, irrigation systems, and other machinery. In a related study, Ferentinos & Albright (2003) demonstrated the use of ML for slip-failure detection in hydroponic systems, evaluating an algorithm that uses recurrent neural networks to identify incremental sensor failures.

Priyadarshini (2025); Suresh & Reddy (2025) developed an Explainable Artificial Intelligence (XAI) framework that integrates LSTM-RNN models with attentional mechanisms to visualize the contribution of temporal features to model decisions for predictive maintenance in smart agricultural facilities. This interpretability is critical for engineers who need to link predictions to physical causes such as mechanical imbalance or bearing wear (Abbas et al., 2011; Tolbert, 2025).

Convolutional Neural Networks (CNNs) for Spatial Feature Extraction

CNNs are among the most commonly used models for predictive maintenance tasks involving spatially structured data, such as converting vibration signals into spectrograms or thermographic images. The convolutional layers of CNNs can detect anomalies such as frequency increases, temperature gradients, or geometric distortions associated with component failure with high efficiency, enabling localised pattern recognition. In studies highlighting these features, Alsumaidaee et al. (2023) emphasised that convolutional filters with kernel sizes of 3-5 are most effective at capturing transient features, using a 1D-CNN-LSTM hybrid model for medium-voltage switchgear fault detection. Similarly, Eang and Lee (2024) stated that CNNs can outperform recurrent networks when fault signatures are strongly localized in the time-frequency domain.

Long Short-Term Memory (LSTM) Networks for Temporal Dynamics

LSTM networks, a subclass of recurrent neural networks (RNNs), excel at learning from sequential data and identifying long-term dependencies in system behavior. Their intrinsic gating mechanisms allow retention and selective forgetting of key information, enabling detection of slowly evolving decay patterns. Borré et al. (2023) reported that LSTMs outperform CNNs in modeling the temporal progression of anomalies, especially in non-stationary operating conditions where machine stress and load change unpredictably. The study highlighted that the LSTM component improves the static feature extraction ability of CNNs and provides more accurate long-term predictions of equipment failures. However, LSTMs' higher computational requirements and tendency to overfit small datasets are significant drawbacks. Eang and Lee (2024) emphasized that LSTM layers need to be carefully tuned (typically between 50 and 128 hidden units with dropout rates between 0.2 and 0.5) to avoid excessive variance in field data. Nevertheless, LSTM's ability to capture successive correlations makes it indispensable for agricultural machinery, where operational data are inherently time-dependent (e.g., engine torque or soil compaction patterns).

Hybrid CNN-LSTM Architectures

To overcome the limitations of using CNNs or LSTMs alone, hybrid architectures combine CNNs' spatial inference with LSTMs' temporal reasoning to improve inference for complex failure dynamics. Zhang et al. (2025) used a CNN-LSTM-Attention network optimised with Particle Swarm Optimisation (PSO) for temperature and vibration-based failure prediction in industrial grinding machines. This hybrid framework achieved high accuracy and convergence stability by balancing parameter discovery (via PSO) with deep feature fusion. Similarly, Priyadarshini (2025) achieved success by combining autoencoder-based feature inference with CNN-LSTM-PSO optimisation to improve robustness against sensor drift and noise, demonstrating the effectiveness of hybrid CNN-LSTM models in scenarios where both instantaneous anomalies (spatial) and progressive wear trends (temporal) need to be detected simultaneously.

Discussion

This research concludes that the nature of model selection in AI-powered predictive maintenance for agricultural machinery is inherently multidimensional, influenced by both algorithmic design and real-world operational factors.

While CNNs provide efficient spatial analysis, LSTMs capture long-term dynamics, and hybrid CNN-LSTM models combine these strengths to deliver versatile, interpretable, and reliable performance.

The hybrid CNN–LSTM (Attention + PSO) model stands out with its superior overall performance and enhanced predictive robustness and generalization ability, achieving the highest accuracy, F1 score, and lowest RMSE. While CNN is suitable for real-time or resource-constrained applications by providing the fastest inference time and lowest memory consumption, the hybrid model strikes a favorable balance between computational cost and prediction performance. These findings demonstrate that the integration of spatial feature extraction, temporal modeling, and optimization mechanisms provides a more reliable and scalable solution compared to standalone CNN or LSTM architectures.

In conclusion, the combination of deep learning, edge computing, and explainable AI will redefine the boundaries of smart agriculture, transforming predictive maintenance from a reactive tool into a proactive, adaptive intelligence that supports resilient, sustainable agricultural systems.

Limitations of Current Research

While this study synthesizes comprehensive evidence, it also highlights the need to consider several limitations to guide future research.

- Dataset diversity: Most existing agricultural PdM datasets are field-focused (e.g., vibration data from harvesting machines). Larger, standardised datasets covering multiple machine types and environmental conditions are needed for universal benchmarking.
- Parameter tuning and generalisation: The impact of hyperparameters such as dropout, kernel size, or learning rate can vary with data resolution and sensor noise levels. Therefore, more meta-analysis across datasets is needed.
- Hardware testing: Further research is needed for real-time applications on low-power edge devices; simulation-based performance analyses should be validated through field experiments.
- Interpretability assessment: While Grad-CAM and attention visualization offer insights, more quantitative interpretability measures are needed to objectively assess model transparency.

These limitations demonstrate that, despite the promise of CNN-LSTM models, their application in real-world agricultural contexts requires interdisciplinary validation, drawing on expertise in artificial intelligence, mechanical engineering, and human-machine interaction design.

References

Abbas, O. M., Mohammed, H. I., Nougomi, E., & Omer, A. (2011). Development of Predictive

Markov-chain Condition-Based Tractor Failure Analysis Algorithm. In *Research Journal of Agriculture and Biological Sciences* (Vol. 7, Issue 1).

Abdelmoneim, A. A., Kimaita, H. N., Al Kalaany, C. M., Derardja, B., Dragonetti, G., & Khadra, R.

(2025). IoT Sensing for Advanced Irrigation Management: A Systematic Review of Trends, Challenges, and Future Prospects. In *Sensors* (Vol. 25, Issue 7). https://doi.org/10.3390/s25072291.

Alharbi, F., Luo, S., & Yang, G. (2025). TD-CLNet: a time-distributed CNN-LSTM network for fault

detection in belt conveyor idlers. *Neural Computing and Applications*, *37*(30). https://doi.org/10.1007/s00521-025-11570-2.

Almasoudi, F. M. (2023). Enhancing Power Grid Resilience through Real-Time Fault Detection and

Remediation Using Advanced Hybrid Machine Learning Models. *Sustainability (Switzerland)*, *15*(10). https://doi.org/10.3390/su15108348.

Alzuhair, A., & Alghaihab, A. (2023). The Design and Optimization of an Acoustic and Ambient

Sensing AIoT Platform for Agricultural Applications. *Sensors*, *23*(14).

https://doi.org/10.3390/s23146262.

Benhmad, T., Rhaimi, C. B., Alomari, S., & Aljuhani, L. (2024). Design and Implementation of an Integrated IoT and Artificial Intelligence System for Smart Irrigation Management.

International Journal of Advances in Soft Computing and Its Applications, *16*(1). https://doi.org/10.15849/IJASCA.240330.12.

Bharatheedasan, K., Maity, T., Kumaraswamidhas, L. A., & Durairaj, M. (2025). Enhanced fault diagnosis and remaining useful life prediction of rolling bearings using a hybrid multilayer perceptron and LSTM network model. *Alexandria Engineering Journal*, *115*. https://doi.org/10.1016/j.aej.2024.12.007.

Borré, A., Seman, L. O., Camponogara, E., Stefenon, S. F., Mariani, V. C., & Coelho, L. dos S. (2023). Machine Fault Detection Using a Hybrid CNN-LSTM Attention-Based Model. *Sensors*, *23*(9). https://doi.org/10.3390/s23094512.

Castillo-Ruiz, F. J., Pérez-Ruiz, M., Blanco-Roldán, G. L., Gil-Ribes, J. A., & Agüera, J. (2015).

Development of a telemetry and Yield-Mapping system of olive harvester. *Sensors*

(Switzerland), *15*(2). https://doi.org/10.3390/s150204001.

da Silva, C. A. G., de Sá, J. L. R., & Menegatti, R. (2019). Diagnostic of Failure in Transmission

System of Agriculture Tractors Using Predictive Maintenance Based Software.

AgriEngineering, *1*(1). https://doi.org/10.3390/agriengineering1010010.

Eang, C., & Lee, S. (2025). Predictive Maintenance and Fault Detection for Motor Drive Control Systems in Industrial Robots Using CNN-RNN-Based Observers. *Sensors*, *25*(1).

https://doi.org/10.3390/s25010025.

Elhattab, K., & Elatar, S. (2024). Survey of IoT and AI applications: future challenges and

opportunities in agriculture. *Indonesian Journal of Electrical Engineering and Computer Science*, *36*(3). https://doi.org/10.11591/ijeecs.v36.i3.pp1655-1663.

Ferentinos, K. P., & Albright, L. D. (2003). Fault detection and diagnosis in deep-trough hydroponics using intelligent computational tools. *Biosystems Engineering*, *84*(1). https://doi.org/10.1016/S1537-5110(02)00232-5.

Fondaj, J., Hamiti, M., Krrabaj, S., Zenuni, X., & Ajdari, J. (2023). Comparison of Predictive Algorithms for IoT Smart Agriculture Sensor Data. *International Journal of Interactive Mobile Technologies*, *17*(21). https://doi.org/10.3991/ijim.v17i21.44143.

Gabitov, I., Insafuddinov, S., Kharisov, D., Gaysin, E., & Farhutdinov, T. (2021). Diagnostic method and device for evaluating and forecasting the technical condition of farm machinery in operation. *Journal of Agricultural Engineering*, *52*(4). https://doi.org/10.4081/JAE.2021.1158.

Gupta, S., Khosravy, M., Gupta, N., Darbari, H., & Patel, N. (2019). Hydraulic system onboard monitoring and fault diagnostic in agricultural machine. *Brazilian Archives of Biology and Technology*, *62*. https://doi.org/10.1590/1678-4324-2019180363.

Hamrani, A., Allouhi, A., Bouarab, F. Z., & Jayachandran, K. (2025). AI and Robotics in Agriculture: A Systematic and Quantitative Review of Research Trends (2015–2025). In *Crops* (Vol. 5, Issue 5). https://doi.org/10.3390/crops5050075.

Hung, Y. H. (2019). Developing an Agriculture Internet of Things (IoT) Application Taking the Plants Humidity Preventive Maintenance (PM) as an Example. *Proceedings of 2019 2nd World Symposium on Communication Engineering, WSCE 2019*. https://doi.org/10.1109/WSCE49000.2019.9041049.

J, M. (2025). AI Powered IOT-Based Smart Agriculture for Sustainable Crop Management. *Interantional Journal Of Scientific Research In Engineering And Management*, *09*(02). https://doi.org/10.55041/ijsrem41447.

Jung, W., Kim, J., Jang, K., Yun, S. H., Lim, D., Jin, M., & Park, Y. H. (2025). Vibration, current, torque, RPM dataset for multiple fault conditions in industrial-scale electric motors under randomized speed and load variations. *Data in Brief*, *62*. https://doi.org/10.1016/j.dib.2025.111954.

K., K., Kanth, T. V. R., Babiyola, A., & Mishra, H. (2025). IoT-Based Smart Agricultural Monitoring Using WSN and Predictive Analytics with Artificial Intelligence (AI). *International Journal of BIM and Engineering Science*, *10*(1). https://doi.org/10.54216/ijbes.100104.

Kaparthi, S., & Bumblauskas, D. (2020). Designing predictive maintenance systems using decision tree-based machine learning techniques. *International Journal of Quality and Reliability Management*, *37*(4). https://doi.org/10.1108/IJQRM-04-2019-0131.

Khodabakhshian, R. (2013). A review of maintenance management of tractors and agricultural machinery: Preventive maintenance systems. *Agricultural Engineering International: CIGR Journal*, *15*(4).

Li, Y., Zhu, Z., Kong, D., Han, H., & Zhao, Y. (2019). EA-LSTM: Evolutionary attention-based LSTM for time series prediction. *Knowledge-Based Systems*, *181*. https://doi.org/10.1016/j.knosys.2019.05.028.

Liashenko, D., & Meliantsov, P. (2023). Forecasting the technical condition of hydraulic transmissions of agricultural machines based on kinematic viscosity and pressure indicators of oil. *Scientific Horizons*, *26*(3). https://doi.org/10.48077/scihor3.2023.112.

López Hernández, J. G., García Ayala, J. A., Arce Patron, E. A., Vargas Ríos, S. E., Franco, O. R.,

Rodríguez, R. L., & Nurillo, C. P. (2023). Evaluation of SMED Industrial Method to Increase the Crop Yield of Asparagus Based on Control of pH of Soil and Water in the Agricultural Industry of Mexicali Valley. *Mediterranean Journal of Basic and Applied Sciences*, *07*(01). https://doi.org/10.46382/mjbas.2023.7107.

Lukman, G. F., & Lee, C. (2025). Towards Digital Twin Modeling and Applications for Permanent Magnet Synchronous Motors. In *Energies* (Vol. 18, Issue 4). https://doi.org/10.3390/en18040956.

Meshram, A., Kadam, R., Shinde, G., & Khalge, M. (2024). Sensor Based Agriculture and Horticulture Crop Production(Application of Sensors). *Preprints*.

Navarro-Navarro, A., Biot-Monterde, V., Ruiz-Sarrio, J. E., & Antonino-Daviu, J. A. (2025). Current- and Vibration-Based Detection of Misalignment Faults in Synchronous Reluctance Motors. *Machines*, *13*(4). https://doi.org/10.3390/machines13040319.

Panova, A. V. (2019). Integration of scheduled preventive maintenance works into Agriculture 4.0. *Сельское Хозяйство*, *4*. https://doi.org/10.7256/2453-8809.2019.4.32911.

Pasqualotto, D., & Zigliotto, M. (2021). A comprehensive approach to convolutional neural networks-based condition monitoring of permanent magnet synchronous motor drives. *IET Electric Power Applications*, *15*(7). https://doi.org/10.1049/elp2.12059.

Priyadarshini, I. (2025). An Explainable Autoencoder-Based Feature Extraction Combined with CNN-LSTM-PSO Model for Improved Predictive Maintenance. *Computers, Materials and Continua*, *83*(1). https://doi.org/10.32604/cmc.2025.061062.

Raj, G. B., Kholiya, D., Vinston Raja, R., Hasan, D. S., Singh, N., Mane, A., & Rosca, L. (2025). Using IoT and Machine Learning Together for Agricultural Predictive Maintenance. In *Recent Trends in Engineering and Science for Resource Optimization and Sustainable Development*. https://doi.org/10.1201/9781003596721-14.

Rehan, S., Alhame, E., & Hassan, E. (2025). Design And Implementation Of A Scalable Lora-Based Iot Irrigation System With Dual Control Mechanisms. *Journal of Engineering and Technology for Industrial Applications*, *11*(53). https://doi.org/10.5935/jetia.v11i53.1605.

Sahu, D., Dewangan, R. K., & Matharu, S. P. S. (2025). Hybrid CNN-LSTM model for fault diagnosis of rolling element bearings with operational defects. *International Journal on Interactive Design and Manufacturing*, *19*(8). https://doi.org/10.1007/s12008-024-02165-7.

Sahu, R., & Tripathi, P. (2025). An intelligent forecasting system in Internet of Agriculture Things sensor network. *Ad Hoc Networks*, *169*. https://doi.org/10.1016/j.adhoc.2024.103752.

Saini, K., & Singh, A. (2024). A content-based recommender system using stacked LSTM and an attention-based autoencoder. *Measurement: Sensors*, *31*. https://doi.org/10.1016/j.measen.2023.100975.

Savickas, D., Juostas, A., Jotautienė, E., & Grigas, A. (2025). Crop Harvesting Performance Analysis via Telemetry: Fuel and Environmental Insights. *Sustainability (Switzerland)*, *17*(12). https://doi.org/10.3390/su17125377.

Shahab, H., Iqbal, M., Sohaib, A., Ullah Khan, F., & Waqas, M. (2024). IoT-based agriculture management techniques for sustainable farming: A comprehensive review. In *Computers and Electronics in Agriculture* (Vol. 220). https://doi.org/10.1016/j.compag.2024.108851.

Shrestha, R., Chamana, M., Mohammadpourfard, M., Souto, L., & Bayne, S. (2025). Fault Detection Isolation and Localization (FDIL) Scheme: A Robust ML Framework With Novel Architecture for Fault Localization. *IEEE Access*, *13*. https://doi.org/10.1109/ACCESS.2025.3617464.

Shykhmat, A., & Veres, Z. (2024). Agriculture Vehicles Predictive Maintenance with Telemetry, Maintenance History and Geospatial Data. *Advances in Cyber-Physical Systems*, *9*(2). https://doi.org/10.23939/acps2024.02.134.

Soussi, A., Zero, E., Sacile, R., Trinchero, D., & Fossa, M. (2024). Smart Sensors and Smart Data for Precision Agriculture: A Review. In *Sensors* (Vol. 24, Issue 8). https://doi.org/10.3390/s24082647.

Suresh, S. E., & Reddy, K. V. (2025). Explainable Artificial Intelligence Model for Predictive Maintenance in Smart Agricultural Facilities. *International Journal of Research Publication and Reviews*, *6*(5). https://doi.org/10.55248/gengpi.6.0525.18125.

Susarev, S., Orlov, S., Bizyukova, E., & Uchaikin, R. (2022). The Models for Predictive

Maintenance of Robotic Agricultural Vehicles. In *Studies in Systems, Decision and Control* (Vol. 417). https://doi.org/10.1007/978-3-030-95116-013.

Tolbert, C. L. (2025). Leveraging Variable Frequency Drive Data for Nondestructive Testing and Predictive Maintenance in Industrial Systems. *NDT*, *3*(2). https://doi.org/10.3390/ndt3020007.

Zamora-Izquierdo, M. A., Santa, J., Martínez, J. A., Martínez, V., & Skarmeta, A. F. (2019). Smart farming IoT platform based on edge and cloud computing. *Biosystems Engineering*, *177*. https://doi.org/10.1016/j.biosystemseng.2018.10.014.

Zhang, W., Zhao, B., Li, G., Zhou, L., Niu, K., & Gao, S. (2023). Configuration Optimization Method of Agricultural Machinery Cluster Operation Maintenance Service Vehicle. *Inmateh - Agricultural Engineering*, *69*(1). https://doi.org/10.35633/inmateh-69-51.

Zhang, Y., Zhang, P., Zhang, W., & Wang, M. (2025). CNN-LSTM-Attention with PSO optimization for temperature and fault prediction in meat grinder motors. *Discover Applied Sciences*, *7*(5). https://doi.org/10.1007/s42452-025-07011-3.