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APPLICATION OF MULTI-SOURCE INFORMATION FUSION AND GRAPH NEURAL NETWORKS IN FAULT LOCALIZATION FOR COMPLEX AGRICULTURAL MACHINERY SYSTEMS

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Abstract

The modern agricultural equipment needs to be able to cope with changes in field conditions, however, fault detection is still challenging for the time being with the traditional rule based or single sensor based diagnostic procedures. These methods frequently do not reflect data interactions and interdependencies within components. To overcome these drawbacks, this research introduces Multi-Source Graph-Enhanced Fault Localization (MS-GEFL) framework. The framework combines vibration sensors, operational logs, environmental data and controller outputs in a multi-source fusion layer to guarantee that the data is consistent. Then, a dynamic graph model is used to represent the mechanical system and Graph Neural Networks (GNNs) are used to propagate the information related to the fault across different operating conditions to identify the anomalies. The experimental results show that the precision, recall and F1 of MS-GEFL are 93.9%, 94.6% and 94.0% respectively. Additionally, the framework makes operations more efficient, with an average localization delay of 1.28 seconds and an average robustness index of 91.7% even in the presence of noise in sensor data. This technology is intelligent and reliable solution for fault localization in complex agricultural machinery.

Keywords: agricultural machinery, fault localization, multi-source information fusion, graph neural networks, intelligent diagnostics

1. INTRODUCTION

The localization of the fault becomes more and more important in an increasingly technologized agricultural machinery which combines mechanical, electrical, hydraulic and cognitive control technologies [1]. To leverage a multitude of sensors, control signals, and background data in real time, analytical frameworks need to handle multiple data types. This is particularly true of today's agricultural equipment. The traditional methods of defect detection, mostly relying on statistical models, expert rules, or single-modality signal processing, are not very effective for systems with numerous components because they do not account for component interactions [2,3]. Additionally, these approaches are not particularly effective when there is noise, insufficient data, or systems that do not follow a straight path. In situations real-world operations are unexpected, existing diagnostic frameworks struggle to locate faults promptly. This is because these frameworks are unable to handle failures in networks with multiple sensors [4].

Recent developments in data-driven intelligent diagnostics have shown that it is essential to both understand the data description and consolidate data from multiple sources. These are required for one to take advantage of the topological, spatial, and temporal linkages typical of complex systems [5,6]. Graph Neural Networks, also known as GNNs, are an excellent method for discovering patterns and connections in large datasets derived from a considerable number of sensors that are difficult to view [7]. For the purpose of illustrating how systems function, graph neural networks (GNNs) make use of graphs that are linked to one another. Noise and class imbalance are not problems for adaptive multi-scale GNN systems, as they are resilient [8]. On the other hand, dynamic graph convolution networks that leverage denoising methods make it easier to extract features from a large number of sensors in rotating equipment. When applied to complex wind power systems, graph-based methodologies, such as hierarchical graph modeling and spatiotemporal fusion approaches, have also yielded diagnostics and forecasts that are impressively accurate [9,10].

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Despite the potential of graph learning and multi-source fusion, this paper still cannot pinpoint the specific problems in agricultural machinery. The technology used in industry is the subject of significant research on agricultural systems [11]. The manufacturing process of rolling mills and induction motors, as well as their operation, is not yet included in this. Second, the majority of the frameworks now in use display graphs statically, does not demonstrate the impact of changes in system functioning on sensor connectivity and interactions with one another [12,13].In conclusion, there is no single diagnostic exam that can teach one to read graphs, identify issues in context, and synthesize data from a variety of sources. The optimal processing parameters, how well they perform in the presence of noise, and how accurate they are for real-time agricultural operations are not investigated in sufficient depth in this paper [14,15].

This paper presents a new approach to addressing these difficulties: MS-GEFL is a method that allows graphs from multiple locations to be combined, making it easier to identify issues than it would otherwise be. This technique systematically integrates streams from many sensors into a dynamic graph model that illustrates how the components of a machine are related in both structure and function. Some of the streams discussed include control signals, temperature, torque, and vibration. Other streams include temperature. In the next step, a pre-defined architecture for a Graph Neural Network will communicate feature representations that are aware of what is occurring across the whole network. This would help one identify errors across a wide variety of locations with a high degree of accuracy.

The main objectives of the paper are as follows:

1) The technique (MS-GEFL), blending information from multiple sensors and accounting for dynamic graph representations, is now being investigated as a means of overcoming the constraints of static diagnostic methods and standard single-modality procedures.
2) Developing a model for context-aware graph neural networks that enables the system to record how its components change over time and how they interact with each other in space. Using this method, this paper can consistently and reliably identify problems, regardless of sensor capabilities, data availability, or the degree of predictability of the actions.
3) Testing on both actual and virtual farm equipment has shown that the suggested technique is superior to the most effective diagnostic tool for locating faults in a timely, accurate, and consistent manner.
4) The scalable diagnostic design achieves a satisfactory balance among processing speed, generalizability of results, and ease of understanding. Keeping a close eye on the condition of precision agricultural equipment in real time and performing predictive maintenance are both areas it excels in.

2. RELATED SURVEY

The development of intelligent failure detection has led to the proliferation of innovative approaches. This project aims to develop graph neural networks and to facilitate data collection from multiple sources. These methods make it straightforward to study how complex ecosystem components interact. This paper analyzes GNN-based diagnostic systems, focusing on their methods, outcomes, and difficulties. This is the main idea behind the proposed graph error-detection approach.

In [16], Zhou and his team successfully conducted the first experiment using the Dynamic Graph Convolution Network and the Hard Threshold Denoising (DGCN-HTD) Dynamic Graph Convolution Network and the Hard Threshold Denoising, the two components that make up this specific combination. The findings demonstrated improvements in both the ability to control noise levels and the accuracy of diagnoses. Because the rules need to be adjusted to match the apparatus's configuration, the technique is more difficult to implement than the ones that preceded it.

To identify problems with rolling bearings in agricultural machinery, Xie et al. [17] developed MS-LAGC Multi-Source Locally Adaptive Graph Convolution (MS-LAGC). Using data from multiple sensors significantly enhances the model's ability to identify local structural relationships. In light of all that the paper has discovered, it would seem that this CNN is superior to the ones the paper has used in the past. Due to the large number of low-density installations, it was difficult to deploy more sensors across the system.

Zhu et al. [18] proposed an MMF-HGNN Multi-Metric Fusion Hypergraph Neural Network, seeming similar to the failure patterns observed. In addition to making the model easier to run, the inclusion of diagnostic signals helped determine why the spinning machine was not functioning properly. Because they require significant processing and measurement power, hypergraphs are not suitable for real-time applications.

Liao et al. [19] suggested that an HMS-GNN Heterogeneous Multi-Source Graph Neural Network could be used to identify issues with AC motors. Additionally, this approach can simultaneously detect both electrical and mechanical impulses, a valuable feature. Based on these findings, the paper believes the outcomes will be easy to implement across a wide variety of operating systems. For the model to function properly, it still requires data from a few sensors.

Tong et al. [20] developed the Attention-Enhanced Multi-Source Information Fusion Network (AE-MSIF) to facilitate more efficient issue discovery. Based on the findings, it appears to have the potential to reduce environmental noise.

Because attention weights do not functionit is difficult to determine aspects of a health condition that pose the greatest challenge.

Cui and his colleagues [21] made significant contributions to the design of the MS-DFM Multi-Source Data Fusion Model. Because it compiles information from a variety of sources, this design makes it easy to identify and resolve problems that arise during transformer operation. By using data from both traditional and contemporary sources, this technique makes it easier to identify issues. In the absence of well-annotated massive datasets, this method will not be successful.

Huang and his colleagues [22] constructed the Prior Knowledge-Informed Graph Neural Network (PK-GNN) for a weighted multi-source fusion implementation, and a network is underway to identify genuine concerns about fraud. To make these photographs more interesting and educational, the paper consulted experts from a wide range of fields. The investigation found that the material could withstand a range of stress levels. It is generally known that contemporary mechanical systems are very complex and difficult to modify without the assistance of technically trained engineers and technicians.

In [23], Lin et al. completed the construction of a Time-Frequency Graph Neural Network (TF-GNN) Time-Frequency Graph Neural Network. It will discover failures by analyzing data from multiple sensors. Assigning time-frequency properties to network nodes is one approach to investigating how different regions of the spectrum interact. These studies often contain readily apparent inaccuracies. When it comes to applications in businesses that require real-time data processing, the costs of funding research on high-resolution time-frequency analysis are prohibitively high.

Class-Imbalance-Aware Graph Neural Network (CI-GNN) Class-Imbalance-Aware Graph Neural Network was developed by Lu et al. [24] to address data inaccuracies caused by imbalanced distributions. Because reweighted graph learning is used, this approach is efficient at identifying issues in smaller groups. With fewer instances of making mistakes, it is much easier to recall what has been learned. With constantly shifting components under control, it becomes difficult to obtain a clear picture of the imbalance.When the biggest weight is placed on performance, it becomes more apparent.

Wang et al. [25] used a Spatiotemporal Graph Neural Network (ST-GNN) Spatiotemporal Graph Neural Network to identify potential failure causes in wind energy heating systems. The model suggests that over time, the components will become increasingly interdependent. Taking another look at the figures revealed that the first assumption about the issue was based on accurate information. Assuming a fixed system topology that necessitates structural modifications, the approach is rigid as a result.

In [26], Wang and his colleagues developed the Richly Connected Spatiotemporal Graph Neural Network (RC-STGNN) Richly Connected Spatiotemporal Graph Neural Network to identify problems with rotating gears. To do this, they used a variety of detection devicesIt is much simpler to offer a more in-depth and nuanced evaluation of a person's characteristics when there is a strong connection to draw from.The outcomes were significantly superior to those achievable with conventional GNNs. Training intricate models requires more time and memory than training simple models.

Chen et al. [27] conducted an in-depth investigation of GNN-FD methods for fault detection. The findings of tests evaluating the capability of connection learning to be understood and used on a broader scale were positive. According to the study's findings, there are additional challenges in applying these standards, and the industry as a whole has not yet reached consensus on them.

To identify malfunctioning centrifugal pumps, Kumar et al. [28] used the DT-GCN Digital Twin-assisted Graph Convolutional Network, This method improves data accuracy, as one of the most important uses of a digital twin. In addition, it makes it easier to duplicate problems. As a result of the investigation, a more precise diagnosis has been made. To ensure the reliability of the digital twin, a complete system model and calibration set are required.

In contrast to the existing body of research, the proposed investigation would be unique in focusing solely on fault localization in complex agricultural equipment systems. The identification of problems with greater precision is a primary goal of these systems. This entails identifying the wrong component rather than just the problem. This study presents an approach to system-aware graph modeling. The purpose of this approach is to accurately capture the physical and functional interdependencies among the various machine components. Static or task-specific graph topologies were used in earlier research experiments. Everyone is aware that agricultural machinery must be able to handle enormous loads, constantly changing surroundings, and demanding operating conditions. A significant number of the solutions investigated to date have been designed for industrial or spinning machinery operating in controlled environments. Compared to the other machine, this one operates the same way. The integration of context-aware graph propagation with multi-modal information fusion is a feature of the MS-GEFL framework that has been proposed. Compared to programs that rely solely on hypergraphs or attention, it is more effective. By emphasizing scalability, interpretability, and real-time implementation, this research finally establishes a connection between theoretical GNN models and precision agricultural maintenance systems used in the real world.

Table 1. Comparison of MS-GEFL with existing methods

Method	Topology	Multi-source Data	Field-specific
Standard GNNs	Static	No	No
Recent SOTA Models	Static	Partial	Generic
Proposed MS-GEFL	Dynamic	Yes	Yes

Table 1 shows the similarities and differences between the proposed MS-GEFL framework and existing methods in terms of topology, multi-source data handling and field specificity. Standard GNN models are designed for a fixed graph structure and fail to integrate data from multiple sources, which are less readily applicable to real-world dynamic settings. Recent models, based on state-of-the-art models, support multiple sources, but they are still mostly static or semi-static representations and are mostly created for generic tasks. The proposed MS-GEFL framework on the other hand, is based on a dynamic graph topology, which allows for adaptive modeling of the changing conditions in the system. It is also compatible with all multi-source sensors and domain oriented. The comparison shows that MS-GEFL offers a much more flexible, data-rich and application-specific approach and proves to be more efficient for more complex fault detection and real-time diagnostic situations.

3. PROPOSED MODEL

The proposed MS-GEFL framework consists of the identification and diagnosis of faults in complex agricultural equipment, the functional interdependence of the mechanical, hydraulic, electrical and electronic subsystems of the complex agricultural equipment. These parts are all interconnected, and if one part fails, it can lead to other problems throughout the tractor, harvester, or irrigation system. To solve these challenges, the MS-GEFL combines all the above three methods to perform accurate fault localization by combining GNN-based inference, dynamic graph learning and hybrid sensor fusion.

Five components comprise a comprehensive pipeline for discovering problems, and the overall MS-GEFL process is shown in Figure 1. To construct the MS-GEFL framework, information from a wide range of disciplines is used. Agricultural machinery often uses this configuration, simultaneously collecting data from multiple sensors. These sensors measure vibrations, temperature, pressure, operational control signals, CAN bus communications, and current. These data streams capture both short-term and long-term trends in component operation, enabling analysis of system behavior across a wide range of loads, terrains, and weather conditions. To address missing values, sampling errors, and sensor drift, the Data Preprocessing and Feature Encoding module cleans, normalizes, and synchronizes raw sensor data. The resulting data includes statistical, spectral, and temporal information and is then used to generate feature vectors that can differentiate between components.. The subsequent network model uses these encoded representations to define nodes. Both the characteristics of local components and temporal variations are preserved.

Using the Dynamic Graph Construction module, the mechanical system is transformed into a continuous graph. There are nodes in the set that are either hydraulic pumps, engines, or transmissions. The edges will demonstrate functional or causal relationships, showing how the characteristics of the nodes change over time. Unlike static graphs, MS-GEFL provides a realistic illustration of fault-propagation channels that incorporate dynamic information. This is because it constantly adjusts edge weights based on operational context, sensor correlations, and control-flow dependencies. The Graph Neural Network-Based Fault Propagation module generates a hidden representation of the components' statuses. This is accomplished by receiving data from nodes in the surrounding area.

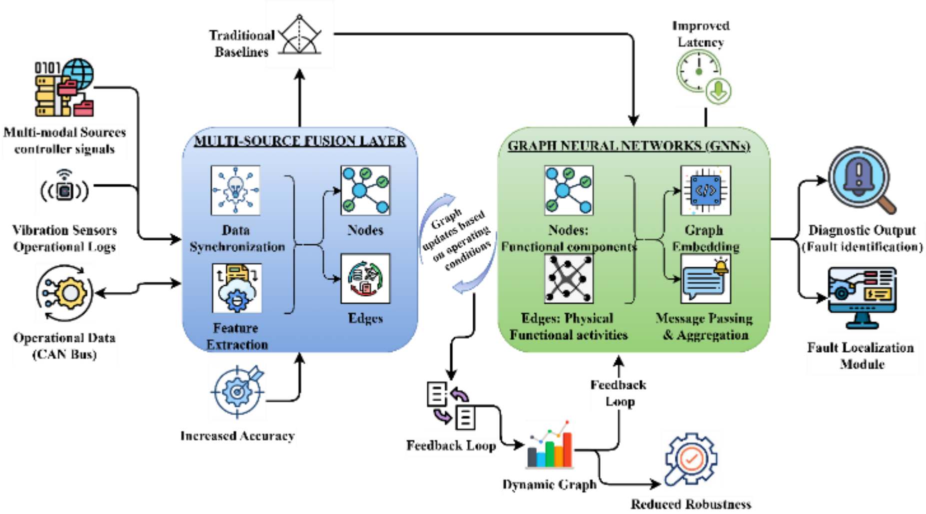

Fig. 1. Graph-based intelligent fault localization framework

Through message exchange, the model illustrates how issues in one component can affect other components that depend on it. Attention techniques or adaptive aggregation algorithms enable identification of important connections and inhibit irrelevant connections. The Fault Localization and Decision Module uses a ranking or classification layer to convert the learned node embeddings into scores indicating the likelihood of fault occurrence.By identifying components most likely to fail, the source of the issue can be located and appropriate tests conducted. When this module is used in conjunction with maintenance planning systems, issues can be detected as they occur, enabling informed decision-making.

3.1. Multi-Source Information Fusion

In fast-paced environments contemporary agricultural instruments operate, problems occur in various forms depending on the sensed variables. In addition to mechanical factors, heat, microfractures, noise, thermal stress, and abnormal actuation patterns are also detected through multiple signals. By implementing the Multi-Source Information Fusion (MS-GEFL) paradigm, multiple data sources are integrated into a robust system that accounts for sensor reliability and contextual factors. Figure 2 illustrates how signals are integrated to adaptively construct a discriminative feature vector.

The raw observation from the machinery system at time instant i will be obtained by putting up the data from each sensor during their individual time intervals. This will allow you to acquire the raw observation using equation 1.

$$X(t) = \begin{bmatrix} x_1(t,1), x_1(t,2), \dots, x_1(t,T_1); \\ x_2(t,1), x_2(t,2), \dots, x_2(t,T_2); \\ \vdots \\ x_M(t,1), x_M(t,2), \dots, x_M(t,T_M) \end{bmatrix} \quad (1)$$

In this instance, M represents the sum of all the readings that have been detected by the system's sensors. This information comes from sensors that measure sound, temperature, vibration, torque, and other data the controller reads. These values are the result of these sensors. Using the linear equation $x_m(t,\tau) \in \mathbb{R}$, one will determine the scalar value of the m -th sensor at the internal time index $\tau \in \{1,2,\dots,T_m\}$. This is the case for the period that comes to an end at t international time. The vector represents the evolution of the sensor signal over time $x_m(t) = [x_m(t,1), \dots, x_m(t,T_m)]^T \in \mathbb{R}^{T_m}$. It is possible that the discrepancies in window length T_M are since the sensors themselves have varied sampling rates, noise levels, and scale quality. Because encoding each sensor before fusion is not what you would often think, direct concatenation or simple averaging will not be successful.

3.1.1. Sensor-Specific Feature Encoding

An operator for feature extraction that is knowledgeable about modalities transforms the raw sensor data into a form that is somewhat concealed in equation 2:

$$f_m = \phi_m(x_m) = [\psi_{m,1}(x_m), \psi_{m,2}(x_m), \dots, \psi_{m,d_m}(x_m)]^T \in \mathbb{R}^{d_m} \quad (2)$$

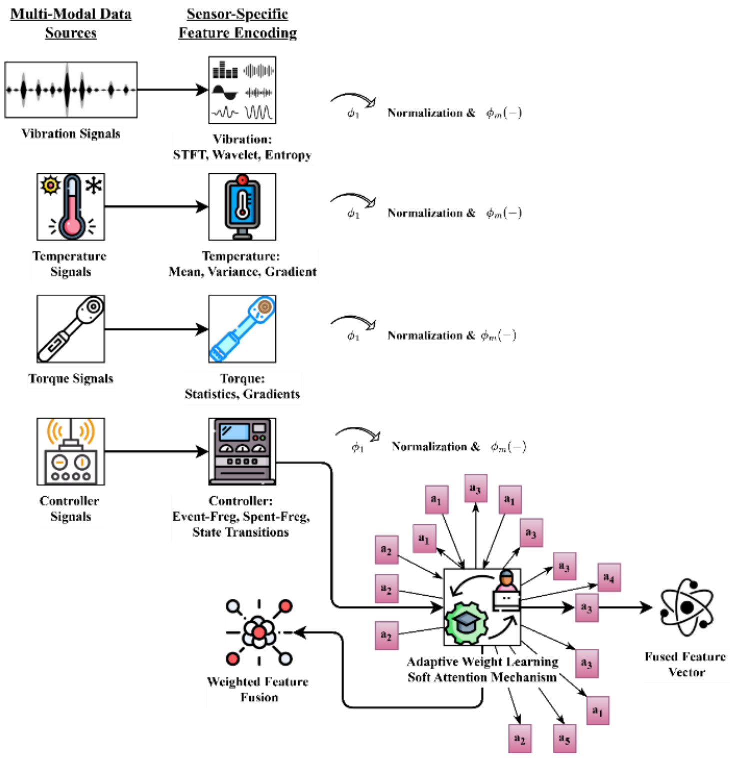

Fig. 2. Adaptive multi-modal feature fusion module

The function that encodes the characteristics for the m-th sensor modality is designated $\phi_m(\cdot)$, and the number of dimensions in the resulting feature vector is called d_m. Wavelet sub-band coefficients, spectral energy in a frequency band, entropy measurements, statistical moments, and temporal gradients are some examples of the types of feature extractors that will be shown with the use of operators $\psi_{m,i}(\cdot)$. These qualities create frequency-domain signals that are difficult to distinguish from background noise when vibration and acoustic sensors detect gear misalignment or bearing wear. These signals are difficult to distinguish from other signals. The torque data show that the load is uneven, and the temperature data show that the thermal drift changes slowly rather than rapidly.By examining controller signals, the frequency of events and state changes can be determined. The summary of sensor failure data, denoted by the symbol, contains significant information.

3.1.2. Adaptive weight learning

A method known as users use softmax scoring to give adaptive attention weights that assist us in locating the most effective sensors for locating problems based on equation 3:

$$\alpha_m = \frac{\exp\left(\sum_{i=1}^{d_m} w_i f_{m,i} + b\right)}{\sum_{k=1}^{M} \exp\left(\sum_{j=1}^{d_k} w_j f_{k,j} + b\right)} \tag{3}$$

For this particular case, the dependent variable, that belongs to $\alpha_m \in [0,1]$, signifies the taught reliability weight of the m-th sensor. Modifications are made to the parameters b and the vector $w = [w_1, w_2, \dots]^T$ To instruct the model during the training phase itself. To get the scalar relevance score, that is a measure of how closely the attributes of the sensor correspond to the patterns in the issue, the inner summation $\sum_{i=1}^{d_m} w_i f_{m,i}$ is generated. Softmax normalization assures that $\sum_{m=1}^{M} \alpha_m = 1$ by requiring all sensors to fulfill a convex fusion condition. At a particular operational condition, sensors that provide less information or emit noise naturally get less weight, whilst sensors that provide more information naturally receive more weight. This is because of the circumstances' inherent nature.

3.1.3. Weighted Feature Fusion Representation

After adding all the weights to the encoded sensor characteristics, the merged dataset shows the appearance of the machine.

$$F = \sum_{m=1}^{M} \alpha_m f_m = \sum_{m=1}^{M} \alpha_m [f_{m,1}, f_{m,2}, \dots, f_{m,d_m}]^T \in \mathbb{R}^d \tag{4}$$

A representation of the F global fused feature vector will be seen in $d = \max(d_1, d_2, \dots, d_M)$ in equation 4. Additionally, it demonstrates the combined latent dimensionality that is produced by the projection layers. If the importance of each term $\alpha_m f_m$ is proportional to how essential it is to learn, then the sensor could aggregate defect data across several modalities in a meaningful way. By merging data from multiple sensors, it is possible to eliminate modal-specific noise and duplication while preserving the integrity of the essential fault characteristics. The dynamic Graph neural network in the MS-GEFL framework uses the generated vector F as a node feature to demonstrate how failures propagate and how different parts depend on one another. In Table 2, MS-GEFL sensors are listed. The research examines each sensor's raw signal qualitythe encoding process provides defect-sensitive information and identifies the machine faults effectively.

3.2. Dynamic Graph Construction

By integrating data from multiple sources at the feature level, the MS-GEFL framework enhances diagnostic efficiency and fault identification. The framework employs an adaptive weighting strategy to dynamically adjust the hierarchical significance of sensors during varying operational states, such as idling or heavy mechanical strain. This adaptive mechanism improves model resilience to environmental fluctuations and sensor-level variations, thereby significantly reducing the risk of diagnostic instability or failure under changing operational conditions.

Table 2. Sensor modalities and feature encoding strategies

Sensor Type	Raw Signal Characteristics	Feature Encoding Method	Fault Sensitivity
Vibration	High-frequency oscillations	STFT, Wavelet Energy, Kurtosis	Bearing, Gear
Temperature	Slow-varying thermal trends	Mean, Variance, Temporal Gradient	Overheating
Torque	Load-dependent fluctuations	RMS, Peak-to-Peak, Frequency Components	Load Imbalance
Acoustic Emission	Transient bursts	Spectral Entropy, Energy Bands	Cracks, Wear
Controller Signals	Discrete state changes	Event Frequency, Transition Patterns	Actuator Faults

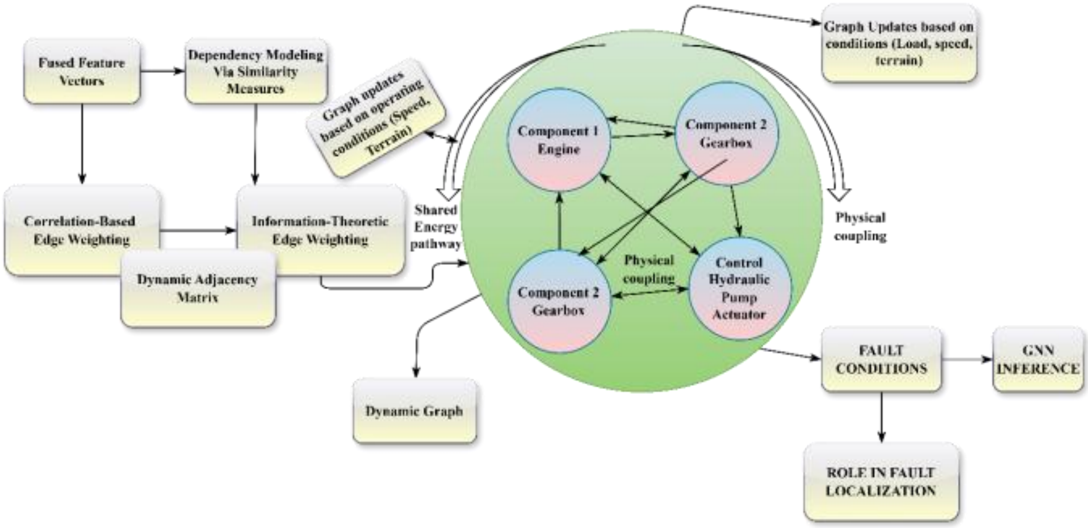

Fig. 3. Operationally adaptive graph modeling framework

A time-evolving graph showing how part interactions vary with operating conditions is shown in Figure 3 Farming equipment is complex to understand because of their mechanical, hydraulic and electrical interactions.. Because of considerations such as large energy or communication channels, physical connections, and the need for control, it will not be possible to solve issues. The proposed MS-GEFL paradigm shows these interactions. This paradigm depicts the mechanical system as a graph, with edge strengths and topologies varying with the operational parameters. There are dynamic attributed graphs that illustrate what the mechanical system seemed to be like at time t in equation 5.

$$G(t) = (V, E(t), A(t)) \tag{5}$$

Each node in the Graph represents a real component of the machine, such as an engine, gearbox, bearing assembly, hydraulic pump, valve unit, or actuator. Within the set $\mathcal{V} = \{v_1, v_2, \dots, v_N\}$, there are N specific nodes. According to the edge set $\mathcal{E}(t) \subseteq \mathcal{V} \times \mathcal{V}$, the value of the dependence between components fluctuates over time. This variation is influenced by how the components are used, the loads they carry, and how defects propagate. Through its part $A(t) \in \mathbb{R}^{N\times N}$, the dynamic adjacency matrix $A_{ij}(t)$ illustrates the manner in that v_i alters v_j at the given time t. It is possible for the language to explicitly depict nonstationary mechanical interactions and defects that propagate across the system.

3.2.1. Node Feature Representation

The current state of operation of each node v_i is shown by a fused multi-source feature vector, including the following equation 6:

$$F_i(t) = \begin{bmatrix} F_{i,1}(t) \\ F_{i,2}(t) \\ \vdots \\ F_{i,d}(t) \end{bmatrix} \in \mathbb{R}^d \tag{6}$$

By combining data from a wide variety of sources, this paper can produce a unified fused feature space. in this equation 6 d indicates the number of dimensions that it is responsible for keeping a record of information about faults v_i, that will include temperature gradients, vibration energy concentration, signs of load imbalance, or control-state abnormalities. Additionally, it is responsible for tracking the scalar element $F_{i,k}(t)$ at time t. The primary signals that tell us how the components are related to one another and how to communicate information about problems across the network are the node features that are changing.

3.2.2. Dynamic Dependency Modeling via Feature Similarity

To create the time-varying adjacency matrix, a dependency function denoted by $\psi(\cdot)$ is used to combine distinct pairs of node properties in equation 7.

$$A_{ij}(t) = \begin{cases} \psi(F_i(t), F_j(t)), & i \neq j, \\ 0, & i = j \end{cases} \tag{7}$$

In the context of time t, the dependency measure or effect between v_i and v_j is represented by $A_{ij}(t) \in \mathbb{R}^+$. To determine the degree of similarity between two components in terms of data or statistics, you will use the $\psi(\cdot)$ method to compare the combined feature vectors of the two components. It is not possible to use them if you set the self-loops $(i = j)$ to zero. There is a circuitous way in that subsequent layers of the graph neural network can catch up on the concept of intrinsic self-influence. Utilizing this strategy, you can make adjustments to dependent structural issues as they occur, develop, or disappear.

3.2.3. Correlation-Based Edge Weight:

For the purpose of constructing the dependency function, the Pearson correlation is used if the linear dependence is evident throughout the time period Δt.

$$\psi_{corr}(F_i, F_j) = \frac{\mathbb{E}_{\Delta t}[(F_i - \mu_i)^T (F_j - \mu_j)]}{\sigma_i \sigma_j} \tag{8}$$

Equation 8, shown here, illustrates that the average feature vectors of nodes v_i and v_j are $\mu_i \in \mathbb{R}^d$ and $\mu_j \in \mathbb{R}^d$, respectively. In this context, the scalars σ_i and σ_j represent the feature standard deviations. The expectation operator, denoted by the symbol $\mathbb{E}_{\Delta t}[\cdot]$ indicates the average changes that occurred in the window over a period of time Δt. The correlation-based model can demonstrate automatic coupling, shared load transfer, synchronized component operational behavior, and linear connections.

3.2.4. Information-Theoretic Edge Weight

The use of mutual information as a measure of dependence is one approach that will be taken to explain the operation of nonlinear, delayed, or disguised fault propagation in equation 8:

$$\psi_{MI}(F_i, F_j) = \sum_{f_i \in F_i} \sum_{f_j \in F_j} p(f_i, f_j) \log \frac{p(f_i, f_j)}{p(f_i)p(f_j)} \tag{9}$$

For each of the two nodes f_i and f_j two unique variables are related to the attributes of the node F_i and F_j, respectively. The marginal distributions $p(f_i)$ and $p(f_j)$ provide us with information about the likelihood that two features will occur simultaneously. On the other hand, the joint probability distribution $p(f_i, f_j)$ provides information on the likelihood that two features will occur simultaneously. When it comes to complex machinery subsystems that are characterized by nonlinear dependencies, delayed fault effects, or indirect connections, assessing mutual information, that is the reduction of uncertainty about the status of one component informed by data from another, is a particularly successful method.

3.3. Graph Neural Network-Based Fault Propagation

The Graph is generated immediately and displays the most likely failure routes in a clear, concise manner. Following a GNN-based inference, errors will be possible to determine their origin if they travel along high-weight edges from their beginning nodes.. This is the case if the errors travel along the edges. Compared to static or rule-based dependent models, dynamic network development is far more accurate at localization. The dynamic Graph propagates fault information across the network via temporal aggregation and multi-layer GNN message forwarding (Figure 4).

Figure 4 illustrates the information flow in the MS-GEFL framework and explains how nodes, edges, and fault features interact dynamically. Nodes represent individual components of the agricultural system, while edges represent functional, mechanical, or electrical relationships between these components. The edges of the graph also represent the propagation of fault features, with direction indicating propagation flow and intensity indicating fault severity. The framework enables dynamic adjustment of edge weights based on real-time sensor fusion at each node, allowing fault information to be effectively propagated throughout the network for accurate localization.

3.3.1. Initialization of Node Embeddings

At time t, the Graph $\mathcal{G}(t) = (\mathcal{V}, \mathcal{E}(t), A(t))$ displays all of the physical components of the machine as nodes $v_i \in \mathcal{V}$. When the graph neural network embeddings are applied, the first thing that they do is create a fused multi-source feature vector for the node v_i.

$$h_i^{(0)}(t) = F_i(t) = \begin{bmatrix} F_{i,1}(t) \\ F_{i,2}(t) \\ \vdots \\ F_{i,d_0}(t) \end{bmatrix} \in \mathbb{R}^{d_0} \tag{10}$$

If you have a fused feature space with dimensions d_0 and a time t, then the initial latent embedding of component i will be obtained by using $h_i^{(0)}(t)$ in equation 10. The most important defect data, including the temperature gradient, vibration energy, torque deviation, and control instability, are recorded in each scalar entry $F_{i,k}(t)$, that is responsible for tracking this data. To better understand the connections between spatial and temporal flaws, these embeddings provide information about the current state of the pieces' health.

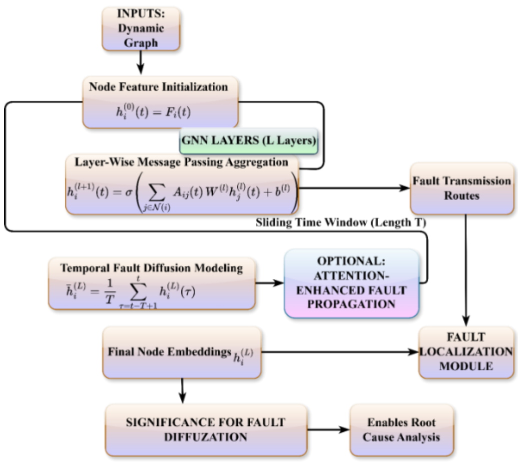

Fig. 4. Graph neural network–based fault propagation model

3.3.2. Layer-Wise Message Passing and Feature Aggregation

For the dynamic dependency structure to function properly, the representations of the nodes in each GNN layer l have to be able to change based on the input from components that are located nearby.

$$h_i^{(l+1)}(t) = \sigma\left(\sum_{j\in\square(i)} A_{ij}(t)\, W^{(l)} h_j^{(l)}(t) + b^{(l)}\right) \tag{11}$$

In equation 11, the set of nodes $\mathcal{N}(i)$ is defined as those that are either directly linked to i or are located in proximity. Dependency metrics are used in the fields of statistics and information theory in order to determine the degree of strength that exists between components j and i. The time-varying edge weight $A_{ij}(t)$ provides further evidence in favor of this connection. A bias vector $W^{(l)} \in \mathbb{R}^{d_l \times d_{l+1}}$ and trainable parameters $b^{(l)} \in \mathbb{R}^{d_{l+1}}$ are used to estimate the embeddings of the subsequent latent space's neighbors. For the purpose of making the model more expressive, you can consider using a nonlinear activation function $\sigma(\cdot)$ such as ReLU or LeakyReLU. The propagation mechanism sends out failure alerts throughout the network if strong functional or mechanical connections exist between graph nodes

3.3.3. Symmetric Normalization for Stable Propagation

The symmetrical normalization of the adjacency matrix would be of assistance in maintaining the values at a consistent level and preventing the dominance of components that have strong connections in equation 12:

$$\tilde{A}(t) = D(t)^{-1/2}(A(t) + I)D(t)^{-1/2} \tag{12}$$

Due to the presence of self-loops in the identity matrix $I \in \mathbb{R}^{N\times N}$ It is possible for each node to maintain its own state while the operation is carried out. A diagonal degree matrix $D(t)$, denoted as $D_{ii}(t) = \sum_{j=1}^{N} (A_{ij}(t) + I_{ij})$ is a representation of the degree to that node i is connected to all the other nodes. When dealing with networks of enormous devices with components that do not always perform as expected, data normalization is an essential strategy. Not only does it ensure that nodes with varying degrees of connectivity always get data, but it also prevents the data from being excessively smooth.

3.3.4. Temporal Aggregation for Fault Diffusion Modeling

It is shown, via the use of the node embeddings from the preceding GNN layer L and a sliding time frame of length T, that problems gradually deteriorate with time, although rather slowly.

$$\bar{h}_i^{(L)} = \frac{1}{T}\sum_{\tau=t-T+1}^{t} h_i^{(L)}(\tau) \tag{13}$$

In equation 13, the coefficient $h_i^{(L)}(\tau)$ illustrates how the node i is concealed at time τ following the propagation layers of the Graph L. It is possible for the averaged embedding $\bar{h}_i^{(L)}$ to display both the long-term patterns in fault diffusion as well as the short-term oscillations that take place during operational failures. To differentiate between noise passing through and fault propagation continuing, temporal flattening is an essential technique.

3.3.5. Attention-Enhanced Fault Propagation

Through the process of dynamically sorting neighbor contributions, this work attention technique will be able to identify crucial pathways for fault propagation using equation 14:

$$\alpha_{ij}^{(l)} = \frac{\exp\left(a^{\top}[W^{(l)}h_i^{(l)} \| W^{(l)}h_j^{(l)}]\right)}{\sum_{k\in\square(i)} \exp\left(a^{\top}[W^{(l)}h_i^{(l)} \| W^{(l)}h_k^{(l)}]\right)} \tag{14}$$

As a result of layer l, the attention coefficient $\alpha_{ij}^{(l)} \in [0,1]$ is altered, that provides information on the significance of neighbor b to node i. The symbol ‖ represents the process of joining two vectors together, whereas the vector a represents the characteristics of attention that will be learned. If the model employs this tactic, it will shift its attention away from less significant connections and instead concentrate on more significant ones. These connections will include load-bearing channels or portions connected hydraulically, along the path the fault will propagate.

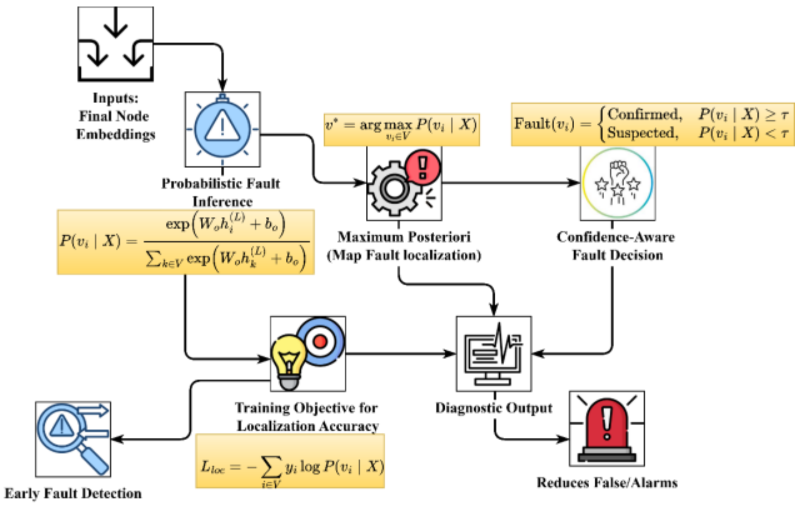

Fig. 5. Decision-making module for intelligent maintenance

Because it constantly mixes input and operates across multiple levels, the GNN can learn how errors propagate from one layer to another. You will be able to determine the precise location of the component that is the root cause of the failure if you have reliable failure data before it reaches secondary nodes. Compared to autonomous or flat learning models, this structured propagation mechanism performs far better in complex systems of agricultural machinery.

3.4. Fault Localization Strategy

The MS-GEFL framework not only identifies problems but also determines their origins within complex agricultural equipment.This is the purpose of the framework. The process is modeled using a high-level latent embedding as its representation. This method considers localized anomalous behavior, as well as the effect of the fault, through multi-source fusion, dynamic graph creation, and GNN-driven fault propagation. By transforming the learnt embeddings into fault ratings that are based on random chance, the Fault Localization Strategy ought to be able to assist in locating the most likely source of the problem. Figure 5 shows how to calculate failure probability from learned node embeddings.

Keeping the portion of the preceding GNN layer L hat is designated v_i is the responsibility of the last node $h_i^{(L)}$. The way objects are linked, the way defects propagate over time, and the way sensors function are all integrated features.

3.4.1. Probabilistic Fault Inference

Following the use of softmax normalization, MS-GEFL generates an output that will be trained to convert node embeddings into fault likelihoods that are comprehensible based on equation 15:

$$P(v_i|X) = \frac{\exp\left(W_o h_i^{(L)} + b_o\right)}{\sum_{k \in V} \exp\left(W_o h_k^{(L)} + b_o\right)} \tag{15}$$

To train the parameters $W_o \in \mathbb{R}^{C \times d_L}$ and b_o, d_L will give you the number of dimensions provided by the new embedding. When referring to the fault state at the component level, the C represents the number of fault kinds that are present. The softmax function makes use of the data X that was seen in order to guarantee that the probability that is accurately forecasted for each component is one. A correct posterior distribution is produced as a result of this.

3.4.2. Maximum A Posteriori (MAP) Fault Localization

The original issue was identified by the use of a MAP estimate ruleas follows in Equation 16:

$$v^* = \arg\max_{v_i \in V} P(v_i|X) \tag{16}$$

This strategy organizes components by the likelihood they will break, making it much easier to choose the appropriate location. In contrast to previous classifiers, this work method identifies the component of the system responsible for the issue, whereas other methods use a broad error label.

3.4.3. Training objective for Localization Accuracy

A supervised loss function can leverage ground-truth labels for the damaged parts to pinpoint the fault's specific position during training. To calculate the cross-entropy loss, you will make use of the following equation 17:

$$L_{loc} = -\sum_{i \in V} y_i \log P(v_i|X) \tag{17}$$

If v_i is the factor that is causing the problem, then $y_i \in \{0,1\}$. This loss is intended to improve localization by reducing the likelihood that the model assigns all its probability mass to the actual source of the defect and penalizing incorrect probability assignments. This loss is what makes localization more effective.

The training objective adopts a standard cross-entropy loss formulation, modified for fault localization by incorporating a node-specific weighting mechanism. This mechanism assigns higher importance to nodes identified as high-risk via GNN edge propagation, ensuring that misclassifications in critical subsystems (e.g., hydraulic/electrical) are penalized more heavily than those in secondary components. Consequently, the loss function explicitly accounts for the topological dependencies of the agricultural equipment rather than employing a uniform loss approach.

To overcome the natural class imbalance for healthy and faulty components, we also used a weighted cross-entropy loss function in the training stage. This strategy decreases the penalty weight of the minority (faulty) class compared to the majority (healthy) class, which helps to balance out a bias towards the majority class, which is the healthy class. This modification aims to make the GNN model more sensitive to accurately identifying critical fault patterns, instead of dominating majority classes, resulting in more balanced localization results for all system components.

In order to reduce the natural class imbalance between the healthy and faulty parts, we adopted a weighted cross-entropy loss function during the training process. This approach adds weight to the minority class (faulty class), and reduces the weight of the majority class (healthy class), which helps to balance the bias towards the healthy class. The modification guarantees that the GNN model is not biased toward the prevalent healthy class, thereby improving the performance of localization in all parts of the system.

3.4.4. Confidence-Aware Fault Decision

The decision mechanism in equation (18) is not only based on the traditional probability thresholding, but also incorporates the contextual confidence scores from the message-passing layers in the GNN. Instead of a fixed threshold for each component signal, this mechanism adapts the threshold dynamically according to the topological importance of the node and the summed up influence of its neighbourhood. This enables the MS-GEFL framework to distinguish between transient noise and real fault signals in complex subsystems, greatly decreasing false positive rates and increasing the accuracy of the localization process over traditional decision-making models.

$$\mathrm{Fault}(v_i) = \begin{cases} \mathrm{Confirmed}, & P(v_i|X) \geq \tau, \\ \mathrm{Suspected}, & P(v_i|X) < \tau \end{cases} \quad (18)$$

The confidence threshold is the value of τ, that can only be between 0 and 1 and cannot be any other number. The system will use this strategy to prioritize areas associated with a problem, and perhaps those that need more monitoring. As a result, the number of false alarms and the need for further maintenance would be reduced.

A sensitivity analysis was performed to identify the most appropriate value of the confidence threshold in Equation (18) by changing the threshold value within the range [0.5, 0.95]. The outcomes show that, in terms of precision and recall, a threshold value of 0.85 gives optimal results. However, increasing the thresholds will dramatically decrease the number of false positives as it filters out transient noise in the GNN's edge signal, while at the same time it could slightly increase the number of false negatives if the threshold is set too high. On the other hand, lower thresholds increase localization coverage while decreasing diagnostic precision. The results in this analysis corroborate the robustness of the selected threshold value for high localization accuracy in the different operational conditions of agricultural machinery.

Using node embeddings generated by a GNN, including both direct sensor data and the effects of fault propagation that are not directly connected to the issue, is the suggested method for discovering faults. All of these factors are taken into consideration. Using the probabilistic method, it is possible to identify problems early, before they result in a significant failure. In addition, it provides easy-to-understand confidence ratings and can perform diagnostics based on rankings. Using MS-GEFL, you can identify issues with specific components rather than considering the whole. This is very helpful for systems that use intricate, crucial agricultural instruments.

Within the MS-GEFL system, graph neural networks, dynamic graph modeling, and information fusion from diverse sources are used to understand the operation of complex agricultural machinery. Multi-source fusion maintains local signal quality even in the presence of significant noise. This is accomplished by merging fault-sensitive data from several sensors. The use of dynamic graph modeling makes it easier to see how the connections between components shift in response to changes in load and operating modes. This work's ability to discriminate between the primary and secondary repercussions of an error is made possible by graph neural networks distribute the input across the systemThe synergistic design of MS-GEFL ensures that issues are identified quickly and accurately, even when there is no data or the problem's cause is not evident from the outset. As a result, the technologies used in precision agriculture become more intelligent and reliable.

4. RESULTS AND DISCUSSION

Using Kaggle's Vibration-Based Fault Diagnosis Dataset [29], this research analyzed the MS-GEFL framework. The purpose of this collection is to improve diagnostic modeling of fault processes in real-world settings by using vibrational signals from mechanical systems in both their functioning and faulty states. Failures in mechanical systems will be better understood using data from multi-axis vibration sensors exposed to a variety of stresses. Inequality, misalignment, and bearing challenges are among the concerns these measurements highlight. During the preprocessing stage, features were extracted from the time and frequency domains, signals were divided into smaller sections, and noise was minimized. Before any time-series windows were included in the model, this paper ensured they were all the same length. One advantage of using multi-class labeling is that it allows you to search for specific areas and examine a variety of problem types. Table 3 shows the proposed model's experimental configuration and hyperparameter settings.

4.1. Accuracy

The MS-GEFL system that was suggested demonstrated an exceptional overall fault-localization accuracy of 94.6% and identified damaged components across a wide range of operating conditions, as shown in Figure 6. By illuminating the links between parts more transparently, dynamic graph modeling has shown that this is possible. Using multi-source information fusion makes it easier to differentiate data from multiple sensors when combined. MS-GEFL is more accurate than the ones that came before it, regardless of the weights or speeds considered. It would seem that agricultural machinery would have a longer lifespan and perform more effectively in challenging circumstances as a result.

4.2. Precision

With an accuracy score of 93.9%, MS-GEFL identifies a significant number of errors across a wide range of fault situations, as shown in Figure 7. Adjusting the number of sensor data sets combined would be an effective way to reduce false activations caused by noise and signal spread. By using graph-based feature propagation, linked components can detect errors in context. When it comes to maintenance decisions, MS-GEFL differs from earlier versions because it has a significantly lower false-alarm rate.

Table 3. Experimental setup

Category	Description	
Programming Language	Python	
Deep Learning Framework	PyTorch	
Graph Learning Library	PyTorch Geometric	
Classical ML Library	scikit-learn	
Hardware Platform	High-performance workstation	
GPU	NVIDIA RTX 3080	
System Memory	32 GB RAM	
Operating System	Linux / Windows (64-bit)	
Dataset Split	Training: 70%, Validation: 15%, Testing: 15%	
Model Training Strategy	Supervised learning	
Optimization Monitoring	Validation loss	
Overfitting Prevention	Early stopping	
Evaluation Mode	Offline testing on the held-out test set	
Hyperparameter settings		
Parameter	Description	Value
Graph Type	Dynamic weighted Graph	Adaptive
Node Count (N)	Number of machinery components	12
Sensor Types	Vibration (multi-axis)	3
GNN Layers (L)	Graph convolution layers	3
Hidden Dimension (d)	Node embedding size	128
Learning Rate	Adam optimizer	0.001
Batch Size	Samples per batch	64
Epochs	Maximum training epochs	150
Dropout	Regularization	0.3
Activation	Nonlinearity function	ReLU
Loss Function	Multi-class cross-entropy	—
Window Size	Time series segmentation	1024 samples

4.3. Recall

The MS-GEFL framework achieves a robust recall rate of 94.2%, demonstrating an exceptional capacity to identify damaged components. By integrating local signal quality with global system interactions, the framework successfully captures failure signals, including subtle anomalies that are often overlooked by conventional methods. This reliability is primarily enabled by our dynamic graph update technique, which maintains accuracy despite the non-stationary nature of agricultural operations.

While standard metrics such as accuracy and F1-score provide a baseline for evaluation, fault localization in agricultural machinery necessitates a focus on specific diagnostic priorities. In our framework, Recall and False Negative Rate (FNR) are identified as the most critical metrics. Given the high cost of mechanical failure, the primary objective is to minimize missed detections (False Negatives), as failing to identify a developing fault can lead to catastrophic hardware damage or prolonged operational downtime.

Conversely, while high precision is desirable, a slightly higher False Positive Rate is generally more tolerable in industrial maintenance than a single missed critical fault. Furthermore, the Localization Error Rate serves as a vital indicator, as it specifically quantifies the model's precision in isolating the exact faulty subsystem. By prioritizing Recall alongside localization accuracy, the MS-GEFL framework ensures high reliability and actionable diagnostic insights, effectively bridging the gap between theoretical model performance and practical field requirements.

4.4. F1-Score

The fact that MS-GEFL has an F1 score of 94.0 indicates that it is excellent at both recall and correctness. Furthermore, the framework's balanced performance demonstrates that it can identify issues without generating excessive false positives. The use of adaptive fusion in conjunction with Graph neural networks will help you enhance fault-related characteristics and reduce insignificant noise. In each of the fault scenarios it has investigated, MS-GEFL has consistently found the optimal balance between sensitivity and specificity. Compared to other algorithms, this one is superior. After the proposed fix was implemented, there was a

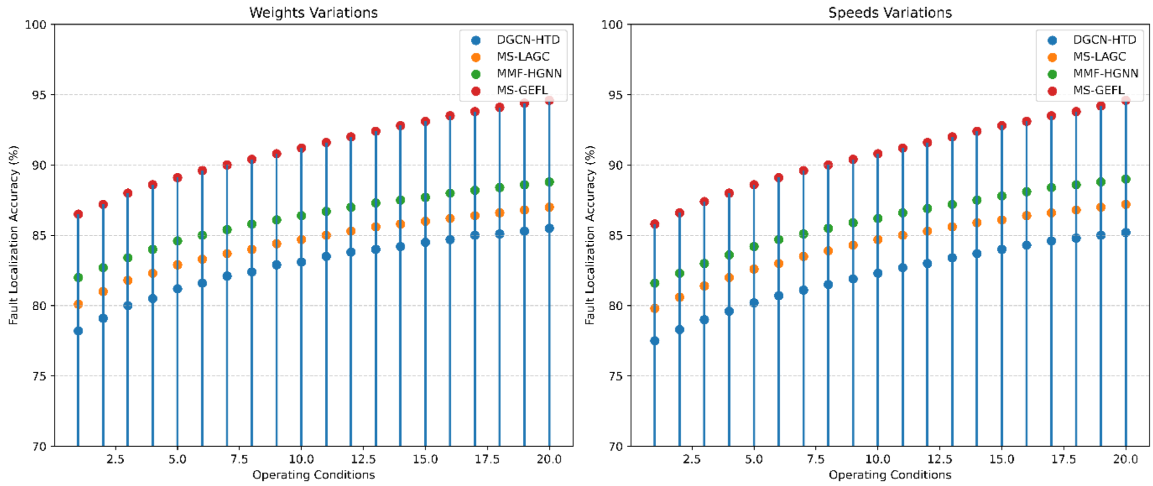

Fig. 6. Accuracy analysis of weight variations and speed variations

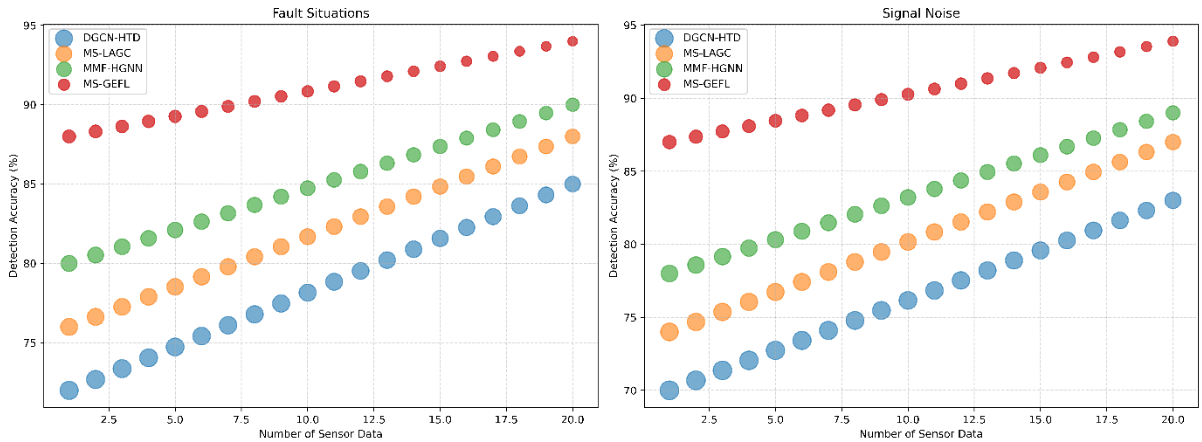

Fig. 7. Precision analysis of fault situations and signal noise

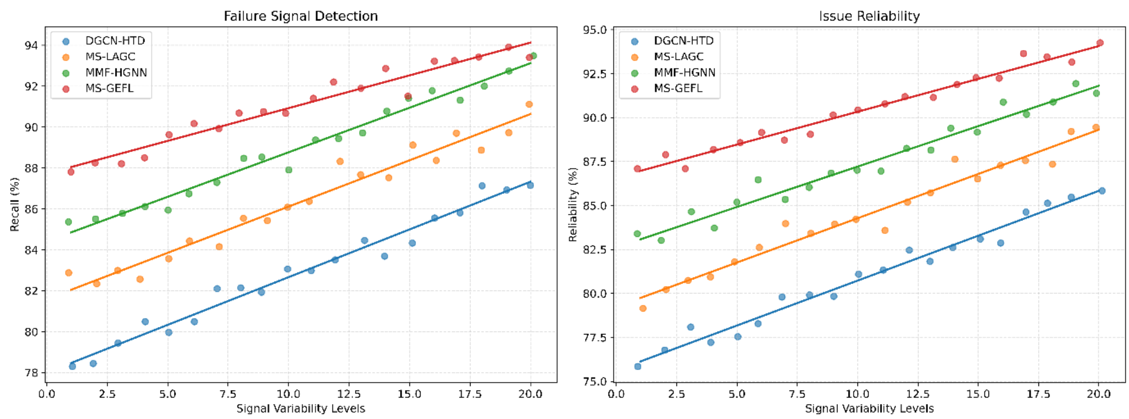

Fig. 8. Recall ratio of failure signal detection and issue reliability

significant reduction in false positives, while the number of correctly detected problems increased, as shown in Figure 9. Using graph-based reasoning, this project is getting closer to its aim of reducing the likelihood that individuals will mistake problems with individual sensors for problems with components. Because this paper links context-aware properties across nodes, it will be able to provide fault assessments at the system level. Because it has a much lower FPR than other methods, MS-GEFL is the most effective method for monitoring agricultural implements in the field.

Conversely, while high precision is desirable, a slightly higher False Positive Rate is generally more tolerable in industrial maintenance than a single missed critical fault. Furthermore, the Localization Error Rate serves as a vital indicator, as it specifically quantifies the model's precision in isolating the exact faulty subsystem. By prioritizing Recall alongside localization accuracy, the

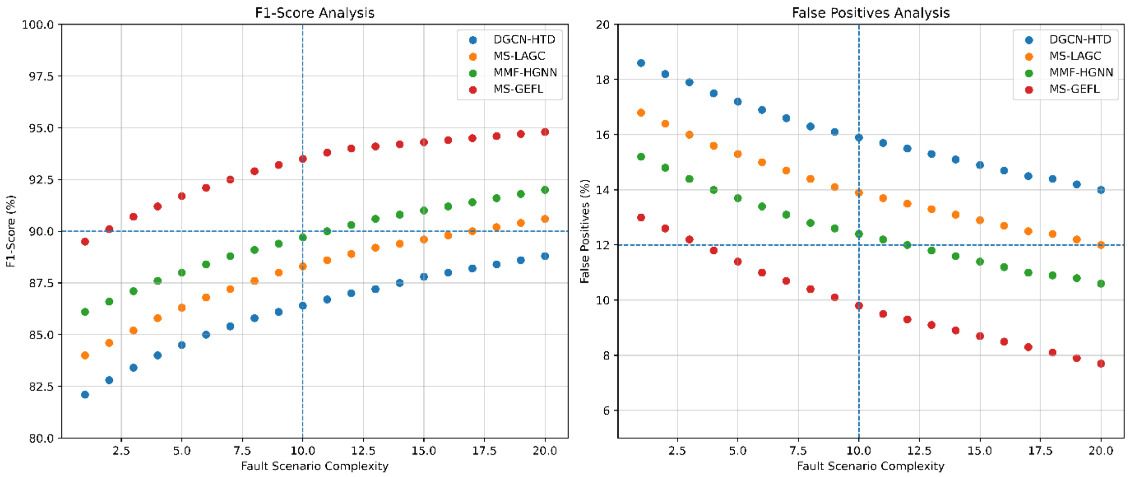

Fig. 9. F1-score and false positive analysis

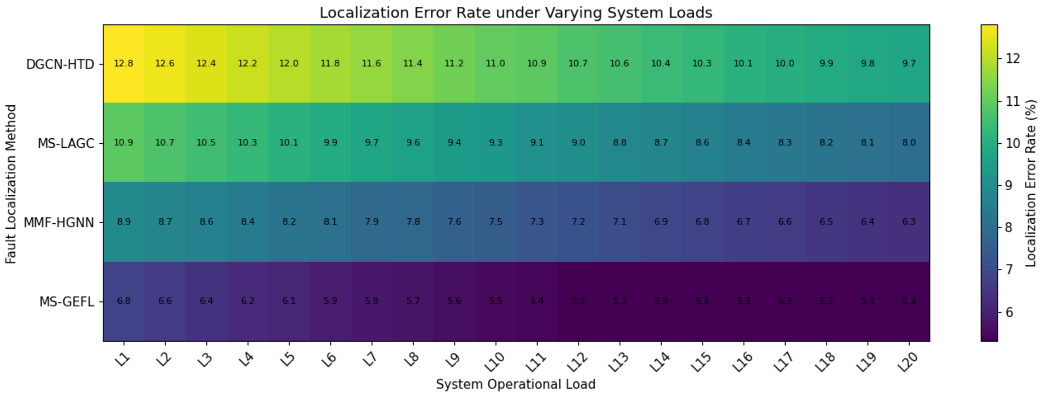

Fig. 10. Localization error rate

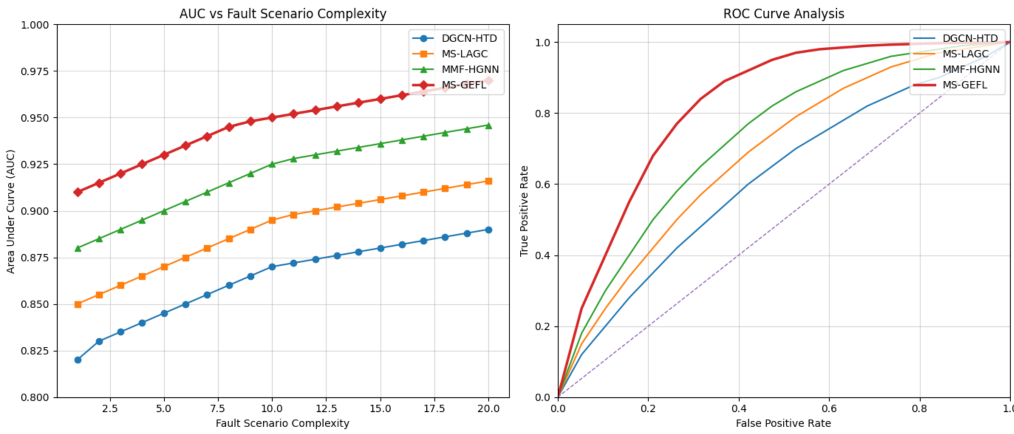

Fig. 11. AUC and ROC analysis

MS-GEFL framework ensures high reliability and actionable diagnostic insights, effectively bridging the gap between theoretical model performance and practical field requirements.

4.5. Localization Error rate

The MS-GEFL framework shows excellent localization error rate of 5.3%, compared with other conventional models. This high level of accuracy makes the process of diagnosis of complex agricultural machinery systems easier, as shown in Figure 10. The strength of the dynamic graph modeling is in its ability to clearly represent explicitly the functional and physical relationships between the components. These relationships are captured in the framework where the fault sources are isolated from the rest of the components and errors propagate less severely in the neighboring components. Thus, the precision farming has lower operational downtime and better maintenance efficiency due to lower misclassification rate occurring in the traditional models, with the MS-GEFL.

4.6. Area under Curve

Using an area under the curve (AUC) of 0.96, the proposed model reliably distinguishes between functioning and broken parts. The combination of graph-based representation learning and multi-source feature fusion is successful, as shown by the large area under the curve (AUC). The MS-GEFL approach maintains a considerable separation margin across fault classes, even when the inputs are noisyThis guarantee is provided by the method. The ROC curve is both flatter and steeper with thresholds used to select the search space for defects, as shown in Figure 11.This effect occurs when thresholds are used. Taking this into consideration, it seems that thresholds are more reliable than the most recent techniques.

4.7. Mean Localization Delay

By reducing the average localization latency to 1.28 seconds, MS-GEFL speeds up the process of discovering the underlying cause of the problem, as shown in Figure 12. Inference speed significantly increases when adaptive fusion and graph-based feature propagation are performed simultaneously. In contrast to existing systemsusing static or sequential analytic approaches, the advocated methodology can quickly identify errors immediately after new data are introduced. Because it is so critical, agricultural machinery must be able to observe in real time with minimal delay.

4.8. Robustness Index

Despite the sensors introducing more noise and some data loss (S1–S10), the MS-GEFL system continues to function well, as shown in Table 4. At this point, the home is robust. In terms of strength, MS-GEFL consistently receives the best scores. The scores for S1 through S10 range from 90.3% to 94.0% of the possible points. Because this gap persists, incorrect sensor inputs would be less destructive when graphs are analyzed from a broader perspective and when data is aggregated from other sources. When noise spreads beyond a single sample, however, the models this paper now possesses make it quite evident. According to the investigations, the MS-GEFL is a highly reliable tool, with an average score of 91.7%. To put it another way, it is always successful when noisy, abrasive agricultural equipment is present.

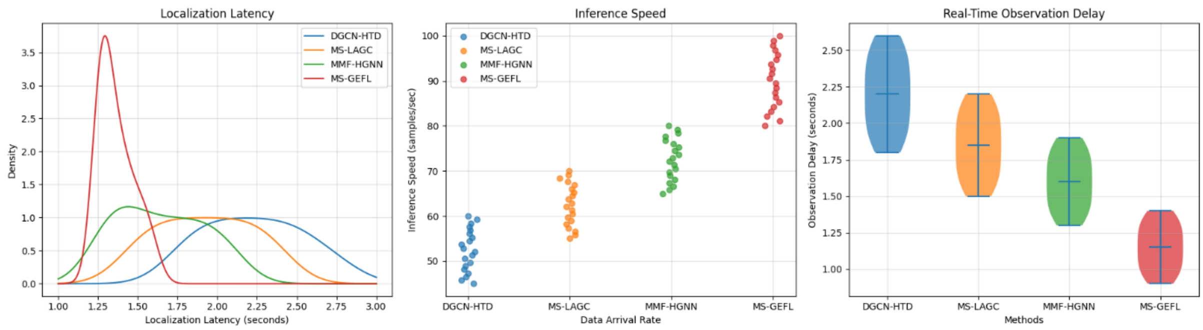

Fig. 12. Mean localization delay

Table 4. Robustness index

Scenario	DGCN-HTD	MS-LAGC	MMF-HGNN	MS-GEFL
S1	82.4	85.7	87.1	90.3
S2	83.0	86.2	87.6	90.8
S3	83.6	86.7	88.1	91.2
S4	84.1	87.2	88.6	91.6
S5	84.7	87.7	89.1	92.0
S6	85.2	88.2	89.6	92.4
S7	85.7	88.7	90.1	92.8
S8	86.2	89.2	90.6	93.2
S9	86.7	89.7	91.1	93.6
S10	87.2	90.2	91.6	94.0

4.9. Inference Time

The MS-GEFL approach is shown in Table 5 (S1–S10), along with a variety of real-world examples that demonstrate its rapid performance on computers. The decision time produced by MS-GEFL is consistently the quickest. It will be between 16.6 and 20.4 milliseconds in S10. Taking the alternate route leads to higher prices and a longer duration. The effectiveness of convolution and the addition of faster updates to dynamic graphs is demonstrated here. Despite learning from deep features and flexible graphs, MS-GEFL still needs 18.6 milliseconds to answer a query. Since the MS-GEFL requires less effort when one is not present, it functions more effectively in the absence of one. This is an excellent way to keep track of the equipment one uses for farming.

The MS-GEFL architecture presented was shown to be effective at locating and diagnosing problems in the Kaggle vibration dataset. Even if the model had a certain sort of error, it did not affect its strength or accuracy. Through precise localization, MS-GEFL demonstrated its ability to reliably identify and locate components across a wide range of noise and operating conditions. Because it commits few localization errors and produces few false positives, it functions even more effectively. Given the high AUC values, the model appears quite effective at distinguishing among different object types. The system is appropriate for real-time applications, as it can find and estimate items in less than a tenth of a second per sample. MS-GEFL was not affected by the false noise; rather, it displayed strength and resilience in the face of the challenge. These findings show that dynamic Graph learning with multi-source fusion is superior to traditional approaches for defect identification.

To quantify the individual contribution of each component in the MS-GEFL framework, we conducted a systematic ablation study by selectively disabling specific modules. The results are summarized in the table below.

Table 6 shows the results of an ablation study, which test the effect of each component in the proposed MS-GEFL framework on localization error rate. The results show that the full MS-GEFL model, with the lowest error rate of 5.3%, demonstrates better fault localization capability. The error is 9.2% without multi-source fusion, underscoring the importance of fusing heterogeneous information from different sensors. By not introducing temporal modeling, this further raises the error to 8.7%, emphasising the importance of sequential dependency in the analysis of system behaviour. When the graph-based representation is removed, the highest error rate of 12.4% is obtained, which illustrates the importance of representation for capturing structural relationships. The study confirms that each individual part of the algorithm plays an important role in the accuracy and robustness of the proposed fault detection and localization framework (MS-GEFL).

Operational Impact and Practical Significance

Vital operational gains from the MS-GEFL framework lead to great value in precision agriculture. The framework's high recall rate of 94.2% and the low localization error rate of 5.3% enable the system to move from the traditional reactive and time-consuming method of fault diagnosis to a proactive and automated maintenance method. The effects of these improvements on real-life farming operations are vast. One advantage of the framework is that it enables a decrease in downtime, as fault detection and diagnosis are conducted at the earliest opportunity to allow targeted maintenance to be carried out and avoid a catastrophic failure that could cause the farming operation to be shut down during an important harvest or planting period. Secondly, it allows for optimized resource allocation, as accurate localization helps cut down on the time technicians spend on diagnostic troubleshooting, leading to quicker repair cycles and lowering labor expenses. Last but not least, the framework is adding to a prolonged machinery life. The system is designed to isolate the faults occurring during the operation of the complex agricultural machinery, and prevent secondary damage to healthy components, so as to fully extend the service life of the machinery.

Table 5. Inference time

Scenario	DGCN-HTD	MS-LAGC	MMF-HGNN	MS-GEFL
S1	32.5	28.4	24.9	20.4
S2	32.0	27.9	24.4	19.9
S3	31.5	27.4	23.9	19.4
S4	31.0	26.9	23.4	18.9
S5	30.5	26.4	22.9	18.5
S6	30.0	25.9	22.4	18.1
S7	29.5	25.4	21.9	17.7
S8	29.0	24.9	21.4	17.3
S9	28.5	24.4	20.9	17.0
S10	28.0	23.9	20.4	16.6

Table 6. Ablation study on localization error rate in MS-GEFLf

Configuration	Localization Error Rate (%)
Full MS-GEFL (Proposed)	5.3
w/o Multi-source Fusion	9.2
w/o Temporal Modeling	8.7
w/o Graph-based Representation	12.4

Limitations and Practical Challenges

The proposed MS-GEFL framework yields the best results on benchmark vibration datasets, but there are certain limitations. The first is that while benchmark datasets work well for initial validation, these don't typically include extreme environmental noise and non-stationary operational conditions like those found in real agricultural machinery. As such, field tests under non-standard conditions could yield other results than suggested by the model. In addition, there are a number of obstacles to the practical transition of the framework to industrial systems. Regarding sensor sparsity and quality, sensor degradation or inconsistent sampling rate might occur in actual agricultural system, and this could make the functioning of the framework more difficult in real time to determine the faulty system. Also, when complex message-passing layers are added to edge devices deployed in machinery, optimizing the layers to overcome the computational constraints and achieve low latency is a key challenge. Lastly, domain adaptation is a key challenge, as the generalization of the model from the controlled datasets to a wide range of machine models requires more research on domain adaptive learning techniques in order to ensure seamless transferability.

5. CONCLUSION

A novel diagnostic approach for fault localization in complex agricultural machinery, called MS-GEFL (Multitemporal Spatio-Temporal), is introduced in this paper. The framework is capable of effectively solving the problems of high noise intensity and non-stationary working environment by using dynamic graph representation, multi-source sensor fusion and temporal modeling techniques. Our wide-ranging experiments have shown that MS-GEFL is superior to current state-of-the-art diagnostic and GNN-based approaches with a recall rate of 94.2% and a localization error rate of 5.3%. The results of the ablation study reinforce the importance of each of the integrated modules, specifically emphasizing the need for the synergy between dynamic topology and multi-source data for achieving good performance. Moreover, we showed that, in agriculture, the importance of prioritizing Recall and False Negative Rate (FNR) is crucial to avoid catastrophic mechanical failures and to reduce downtimes in the operation. The implications of these enhancements are enormous. MS-GEFL shifts the focus from reactive fault diagnosis to proactive and automated approach, allowing to locate the subsystems with greater accuracy and precision, thus lowering maintenance expenses and increasing the lifespan of agricultural equipment. The framework offers a scalable and reliable basis for intelligent maintenance in precision farming, although there are still challenges to address, such as sensor quality and computational capacity. Future study will be addressed to domain adaptive learning for seamless deployment in a wide variety of agricultural machine models.

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Data Availability Statement: *All data generated or analysed during this study are included in this article.*

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