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Review

From Passive Redundancy to Active Perception: A Comprehensive Review of AI-Enhanced Fault Diagnosis and Digital Twin Simulation for Combine Harvesters

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Abstract

Combine harvesters operate under harsh, time-varying field conditions, where unplanned downtime causes significant timeliness losses. This review systematically examines advances in structural fault diagnosis for combine harvesters, tracing the evolution from passive structural redundancy to active state perception and simulation-driven health management. Following a systematic search and screening methodology, the review analyzes the boundaries of structural optimization under fluctuating field conditions, evaluates traditional machine learning (ML) methods with handcrafted features, and surveys deep learning (DL) and multi-sensor fusion advances across vibration, acoustic, and visual modalities. A structured comparison across feature learning, generalization, diagnostic coverage, computational cost, and interpretability highlights the complementary strengths of traditional ML and DL paradigms. Key deployment challenges are identified: weak fault features under strong field noise, data distribution shift under multi-condition coupling, extreme sample scarcity and class imbalance, limited onboard computing and real-time latency constraints, interpretability gaps, hydraulic and pneumatic diagnostic neglect, functional safety compliance (ISO 25119), and the heightened reliability demands of unmanned autonomous operation. To address these challenges, future directions include physics-informed hybrid models, self-supervised pre-training and few-shot learning, lightweight edge inference, staged pre-deployment verification, model updating and lifelong learning strategies, cross-energy-domain diagnosis with fault-tolerant control, human-factors-aware interface design, and digital twin (DT) augmentation—the latter regarded as a strategic research vision requiring incremental validation rather than a near-term deployable solution. This review provides a reference for enhancing combine harvester mission reliability through the integration of AI-enabled perception, multi-source fusion, and simulation-driven health management.

Keywords: combine harvester; fault diagnosis; machine learning; deep learning; multi-sensor fusion; structural health monitoring; variable operating conditions; interpretability; physics-informed; digital twin

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1. Introduction

Grain crops are fundamental to global food security. In China, the world's most populous country, reducing paddy rice harvest losses by just 1% could save approximately

10 billion kilograms of grain annually—enough to feed 20 million people [1]. This imperative for minimizing harvest loss extends beyond cereals: potato, a staple food for over 70 countries including China, India, and the United States, is equally vital for both food supply and industrial processing [2]. Combine harvesters, by integrating cutting, threshing, separating, and cleaning into a single pass, are the core equipment for ensuring timely harvest completion and minimizing field losses [3]. The automation and intelligent control of these machines further reduce operator labor intensity and help alleviate agricultural labor shortages [4]. However, the harsh and variable field conditions under which combine harvesters operate pose significant challenges to their structural reliability, making fault diagnosis a critical enabler of harvest efficiency and food supply resilience.

Combine harvesters typically operate for no more than two months per year [5]; however, during the harvest season, harvester operators often operate the combine for more than 12 h per working day [6]. Harvesting is a highly time-sensitive operation; failing to complete the harvest within the narrow window of the optimal harvest timing will result in significant "timeliness loss" [7]. Within this harvest window, any unplanned downtime will lead to economic losses. When insufficient technical service support causes delays in the supply of spare parts, the downtime of the harvester can account for 10–50% of its total usage time [5]. Moreover, the skill level of maintenance service providers directly affects the efficiency of fault recovery; targeted training enhances the responsiveness of agricultural socialized services [8]. The economic consequence of harvest loss is substantial: in China, the average wheat harvest loss rate reaches 2.43% [9], underscoring the urgent need for real-time monitoring of machine performance during harvesting operations. When the harvest time exceeds the optimal window, each hour of downtime increases the grain loss rate by 0.004% to 0.006% [10]. Beyond harvest delays, structural issues during threshing can also cause internal grain damage that degrades crop quality [11]. In addition to crop losses, the materials and energy consumed for repair and component replacement further exacerbate the economic losses caused by failures [12].

During rice harvesting, excessive stalk breakage during threshing not only increases energy consumption but also elevates the volume of small straw fragments entering the cleaning system, thereby increasing the cleaning burden and reducing overall efficiency [13]. Crop physical characteristics further complicate machine design. For thick-stalked crops such as industrial hemp, the tall, rigid stems tend to break and twist during clamping and conveying, causing inconsistent laying angles that hinder subsequent field operations [14]. Crops with unconventional physical characteristics require dedicated machine designs to achieve viable mechanized harvesting. For example, tiger nut (Cyperus esculentus) has irregular seed morphology, an uneven surface, and an entangled root–soil–tuber matrix that render conventional root crop harvesters ineffective [15].

However, the complex kinematics and structure of combine harvesters, their high-intensity use, and the harsh and variable operating environments [16,17] pose technical challenges for Fault Detection and Diagnosis (FDD). In this review, we use fault diagnosis interchangeably with FDD to refer specifically to the identification and classification of structural and mechanical faults in combine harvesters through sensor-based monitoring and machine learning (ML) methods. We use structural health monitoring (SHM), a broader term encompassing continuous condition assessment of civil and mechanical structures, only when discussing general methodological frameworks that extend beyond agricultural machinery. Structural failures are one of the major factors causing unplanned downtime and impairing harvesting performance.

Artificial intelligence has increasingly permeated agricultural production, with multi-source sensor fusion, deep learning (DL), and adaptive control enabling advances from remote sensing to real-time field perception [18]. In crop monitoring, Unmanned Aerial

Vehicle-based hyperspectral imaging combined with ML now permits non-destructive estimation of water status, while Light Detection and Ranging-based 3D point clouds map height distributions in rice [19], and unmanned aerial vehicle-based structure-from-motion techniques have enabled maize plant height estimation from RGB imagery [20]. In real-time field perception, vision-based DL measures the lateral deviation from the grain divider to the harvesting boundary via inverse perspective mapping [21] and detects all-day tea shoots under both natural and artificial lighting using a lightweight YOLOv4-based model [22]. As a single-stage real-time object detector, the YOLO architecture predicts bounding boxes and class probabilities in a single forward pass, making it well-suited for time-sensitive agricultural perception tasks. Across crops and production stages, fused deep networks further classify nursery tree species and segment crowns and trunks from point clouds [23], recognize rice false smut offline under variable illumination [24], and detect branch-infected mulberries in aeroponic cultivation using hybrid convolutional neural network-gated recurrent unit (CNN-GRU) architectures [25].

While this review draws on international literature to provide comprehensive methodological coverage, this review anchors its analytical focus in the technological and operational realities most relevant to the Chinese agricultural context—the world's largest combine harvester market, where medium-to-large wheeled and tracked machines operate across diverse cropping systems spanning from the North China Plain to the hilly southwest. Regional differences in farm scale, crop varieties, field conditions, and maintenance infrastructure—within China and globally—can significantly influence the applicability and prioritization of diagnostic approaches. For example, harvesters operating in the small, fragmented, high-moisture paddy fields of southern China—characterized by heavy clay soils and limited bearing capacity [26]—face fundamentally different fault mode distributions and sensor installation constraints than large machines working extensive wheat or corn fields in the northeast. High-moisture rice, in particular, is prone to forming clumps that clog conveying, threshing, and cleaning devices [27], a challenge far less pronounced in dryland crop harvesting. Similarly, crop-specific harvesting challenges impose distinct mechanical loads and failure patterns: the thin, fragile seed coat of sunflower seeds makes them highly susceptible to mechanical damage during conveying [28], while the hilly and mountainous terrain prevalent in parts of China's maize-growing regions demands specialized low-center-of-gravity harvester designs to maintain stability and reduce grain loss [29]. Where relevant, the review notes these regional and crop-specific factors throughout, but a comprehensive treatment of geographic, climatic, and socio-economic determinants of harvester reliability lies beyond its scope and warrants dedicated comparative investigation.

This trend places unprecedented demands on the reliability of combine harvesters, as any unplanned downtime directly interrupts the automated precision operation chain. Developing advanced fault diagnosis technologies that match these demands is therefore essential for both harvest efficiency and the broader goal of alleviating agricultural labor shortages.

During field operations, agricultural machinery endures harsh environmental stressors—high dust concentrations, rapid humidity swings, broadband mechanical vibrations, and transient impact loads—which collectively induce continuous, non-periodic fatigue in structural components, accelerating cumulative damage and performance degradation [30,31] while also compromising electronic reliability. Common structural failure modes span five categories: (i) wear and fatigue fracture of transmission components, with the power train being the most frequently failing system in combine harvesters [32]; (ii) loosening of critical fasteners under vibratory loads, a dominant failure mode at connection points of working parts such as the vibrating screen [33]; (iii) abrasive wear and surface degradation of grain-contacting parts, which the silica-rich rice–steel friction pair drives [34]; (iv) fatigue failure of reciprocating components under prolonged alternating loads, for example rubber bearing wear, bearing housing fracture, and weld failure in the cleaning sieve [35]; and (v) blockage resulting from abnormal material accumulation, including straw winding on rotary tillage components in high-stubble clay soils [36] and vine clogging in peanut clamping–conveying systems [37].

In 2023, the Department of Agricultural Mechanization Management of China's Ministry of Agriculture and Rural Affairs conducted a quality survey on corn harvesters (grain harvesting type) in nine major corn-producing regions. The results are shown in Figure 1. During operation, 22.98% of the surveyed machines experienced a total of 298 failures. Among these, failures of the threshing unit, header system, and transmission system accounted for the dominant share (Figure 2), indicating a high degree of concentration at these three failure sites.

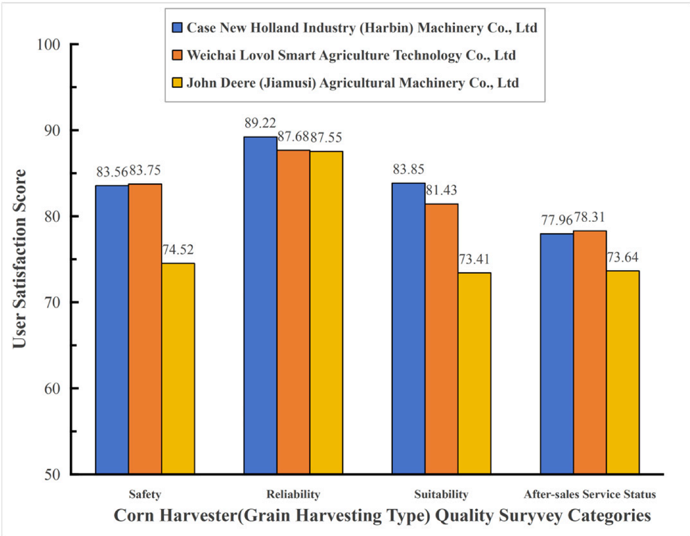

Figure 1. User satisfaction evaluation results of the 2023 quality survey on corn combine harvesters (grain harvesting type). Data source: [38].

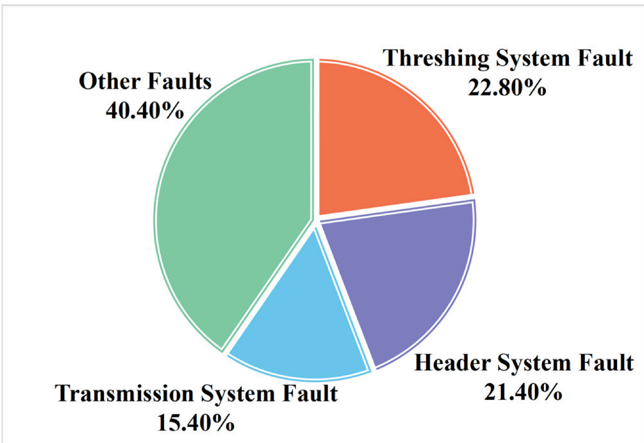

Figure 2. Failure types and their proportions of the surveyed corn combine harvesters (grain harvesting type). Data source: [38].

Traditional methods rely on manual inspection and empirical judgment, which offer limited efficiency and accuracy. The structural complexity of combine harvesters, variable working conditions, scarcity of fault samples, non-stationary signals, and strong background noise all pose significant challenges to FDD. In manned operations, fault identification depends primarily on operators' auditory, tactile, and visual experience—detecting abnormal noise, vibration, or sudden increases in resistance. Recent advances in sensor technology, data science, and computational power have driven fault diagnosis toward higher levels of intelligence.

2. Review Methodology

2.1. Search Strategy

The literature search for this review was conducted across six major academic databases: Web of Science Core Collection, Scopus, IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar. The search aimed to identify peer-reviewed journal articles and conference papers addressing fault diagnosis, condition monitoring (CM), and structural health management of combine harvesters. The search strategy combined terms related to the target machinery with terms describing diagnostic methodologies and enabling technologies. To reduce the risk of omission, the reference lists of all retrieved papers and relevant review articles were manually examined for additional studies that may not have been captured by the initial database queries. All retrieved records were subsequently deduplicated and consolidated.

The search period was set from January 1980 to May 2026, with the final update conducted in April 2026. This time frame captures the major developments in intelligent fault diagnosis and sensor-based CM of agricultural machinery, from early statistical reliability analysis and expert systems in the 1980s–1990s to the DL and multi-sensor fusion approaches of the past decade.

2.2. Inclusion and Exclusion Criteria

Studies were selected according to predefined inclusion criteria: (i) the work focused on fault diagnosis, failure detection, or health monitoring of structural components in combine harvesters or comparable agricultural machinery, including headers, threshing drums, cleaning sieves, transmission systems, chassis frames, and bearings; (ii) sensor-based data acquisition was employed, encompassing vibration, acoustic, speed, temperature, strain, or visual signals; (iii) the methodology involved ML, DL, multi-sensor fusion, or advanced signal processing; and (iv) the work was published as a peer-reviewed journal article or conference paper in English or Chinese.

Studies were excluded if they: (i) addressed purely agronomic perception tasks without diagnostic intent; (ii) focused exclusively on structural optimization or durability design without a CM component; (iii) were non-peer-reviewed preprints, dissertations, or patents; (iv) represented duplicate publications of the same work; or (v) lacked full-text accessibility.

2.3. Screening Process

The study selection followed a four-stage procedure based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses 2020 framework. First, we merged records retrieved from different databases and removed duplicate entries. Second, we screened titles and abstracts to exclude studies clearly irrelevant to the structural fault diagnosis of combine harvesters. Third, we assessed the full texts of the remaining studies and retained only those that explicitly addressed the target diagnostic tasks and provided sufficient methodological detail or experimental validation. Finally, we conducted backward reference tracking on the included studies to supplement the dataset and further reduce the risk of missing relevant publications.

2.4. Analytical Framework and Limitations

For the synthesis and structured comparison of the selected literature, we established a three-level taxonomy. Studies were grouped by the physical subsystem under diagnosis (structural module level; Figure 3), by methodological approach spanning traditional ML, DL, and multi-sensor fusion (methodological level), and by practical challenges constraining field deployment (deployment-readiness level).

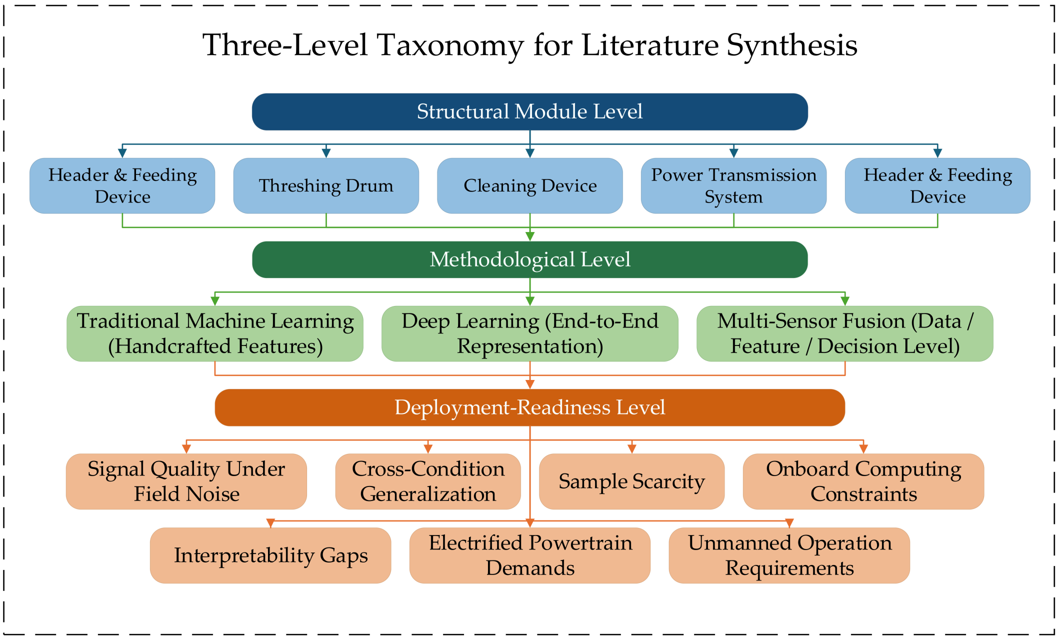

Figure 3. Three-level taxonomy for literature synthesis and structured comparison adopted in this review.

Notably, we did not perform a formal quality assessment of individual studies. This review prioritizes methodological coverage and technological evolution over quantitative evidence synthesis; accordingly, we treated all peer-reviewed publications as equally credible sources of methodological insight, which may introduce bias. Furthermore, the literature surveyed predominantly reports successful diagnostic outcomes with high accuracy or F1 scores, likely reflecting publication bias—studies with negative or inconclusive results are less likely to be submitted—and an editorial preference for novel algorithmic contributions over replication studies. Both mechanisms skew the published literature toward optimistic performance estimates, and the diagnostic performance figures compiled in this review may therefore overestimate the real-world effectiveness of certain methods. Future systematic reviews in this field would benefit from including grey literature and preregistered studies to mitigate these biases.

First, the scope of this review is constrained to structural and mechanical fault diagnosis of combine harvesters; related topics—hydraulic and pneumatic system diagnostics, risk analysis, onboard computer architectures, communication networks, satellite positioning, and anthropogenic factors—are beyond its methodological focus and warrant dedicated reviews. Second, the literature search was limited to publications in English and Chinese, which may introduce language bias by omitting relevant work in Russian, German, and Japanese. Third, non-peer-reviewed sources such as preprints, dissertations, patents, and manufacturer technical reports were excluded by design, meaning that practical diagnostic solutions from industry may be underrepresented. Fourth, the literature search was conducted with a cutoff date of May 2026; any relevant studies published after this date are not included. The coverage of this review is therefore systematic but not exhaustive.

3. Introduction to Typical Fault Classification and Characteristic Analysis of Combine Harvesters

3.1. Brief Description of the Structural Composition of Combine Harvesters

A combine harvester is a highly integrated operation platform that incorporates complex mechanical, hydraulic, electrical, and electronic systems. Its operational workflow encompasses key stages such as crop cutting, feeding, threshing, separating, cleaning, and grain collection. To perform these functions, the whole machine consists of several core structural modules. Specifically, the header at the front cuts the crop; the feeding device conveys the cut material uniformly to the threshing system; the threshing and separating unit accomplishes the detachment and separation of grain from straw; the cleaning system removes impurities to obtain clean grain; the grain tank serves as a temporary storage container for cleaned grain; and the conveying auger transports the cleaned grain into the grain tank and discharges the grain from the tank during unloading [39,40]. In addition, the driving force for the working components mainly comes from the engine and is transmitted through a complex transmission system (including gearboxes, bearings, belts, chains, etc.) [41,42]. The hydraulic system is responsible for controlling the lifting and lowering of the header, the rotation of the unloading auger, and the steering of the whole machine. The main supporting structure consists of the chassis frame and the undercarriage, and the machine primarily achieves field mobility through wheeled, tracked, or composite traveling mechanisms [43]. Each of the aforementioned modules contains many structural parts. The interactions among these parts and the complexity of integration lead to diverse structural failure modes. Figure 4 shows the typical structure of a combine harvester.

Figure 4. Structure and major components of a typical combine harvester.

3.2. Fault Research on Critical Structural Components

Combine harvesters operate for long periods under high loads and harsh field conditions, making components within structural modules prone to various structural failures.

We selected these five subsystems for detailed analysis because they dominate field failure statistics. As noted in Section 1, the 2023 national quality survey of corn combine harvesters in China [44] identified the threshing unit, header system, and transmission system as the three most frequent failure sites, collectively accounting for 59.6% of the 298 failure events recorded (Figure 2). We include the cleaning device and chassis frame here because, although they may fail less frequently, their failure consequences are disproportionately severe: a cleaning sieve blockage can halt harvesting entirely, and a chassis frame fracture renders the machine inoperable until major structural repair is completed. We address hydraulic and pneumatic subsystems separately in (6) and (7) below. While this subsystem taxonomy does not claim to be exhaustive—components such as the grain tank, unloading auger, and electrical wiring harness also experience field failures—the five mechanical subsystems examined here encompass the most structurally critical and diagnostically challenging elements of a combine harvester, and the peer-reviewed literature provides sufficient depth on these subsystems to support a structured review.

(1) The header and feeding device: In the workflow of a combine harvester, the header and feeding device, as the components that first come into contact with the crop, perform the critical functions of cutting, conveying, and feeding the crop into the threshing unit. Rough field terrain and uneven crop density subject the header and feeding device to complex, time-varying external excitations, which induce severe vibration and failure (Figure 5). Excessive vibration of the header may cause harvest loss, shorten the service life of the combine harvester, and affect working accuracy and driver comfort [45,46].

(**a**) (**b**)

Figure 5. (**a**) Feeding device chain fracture [5], (**b**) Header drive wheel damage [5].

Researchers have directly quantified the relationship between header vibration and crop loss in rape harvesting, where high temperatures and humidity during the May harvest season render mature pods highly susceptible to shattering under the vibration of vertical cutters, with header losses accounting for 50–70% of total harvest loss in the late ripening stage [47]. Crop-specific traits further compound the susceptibility of rapeseed to harvest loss. Pod shatter resistance varies significantly among varieties and is closely correlated with pod length, pericarp thickness, and moisture content [48], while the geometry of the reel tines—the first component to contact the crop—directly influences the magnitude of impact-induced pod shattering [49]. Tang et al. [50] established a three-dimensional model and combined it with modal analysis to explore the excitation sources affecting header resonance. They then employed a lightweight topology optimization method that effectively reduced vibration during header operation and avoided resonance. Ebrahimi et al. [51] conducted modal tests on the header, using operational modal analysis and the frequency domain decomposition technique to identify that the natural frequency of the fifth mode shape (50 Hz) coincided with the excitation frequency of the cutter bar driver, producing a resonance condition. They applied calculated masses to the cutting platform, shifting the fifth mode natural frequency from 50 Hz to 47.87 Hz and thereby reducing the vibration by mitigating the resonance condition. He et al. [52] used in situ modal testing and Lagrangian methods to reveal the intrinsic multi-harmonic coupling relationship between header vibration and the threshing drum. They also established a damped pendulum model for the cantilever feeding device and accurately predicted the structural steady-state response with an error of less than 5%. Zhang et al. [34] systematically revealed the composite wear mechanisms of the rice–steel friction pair through bench friction tests, discrete element method (DEM) and wear model (DEM-Wear), and surface characterization techniques, elucidating the fundamental friction and wear phenomena at the microscopic level. They also developed a novel DEM-Wear model capable of predicting macroscopic wear "hot spots" on the header, and established the fractal dimension (Ds) as a sensitive indicator for measuring wear severity. Furthermore, crop characteristics such as pod shatter resistance [48] and reel kinematics tailored for specific crops [49] significantly influence the dynamic loads and excitation on the header.

(2) Threshing drum: The threshing drum, the core component of the threshing stage, often suffers severe vibration from imbalance during operation. This vibration leads to bearing wear, shaft deformation, and cracks, shortens part service life, and ultimately causes failure [53–55]. Crop mechanical properties also influence threshing loads: maize compressive strength and elastic modulus vary with moisture content and loading speed, directly affecting grain detachment force and drum stress [56]. The threshing drum can also become blocked by sudden changes in feed rate or high grain moisture content (Figure 6). Goodman [57] proposed the influence coefficient method, the most widely used approach in rotor dynamics balancing. Building on this, researchers have developed robust balancing strategies for multi-source excitation uncertainties under field conditions, including centroid propagation modeling for assembly imbalance [58], maximum entropy-enhanced dual-speed influence coefficients [59], and prestressed support beams for structural vibration suppression [60]. An on-site dynamic balancing process based on a double-speed influence coefficient method achieved an 85.8% vibration reduction rate in field tests [60]. Tang et al. [61] further addressed chain drive-induced unbalanced vibration in double-drum systems through a step-by-step balancing method, revealing that the chain drive wrap angle directly affects the phases of the two equivalent unbalanced masses. A variable-diameter threshing drum with movable radial plates adapts to fluctuating feed rates, reducing blockage risk [62]. Gu et al. [63] proposed a surrogate model-based structural optimization scheme for the plate–shell threshing structure. Using Latin Hypercube Design, Kriging response surfaces, and a multi-objective genetic algorithm, they increased the first-order natural frequency by 14.6%, avoiding the main machine excitation range, and reduced the dynamic response under multi-point forces by 62.4%.

(**a**)

(**b**)

Figure 6. (**a**) Severe blockage of the threshing drum [64], (**b**) Crack on the left side of the thresher frame (in the direction of the arrow, a reinforcing plate applied) [5].

(3) Cleaning device: The cleaning sieve and the fan are the core working components of the cleaning device. The cleaning sieve is heavy, structurally complex, and undergoes eccentric rotary motion. Each component endures prolonged, complex alternating loads, leading to rubber bearing failure [65] (Figure 7). The rubber bearings exhibit progressive degradation characterized by aging, abrasive wear, surface scaling and delamination, and inner diameter enlargement. As the weakest link, the most vulnerable bearing degrades first, altering the motion parameters of the two four-bar linkages

of the screen box, which in turn compromises cleaning performance and accelerates the failure of adjacent rubber bearings and connected components. Under severe overloading, insufficient airflow velocity causes the grain–MOG mat to collapse into mechanical separation, blocking the sieve openings and discharging grain at the rear; if the sieve overloads first, the tailings return also blocks, significantly degrading cleaning performance [66–68]. Liang et al. [69] quantified the terminal velocities of different threshed output fractions, used turbine flowmeter measurements to characterize airflow distribution; incomplete cleaning also raises food safety concerns, as mycotoxins such as deoxynivalenol concentrate in the outer bran layers of wheat grain [70]. Building on these findings, they proposed a multi-duct cleaning device with a return pan that reduced cleaning sieve loss by 85% and grain impurity rate by 73% compared with a commercial system. Cheng et al. [71] designed a modified cleaning sieve coated with Polytetrafluoroethylene to address wetness and stickiness, effectively reducing adhesion and blockage. Wang et al. [72] designed a laminated elastic steel rod oscillating screen that overcomes blockage by impurities and debris while improving cleaning quality and speed. A subsequent study [73] combined EDEM-RecurDyn co-simulation with a back-propagation neural network (BPNN) to predict material distribution on a variable-amplitude screening mechanism under feed rate fluctuations, providing a basis for intelligent anti-blocking control. Further investigation of variable-amplitude screening under multipoint feeding has optimized material distribution [74]. Studies have also evaluated detection air duct performance and cleaning fan airflow distribution [75], and multi-parameter control models have been proposed to coordinate threshing and cleaning under fluctuating feed rates.

Figure 7. Rubber bearing wear diagram [65].

(4) Power transmission system: The power transmission system is among the most failure-prone components of a combine harvester [32,76]. Figure 8 shows a gearbox failure. In a typical crawler combine harvester power transmission system, such as those widely used in China, the belt drive serves as the first power transmission stage from the engine to the hydrostatic transmission unit and ultimately to the gearbox. Dynamic stress fluctuations in the transmission belt, arising from load variations and speed changes during field operation, pass downstream through the drive chain to the gearbox, accelerating wear and fatigue of gears and bearings over time. Guan et al. [77] proposed a reliability calculation method based on dynamic analysis of the transmission belt, establishing a nonlinear dynamic string-beam model to derive the relationship between belt speed and dynamic stress and thereby identifying the dangerous belt speed range for design and reliability calculation. Li et al. [78] conducted modal experiments and vibration transmission path analysis on a multi-cylinder bilateral chain drive system, finding that the transmission chain and driving

mode affect stiffness, damping, and fundamental-frequency vibration response, and that the frame serves as the main vibration transmission path, with transmission efficiency exceeding 80% at different frequencies.

Figure 8. Break in the gearbox cover [5].

(5) Chassis frame: The chassis frame serves as the supporting structure of the combine harvester and carries the entire weight of the machine. When the chassis frame fails, the combine harvester breaks down and ceases operation (Figure 9). Chen et al. [79] derived the vibration response of a combine harvester frame under multi-source excitation, finding that the constant modal frequencies of the complete machine are directly related to the independent modal frequencies of the chassis and threshing frames, and that the sixth-order constant modal frequency lies within the operating frequency range that may cause complex vibration coupling and resonance. Hu et al. [80] analyzed the mechanical causes of tipping instability in crawler combine harvesters and designed an omnidirectional attitude-adjustable chassis based on a five-bar mechanism; dynamic stress analysis and omnidirectional leveling control of this chassis have further provided insights into structural reliability and terrain adaptability under complex conditions [81]. During daily operation, track slippage and soil buildup on wet, soft fields also affect stable operation [82]; bionic designs on track surfaces, such as copying grouser and convex hull patterns, have been explored to enhance traction and reduce soil adhesion [83]. The traditional single-side braking steering method, with its large turning radius, tends to cause severe soil buildup and creeping in soft soil, which can lead to track slippage and traveling failure.

Figure 9. Track disassembly for field repair (illustrative photograph).

(6) Hydraulic system: The hydraulic system serves as the actuation backbone for several critical functions—header height adjustment, reel position control, unloading auger swing and extension, and hydrostatic transmission steering. Unlike mechanical failures, which are often visually observable (Figures 5–9), hydraulic failures—internal leakage, valve spool binding, seal degradation, and fluid contamination—are inherently concealed within pressurized conduits and rarely produce externally visible damage.

Hydraulic diagnostics therefore rely primarily on sensor-acquired data—pressure, flow, temperature, and oil quality—rather than visual inspection.

A review of agricultural machinery hydraulic diagnostics identified three predominant failure modes [84]: abrasive wear of pump and motor components from particulate-contaminated oil; seal and O-ring degradation causing internal and external leakage; and solenoid valve malfunction from coil burnout or spool binding due to silting. These modes are aggravated by the harsh field environment—high ambient temperatures accelerate oil oxidation and viscosity loss, while dust ingress through breather caps and cylinder rod seals introduces abrasive contaminants throughout the circuit. Vibration-based fault diagnosis using power spectral density analysis has been applied to hydraulic pumps in tractor steering systems [85], and support vector machine (SVM)-based classification of shift solenoid valve faults under small-sample conditions has been explored for electro-hydraulic control systems on heavy tractors [86]. A hierarchical diagnostic framework for combine harvester hydraulic systems has been proposed, guiding fault localization from subsystem to component level using the grain unloading electro-hydraulic circuit as a representative case [87].

For combine harvesters specifically, researchers have developed an on-line monitoring system that integrates multi-sensor fusion technology—pressure transducers at the cutting table, screw conveyor, conveyor trough, and threshing drum hydraulic actuators—to provide real-time operational parameter display and fault alarm functions [88]. More recently, DL architectures that combine stacked autoencoders with deep belief network have emerged for CM of combine harvester hydraulic systems, enabling end-to-end feature extraction directly from raw sensor signals and establishing nonlinear mappings between hydraulic state parameters and system health status [89]. These developments indicate that hydraulic system diagnostics for combine harvesters is gradually transitioning from empirical threshold-based alarm systems toward data-driven intelligent monitoring.

Despite these advances, hydraulic fault diagnosis for combine harvesters faces challenges distinct from mechanical component diagnosis. Pressure and flow transients are inherent to normal operation—header lifting and lowering, variable-speed hydrostatic steering, and intermittent unloading auger actuation all produce dynamic fluctuations that can mask the signatures of incipient faults. This transient-rich operating environment makes threshold-based fault detection prone to false alarms and motivates adaptive diagnostic models that can distinguish normal operational dynamics from fault-induced anomalies. Moreover, hydraulic diagnostic techniques developed for stationary industrial systems have achieved compound fault decoupling through sensor-pair joint analysis and DL models [90]. However, these techniques do not transfer seamlessly to mobile agricultural machinery, where operating conditions are far more variable and sensor installation is constrained by cost, durability, and accessibility. Systematic research on hydraulic fault diagnosis specifically tailored to the combine harvester context remains scarce, representing a significant gap that warrants dedicated investigation.

(7) Pneumatic system: Beyond the cleaning fan—a pneumatic component whose mechanical fault modes (bearing wear, imbalance, blade damage) are addressed in the cleaning device subsection (Section 3.2 (3))—modern combine harvesters employ pneumatic systems for several functions: pneumatic recovery devices for reducing header side-cutting loss in rapeseed harvesting [91], pneumatic conveying for grain transfer [92], pneumatic actuation for driving the header, threshing mechanism, and unloading system [93], and onboard compressed air for machine cleanout [94]. Despite these deployments, a systematic literature search revealed virtually no peer-reviewed studies specifically addressing pneumatic system fault diagnosis on combine harvesters. Industrial pneumatic diagnostics has developed methods that could in principle be

adapted to agricultural machinery—systematic failure detection frameworks for compressed air systems [95], pressure signal analysis for fault identification in pneumatic circuits [96], and acoustic emission (AE) monitoring for pneumatic actuator leakage detection [97]—but no published work has yet attempted this transfer. This constitutes a clear gap in the literature and a necessary direction for future research as pneumatic functions continue to proliferate on automated and electrified harvester platforms.

Hydraulic and pneumatic system faults present characteristics distinct from those of the five mechanical subsystems discussed above, relying on pressure, flow, and fluid CM rather than vibration or visual inspection. Table 1 summarizes the typical failure modes, main causes, and operational consequences for the five mechanical structural modules.

Table 1. Summary of failure mode classification.

Structural Module	Failure Mode	Main Cause	Consequence
Header and feeding device	Chain fracture, drive wheel damage, resonance	Sudden feed rate changes, terrain excitation, multi-harmonic coupling	Harvest loss, downtime
Threshing drum	Imbalance, blockage, bearing wear	Feed rate shock, high grain moisture content, chain drive imbalance	Severe vibration, cracks, downtime
Cleaning device	Rubber bearing wear, sieve blockage	Eccentric rotary motion, high load, material adhesion	Increased cleaning loss, high impurity rate
Power transmission system	Gear fracture, belt slippage, chain drive vibration	Alternating load, wear, misalignment	Transmission failure, downtime
Chassis frame	Fatigue cracks, resonance, tipping	Multi-source excitation coupling, specific terrain	Complete machine breakdown

3.3. Applicability Boundaries of Passive Structural Strategies Under Complex Field Conditions

Much of the aforementioned literature demonstrates that structural optimization, process improvement, and other approaches effectively enhance the reliability of critical components. These studies fundamentally strengthen the load-bearing capacity and vibration resistance of the components. However, these improvements generally rely on specific assumptions. When transitioning from simulation or bench tests to real-world, complex field conditions, the difficulties of passive structural strategies gradually become apparent.

3.3.1. Deviation from Deterministic Assumptions Under Time-Varying Operating Conditions

Existing structural optimization studies generally assume deterministic load inputs. The effectiveness of Tang et al.'s topology optimization of the header and Ebrahimi et al.'s modal-analysis-based structural improvement of the header both depend on the matching between the excitation frequency and the preset frequency avoidance range—suppressing the vibration response by avoiding specific resonant frequencies. Although the damped pendulum model of the cantilever feeding device established by He et al. [52] can predict the steady-state response with high accuracy (error < 5%), it mainly applies to steady-state response tests; its ability to predict transient processes remains unverified.

However, combine harvesters face time-varying operating conditions in the field, with real-time fluctuations in crop density, traveling speed, and terrain undulations. Ding et al. [98] studied the vibration characteristics of combine harvesters under feed rate disturbance and found that changes in feed rate can cause the peak excitation frequency of the threshing drum to shift significantly from 195 Hz to 117 Hz, with a maximum amplitude variation of up to 83.5%. This downward frequency shift arises from the damping effect of the crop material as it flows through the drum. A shift in this magnitude implies that structural optimization schemes based on a specific frequency avoidance range may lose validity under variable feed rate conditions, since the dominant excitation spectrum moves outside the original target band. A frequency shift in this magnitude implies that structural optimization schemes designed based on a specific frequency avoidance range may fail under variable conditions due to the overall shift in the excitation spectrum. Rezaei et al. [99] measured the actual loads on the rear axle of a combine harvester on different roads. The actual load fluctuated between 18.8 kN on asphalt pavement and 49.2 kN on field dirt roads, a difference of more than 2.6 times. Wang et al. [100] investigated the transient impact and alternating loads on harvester bolts and found that the random peak vibration of bolts and connectors at the vibrating sieve reached 12.5622, which falls within the severe impact and collision standard and makes them susceptible to damage. These studies indicate that the preset loads underlying deterministic design represent only a single instant in the load distribution under complex field conditions. When the value of the transient response exceeds the preset boundary, the vibration suppression effect of structural optimization diminishes accordingly.

3.3.2. As-Manufactured Reliability Versus Performance Degradation After In-Service Wear

Structural optimization is essentially a static design oriented towards the as-manufactured state. Whether avoiding resonance frequencies or improving dynamic balancing calibration, these optimizations all rely on the initial state at the factory. However, as the service time increases, the originally designed structure gradually wears during operation.

Zhang et al. [34] showed that wear continuously alters component geometry, surface roughness, and fit clearance, shifting the mass distribution and boundary conditions on which structural optimization depends. Taking the threshing drum as an example, even if on-site dynamic balancing is performed at the factory using the double-speed influence coefficient method [58], subsequent bearing wear, shaft deformation, and cracks gradually disrupt the balanced state and introduce new unbalanced excitation. Jankauskas et al. [30] found that straw chopper knife wear differed substantially between a season with lodged crops and severe contamination (2022) and one with favorable conditions (2023), confirming that unpredictable field conditions directly govern wear rates. These studies demonstrate that component wear and performance degradation after long-term service fundamentally limit the reliability of structural optimization.

3.3.3. Conflict Between Component Optimization and System Coupling Response

Most structural optimization studies focus on individual components—lightweight header design, Polytetrafluoroethylene-coated cleaning sieves, or improved plate–shell threshing structures—without considering system-level interactions. However, the components within a combine harvester exhibit mutual interactions. He et al. [52] revealed a multi-harmonic coupling relationship between header vibration and the threshing drum. Chen et al. [79] demonstrated that the constant modal frequencies of the complete harvester are directly related to the independent modal frequencies of the chassis and threshing frames, and that the sixth-order constant modal frequency may cause complex vibration coupling and resonance. These findings imply that adjusting the stiffness or mass of a single component alters the dynamic characteristics of adjacent structures, changing the vibration transmission of the whole machine. In the absence of a whole-machine-level multi-body dynamics coupling model, the reliability of isolated component optimization remains uncertain.

3.3.4. Blind Spots in Protection Between Predictable Progressive Failures and Random Sudden Events

Structural optimization primarily addresses predictable, gradual failure modes—cumulative wear, vibration-induced loosening of connectors, and progressive material blockage—as demonstrated by structural optimization of the plate–shell threshing structure [63] and multi-duct cleaning design against overload blockage [69]. However, the field also witnesses numerous random, sudden events with extremely short action times and loads far exceeding design conditions, triggering failure modes completely different from gradual degradation. Wang et al. [100] found that random peak vibration of vibrating sieve connectors reached the severe impact and collision standard. Low-probability events—such as feed rate fluctuations and instantaneous impacts from ground bumps—exceed normal design safety margins, and structural optimization offers relatively limited protection against such events.

3.4. Summary: From Passive Structural Redundancy to Active State Perception

The random time-varying nature of operating conditions, performance degradation, transmission of system coupling responses, and the unpredictability of sudden events jointly define the effective boundary of purely passive structural strategies in actual field environments. The existence of this boundary does not negate the fundamental role and necessity of structural optimization as a means of preventing failures. Sound structural design is the first line of defense for ensuring the reliability of a combine harvester. It is the physical prerequisite for the effective implementation of fault diagnosis.

Indeed, it is precisely this boundary that drives the evolution of fault research on combine harvesters from passive structural redundancy to active state perception. Excellent structural design can reduce the probability of failure but cannot eliminate it completely. It can delay performance degradation but cannot prevent it ultimately. Therefore, actively sensing, diagnosing, and predicting faults, combined with excellent structural design, can minimize the incidence of serious failures, avoid unplanned downtime, and reduce the economic losses caused by failures.

4. Fault Diagnosis Methods Based on Traditional Machine Learning

In the fault diagnosis framework based on traditional ML, signal acquisition, preprocessing, and handcrafted feature extraction together constitute the front-end stages of the diagnostic process. Their quality directly determines the upper limit of the subsequent model's classification performance. For agricultural machinery such as combine harvesters operating under harsh field conditions, the raw signals collected by sensors are often contaminated by strong background noise; therefore, signal preprocessing and feature engineering are essential.

4.1. Historical Context

Before sensor-based intelligent diagnosis, fault management for combine harvesters and agricultural machinery relied on two complementary approaches: statistical reliability analysis and knowledge-based expert systems. Early reliability studies in the 1980s modeled failure characteristics of combine harvester subsystems using Weibull distributions to estimate time-between-failure intervals [101]. Extending into the 1990s, reliability studies on agricultural tractors identified three fundamental failure categories—early failures, random failures, and wear-out failures—and highlighted the severe economic consequences of machinery downtime during time-sensitive operations [102]. By the late 2000s, reliability analysis had advanced to incorporate Monte Carlo simulation for predicting failure intervals across entire harvester fleets [103]. These statistical approaches, however, characterized only aggregate failure trends across populations; they offered no real-time diagnostic capability for individual harvesters in the field.

In parallel, growing machinery complexity motivated knowledge-driven diagnostic approaches, including expert systems encoding domain expertise as rule sets and fuzzy logic classifiers applied to gearbox fault diagnosis using vibration signal features. Despite these efforts, a landmark review by Craessaerts et al. [104] concluded that fault diagnostic systems had received little attention in agricultural machinery research and remained largely untested on mobile equipment. The subsequent decade witnessed a rapid expansion of sensor-based monitoring and data-driven diagnostics—the developments that form the core of this review.

4.2. Typical Diagnostic Process: Signal Acquisition, Preprocessing, and Handcrafted Feature Extraction

4.2.1. Signal Acquisition: Common Sensor Types and Monitored Physical Quantities

Traditional ML-based diagnostic methods rely on a few sensor types to acquire equipment status information, each corresponding to different monitored physical quantities and typical installation positions. Accelerometers at bearing housings and gearbox casings capture vibration responses. Speed sensors (Hall sensors, photoelectric encoders, etc.) on the shaft ends of rotating components such as the threshing drum and conveying auger provide phase reference and speed feedback. Acoustic sensors (microphones or contact-type AE sensors) can non-contactly acquire internal status information of the equipment. Temperature sensors (thermocouples, resistance temperature detectors) commonly monitor oil temperature and bearing temperature rise to assist in judging lubrication and friction anomalies. Pressure sensors, installed on hydraulic lines, capture pressure transients indicative of leakage, blockage, or component degradation. Visual sensors—conventional cameras and infrared thermal imagers—detect visually evident faults such as header blockage and belt slippage [105], while thermal imaging captures abnormal temperature distributions associated with bearing or motor degradation [106–108].

Beyond the diagnostic sensors listed in Table 2, specialized operational monitoring sensors provide contextual data—feed rate, grain loss, throughput—that can inform diagnostic inference. Piezoelectric-based sensors with adaptive neuro-fuzzy inference for signal fusion have quantified grain loss during cleaning, reaching measurement ranges up to 1500 grains per second [109]. Grain mass flow has been estimated via near-infrared light attenuation through discrete grain streams [110], while impact-based flow sensors with strain-gauge vibration compensation have been employed for in-field grain yield mapping [111]. Feed rate effects on threshing performance have been modeled through response surface methodology for hydraulic variable-diameter threshing drums, establishing quantitative relationships between feed rate, threshing gap, and hydraulic oil pressure [112].

Table 2. Summary of commonly used sensors and monitored physical quantities.

Sensor Type	Monitored Physical Quantity	Typical Installation Position	Diagnostic Application	Ref.
Accelerometer	Vibration	Bearing housing, gearbox, frame	Bearing fault, gear fault, imbalance, misalignment	[113,114]
Speed sensor (Hall/encoder)	Rotational speed	Threshing drum shaft, conveying auger shaft	Blockage detection, belt slippage	[114,115]

Table 2. *Cont.*

Sensor Type	Monitored Physical Quantity	Typical Installation Position	Diagnostic Application	Ref.
Microphone	Sound pressure	Non-contact, near cleaning system	Acoustic fault signature, cleaning loss anomaly	[116]
Temperature sensor	Temperature	Oil pan, bearing housing, hydraulic reservoir	Lubrication failure, overheating	[117]
Strain gauge	Stress/strain	Vibrating sieve bolts, frame members	Bolt loosening, structural overload	[118]
Pressure sensor	Pressure	Hydraulic lines	Hydraulic fault diagnosis	[90]
Camera	Visual image	Header, threshing drum, grain tank	Blockage, belt slippage, material accumulation	[105]
Infrared thermal camera	Temperature distribution	Bearing housing, motor casing	Overheating, thermal fault classification	[106–108]

Table 2 summarizes the sensor types, their monitored physical quantities, typical installation positions, and representative diagnostic applications, providing a hardware-level reference for subsequent signal preprocessing and feature extraction.

Vibration signals are the most widely adopted monitoring signal source. A combine harvester contains numerous rotating components—threshing drum, conveying auger, fan, gearbox, bearings, and transmission shafts—whose localized defects induce characteristic vibration responses, captured by accelerometers at key measurement points such as bearing housings, gearbox casings, and weak points on the frame. For example, Ruiz-Gonzalez et al. [113] evaluated the feasibility of estimating the state of various rotating components from a vibration signal acquired at only a single point on the combine harvester chassis.

In addition to vibration sensors, speed sensors widely monitor the rotational speed of critical rotating components. Speed signals can serve as an independent diagnostic parameter—detecting faults such as blockage and slippage through speed drops or abnormal fluctuations—and are often acquired synchronously with vibration signals to provide a speed reference for non-stationary signal processing methods such as order analysis and computed order tracking (COT). For instance, Wang et al. [114] combined a speed sensor with a vibration sensor to achieve COT and early-stage pitting fault feature extraction for agricultural machinery bearings under variable-speed conditions.

Acoustic signals have also been applied in combine harvester fault diagnosis, offering the advantage of non-contact installation without structural modification. Shen et al. [116] found that the characteristic frequency regions of grain and stalks differ significantly, enabling a method for separating grain and stalk signals. Acoustic signals, however, are highly susceptible to environmental noise, and their specificity is weaker than that of vibration signals.

Temperature signals also contribute to fault diagnosis: abnormal increases in hydraulic oil, gearbox oil, or bearing housing temperature often indicate poor lubrication, excessive friction, or impending component failure. Temperature sensors are low-cost and easy to install, but their considerable thermal inertia makes them insufficiently sensitive to sudden faults. In addition, strain signals have been introduced to monitor the stress state of structural components [118], along with process parameter sensors—such as feed rate and grain loss sensors—for operational status information.

4.2.2. Signal Preprocessing

The field operating environment contains noise sources such as high-concentration dust, mechanical vibrations, and electromagnetic interference (EMI). Raw sensor signals usually exhibit a low signal-to-noise ratio (SNR); signal preprocessing is therefore necessary for effective feature extraction. Common preprocessing techniques include time-domain filtering (low-pass, high-pass, band-pass), which removes irrelevant signals outside specific frequency bands. For example, Ji et al. [119] combined low-pass filtering with ensemble empirical mode decomposition (EEMD) to remove high-frequency noise from combine harvester vibration signals. Adaptive signal decomposition and denoising techniques, such as empirical mode decomposition and its variants including EEMD and the complete EEMD with adaptive noise, decompose non-stationary, nonlinear signals into several intrinsic mode function. Subsequently, specific criteria—such as the minimum energy criterion or correlation coefficient—select the signal-dominant intrinsic mode function components, effectively separating signal from noise. Du et al. [120] used empirical mode decomposition with the minimum energy criterion to design a cleaning loss monitoring sensor that successfully separated structural vibration, working noise, and trash interference. Wavelet threshold denoising is also widely used in agricultural machinery CM; its combination with the complete ensemble method has been validated in scenarios such as cotton seed metering monitoring [121]. For non-stationary problems caused by speed fluctuations, COT resamples time-domain signals into equal-angle signals, eliminating the influence of speed variation on spectrum analysis [115]. For acoustic signals, Darabian et al. [122] adopted pre-emphasis, framing, and windowing for denoising and signal enhancement before Mel-frequency cepstral coefficient (MFCC) feature extraction.

4.2.3. Handcrafted Feature Extraction

Under the traditional ML framework, feature extraction is the most critical and domain-knowledge-intensive step. The extraction of physically interpretable and fault-discriminative features from preprocessed signals directly determines the diagnostic accuracy of the classifier. Handcrafted features for vibration signals are typically extracted from three domains:

(1) Time-domain features: These include dimensional indicators such as root mean square (RMS), peak value, kurtosis, skewness, crest factor, and impulse factor, as well as statistical quantities like mean and variance. RMS reflects overall signal energy and has been used to establish feed rate prediction models; the crest factor and kurtosis are exceptionally sensitive to impulse-type faults and are among the most commonly used indicators in rotating machinery fault diagnosis [123].

(2) Frequency-domain features: The fast Fourier transform produces the frequency spectrum, from which parameters such as the amplitude at characteristic frequencies, power spectral density, spectral centroid, and frequency variance are extracted. Spectrum envelope analysis and spectral kurtosis analysis have analyzed the main impact frequencies of the threshing drum under field working conditions and, combined with time–frequency domain analysis, have revealed the vibration characteristics during the threshing process [124].

(3) Time–frequency-domain features: To address the non-stationary characteristics caused by frequent speed and load changes, researchers widely adopt time–frequency methods such as the short-time Fourier transform (STFT) and wavelet transforms (continuous wavelet transform, CWT; discrete wavelet transform, DWT). One study applied DWT to tractor auxiliary gearbox vibration signals, extracting wavelet coefficients at different decomposition levels as classification features [125]. Entropy-based features have also been introduced: multi-scale sample entropy and refined composite

multivariate multiscale sample entropy extract nonlinear dynamic features from multi-channel bearing vibration signals, measuring signal complexity and irregularity [126], while composite-scale variable dispersion entropy (CSVDE) has been investigated for rolling bearing fault diagnosis in combine harvesters [127].

For acoustic signals, MFCC are among the most widely used handcrafted features. MFCC simulate the nonlinear perceptual characteristics of the human ear for sound waves of different frequencies and have demonstrated good classification performance in acoustic fault diagnosis of agricultural machinery. For temperature signals, commonly used handcrafted features include the mean temperature, temperature rise rate, and temperature gradient. Feature extraction for speed signals usually couples with vibration signals: COT produces the order spectrum, from which the amplitude of each order component is extracted as features [115,128].

Handcrafted feature extraction is essentially a form of information compression. Statistical quantities summarize the vast amount of detail in the original signal. This, on the one hand, enhances the physical interpretability of the features; on the other hand, it inevitably discards data structures that may contain discriminative information. Xie et al. [129] showed in their batch-training long short-term memory (LSTM) study that, under complex data characteristics, improper batch partitioning can lead to further loss of critical information during training. In contrast, the variational autoencoder proposed by Kingma et al. [130] has opened a new avenue for reducing such information loss. By assuming that latent variables follow a specific prior distribution, the variational autoencoder can learn the probability generation law of data under unsupervised conditions, thereby preserving the distribution information of the original data as much as possible while reducing dimensionality. This tension between "lossy compression" and "lossless representation learning" naturally drives the evolution of diagnostic methods from handcrafted feature engineering to DL-based representation learning.

Table 3 summarizes these handcrafted features by domain, their physical meanings, and the fault types to which they are most sensitive.

Table 3. Summary of handcrafted features (classified by domain).

Feature Domain	Typical Features	Physical Meaning	Sensitive Fault Type	Ref.
Time domain	RMS, kurtosis, crest factor	Signal energy, impulse severity	Bearing pitting, gear tooth breakage	[123]
Frequency domain	Characteristic frequency amplitude, spectral centroid	Modulation of specific fault frequencies	Imbalance, misalignment	[124]
Time–frequency domain	STFT/CWT coefficients, wavelet packet energy	Time-varying frequency components of non-stationary signals	Blockage under feed rate fluctuations	[125]
Entropy features	Sample entropy, multi-scale entropy, CSVDE	Signal complexity, irregularity	Early-stage weak faults	[126,127]

4.2.4. Feature Dimensionality Reduction and Selection

Handcrafted feature extraction often produces a high-dimensional set in which some features are redundant or irrelevant; dimensionality reduction or feature selection is therefore essential to improve computational efficiency and avoid the "curse of dimensionality." Principal component analysis (PCA), the most commonly used linear method [131,132], maps the original high-dimensional feature space into a low-dimensional principal component subspace through orthogonal transformation, retaining the main variance information.

Linear discriminant analysis [133,134] is a supervised technique that maximizes between-class scatter while minimizing within-class scatter, generally outperforming PCA when labeled data are available. Feature selection based on sensitivity analysis has also been applied to fault feature screening in combine harvesters. One study found that most individual time–frequency features have limited discriminability for vibrating screen bolt fault identification, requiring multi-feature fusion for effective diagnosis [135].

Before proceeding to the specific models, we clarify the scope of "traditional ML" as used in this review, which encompasses three interrelated categories. The first comprises statistical signal processing and feature engineering techniques—time-domain indicators, frequency-domain spectral analysis, time–frequency decompositions, and entropy-based complexity measures—serving as the front-end representation layer. The second consists of shallow classification and regression models—SVM, random forest (RF), K-nearest neighbors (KNN), artificial neural networks (ANN), naïve Bayes (NB), and extreme learning machines (ELM)—which map feature vectors to fault mode labels. The third covers early multi-source fusion strategies at the data, feature, and decision levels, integrating heterogeneous sensor information before the advent of DL-based adaptive fusion. These three categories are discussed under the unified label of "traditional ML" to establish a clear methodological contrast with the DL paradigm of Section 5, which features end-to-end representation learning, automated hierarchical feature extraction, and adaptive multi-modal fusion. This classification is not meant to imply that traditional approaches are methodologically homogeneous; the following sections explicitly examine each technique in terms of its specific operating principles, strengths, and limitations.

4.3. Application of Shallow Models: Performance of SVM, RF, etc., in Combine Harvester Fault Diagnosis

Once handcrafted feature extraction is complete, traditional ML-based fault diagnosis methods use shallow classification models to map multi-dimensional feature vectors to fault mode categories.

(1) SVM: SVM is one of the most widely used shallow classifiers in this field. It maps linearly inseparable low-dimensional features into a high-dimensional space via a kernel function to find the optimal separating hyperplane. Its strong generalization under small-sample conditions makes it particularly suitable for the scarcity of fault samples in diagnosis. For example, an improved particle swarm optimization-SVM method was applied to blockage prediction and speed control of an unmanned combine harvester, automatically optimizing hyperparameters to prevent blockage and ensure stable operation [136].

In rolling bearing fault diagnosis, SVM has been used for multi-domain state identification, with data augmentation strategies addressing sample imbalance to enable early-stage fault detection. The choice of kernel function (linear, polynomial, RBF) and penalty parameter C significantly affect accuracy and is typically tuned via grid search, genetic algorithms, or particle swarm optimization [137]. SVM naturally handles binary classification; for multi-class problems, "one-versus-all" or "one-versus-one" extension strategies are typically adopted.

Lian et al. [138] targeted loosening and fatigue of bolted conveyor trough connections under complex vibration. Using multi-point vibration signals, they identified sensitive transient response regions and developed an operating state identification model with a one-versus-one SVM. Field validation achieved 96.9–99.7% accuracy, confirming the strong potential of vibration features and ML for combine harvester fault diagnosis.

(2) RF: RF makes classification decisions by aggregating the voting results of multiple decision trees. It is robust to noise and overfitting, handles high-dimensional features,

and requires little parameter tuning. In silage harvester fault diagnosis, an improved RF algorithm incorporating the NB idea to boost individual tree accuracy achieved 97.9% accuracy, outperforming standard RF (93.27%) [139] RF has also been applied to tractor gearbox fault diagnosis, where vibration signals under three operating conditions were classified using DWT-extracted features [125]. Additionally, RF provides feature importance ranking, helping identify the most discriminative handcrafted features for specific fault types.

(3) KNN: KNN is a straightforward non-parametric classifier that requires no explicit training; classification is based solely on the labels of the K-nearest training samples in the feature space. In rotating machinery imbalance detection, KNN has been compared with SVM, verifying the feasibility of supervised learning-based intelligent fault detection [140].

For CM of agro-industrial rotating machinery, a KNN classifier combined with a harmony search algorithm for frequency band selection was validated on an experimental dataset containing healthy and multiple fault states [141].

The main advantages of KNN are its simplicity and freedom from assumptions about data distribution; however, computational complexity grows linearly with the number of training samples, and sensitivity to feature scales necessitates prior standardization or normalization.

(4) ANN: Shallow artificial neural networks, as distinguished from deep architectures, are classic models in traditional fault diagnosis. The feedforward BPNN learns the nonlinear mapping between features and fault modes by adjusting inter-layer connection weights through error back-propagation. A Fuzzy Neural Network-based fault diagnosis system using sensor signals for training and classification has provided a feasible real-time monitoring solution for combine harvesters [142]. Additionally, BPNN combined with Dempster–Shafer (D-S) evidence theory has been applied to blockage fault diagnosis, where evidence theory fused multi-source BPNN outputs to improve diagnostic reliability [143]. The advantage of traditional ANN lies in strong nonlinear fitting ability, though it is prone to overfitting with small samples and requires empirical selection of the network structure.
(5) NB: In a comparative evaluation of classifiers for fault detection, NB, KNN, and ANN were systematically compared, with NB and ANN both achieving 99.9% accuracy and the highest AUC values [144]. A further comparative experiment between SVM and NB under multiple fault conditions—healthy, imbalance, misalignment, gear fault, and bearing inner/outer race faults—confirmed NB's strong performance on small-scale data [145]. The advantage of NB lies in its computational efficiency and small-sample performance; however, its assumption of feature independence often fails with highly coupled features in practical engineering scenarios.
(6) ELM: a single-hidden-layer feedforward neural network, is notable for its extremely fast training speed. To address the low fault identification rate of rolling bearings in combine harvester walking gearboxes, a Dragonfly Algorithm-optimized Kernel ELM method was proposed, achieving effective fault type identification from vibration signal features [146]. ELM significantly reduces training time while maintaining acceptable classification accuracy, making it suitable for online diagnostic scenarios with high real-time requirements.

Knowledge-driven methods based on fuzzy logic and rule-based reasoning also contribute to traditional fault diagnosis. One study constructed a decision-tree knowledge base from fault function tables for combine harvester troubleshooting, achieving accurate fault localization in the electrical equipment subsystem through optimal search of the troubleshooting path [147]. This approach explicitly encodes domain expert knowledge into classification rules, making it suitable when fault data are scarce or new fault types lack historical coverage.

The preceding subsections have elaborated on SVM, RF, KNN, ANN, NB, and ELM in combine harvester and related agricultural machinery fault diagnosis. Although these studies demonstrate the effectiveness of individual models, evaluations focus predominantly on single-dataset classification accuracy, with no systematic comparison of their applicability under field conditions. To address this, Tables 4 and 5 summarize their core principles, advantages, limitations, potential strengths, and technical difficulties in the combine harvester context—characterized by scarce and class-imbalanced fault samples, strong non-stationary noise, multi-factor coupled fluctuations, and limited onboard computing resources.

Table 4. Core principles, advantages, and limitations of traditional Machine Learning models in fault diagnosis.

Model	Core Principle	Main Advantages	Main Limitations	Ref.
SVM	Maps features to a high-dimensional space via kernel function to find the optimal separating hyperplane.	Strong small-sample generalization; solid mathematical basis; handles high-dimensional features.	Requires multi-class extension strategy; empirical kernel and parameter selection; slow on large datasets.	[136–138]
RF	Ensemble of decision trees with majority voting.	Robust to noise and overfitting; handles high-dimensional features; provides feature importance; minimal hyperparameter tuning.	Large model size; sensitive to extreme class imbalance; weaker interpretability than a single tree.	[125,139]
KNN	Classifies based on the majority label of the K-nearest neighbors; no explicit training.	Simple, training-free; no data distribution assumption; easy implementation.	Computational complexity grows linearly with samples; scale-sensitive; lacks noise tolerance.	[140,141]
ANN	Learns nonlinear input–output mapping through multiple neuron layers, typically shallow (e.g., BPNN).	Strong nonlinear fitting; flexible architecture; learns complex feature–fault relationships.	Overfits with small samples; empirical network structure selection; weak interpretability.	[142,143]
NB	Computes posterior probability via Bayes' theorem assuming feature independence.	Computationally efficient; performs well on small datasets; provides probabilistic output.	Independence assumption often invalid; limited capability with highly coupled features.	[144,145]
ELM	Random input weights; output weights solved analytically by least squares.	Extremely fast training; simple parameter setting; avoids gradient-based local optima.	Random weights cause instability; requires regularization for generalization.	[146]

Table 5. Applicability of traditional Machine Learning models in the combine harvester field environment.

Model	Potential Strengths in Field Operation	Technical Difficulties in Field Operation	Ref.
SVM	Excels with scarce fault samples; good at handling high-dimensional handcrafted features.	Sensitive to feature drift under variable conditions; kernel struggles to adapt to nonlinear shifts caused by feed rate fluctuations.	[137,138]
RF	Naturally robust to field noise; feature ranking helps identify sensitive features, reducing domain knowledge reliance.	Cannot actively adapt to time-varying conditions; lacks extrapolation ability under multi-factor coupling (feed rate, moisture, etc.).	[125,139]
KNN	Zero training cost, ideal for rapid prototyping; works directly with physically meaningful features.	Overlapping operating conditions blur decision boundaries; heavily dependent on feature normalization.	[141]
ANN	Models nonlinear relationships in multi-component compound faults; enables parallel multi-fault identification.	Scarce field samples cause training difficulties; no guaranteed generalization for transient conditions like feed rate shocks.	[143]
NB	Low computational cost suitable for onboard screening; probabilistic output facilitates decision-level fusion.	Strong coupling among vibration/acoustic features often violates the independence assumption.	[145]
ELM	Fast training speed supports online model updating; suitable for high-real-time diagnostic tasks.	Random weights reduce robustness to strong noise; difficulty handling non-stationary signals caused by feed transients.	[146]

4.4. Early Practices of Feature Fusion Strategies

Fault identification relying on a single sensor or feature domain has clear limitations, and multi-information fusion can significantly improve diagnostic accuracy and reliability [148,149]. For example, most individual time–frequency features of vibrating screen bolts overlap highly when distinguishing loosening from fracture, making independent accurate classification difficult [135]. This motivated early feature fusion practices, which integrate heterogeneous information from multiple sources and domains to characterize the mechanical health state more comprehensively. These strategies are classified into data-level, feature-level, and decision-level fusion according to their integration stage.

Feature-level fusion is the most commonly used strategy. Handcrafted feature vectors from multiple sensors or analysis domains are concatenated into a high-dimensional feature set, reduced via PCA or Linear Discriminant Analysis to eliminate redundancy, and then fed into a shallow classifier. For example, integrating wavelet packet energy features of vibration signals with MFCC of acoustic signals has improved detection sensitivity for early rolling bearing wear [150].

In a study on gear progressive wear monitoring, Loutas et al. [151] simultaneously acquired vibration, AE, and oil debris monitoring signals, extracted time-domain, frequency-domain, and wavelet-domain features from each channel and, after screening, integrated them into a single data matrix. PCA was then used for dimensionality reduction, followed by independent component analysis to establish correspondence between the reduced independent components and different gearbox damage modes. This study demonstrated the synergistic value of PCA and independent component analysis in reducing heterogeneous feature redundancy and separating fault sources, providing a reference for multi-source diagnosis of combine harvester transmission systems.

Multi-source feature fusion has also been achieved at the model input stage through sensitivity analysis to select highly discriminative feature subsets, improving SVM or RF classification accuracy [152,153]. These early attempts demonstrated that multi-dimensional joint features provide complementary diagnostic information and enhance robustness across operating conditions. In wind turbine gearbox fault diagnosis, Feng et al. [117] used lubricating oil and bearing temperature data from the Supervisory Control and Data Acquisition system for early fault warning, combined with condition monitoring system (CMS) vibration envelope and oil debris count for precise fault localization, establishing a closed loop from warning to diagnosis. This approach directly informs the design of multi-source fusion diagnostic architectures for combine harvesters.

Decision-level fusion integrates the independent outputs of each diagnostic channel through specific rules, with D-S evidence theory as a typical example. In combine harvester blockage diagnosis, BPNN outputs from multiple vibration measurement points were fused via the Dempster combination rule, yielding more reliable diagnosis and overcoming false positives and missed detections from single-source information [143]. Data-level fusion, which mainly averages and denoises raw waveforms from homogeneous sensors, saw relatively few applications during the traditional methods period due to high alignment requirements and computational complexity for heterogeneous signals. Overall, these early practices confirmed that the collaborative integration of features and decisions can overcome the limitations of a single information dimension, although their fusion architectures still relied on manually preset rules rather than end-to-end adaptive joint learning.

4.5. Advantages and Limitations of Traditional Methods

The studies reviewed above demonstrate that handcrafted feature engineering combined with shallow ML provides an interpretable, easy-to-implement framework for component-level fault diagnosis under specific conditions. However, when extending from single-component diagnosis to simultaneous identification of multiple fault modes at the whole-machine level, inherent limitations in data requirements, feature construction, and model generalization become apparent.

Traditional methods offer considerable practical value for component-level diagnosis with clear physical mechanisms and singular fault characteristics. By extracting features such as kurtosis and envelope spectra from vibration signals and coupling them with SVM or KNN classifiers, bearing fault types can be identified with high accuracy [154]. The explicit physical meaning of these features facilitates direct correlation with failure mechanisms, and shallow models can control overfitting through regularization under small-sample conditions. This advantage, however, is highly dependent on fine-grained manual diagnostic design—sensor placement adjacent to the fault source and feature selection driven by expert knowledge of failure mechanisms. This strong domain dependence is the first barrier to application in complex field scenarios.

First, the domain dependence and incompleteness of feature engineering. The quality of handcrafted features is entirely constrained by human experts' prior knowledge of specific fault mechanisms. In component-level diagnosis, fault feature libraries for standard components such as bearings and gears are relatively mature. However, for whole-machine-level anomaly detection in combine harvester headers and transmission systems, the complex nonlinear responses from multi-source coupled excitations often place the deterministic mapping between faults and features outside established knowledge. For example, a multi-source vibration study on a combine harvester chassis indicated that the constant modal frequency of the frame is directly related to the independent modal frequency of the threshing frame, readily inducing complex coupled resonances [79]. This system-level vibration coupling makes it extremely difficult for handcrafted features relying on single points and single domains to effectively characterize compound fault modes across multiple components. When confronting unknown or compound faults, these features have almost no ability to automatically mine potential discriminative information.

The current state of research corroborates this point. Most published diagnostic studies on combine harvesters and similar agricultural machinery remain confined to component-level faults. Rolling bearings have received the most extensive attention. Individual studies have addressed: fault feature extraction under variable-speed conditions using variational mode decomposition and COT [114]; entropy-based degradation indicators including Refined Composite Multivariate Multiscale Sample Entropy [126] and CSVDE [127]; classifier optimization via metaheuristic algorithms (e.g., dragonfly-optimized kernel ELM) [146]; acoustic-based diagnosis combining MFCC with wavelet packet energy [150]; multi-sensor comparative studies integrating vibration, AE, and Oil Debris Monitoring for gear wear assessment [151]; and Supervisory Control and Data Acquisition-based temperature monitoring integrated with CMS vibration envelope analysis for early fault warning and localization [117]. Wavelet-based feature extraction from vibration signals has been applied to gearbox diagnostics [125], while comparative evaluations of shallow classifiers such as SVM versus NB have been conducted for bearing and centrifugal pump fault identification [145], and wavelet packet energy features combined with Particle Swarm Optimization SVM have been employed for bearing fault classification [154]. In contrast, studies targeting the simultaneous identification of multiple fault modes at the whole-machine level—spanning the threshing unit, header, and transmission system—remain scarce [155]. This imbalance represents a critical gap in the existing literature.

Second, the limited capability of shallow models in expressing complex nonlinear relationships. Shallow classifiers such as SVM and RF often struggle to construct decision boundaries when facing high overlap and nonlinear separability in the high-dimensional feature space of combine harvesters. Fault-induced signal features—from header vibration or feeding device blockage, for instance—often exhibit complex manifold distributions with blurred boundaries between fault mode clusters. In the diagnosis of misalignment and looseness faults in chain transmission systems, frequency-domain features can drift significantly under varying speeds and loads, making linear or kernel-based classifiers prone to misjudgment [78]. This insufficient ability to model complex decision boundaries restricts the capacity of shallow models to capture the subtle nuances of the whole machine's state in real-world environments.

Third, poor adaptability to time-varying operating conditions. As demonstrated in Section 3.3.1, the continuously fluctuating field environment—including variations in feed rate, terrain, and crop conditions—causes significant shifts in the statistical distribution of sensor features. A traditional model trained under a single operating condition therefore suffers severe accuracy degradation when deployed under new conditions [98]. The model cannot autonomously learn from the source and compensate for the changes in signal characteristics caused by variations in operating conditions. As a result, its generalization ability and robustness in the field are difficult to guarantee. To address this, a real-time adaptive diagnosis framework based on broad learning extracts dynamic features via latent variables and, through pseudo-label incremental updates and statistical condition detection, maintains model effectiveness during performance degradation with extremely low labeling costs [156]. This offers a feasible direction for overcoming time-varying condition-induced model degradation, though its applicability to combine harvesters requires further field validation.

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In summary, traditional ML diagnostic methods offer good interpretability and implementation efficiency in component-level and steady-state scenarios. Their inherent limitations—domain dependence, limited nonlinear modeling capability, and poor adaptability to variable conditions—constrain their applicability to whole-machine, multi-fault diagnosis in complex field environments. A systematic comparison of these limitations against the capabilities of DL-based approaches is provided in Section 5.4.

5. Deep Learning and Multi-Sensor Fusion-Based Intelligent Diagnosis Frontiers

The previous chapter detailed the inherent limitations of traditional ML diagnostic methods: strong dependence on handcrafted feature engineering, limited ability to model complex nonlinear relationships, and poor adaptability to time-varying operating conditions. Consequently, they cannot independently perform whole-machine-level intelligent diagnosis of combine harvesters in real field environments. Recent advances in DL have opened new pathways to break through these bottlenecks, and DL has gradually become a mainstream research method in agriculture [157–160]. The joint deployment of multimodal sensors and the deep fusion of heterogeneous information further enable comprehensive sensing of the multi-component coupled operating state of combine harvesters. Industry-specific DL methods are becoming standard for fault diagnosis [161–163]. This chapter sequentially introduces the general paradigm of DL fault diagnosis, reviews the specific applications of deep models in vibration, acoustic, and visual signals, discusses the evolution of multi-source signal fusion strategies, and systematically compares them with traditional methods.

5.1. General Paradigm of Deep Learning Fault Diagnosis

Unlike the traditional pipeline of "signal preprocessing $\rightarrow$ handcrafted feature extraction $\rightarrow$ feature dimensionality reduction $\rightarrow$ shallow classification," deep diagnostic models form an end-to-end trainable system: raw time-domain signals serve as the network input, and through serialized nonlinear transformations across multiple hidden layers, fault features are progressively abstracted from low-level textures to high-level semantics, with the output layer directly yielding fault category or health indicator predictions. This paradigm jointly optimizes feature extraction and classification, eliminating the need to predefine sensitive frequency bands or statistical quantities based on specific fault mechanisms [164].

Among typical network structural components, convolutional layers, with their local receptive fields and weight sharing, excel at capturing local impulse patterns in vibration signals and spatial textures in time–frequency images. Pooling layers reduce dimensionality and enhance translation invariance while also suppressing noise. Recurrent layers (e.g., LSTM, GRU) and their variants, with memory and forgetting mechanisms for sequential states, naturally handle time-dependent degradation processes caused by speed fluctuations and gradual load changes. Autoencoders learn low-dimensional representations of data manifolds via reconstruction error and are particularly valuable in unsupervised pre-training and anomaly detection. Attention mechanisms can adaptively weight different channels, time steps, or sensor nodes, enabling the model to focus on the signal components with the strongest fault discriminability. These components can be combined according to task requirements into convolutional neural network (CNN), residual network (ResNet), vision transformer (ViT), or hybrid architectures to handle different forms of input.

Training strategies for deep diagnostic models also vary significantly. Supervised learning relies on complete fault category labels, and most current combine harvester fault diagnosis studies adopt this approach. When labels are scarce, unsupervised pre-training can leverage large amounts of unlabeled operating data to initialize network parameters, followed by supervised fine-tuning with few labeled samples. Transfer learning can alleviate the scarcity of fault samples in the target domain (e.g., field combine harvesters) by reusing model weights pre-trained on source–domain data (e.g., laboratory bench data or similar rotating machinery). In addition, advanced training paradigms such as meta-learning and domain adaptation [165,166] are being introduced to enhance the model's small-sample adaptability under variable operating conditions.

The choice of input data form directly influences network architecture design. In current combine harvester research, the most common forms include: (1) one-dimensional raw vibration/acoustic signals fed directly into 1D-CNN or LSTM networks; (2) two-dimensional time–frequency images, where STFT or CWT maps the signal to the time–frequency plane for feature extraction by 2D-CNN or ViT; and (3) multi-channel fusion input, where data from different sensors or modalities are concatenated along the channel dimension and fed into a multi-branch network. The following sections detail the application of these architectures to specific signal modalities in combine harvester fault diagnosis.

5.2. Application of Deep Neural Networks in Vibration, Acoustic, and Visual Signal-Based Diagnosis

5.2.1. Deep Diagnostic Models Based on Vibration Signals

As discussed in Section 4.2.1, vibration signals are the primary monitoring modality for combine harvester fault diagnosis, and DL models have been extensively applied across a range of vibration-based architectures. CNNs were among the earliest: the 1D-CNN approach demonstrated real-time structural damage detection directly from raw time-domain acceleration signals without handcrafted feature extraction [167]. In parallel, 2D-CNNs emerged by integrating CWT scalograms as inputs to simultaneously capture temporal and spectral fault features directly from the full wavelet coefficient matrix [168].

Autoencoders and their variants have shown unique advantages in whole-machine multi-component CM. Stacked denoising autoencoders (SDAE) inject random noise into the input and train the network to reconstruct noise-free signals, forcing learning of disturbance-insensitive features. An SDAE-SVM hybrid architecture using deep features from multi-component speed signals achieved 95.31% accuracy, significantly outperforming standard SVM (77.03%) and BP network (74.61%) under strong noise [169]. Similarly, the SDAE-BP model took the rotational speeds of six key components—feeding auger, tailings auger, grain auger, fan, threshing drum, and conveyor chain—as input, using a layer-wise DAE strategy with differentiated Gaussian noise centers to integrate local and global information for whole-machine state identification, achieving 99.00% accuracy [170].

The combination of ResNet and ViT represents a more recent advance. A diagnostic method integrating SVD-EDS denoising, generalized S-transform time–frequency imaging, and a ResViT model—using ResNet-34 for feature pre-extraction and an improved ViT to integrate global and local information—achieved 99.08% average accuracy for rolling bearing diagnosis under dust and varying loads, significantly outperforming pure CNN, LSTM, and the original ViT.

Gated recurrent architectures, particularly LSTM and Bidirectional LSTM, capture long-term temporal dependencies in fault evolution under complex excitations such as feed rate fluctuations, ground bumps, and strong background noise. For example, a deep feature extraction module integrating a multi-scale 1D-CNN with multi-head attention and an adaptive soft-thresholding function was combined with a Bidirectional LSTM classifier to achieve over 98% accuracy for transmission system defect identification [171].

5.2.2. Deep Diagnostic Methods Based on Acoustic Signals

Acoustic signals offer non-contact acquisition, providing a supplementary sensing channel for combine harvester fault diagnosis. Unlike traditional methods relying on handcrafted features such as MFCC, DL can directly learn high-level representations from raw acoustic waveforms or spectrograms, though strong field background noise demands higher model robustness. Cross-modal joint learning of acoustic and vibration signals has become the mainstream approach. For example, a multi-channel multi-scale spatiotemporal convolutional cross-attention fusion network converts synchronously collected vibration and acoustic signals into time–frequency images, and a dual cross-attention mechanism adaptively fuses inter-modal information, outperforming single-modality approaches in bearing fault diagnosis [172]. Nevertheless, DL studies targeting whole combine harvesters using only acoustic signals remain rare.

5.2.3. Diagnostic Exploration Based on Visual Signals

Visual signals—visible light images and infrared thermal images—are still at an early exploratory stage for combine harvester fault diagnosis. Visible light images can intuitively reflect faults with obvious appearance characteristics such as header blockage, belt slippage, and material accumulation, while infrared thermal imaging is sensitive to thermophysical features such as abnormal temperature rise and local overheating before bearing failure. Some studies have employed USB cameras for surveillance video of working areas and CNNs or object detection models for abnormal state identification [105]. Infrared thermal images have also been used for bearing fault classification, with CNNs learning temperature distribution patterns corresponding to fault modes in an end-to-end manner [106–108].

However, field conditions pose significant challenges: high dust reduces visibility, mud occludes targets, lighting varies drastically, and early internal faults such as bearing micro-pitting cannot be captured externally. These factors constrain the reliability of visual diagnosis as an independent modality.

Beyond environmental challenges, visual diagnosis also faces fine-grained discrimination difficulty—fault types often exhibit high inter-class similarity and intra-class variance under different conditions, a problem well-recognized in crop disease diagnosis where multi-granularity feature aggregation and self-attention mechanisms have been applied. These approaches provide useful references for combine harvester visual fault diagnosis.

Although visible light images can intuitively reveal faults with obvious visual manifestations such as header blockage and material accumulation, mature vision-based object detection in agriculture still focuses mainly on agronomic processes—crop monitoring, weed identification, and pest and disease diagnosis [173]. These efforts have accumulated practical experience with field visual challenges, providing a methodological basis for transferring object detection frameworks to abnormal state identification on combine harvesters. However, early internal faults such as bearing micro-pitting and gear micro-cracks are difficult to capture externally, restricting independent pure visual diagnosis. Currently, visual signals serve primarily as auxiliary verification for vibration- or acoustic-based diagnosis.

5.3. Evolution of Multi-Source Heterogeneous Signal Fusion Strategies

The operational state information of a combine harvester's core components—header, threshing drum, cleaning sieve, transmission system—is distributed across heterogeneous signals such as vibration, rotational speed, acoustics, temperature, and images. Multi-sensor information fusion has also benefited field environmental sensing [174]—for example, estimating soil surface roughness from ultrasonic echoes [175]—yet most diagnostic studies still rely on single-sensor data, limiting information diversity and accuracy. Existing multi-source fusion methods generally apply basic feature concatenation or statistical weighting, failing to fully exploit the complementary features embedded in heterogeneous data sources [176].

A single sensor modality captures only limited information dimensions and cannot comprehensively reflect the system-level, multi-component coupled fault state. Multi-sensor fault diagnosis is generally more reliable than single-sensor methods [177]—an understanding already established during the traditional method stage (Section 4.4)—and DL has further enhanced the automation and adaptability of multi-source fusion. Current fusion strategies are divided into three levels: data-level, feature-level, and decision-level.

Data-level fusion concatenates or stacks raw signals from multiple homogeneous or heterogeneous sensors into a multi-dimensional input matrix after synchronization, which a deep network then processes. For example, raw waveforms from AE and vibration sensors fed into a one-dimensional CNN (DE-1D-CNN) achieved strong results in extremely low-speed bearing fault diagnosis [178]. The principal advantage of data-level fusion is maximal preservation of original signal information, avoiding information loss from preprocessing; its drawbacks include stringent cross-modal synchronization requirements and, when sensor heterogeneity is pronounced—as with vibration acceleration versus temperature—differences in physical dimensions and dynamic ranges that complicate network training.

Feature-level fusion dominates current DL applications and offers a key advantage over traditional methods. Where traditional approaches manually extract time-domain, frequency-domain, and time–frequency-domain features from each modality for concatenation and linear dimensionality reduction, deep networks achieve end-to-end adaptive fusion through multi-branch architectures: each modality passes through independent convolutional or recurrent sub-networks, and the resulting deep features undergo concatenation, weighted summation, or cross-attention interaction in a common latent space before final classification.

CWT offers advantages for analyzing the non-stationary vibration signals encountered in combine harvester field operations. Unlike the fixed-resolution spectrograms from short-time Fourier transform (STFT), CWT provides variable time–frequency resolution through scalable wavelet basis functions, capturing transient high-frequency fault impulses—such as those from bearing pitting or gear tooth breakage—alongside the slowly varying low-frequency components that arise from engine speed fluctuations and feed rate variations. This multiresolution capability exceeds what STFT can achieve in a single representation. In the study by Li et al. [172], vibration and acoustic signals undergo CWT to produce time–frequency images; parallel ResNet branches then extract visual features, followed by a multi-head spatiotemporal attention module and multi-scale temporal convolution for cross-modal enhancement and fusion. Separately, a parallel GRU architecture with multi-head attention models the spatial dimension (multi-sensor channels) and temporal dimension (sequence evolution) independently, enabling flexible information scheduling among sensors with strong stability under small-sample and imbalanced data conditions [179].

Decision-level fusion integrates soft probability outputs or hard labels from independent diagnostic channels—for example, separate deep models for vibration, acoustics, and temperature—into a comprehensive decision via weighted voting, Bayesian inference, or D-S evidence theory. An existing combine harvester remote monitoring system fused speed indicators, component slip rates, and adaptive threshold judgments to identify operating conditions, achieving 97.46% accuracy [180]. The key advantage of decision-level fusion is full channel decoupling: failure of a single sensor does not paralyze the entire system. However, information interaction among channels occurs only at the final decision stage, precluding the fine-grained representation-level collaboration that feature-level fusion achieves.

Tables 6 and 7 systematically compare the three fusion strategies across fusion stage, end-to-end property, synchronization requirements, information retention, and applicable scenarios in combine harvester fault diagnosis, providing a reference framework for fusion architecture selection.

Table 6. Technical characteristics of multi-source fusion strategies.

Fusion Level	Fusion Timing	End-to-End	Synchronization Requirement	Information Loss	Ref.
Data-level	Pre-input concatenation	Yes	Extremely high	Minimal	[178]
Feature-level	Intermediate layer fusion	Yes	Medium	Medium	[172]
Decision-level	Post-output integration	No (channels independent)	Low	Independent per channel	[143,180]

Table 7. Architectures and applicable scenarios of multi-source fusion strategies in combine harvesters.

Fusion Level	Typical Architecture	Applicable Scenarios in Combine Harvesters	Ref.
Data-level	DE-1D-CNN	Homogeneous multi-sensor (e.g., multiple accelerometers)	[178]
Feature-level	Multi-branch CNN + cross-attention	Vibration–acoustic multimodal parallel	[172]
Decision-level	Weighted voting/D-S evidence	Heterogeneous sensor high-reliability redundancy system	[143,180]

5.4. Systematic Comparison with Traditional Machine Learning Methods

This section provides a systematic comparison between the traditional ML paradigm (Section 4.5) and the DL-based approaches surveyed in this chapter. Table 8 summarizes the differences across five dimensions—feature learning capability, generalization under variable conditions, diagnostic coverage, computational cost, and interpretability—each discussed in the following subsections.

Table 8. Strategy comparison table.

Dimension	Traditional Machine Learning	Deep Learning
Feature learning	Handcrafted design, reliant on domain knowledge	Automatic hierarchical feature learning
Generalization under variable conditions	Poor; requires separate calibration for each condition	Can be enhanced via transfer learning and domain adversarial training
Diagnostic coverage	Mostly component-level single faults	Capable of extending to whole-machine-level multi-component faults
Computational cost	Low; suitable for embedded deployment	High; requires edge acceleration or cloud collaboration
Interpretability	Strong; features have explicit physical meaning	Weak; requires post hoc explanation tools or physics-informed integration
Data efficiency	High; performs well with small labeled datasets	Low; typically requires large labeled datasets for end-to-end training

5.4.1. Feature Learning Capability

As analyzed in Section 4.5, the quality of handcrafted features is fundamentally constrained by the completeness of prior domain knowledge, and traditional feature libraries cannot automatically discover discriminative information for novel or compound faults. DL methods address this limitation by learning hierarchical fault representations directly from raw data. For example, Liu et al. [181] developed an autoencoder network that achieves unknown anomaly detection without fault samples, using only frequency-domain features and reconstruction error; integrating convolutional and LSTM structures further enhanced autonomous spatiotemporal feature extraction. Sun et al. [182] proposed an open-set classification method based on time–frequency fusion and latent representation prompts, adaptively constructing complementary time–frequency joint representations and guiding the clustering of similar latent representations to automatically identify unknown faults without requiring domain experts to predefine fault modes. This end-to-end representation learning capability reduces reliance on domain expert knowledge and enables automatic discovery of unknown fault modes.

However, the advantages of DL are context-dependent. When fault modes are well-defined and their physical signatures are well understood—bearing characteristic frequencies, gear mesh harmonics, bolt loosening patterns—handcrafted features with optimized SVM or RF classifiers can match or exceed DL accuracy. A one-versus-one SVM using multi-point vibration features achieved 96.9–99.7% accuracy for bolt state identification on a combine harvester conveyor trough [138], and an improved RF algorithm reached 97.9% for silage harvester blockage diagnosis [139]—on par with the 98–99% reported for DL-based approaches [170,171]. Under small-sample conditions, the norm in field fault diagnosis, shallow models with appropriate regularization often generalize more robustly than overparameterized deep networks prone to overfitting. The principal contribution of DL therefore lies not in marginal accuracy gains on well-characterized component faults, but in extending diagnostic capability to scenarios where manual feature engineering is infeasible—compound faults under multi-source coupled excitation, end-to-end learning from heterogeneous multi-sensor streams, and cross-condition generalization under continuously time-varying operations. Traditional ML and DL are thus complementary rather than competing paradigms, a distinction essential for guiding practical method selection.

Beyond the traditional-versus-DL debate lies a further methodological concern: published diagnostic accuracy figures almost universally lack uncertainty quantification. With few exceptions, the studies reviewed in Sections 4 and 5 report point-estimate accuracies—often to two or three decimal places—without confidence intervals, standard deviations from repeated trials, or per-class metrics such as precision, recall, and F1-score. This has two consequences. First, it renders performance comparisons across studies unreliable: a reported 97.5% versus 96.8% may suggest a genuine gap, but without error bars one cannot determine whether the difference is statistically significant or merely reflects variation in train–test splits, sensor placement, or specific fault instances. Second, omitting per-class metrics is particularly problematic in the combine harvester context, where severe class imbalance allows a model to achieve high overall accuracy by correctly classifying abundant healthy instances while systematically misclassifying rare but critical fault modes. Reporting per-class precision, recall, and F1-score would expose such behavior; aggregate accuracy alone conceals it. Future studies should, as a minimum standard, report results with ± one standard deviation over at least five independent trials with different random seeds, and provide confusion matrices or per-class metrics for all fault categories. Bootstrap confidence intervals should also be reported where computational resources permit, following established practices in the broader ML reproducibility literature.

5.4.2. Generalization Ability Under Variable Operating Conditions

As discussed in Section 4.5, continuously varying field conditions cause significant drift in the statistical distribution of handcrafted features, limiting cross-condition generalization of traditional models. DL offers training strategies to mitigate this challenge. Domain adaptation and transfer learning, for instance, reduce the distribution discrepancy of deep features between source and target domains, encouraging the model to learn fault-discriminative features less sensitive to specific operating conditions. These techniques do not yet guarantee a solution for the full spectrum of time-varying field conditions combine harvesters encounter; robust generalization under continuous multi-factor coupling remains an active research frontier. A multi-stage transfer learning framework progressively adapted a CNN pre-trained on laboratory or public datasets through three stages—freezing general feature layers, adjusting for specific vibration representations, and task-focused fine-tuning—enabling effective reuse under different rotational speeds while preserving general low-level representations and optimizing high-level speed-related fault features [183]. To address extremely scarce fault samples in combine harvester gearboxes under variable conditions, a meta-transfer learning-driven few-shot diagnosis method combines meta-learning for rapid cross-task adaptation, a conditional domain adversarial network for cross-domain discriminative features, and multi-step loss optimization to resolve gradient instability, preliminarily verifying effective fault diagnosis under variable-condition, few-shot scenarios [184].

Deep models can also alleviate bias from imbalanced fault categories through data augmentation (random noise injection, time warping, masking), resampling, and cost-sensitive loss functions, offering advantages for scenarios with scarce, unevenly distributed fault samples—though their practical deployment still faces the challenges discussed in the following chapter.

5.4.3. Diagnostic Level and Coverage

The literature clearly shows that traditional methods succeed most on component-level faults—particularly standard parts such as rolling bearings and gearboxes with well-defined characteristic frequencies and mature diagnostic knowledge bases (Section 4.5). DL, in contrast, extends toward whole-machine-level, multi-component synchronous diagnosis. Architectures such as SDAE-SVM and SDAE-BP simultaneously take the rotational speed signals of six core working components—feeding auger, tailings auger, grain auger, fan, threshing drum, and conveyor chain—as input, enabling collaborative monitoring and fault prediction across multiple components at the whole-machine level [170]. Whole-machine-oriented multi-sensor fusion and multi-task learning architectures can potentially achieve synchronous identification of fault-prone parts such as the threshing unit, header system, and transmission system [180,185]. This broader diagnostic coverage extends the potential of deep models for full-lifecycle engineering applications. For well-characterized component-level faults, however, traditional methods and DL achieve comparable accuracy, yet traditional methods do so with fewer training samples and lower computational cost—making them the more practical choice under the data-scarce conditions typical of field diagnosis. The principal contribution of DL lies instead in extending diagnostic capability to complex, multi-fault, whole-machine scenarios where manual feature engineering is infeasible.

5.4.4. Computational Cost and Deployment Feasibility

Computational cost remains a primary bottleneck for deploying deep models in the field. Traditional shallow models (SVM, RF, KNN) offer fast training, few parameters, and efficient execution on low-power embedded microcontrollers. Deep networks, especially large Transformer-based architectures, rely on GPU acceleration, and their memory footprint and power consumption challenge edge computing platforms in mobile scenarios. Recent years have seen rapid development of compression techniques: knowledge distillation trains a lightweight student network to inherit the teacher's diagnostic capability; network pruning and quantization accelerate inference by removing redundant connections or reducing numerical precision. Cloud–edge collaborative architectures provide a practical system-level compromise. In aircraft fuel pump monitoring, a three-tier architecture performs multi-type signal acquisition at the sensor layer, real-time anomaly detection at the edge layer, and computationally intensive fault classification in the cloud [186]. Complementarily, lightweight ML models on embedded hardware rank data by novelty at the source, using prediction error and confidence quantification to transmit only information-rich data and reduce communication bandwidth by orders of magnitude in gas turbine monitoring [187]. Nevertheless, running highly complex real-time diagnostic models stably under the harsh power supply, heat dissipation, and network conditions of agricultural machinery remains an open practical challenge.

5.4.5. Interpretability

A key advantage of traditional methods is the explicit physical interpretability of handcrafted features: an increase in kurtosis directly indicates impulse-type faults, an amplitude rise at specific bearing characteristic frequency pinpoints the defect location, and abnormal temperature signals poor lubrication or overload friction. These indicators maintain clear causal chains with failure mechanisms, making them intuitive for operators to understand and trust.

In contrast, the black-box nature of deep neural networks obscures the decision-making process. Which input patterns lead the model to decide "drum blockage is imminent" or "transmission chain wear is intensifying"? Without additional tools, the answers remain hidden among millions of weights. For safety-critical agricultural machinery, this opacity can directly undermine operator trust and adoption of automated warnings.

Post hoc interpretability techniques have seen increasing adoption in rotating machinery fault diagnosis. Gradient-weighted Class Activation Mapping (Grad-CAM) has been integrated into multi-scale CNN frameworks with vibration image encoding to visualize the time–frequency features driving diagnostic decisions [188], applied to explain 1D-CNN classifications on synthetic rotor fault data [189], and comparatively evaluated alongside Layer-wise Relevance Propagation (LRP) and a modified Local Interpretable Model-agnostic Explanations (LIME) algorithm under variable-speed conditions [190]. Integrated Gradients (IG) with SmoothGrad (SG) have been employed to guide data preprocessing by selecting informative frequency ranges for CWT input to CNN [191]. SHapley Additive exPlanations (SHAP)-based recursive feature elimination (RFE) has enabled transparent feature selection in SVM classifiers for bearing fault diagnosis, achieving high accuracy and model-level interpretability without deep network opacity [192].

A further step toward intrinsic interpretability integrates physical knowledge directly into DL architectures. Physics-informed neural networks for fault diagnosis embed governing equations—bearing characteristic frequency relationships, gear mesh dynamics, rotor vibration models—into the loss function or network architecture, constraining learned representations to remain consistent with known physical laws. For rotating machinery, two complementary paradigms have demonstrated success. The first embeds physical knowledge into the network structure: a physics-informed feature weighting method for bearing diagnostics assigns higher weights to features near bearing fault characteristic frequencies in the order spectrum, guiding the network toward physically meaningful signatures and producing more interpretable outputs than purely data-driven CNN [193]. The second embeds physical knowledge into the loss function and encoding layers: a physics-informed attention LSTM framework incorporating the single-degree-of-freedom dynamic equation of rolling bearings into an attention-based LSTM encoder constructed a dual-knowledge fusion model, achieving over 99% diagnostic accuracy under small-sample conditions while endowing the learned representations with physical significance [194]. These implementations demonstrate that physics-informed architectures can provide intrinsic interpretability—model representations anchored to physically meaningful quantities—without sacrificing DL's representational power. However, physics-informed diagnostic models for the multi-component coupled dynamics of combine harvesters remain an open research frontier; the successful demonstrations above come primarily from single-component rotating machinery and have yet to be systematically extended to the whole-machine, multi-fault scenarios characteristic of field harvesting operations.

5.5. Chapter Summary

This chapter has reviewed the progress of DL in combine harvester fault diagnosis, progressing from general paradigms to specific applications, from single-modality perception to multi-source fusion, and concluding with a systematic comparison with traditional methods.

The general technical framework of DL fault diagnosis replaces the traditional separated process with end-to-end joint optimization. Through the flexible combination of convolution, recurrence, autoencoders, and attention mechanisms, hierarchical representations are automatically learned from low-level signal textures to high-level fault semantics. The main training strategies span supervised learning, unsupervised pre-training, transfer learning, and meta-learning, with input forms including one-dimensional waveforms, two-dimensional time–frequency images, and multi-channel fusion.

Among the three signal modalities reviewed, vibration diagnosis has the richest signal information and most mature technical foundation, with architectures such as CNN, SDAE, ResViT, and LSTM validated on key combine harvester components including bearings, gearboxes, and threshing drums. Acoustic diagnosis, enabling non-contact acquisition, is advancing through vibration–acoustic cross-modal fusion. Visual diagnosis remains at an exploratory stage, serving mainly as an auxiliary means for detecting faults with obvious appearance characteristics; its field reliability requires further improvement.

At the multi-source sensor fusion level, DL has enabled a shift from data-level concatenation to adaptive feature-level fusion, where multi-branch networks with attention mechanisms learn optimal fusion weights and modality interactions end-to-end. Decision-level fusion meanwhile provides the basis for highly reliable distributed diagnostic architectures. The three strategies each have distinct applicable boundaries, jointly constituting a multi-level state perception system.

Finally, a systematic five-dimension comparison with the traditional ML methods of Section 4—feature learning capability, generalization under variable conditions, diagnostic coverage, computational cost, and interpretability—defines the relative advantages and complementary nature of the two paradigms. Traditional methods retain practical value under stable conditions with well-defined fault modes, scarce data, and high interpretability requirements. In complex scenarios characterized by multiple coexisting faults, severe time-varying conditions, and multi-source heterogeneous data, DL offers irreplaceable advantages through representation learning, adaptive fusion, and cross-domain generalization. Physics-informed deep diagnosis, whole-machine-level multi-task collaborative perception, lightweight edge deployment, and trustworthy interpretable diagnosis will be key directions for advancing this field from theory to reliable field application.

6. Challenges for Real-Time Fault Diagnosis

Although DL and multi-sensor fusion have significantly enhanced diagnostic intelligence, bridging the gap from laboratory validation to real-time field deployment remains a substantial engineering challenge. The particularity of combine harvester operating conditions, the evolution of power architectures, and the shift toward unmanned operation confront real-time diagnostic systems with increasingly complex bottlenecks.

6.1. Separation of Weak Fault Features Under Strong Background Noise

Combine harvester fault diagnosis shares fundamental challenges with CM in adjacent domains—wind turbine drivetrains, construction and mining equipment, and off-road heavy vehicles. These domains all involve rotating machinery under non-stationary speed and load, where broadband noise masks fault signatures, fault samples are scarce and imbalanced, and operating environments are harsh and uncontrolled [104,195,196]. Wind turbine CM, particularly well-studied, has identified challenges—data scarcity, low cross-condition generalization, insufficient explainability—that closely parallel those discussed below for combine harvesters [197]. The non-stationary nature of field operation is a shared cross-domain concern: vibration signals under continuously variable speed and load violate the stationarity assumptions of conventional spectral analysis, and traditional diagnostic techniques designed for steady-state operation do not transfer well to nonlinear, non-stationary processes [198], motivating the development of advanced time–frequency methods and transfer learning strategies directly relevant to combine harvester diagnostics [199]. Combine harvesters, however, face additional specificities—extreme non-stationarity from continuous feed rate and terrain fluctuations, multi-crop variability, seasonal duty cycles with long idle periods, and the paramount economic sensitivity of harvest timeliness—that collectively define a more complex diagnostic problem than those in manufacturing or power generation, and motivate the detailed examination of individual challenges in the following subsections.

The dust-laden airflow, mechanical vibrations, and EMI generated during field operations constitute broadband, high-energy background noise that readily submerges the vibration or acoustic signatures of early-stage weak faults such as bearing pitting and gear micro-cracks, severely degrading the SNR at their characteristic frequencies. Existing denoising algorithms mostly rely on the stationarity assumption, whereas the non-stationary noise from drastic fluctuations in harvester operating conditions challenges adaptive filtering. Furthermore, the transient response of the threshing drum under feed rate shocks and fault impulse features often occupy the same analysis scale, with no effective criteria to separate "damaging impulses" from "process impulses" within mode mixing.

Beyond signal-level interference, field conditions impose direct physical challenges on mechanical components. In high-moisture clay-loam soils, severe soil adhesion on tillage and harvesting components reduces working efficiency and increases energy consumption—a problem that has motivated biomimetic surface designs modeled on soil-burrowing animals such as the badger [200].

6.2. Data Distribution Shift and Model Generalization Under Multi-Condition Coupling

As discussed in Sections 3.3.1 and 4.5, the time-varying field conditions of combine harvesters cause significant distributional shifts in monitoring data, degrading the cross-condition performance of both traditional and DL-based diagnostic models. A more fundamental challenge, however, is that field operating conditions exhibit continuous multi-factor coupling rather than discrete source–target domain switching. Achieving adaptive model generalization to continuously time-varying conditions—without large volumes of fully condition-labeled data—therefore remains a largely unsolved challenge.

6.3. Data Hunger and Extreme Imbalance of Abnormal Samples

Reliable DL models typically require massive fault samples, yet long periods of normal operation are the norm on modern high-reliability combine harvesters. Real physical fault data—especially full-lifecycle data capturing natural degradation to failure—are extremely scarce and costly to acquire, leading to typical "zero-shot" or "few-shot" learning dilemmas. Moreover, fault simulation experiments often obtain samples by artificially implanting damage, and the fault characteristics generated by such "accelerated failure" differ in distribution from those of natural gradual wear in the field. Models trained on artificial data may therefore exhibit high false alarm rates when deployed. Addressing deficiencies in both the quantity and quality of fault samples is key to transitioning from data-driven approaches to actual field deployment.

Promising steps toward overcoming this data bottleneck have been taken for combine harvester gearboxes. A recent meta-transfer learning method combining multi-step loss optimization and a conditional domain adversarial network demonstrated effective cross-condition generalization for gearbox fault diagnosis with few-shot data, simultaneously addressing domain shift and sample scarcity [184].

Several methodological strategies address class imbalance at the algorithmic level. Data-level techniques include oversampling the minority class through synthetic sample generation, successfully applied to bearing fault diagnosis under imbalanced data [201], and undersampling of abundant normal-condition data, either randomly or through informed selection, to balance the training distribution. At the algorithm level, cost-sensitive learning [202] assigns higher misclassification penalties to the minority class, forcing the classifier to attend to fault samples even when vastly outnumbered. In the DL context, specialized loss functions such as focal loss [203] down-weight well-classified majority-class examples, focusing optimization on challenging minority-class instances. These strategies are not mutually exclusive—combining synthetic oversampling with cost-sensitive training, for instance, can improve diagnostic performance under extreme imbalance. Despite demonstrated effectiveness in related domains, the systematic application and comparative evaluation of these strategies specifically for combine harvester fault diagnosis remains an open research gap and a necessary direction for advancing field-deployable diagnostic systems.

More fundamentally, the field lacks publicly available benchmark datasets and standardized evaluation protocols for combine harvester fault diagnosis. The studies reviewed in Sections 4 and 5 used proprietary datasets from different harvester models, operating conditions, sensor configurations, and fault severity levels, rendering reported accuracies incomparable—97% on one dataset does not imply superiority over 95% on another when the underlying classification task difficulty is unknown. The contrast with neighboring fields is instructive. In rolling-element bearing diagnostics, open benchmark datasets have decisively accelerated methodological progress: the Case Western Reserve University (CWRU) bearing dataset became a de facto standard, used in at least 41 papers published in Mechanical Systems and Signal Processing alone between 2004 and early 2015 [204]; the Paderborn University (PU) bearing dataset extended this paradigm to motor current signal-based diagnosis, showing that controlled fault generation and systematic labeling enable reproducible evaluation across sensing modalities [205]. A task-oriented characterization of widely used bearing benchmarks further revealed that dataset properties—fault generation mechanisms, temporal structure, labeling granularity—directly determine which diagnostic tasks they can validly support, underscoring the need for task-oriented benchmark design [206]. Standardized evaluation frameworks for domain adaptation in fault diagnosis have since been proposed, with parametric partitioning schemes and controlled protocols that isolate individual domain shift factors such as operating condition and fault severity [207], and benchmark studies for domain generalization have demonstrated the value of open-source datasets and reproducible code frameworks for rigorous cross-domain evaluation [208].

No comparable infrastructure exists for combine harvesters. Establishing such benchmarks would require multi-institutional collaboration to acquire instrumented field data across representative harvester models, fault types, crop varieties, and harvesting environments—a non-trivial undertaking whose payoff in methodological rigor and accelerated research progress would be substantial. Until such benchmarks emerge, adopting minimum reporting standards—confusion matrices, per-class metrics, and cross-condition evaluation results, as advocated in Section 5.4.1—would improve the comparability of results across existing proprietary-dataset studies. As a minimum reporting standard for the field, we propose that future diagnostic studies on combine harvesters report: (1) confusion matrices for all fault categories, including the healthy/normal class; (2) per-class precision, recall, and F1-score; (3) mean and standard deviation of accuracy over at least five-fold cross-validation with different random seeds; and (4) metadata on operating conditions—crop type and moisture content, terrain slope, harvester model and engine speed, sensor types and installation positions—under which data were acquired. These requirements mirror reporting standards adopted in related fields such as rotating machinery diagnostics, where benchmark datasets with controlled fault generation and systematic labeling have enabled reproducible evaluation across different sensing modalities. Their adoption in combine harvester fault diagnosis would substantially improve the comparability and reproducibility of published results, even in the absence of shared benchmark datasets.

6.4. Conflict Between Limited Onboard Computing Power and Real-Time Requirements

Computationally intensive DL models—deep Transformers and multimodal fusion architectures—conflict with the reality that combine harvesters cannot accommodate expensive, high-power industrial computers. The hot, high-vibration field environment strictly limits the computing power, memory, and thermal stability of edge computing hardware such as GPU embedded modules.

Real-time diagnosis demands not only fast single inference but also sustained computation without thermal throttling under continuous high load. A structural tension therefore exists between high-precision large models and low-latency real-time inference. Bridging this gap requires structurally lightweight, hardware-friendly efficient inference networks and cloud–edge collaborative elastic computing frameworks.

Beyond general computational efficiency, safety-critical real-time fault diagnosis imposes specific constraints on inference latency, jitter, and determinism. Inference latency—from sensor acquisition to diagnostic output—determines how quickly a developing fault can be detected and acted upon. For rapidly propagating faults such as bearing seizure or belt slippage under high load, latency on the order of seconds may be acceptable; for impending threshing unit blockage, where feed rate can surge within milliseconds, sub-second latency is essential to enable preventive action before material accumulation reaches a critical level. Lightweight DL models on edge platforms have demonstrated sub-second inference for rotating machinery fault diagnosis: an efficient CNN achieved 0.31 s per sample on an edge device while maintaining high accuracy [209], and a lightweight FT–CNN–Transformer on a Raspberry Pi achieved significantly faster inference than previous 2D image-based approaches by directly processing one-dimensional time-domain signals, showing that careful architectural design can reconcile accuracy with stringent latency demands [210]. Jitter—inference latency variability across diagnostic cycles—is equally important: high jitter introduces timing uncertainty, potentially causing missed intervention windows or false alarms from timing artifacts. Determinism—the guarantee that inference completes within a bounded time under all conditions—is a prerequisite for integrating diagnostic outputs into automated control loops, since non-deterministic delays could cause safety-critical actuation such as emergency power reduction or header disengagement to occur too late. These timing requirements constitute functional safety constraints: standards such as ISO 25119 [211] specify acceptable failure rates and response times for safety-related control systems, and diagnostic modules feeding into such systems must meet commensurate temporal specifications. Addressing these constraints demands co-design of diagnostic algorithms and execution hardware—the algorithm's worst-case execution time must be bounded, and the hardware must provide sufficient computational margin to absorb transient load spikes without violating latency bounds. This co-design paradigm departs fundamentally from the accuracy-centric optimization prevalent in current research and is a necessary step toward field-deployable, safety-qualified diagnostic systems.

6.5. Trust and False Alarm Problems Caused by Lack of Interpretability

The black-box nature of DL models means that even high-confidence fault warnings come with opaque decision logic, breeding operator distrust. Random transient interference can produce isolated false alarms that, if they frequently trigger shutdown inspections, exacerbate timeliness loss. Currently, post hoc interpretability methods often generate saliency maps (heatmaps) that appear scattered and blurred due to physically meaningless noise interference. Developing physics-constrained neural network architectures jointly trained with data and domain knowledge is essential to achieve transparent, reliable decision logic.

Beyond the technical dimensions of interpretability, the human side of fault diagnosis has received little attention in the combine harvester literature. Operator trust is not a simple function of accuracy—it reflects prior experience with false alarms, the perceived transparency of decision logic, and the alignment between machine recommendations and the operator's own sensory observations. In field environments where experienced operators have long relied on auditory, tactile, and visual cues, a diagnostic system that cannot explain its reasoning in terms that resonate with that experiential knowledge risks being ignored regardless of its statistical performance. Alarm fatigue—progressive desensitization to frequent warnings—poses a related challenge: even a modest false alarm rate over hundreds of operating hours can condition operators to disregard all alerts, including genuine early warnings. The design of the human–machine interface—how diagnostic information is prioritized, formatted, and presented to operators with varying technical training—directly mediates these risks, yet human-factors evaluation of diagnostic interfaces for agricultural machinery remains largely unexplored. As combine harvesters transition toward higher levels of autonomy, the human role shifts from direct operator to supervisory controller, and the interaction design problem becomes one of maintaining appropriate trust and situation awareness rather than simply conveying fault codes. Design recommendations for diagnostic HMIs in agricultural machinery include tiered alert displays that distinguish critical safety warnings from advisory notifications, confidence-level indicators that convey diagnostic uncertainty to operators, and multimodal alert delivery—visual, auditory, and haptic—to accommodate the high-noise cabin environments typical of harvester operation. While human-factors standards for diagnostic interfaces exist in adjacent domains—such as ISO 9241 for ergonomics of human–system interaction [212] and ISO 11064 for control center design [213]—agricultural machinery currently lacks equivalent guidelines tailored specifically to fault diagnostic displays, and human-factors evaluation of diagnostic interfaces for harvesters remains an open research area. Systematic investigation of these human-factors dimensions is an essential complement to the algorithmic advances surveyed in this review.

6.6. New Diagnostic Complexity Introduced by Electrified Power Architectures

The power architecture of combine harvesters is gradually evolving toward hybrid electric and fully electric drive for constant engine speed operation, braking energy recovery, and reduced fuel consumption [214]. Battery electric drive systems have also been validated in other agricultural machinery such as small orchard tractors [215]. However, high-voltage battery packs, drive motors, inverters, and DC-DC converters significantly expand the fault mode space. Electrical faults—inter-turn short circuits and demagnetization of permanent magnet synchronous motors, thermal cycling fatigue of power modules, aging of DC-link capacitors—produce characteristic signals (current ripple, partial discharge, hot spots) that differ from traditional mechanical vibrations, compelling diagnostic systems to integrate electrical monitoring channels. More critically, the high-intensity EMI generated by high-frequency switching of high-power inverters couples into vibration and acoustic sensor circuits through conducted and radiated paths, further degrading the already weak SNR of mechanical fault signals. Existing shielding and filtering measures offer limited effectiveness against such broadband electromagnetic aggression. Integrated electro-mechanical diagnosis and electromagnetic compatibility (EMC) co-design therefore constitutes a new and necessary challenge for hybrid harvester diagnosis.

Mitigating these effects requires a layered EMC strategy spanning sensor selection, signal conditioning, and algorithmic robustness. At the sensor and cabling level, differential-output accelerometers and microphones with balanced line drivers offer substantially greater common-mode noise rejection than single-ended alternatives; in extreme cases, fiber-optic acoustic or strain sensors provide galvanic isolation that eliminates conducted interference paths entirely. At the signal conditioning level, anti-aliasing filters with cutoff frequencies tuned to the diagnostic bandwidth of interest—rather than the full Nyquist bandwidth—suppress high-frequency EMI before digitization. At the algorithmic level, diagnostic models can be explicitly trained or fine-tuned on data acquired under representative electromagnetic conditions, including during maximum-power inverter operation, to learn interference-robust feature representations. The automotive industry has developed standardized EMC test protocols—ISO 11452 [216] for component-level radiated immunity and CISPR 25 for emission limits in vehicles—that could be adapted to agricultural machinery to establish minimum electromagnetic immunity requirements for diagnostic sensor systems. Systematic investigation of EMI effects on diagnostic signal integrity and the development of agricultural-specific EMC design guidelines for onboard sensing systems are necessary steps toward robust diagnosis on electrified harvesters, yet remain absent from the current literature.

The distinction between retrofit and new-design scenarios is particularly relevant for EMI management. New harvester designs can integrate shielding, filtering, and harness layout optimization at the manufacturing stage, whereas retrofitting diagnostic systems onto existing machines must contend with pre-existing cable routing and limited access for EMI countermeasures. Beyond EMI, electrified powertrains introduce diagnostic challenges from novel fault modes—including power electronic device degradation, motor winding insulation breakdown, and battery state-of-health deterioration [217,218]—that produce electrical signature patterns fundamentally different from the vibration-based fault features discussed in Sections 4 and 5. These fault modes demand diagnostic approaches distinct from the vibration-based methods that dominate the existing combine harvester literature, and their gradual degradation trajectories suggest that future diagnostic frameworks must incorporate life-cycle monitoring capabilities beyond traditional fault classification. The harsh agricultural environment—extreme temperature variations, high humidity, dust, and persistent broadband vibration—further compounds these challenges through multistress coupling effects on power converters and motor drive systems [217], representing a necessary direction for future research as electrification progresses.

6.7. Special Requirements for Diagnostic System Autonomy in Unmanned Operations

Deploying unmanned combine harvesters eliminates the driver's role as a multimodal perception and decision-making center. Perceptual dimensions once provided by the driver—detecting abnormal noise, burnt smell, and abnormal vibration—must now be fully inherited by microphone arrays, electronic noses, thermal imagers, and multi-axis vibration sensors. The diagnostic system thus shifts from assisting the operator to replacing the operator: its output becomes not a suggestion correctable by a human but a safety command directly triggering power reduction, emergency shutdown, or remote intervention.

This shift imposes near-absolute demands on diagnostic reliability. A false alarm causing full machine shutdown inflicts irreparable timeliness loss, while a missed detection allows the machine to continue operating with faults until catastrophic failure occurs without human intervention.

Furthermore, in remote fields with weak or no network connectivity, the edge diagnostic unit must possess fully local autonomous decision-making capability and comply with the strict failure rate constraints that agricultural machinery functional safety standards—ISO 25119—impose on safety-related control systems. Compressing high-precision DL models into embedded systems that meet functional safety integrity levels while maintaining extremely low false alarm and missed detection rates presents a multi-objective optimization challenge.

6.8. Model Degradation and Adaptation over Operational Lifetimes

An equally critical but less explored challenge is ensuring that a deployed diagnostic model maintains its performance over the multi-year operational lifetime of a combine harvester. Two interrelated phenomena drive model degradation: concept drift and the emergence of novel fault modes.

Concept drift occurs when the statistical properties of sensor data gradually shift over time. In wind turbine CM, concept drift has been systematically defined as machine performance deviating significantly from an established baseline, often signaling incipient faults [219]. For combine harvesters, similar drift arises from multiple sources: component wear shifts the vibration signature of a healthy transmission away from its factory-calibrated baseline; seasonal variations in crop properties alter dynamic loads on structural components; changes in field terrain introduce new excitation patterns; and sensor degradation over time introduces measurement bias. A model trained on wheat-harvesting data may therefore exhibit systematically degraded performance when deployed for soybean or corn, owing to differences in crop physical characteristics and resulting machine dynamics.

The emergence of novel fault modes—failure types absent from the original training data—poses an even steeper challenge. As the open-set fault diagnosis literature has comprehensively documented, conventional diagnostic models operate under a closed-set assumption, presuming all possible fault classes are known and represented during training [220]. Over a harvester's service life, previously undocumented failure patterns may surface due to design modifications, new materials in replacement parts, or evolving operational practices. A classifier trained to distinguish healthy, bearing fault, and gear fault states cannot recognize a previously unseen seal leak or solenoid valve malfunction; it will either misclassify the novel fault as a known category or, if equipped with open-set recognition, correctly flag it as "unknown" without providing actionable diagnostic information.

Promising directions for addressing model degradation have emerged in incremental learning-enabled fault diagnosis [221]. These include periodic retraining with field data accumulated during normal operation, incremental architectures that update model parameters without full retraining from scratch, and open-set recognition frameworks that flag distributional shifts for expert review. Each approach, however, introduces its own difficulties: incremental learning risks catastrophic forgetting, where previously acquired diagnostic knowledge erodes as the model adapts to new data [220]; retraining demands ground-truth labels that are scarce in field environments, since harvesting operations are rarely interrupted for detailed failure analysis; and open-set recognition generates "unknown" alarms that, without subsequent expert annotation and model updating, contribute little to improving diagnostic coverage. For combine harvesters operating in remote fields with intermittent connectivity, any model updating strategy must also contend with bandwidth constraints for transmitting training data and the limited computational budget of onboard edge hardware.

The systematic investigation of model updating and lifelong learning strategies for agricultural machinery fault diagnosis remains a nascent research area [221], yet advancing it is essential for transitioning diagnostic systems from one-time deployment to sustained, trustworthy operation over a combine harvester's entire service life.

6.9. Functional Safety Compliance for Diagnostic Systems

Beyond achieving high diagnostic accuracy, any fault diagnosis system feeding into safety-related control functions must satisfy agricultural machinery functional safety standards. ISO 25119, "Tractors and machinery for agriculture and forestry—Safety-related parts of control systems," is the principal normative framework. The standard comprises four parts—general principles (Part 1), concept phase (Part 2), hardware development (Part 3), and software development (Part 4)—and defines Safety Integrity Levels from SIL 1 (lowest) to SIL 4 (most stringent).

For combine harvester fault diagnosis, ISO 25119 is relevant in two respects. First, when a diagnostic module directly triggers safety actions—emergency engine power reduction upon detecting imminent threshing drum seizure, or automatic header disengagement upon critical structural failure—that module becomes part of a safety-related control system and must meet the appropriate SIL. The standard requires that software-based diagnostic functions undergo rigorous verification and validation, that their failure modes and rates be systematically analyzed, and that their response times be deterministically bounded. The real-time latency and determinism requirements discussed in Section 6.4 are thus functional safety prerequisites, not merely performance preferences. Second, even a purely advisory diagnostic system—issuing alerts without automated intervention—remains subject to risk assessment and hazard analysis. A false alarm distracting the operator during a safety-critical maneuver, or a missed detection allowing a degrading component to fail catastrophically, can contribute to hazardous situations even though the diagnostic system itself is not a safety actuator.

Despite its centrality to deploying intelligent diagnostic systems on agricultural machinery, the literature surveyed in this review is almost entirely silent on functional safety. None of the studies reviewed explicitly addresses ISO 25119 compliance or conducts a formal hazard and risk analysis for their proposed diagnostic methods. This gap between the data-driven diagnostic research community and the functional safety engineering discipline represents a significant barrier to industrial adoption. Future work, particularly that targeting deployment on unmanned combine harvesters (Section 6.7), must bridge this gap by incorporating functional safety considerations from the earliest design stages: defining safety goals and corresponding SIL requirements; designing diagnostic architectures with hardware and software redundancy commensurate with the target SIL; and providing evidence that diagnostic performance metrics—false alarm rate, missed detection rate, and inference latency—satisfy the quantitative targets derived from the hazard analysis. Translating ISO 25119 into specific diagnostic system design requirements remains an unexplored research area. Key questions that future work must address include determining appropriate SIL targets for different failure severities in harvesting operations, defining diagnostic coverage requirements for each target SIL, and establishing proof-test intervals for periodic validation of diagnostic functions. These requirements collectively inform sensor redundancy, voting architectures, fail-safe design, and the rigor of verification and validation activities—an integration that, despite established parallels in automotive and industrial machinery functional safety, has yet to be addressed in the combine harvester diagnostic literature.

7. Future Outlook

Before addressing individual research directions, Figure 10 provides a panoramic overview of the challenges analyzed in Section 6 and their relationship to the future directions discussed in this section. The figure organizes challenges and directions into four thematic groups—signal and data, computation and deployment, trust and safety, and lifecycle and extension. The grouping reflects thematic affinity rather than strict one-to-one mapping. Notably, physics-informed approaches (Section 7.1) serve a dual role—enhancing signal robustness against field noise and model interpretability for operator trust—and this dual contribution is reflected in their appearance across two groups. Subsection numbers annotated in each block allow readers to locate the corresponding detailed discussion in Sections 6 and 7.

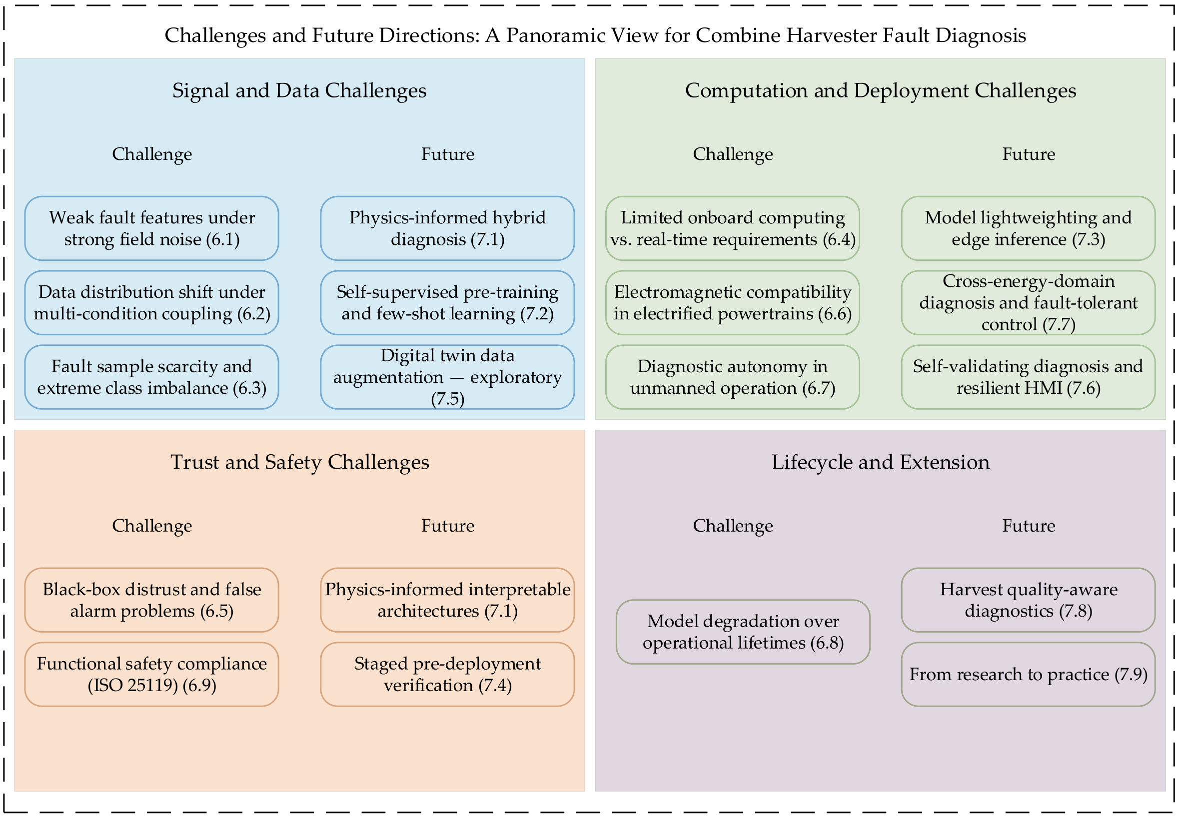

Figure 10. Panoramic overview of challenges (Section 6) and future directions (Section 7) in combine harvester fault diagnosis [211].

To overcome these challenges, advancing combine harvester fault diagnosis to practical application requires systematic exploration of physics-data fusion paradigms, autonomous diagnostic architectures, edge intelligent hardware, and support for new power systems and unmanned operations.

7.1. Hybrid-Driven Diagnosis with Embedded Physical Information

Purely data-driven approaches struggle with generalization and interpretability, while purely physical models cannot capture the full complexity of field conditions. A promising direction embeds dynamic mechanism equations and wear degradation models as physical constraints or inductive biases into neural network architectures or loss functions, constructing physics-informed ML models that reduce data dependence, enhance extrapolation across operating conditions, and improve decision interpretability. For hybrid systems, an electromechanical coupling physical model can serve as a regularization term, guiding reasoning logic under combined electromagnetic and mechanical faults.

7.2. Self-Supervised Pre-Training and Few-Shot Diagnostic Paradigm

Given the scarcity of fault samples in high-end combine harvesters, the field must move beyond the fully supervised annotation paradigm. The vast quantities of unlabeled normal operating data generated daily can be exploited for self-supervised pre-training based on contrastive learning or masked autoencoders, enabling the model to learn generalized signal representations. Subsequent fine-tuning with very few fault samples can then achieve few-shot or even zero-shot anomaly detection. This "general education first, specialization later" paradigm promises to replace the current closed setting of "one fault, one training session" with a general whole-machine state representation foundation model, and is particularly suited to hybrid and unmanned agricultural machinery scenarios where data are even scarcer.

7.3. Model Lightweighting and Hardware Acceleration for the Edge

Bridging the gap between high-precision models and limited onboard computing power requires collaborative software and hardware optimization. On the algorithm side, techniques such as neural architecture search and dynamic width/depth inference can seek a Pareto optimum between diagnostic accuracy and inference latency. For real-time diagnosis in unmanned contexts, model inference must meet functional safety constraints on response time and determinism. On the deployment side, low-power edge AI hardware—processing-in-memory and event-driven brain-inspired chips—requires exploration for agricultural machinery, along with EMC reinforcement to cope with the interference environment of hybrid electric powertrains.

7.4. Staged Verification Strategy for Pre-Deployment Validation

A structured verification framework is essential to ensure diagnostic models perform reliably before entrusting them with real-time decisions on operating harvesters. Drawing on established practices in aerospace and industrial CM [222], we propose a three-stage verification pipeline for agricultural machinery fault diagnosis.

The first stage is offline validation on curated datasets. Diagnostic models should be evaluated not merely on aggregate accuracy but on per-class metrics—precision, recall, and F1-score—computed for each fault mode under multiple operating conditions. Cross-condition testing protocols, training on one set of operating parameters and testing on another, can expose brittleness to distributional shift before field deployment [223]. Publicly available benchmark datasets, such as those from the Case Western Reserve University bearing data center and the Paderborn University bearing dataset [204], can serve as standardized testbeds for initial algorithm comparison, though their transferability to agricultural machinery must be critically assessed.

The second stage is hardware-in-the-loop (HIL) simulation [224]. After compression into their deployable lightweight form, diagnostic algorithms execute on the target edge computing hardware, fed with real sensor signals replayed from pre-recorded field data or generated by real-time simulators. This stage verifies that inference latency, memory consumption, and thermal behavior remain within acceptable bounds under sustained operation, and provides a controlled environment for injecting simulated fault signatures into normal-condition recordings, enabling quantitative assessment of detection sensitivity without requiring actual component damage.

The third stage is controlled field testing under instrumented conditions. Prior to full autonomous deployment, the diagnostic system operates in a passive monitoring mode on a manned harvester, logging its predictions alongside conventional inspection records. Comparing diagnostic outputs with ground-truth maintenance findings over an entire harvest season yields estimates of false alarm rate, missed detection rate, and mean time to first detection. Only after these metrics satisfy predefined acceptance criteria—established in consultation with domain engineers and aligned with relevant functional safety standards—does the diagnostic system transition to active decision-making roles.

This staged approach acknowledges that no single validation metric or laboratory benchmark can capture the full complexity of field conditions. It provides a pragmatic roadmap from algorithm development to trustworthy deployment, while generating the real-world case studies whose absence the existing literature currently notes as a limitation.

7.5. Fault Data Sample Augmentation Enhanced by Digital Twins

A comprehensive review of digital twin (DT) in agriculture has outlined the generic framework and potential applications, which can be adapted for the SHM of combine harvesters [225]. High-fidelity DT of key components—including the electric motor, inverter, and transmission mechanism in hybrid electric systems—can be constructed for virtual-real interactive mapping. Injecting multiple fault modes and random operating condition combinations into the virtual space then generates massive quantities of high-fidelity, labeled fault simulation data. Combined with domain randomization, models extensively trained on virtual data require only fine-tuning to transfer to physical entities, potentially overcoming the data hunger caused by extreme operating conditions and scarce fault samples, and providing a full-lifecycle offline training and verification environment for the diagnostic systems of unmanned agricultural machinery.

These opportunities, however, require careful contextualization. DT technology in general—and its application to agricultural machinery in particular—remains at a relatively early stage. A cross-industry umbrella review found DT research fragmented across domains, with inconsistencies in definitions, methodologies, and recognized challenges [226]. Even in manufacturing, the most mature DT domain, core challenges persist in modeling fidelity, real-time synchronization, and verification and validation, with no structured validation framework yet established [227]. This contrasts with domains such as wind energy, where DTs have progressed to operational deployment for performance optimization and predictive maintenance [228]. In agricultural machinery, a systematic review concluded that practical, IoT-powered DT applications remain nascent, limited by data integration, optimization, and communication constraints, and the literature lacks structured classification of physical twin components and standardized definitions of physical–virtual integration levels for off-road machinery [225]. For combine harvesters specifically, DT systems remain scarce and limited to specific subsystems or offline simulation; no peer-reviewed study has demonstrated a fully operational DT for combine harvester SHM that generates vali-

https://doi.org/10.3390/app16147319

dated fault simulation data for diagnostic model training [229]. The DT direction outlined here should therefore be viewed as a strategic research vision rather than a near-term deployable solution. Incremental progress is more realistic, beginning with hybrid models that embed partial physical constraints into data-driven architectures, validated on individual subsystems under controlled conditions, before scaling toward whole-machine, multi-physics, full-season DT implementations. In the near term, physics-informed hybrid models (Section 7.1) and staged verification on individual subsystems (Section 7.4) offer more immediately achievable pathways toward simulation-driven diagnostics. Full DT integration represents a longer-term vision, contingent on advances in modeling fidelity, real-time synchronization, and validation frameworks that are only beginning to emerge in agricultural machinery.

7.6. Resilient Diagnostic Interaction Architecture for Diverse Human–Machine Relationships

The operation mode of combine harvesters is gradually transitioning from manual driving and remote control toward full autonomy, with multiple modes coexisting for the foreseeable future. The diagnostic system must accordingly shift from an "assistant tool" to a "resilient agent."

In manned or semi-autonomous scenarios, decision-level human–machine collaboration is central. The diagnostic output should convey not merely a fault probability but the fault location, severity, and recommended actions in an interpretable manner—for instance, through feature attribution grounded in physical constraints or natural language descriptions. A human-in-the-loop mechanism allows operators to provide annotation feedback for ambiguous alarms, while active learning enables the model to evolve online, mitigating the trust crisis that false alarms create.

In fully autonomous operation, the diagnostic system must possess self-validation capability—assessing the uncertainty of its own judgments in real time before issuing safety-critical decisions. This requires a confidence modeling layer based on Bayesian inference, evidence theory, or conformal prediction at the output of the diagnostic network. When uncertainty exceeds a safety threshold, the system should automatically degrade operation or request remote intervention rather than blindly executing high-risk commands.

This self-validation engine also serves human–machine collaboration: when the diagnostic system lacks confidence in its judgment, it actively requests operator intervention. The future diagnostic interaction architecture should thus synchronously increase diagnostic autonomy and output confidence—autonomous execution at high confidence, intervention request at low confidence. Human–machine collaboration and self-confirming diagnosis are not mutually exclusive but rather adjacent segments on a single spectrum of resilient autonomous diagnosis.

7.7. Cross-Energy-Domain Diagnosis and Fault-Tolerant Control Adapted to New Power Architectures

As combine harvester electrification deepens, future diagnostic frameworks must fuse mechanical, hydraulic, and electrical physical quantities. Mechanic–electronic–hydraulic powertrain systems in agricultural tractors have demonstrated measurable energy savings, offering a reference for next-generation hybrid combine harvesters [230]. Energy optimization control based on quasi-cycle power demand estimation has also been explored for extended-range hybrid harvesters to balance efficiency and operational demands [231]. Future work should model fault propagation based on power flow topology, locating root causes through energy flow anomalies rather than analyzing single-component signals in isolation. Diagnostic results should directly drive fault-tolerant control strategies: upon detecting abnormal temperature in a motor winding, for example, torque redistribution can derate the faulty motor while the remaining motors compensate, allowing harvesting to continue uninterrupted while ensuring safety. This integrated diagnosis-to-fault-tolerance design will become a key technology for improving the mission reliability of hybrid and electric combine harvesters.

7.8. Harvest Quality-Aware Diagnostics

Beyond preventing mechanical downtime, future diagnostic systems could monitor parameters directly affecting harvested grain quality. Post-harvest storage conditions—particularly elevated temperature and moisture—accelerate nutrient degradation and the production of acidic compounds in rice, paddy, and soybean, compromising freshness and market value [232]. The nutritional value of harvested grain—including bioactive compounds such as bound polyphenols with documented antioxidant and antitumor properties [233] and the health benefits of grain-derived dietary fiber [234]—suggests that future harvest quality metrics should encompass not only physical integrity but also the preservation of nutritional and functional components. Integrating quality-centric sensing into harvester health management frameworks would thus extend onboard diagnostics from machine reliability to crop quality assurance, creating a unified platform for both operational efficiency and food quality protection.

7.9. From Research to Practice

Translating the diagnostic advances reviewed in this paper into operational systems on working harvesters requires bridging gaps that extend well beyond algorithmic performance. The deployment pathway spans sensor selection and placement that balance diagnostic coverage against cost and installation complexity; edge computing platforms that meet the latency, thermal, and vibration constraints of field environments; and validation protocols that establish trustworthiness before diagnostic outputs guide maintenance or control decisions.

Practical deployment also demands economic viability—the upfront hardware and integration cost must be justified by demonstrable reductions in downtime-related losses—yet cost–benefit analyses specific to agricultural machinery fault diagnosis remain conspicuously absent from the literature. A structured cost–benefit analysis for agricultural machinery fault diagnosis would account for cost components—sensor hardware, installation labor, edge computing units, data transmission infrastructure, and ongoing maintenance—and benefit categories—reduced downtime, repair cost savings, avoided timeliness loss, extended component service life, and lower insurance premiums. While such analyses remain absent from the agricultural machinery literature, cost–benefit frameworks from adjacent domains provide methodological references. A systematic review of 42 CMS evaluation studies across industrial applications identified established approaches—including cost–benefit analysis, cost-effectiveness analysis, and net present value methods—though it found that only one-third of studies comprehensively incorporate equipment, maintenance, and CMS-related costs [235]. A review of SHM cost-effectiveness in aviation similarly noted that maintenance manpower, fuel consumption, and sensor costs are the most commonly modeled cost variables, while downtime costs and sensor reliability are frequently neglected despite their significant economic impact, and called for standardized frameworks to ensure consistency across future studies [236]. A concrete example from wind turbine CM demonstrated a net present value model for journal bearing CMS that identified failure detection rate, sensor hardware cost, and bearing failure rate as the most influential parameters, and explicitly distinguished between retrofit and new-installation scenarios—a distinction equally relevant to agricultural machinery [237]. These precedents collectively provide both a reference framework and cautionary guidance for structuring cost–benefit analyses for agricultural machinery fault diagnosis.

While comprehensive multi-season field deployment studies remain scarce, individual studies have demonstrated promising field validation results that offer proof-of-concept evidence for broader deployment. For instance, a one-versus-one SVM model using multi-point vibration features achieved 96.9–99.7% accuracy for bolt state identification on a combine harvester conveyor trough under field conditions [138], and a dual-speed robust balancing method achieved residual unbalances of 37 g and 45 g on two combine harvester models in field tests [59]. These examples, though limited in scope, demonstrate that data-driven diagnostic and physics-based correction methods can perform effectively outside the laboratory when properly validated.

Similarly, documented case studies of multi-season field deployments with transparent reporting of both successes and failures are urgently needed to ground the research literature in operational reality. A further rarely addressed dimension is the distinction between retrofitting diagnostic systems onto existing harvester fleets—where sensor installation is constrained by pre-existing mechanical and electrical architectures—and designing diagnostic capability into new harvester models from the outset, where sensors, wiring harnesses, and computing modules can be optimally integrated during manufacturing. These two deployment scenarios impose fundamentally different constraints on sensor selection, signal conditioning, and system cost, yet the current literature offers no systematic comparison between them. The staged verification framework outlined in Section 7.4 and the human–machine interaction principles discussed in Section 7.6 provide starting points for translational work, but systematic, cross-disciplinary efforts engaging equipment manufacturers, maintenance service providers, and agricultural economists alongside diagnostic algorithm developers will be essential to move the field from laboratory demonstrations to commercially viable, trusted products.

8. Conclusions

This review has systematically examined the progress of structural fault diagnosis for combine harvesters, tracing a trajectory from passive structural redundancy to active state perception. Structural optimization strategies remain an irreplaceable first line of defense, yet time-varying operating conditions, system degradation, coupling transmission, and random overloads constrain their effective boundaries. These boundaries have driven the shift toward data-driven fault diagnosis. Traditional ML methods offer advantages in physical interpretability and small-sample performance, but exhibit fundamental limitations: high dependence on expert knowledge, inability to capture deep-level features, and poor cross-condition generalization.

DL with multi-sensor fusion has recently overcome many bottlenecks of traditional methods, providing a new diagnostic paradigm. Moving toward field deployment, however, real-time diagnostic systems face both persistent obstacles—strong noise interference, cross-condition generalization, scarce fault samples, limited onboard computing power, and insufficient interpretability—and new challenges from powertrain electrification: electromechanically coupled faults, EMI, and the stringent requirements for diagnostic autonomy and functional safety in unmanned operations.

These research directions fall along a temporal horizon that can guide future efforts. Short-term priorities—immediately actionable, building on existing methods—include physics-informed hybrid models, self-supervised pre-training and few-shot learning, and staged verification frameworks. Medium-term priorities, requiring further methodological development and field validation, include lightweight edge inference, incremental learning for model updating, and open-set recognition for novel fault modes. Long-term visions, contingent on advances in enabling technologies, include full DT integration and cross-energy-domain diagnosis with fault-tolerant control. This temporal framing highlights that near-term progress on physics-informed and self-supervised approaches can yield practical benefits while laying the groundwork for more ambitious long-term goals.

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Overall, the future reliability assurance system for combine harvesters must integrate a robust physical structure, an efficient electrified drive, a multimodal sensing system, safety-critical autonomous diagnosis, and cloud-based intelligence. Whether for manned or unmanned operation, purely mechanical transmission or hybrid drive, this system must take mission reliability as its core and shift from single-fault detection to holistic production risk management. Such a multi-layered virtual–physical fusion architecture can approach the ideal of "zero unplanned downtime," providing key technical support for global grain supply chain resilience and sustainable agricultural development.

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Abbreviations

The following abbreviations are used in this manuscript:

AE	Acoustic Emission
ANN	Artificial Neural Network
BPNN	Back-Propagation Neural Network
CM	Condition Monitoring
CMS	Condition Monitoring System
CNN	Convolutional Neural Network
COT	Computed Order Tracking
CSVDE	Composite-Scale Variable Dispersion Entropy
CWT	Continuous Wavelet Transform
D-S	Dempster–Shafer evidence theory
DEM	Discrete Element Method
DL	Deep Learning
DT	Digital Twin
DWT	Discrete Wavelet Transform
EEMD	Ensemble Empirical Mode Decomposition
ELM	Extreme Learning Machine
EMC	Electromagnetic Compatibility
EMI	Electromagnetic Interference
FDD	Fault Detection and Diagnosis
KNN	K-Nearest Neighbor
LSTM	Long Short-Term Memory
MFCC	Mel-Frequency Cepstral Coefficient
ML	Machine Learning
NB	Naïve Bayes
PCA	Principal Component Analysis

ResNet	Residual Network
RF	Random Forest
RMS	Root Mean Square
SDAE	Stacked Denoising Autoencoder
SHM	Structural Health Monitoring
SNR	Signal-to-Noise Ratio
STFT	Short-Time Fourier Transform
SVM	Support Vector Machine
ViT	Vision Transformer

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