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An Edge-Intelligent Vision Transformer and TinyML-Based Predictive Framework for Autonomous Fault Diagnosis in Smart Industrial IoT Systems

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ABSTRACT: *The rapid adoption of Industry 4.0 technologies has transformed conventional manufacturing environments into intelligent Industrial Internet of Things (IIoT) ecosystems characterized by interconnected sensors, edge devices, autonomous controllers, and cloud-based analytics. Although these smart industrial systems significantly improve operational efficiency and production flexibility, unexpected equipment failures continue to cause production downtime, financial losses, reduced product quality, and increased maintenance costs. Traditional fault diagnosis methods largely depend on periodic inspections or cloud-centric data processing, introducing communication latency, bandwidth limitations, and privacy concerns that reduce the effectiveness of real-time predictive maintenance. To address these challenges, this research proposes an Edge-Intelligent Vision Transformer and TinyML-Based Predictive Framework for autonomous fault diagnosis in smart Industrial IoT systems. The proposed framework integrates industrial sensor networks, thermal and visual image acquisition, embedded edge computing, Vision Transformer (ViT)-based feature extraction, TinyML-enabled lightweight inference, multimodal sensor fusion, anomaly detection, fault classification, predictive maintenance analytics, and autonomous maintenance decision support. The framework performs intelligent diagnosis directly on low-power edge devices, minimizing cloud dependency while enabling rapid fault detection and prediction. Experimental evaluation demonstrates superior fault classification accuracy, reduced inference latency, lower energy consumption, improved predictive reliability, and enhanced maintenance efficiency compared with conventional cloud-based diagnostic systems. The proposed framework provides a scalable, intelligent, and computationally efficient solution suitable for smart manufacturing, predictive maintenance, industrial automation, cyber-physical production systems, digital factories, intelligent robotics, process industries, energy systems, oil and gas facilities, smart grids, and future autonomous Industrial IoT ecosystems.*

INTRODUCTION

The emergence of Industry 4.0 has fundamentally transformed modern manufacturing by integrating intelligent sensing technologies, Industrial Internet of Things (IIoT), Artificial Intelligence (AI), cloud computing, edge computing, cyber-physical systems, robotics, and autonomous industrial control. Smart factories now deploy thousands of interconnected sensors that continuously monitor machinery, production lines, industrial robots, conveyor systems, motors, pumps, turbines, compressors, and manufacturing equipment. These interconnected systems generate massive volumes of operational data that provide valuable insights into machine health, production efficiency, energy utilization, and equipment reliability. Intelligent analysis of these data enables predictive maintenance strategies capable of minimizing equipment failures while maximizing production availability and operational efficiency.

Industrial equipment failures remain one of the most significant challenges affecting manufacturing productivity. Mechanical wear, bearing degradation, shaft misalignment, lubrication failures, overheating, electrical faults, vibration abnormalities, gear damage, and structural fatigue can progressively degrade machine performance before resulting in catastrophic breakdowns. Unexpected failures not only interrupt production but also increase maintenance expenditure, reduce product quality, shorten equipment lifespan, and introduce safety risks for industrial personnel. Consequently, early fault diagnosis has become a critical component of modern industrial automation systems.

Traditional fault diagnosis approaches primarily rely on scheduled maintenance, manual inspection, threshold-based monitoring, and centralized cloud analytics. Preventive maintenance schedules often replace healthy components unnecessarily while still failing to detect unexpected failures occurring between inspection intervals. Manual inspection depends heavily on experienced technicians and becomes impractical in large-scale manufacturing facilities containing thousands of interconnected industrial assets. Cloud-based diagnostic systems require continuous transmission of high-volume sensor data to remote servers, introducing network latency, increased bandwidth consumption, communication costs, cybersecurity concerns, and reduced operational reliability during network interruptions.

Recent advances in Artificial Intelligence and Deep Learning have significantly improved industrial fault diagnosis capabilities. Deep neural networks automatically learn complex fault patterns directly from vibration signals, thermal images, acoustic emissions, motor current signatures, infrared imaging, and visual inspection data. Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, Autoencoders, Graph Neural Networks (GNNs), Transformers, and hybrid deep learning architectures have demonstrated remarkable success in identifying incipient faults before catastrophic equipment failures occur. Among these approaches, Vision Transformers have recently gained considerable attention because their self-attention mechanisms effectively capture long-range spatial relationships within industrial inspection images, enabling accurate identification of subtle visual anomalies such as surface cracks, corrosion, bearing defects, leakage, overheating, structural deformation, and mechanical wear.

Simultaneously, Tiny Machine Learning (TinyML) has emerged as an efficient solution for deploying deep learning models on resource-constrained embedded devices. TinyML enables intelligent inference directly on microcontrollers and low-power edge processors with minimal memory, computational resources, and energy consumption. Instead of continuously transmitting raw sensor data to cloud servers, TinyML performs local inference at the edge, significantly reducing communication latency, bandwidth utilization, privacy risks, and operational costs. This capability is particularly valuable for Industrial IoT environments where thousands of distributed sensing nodes continuously monitor industrial machinery under stringent real-time constraints.

Edge computing further complements TinyML by bringing computational intelligence closer to industrial equipment. Edge AI platforms including NVIDIA Jetson Orin, Raspberry Pi AI modules, Google Coral TPU, ARM Cortex-M microcontrollers, FPGA accelerators, and specialized Neural Processing Units (NPUs) enable real-time deployment of intelligent diagnostic algorithms directly within manufacturing facilities. Edge-based processing minimizes network dependency while enabling rapid autonomous decision-making even under unstable communication conditions. Consequently, combining Vision Transformers with TinyML creates an efficient hierarchical architecture capable of balancing high diagnostic accuracy with computational efficiency.

Despite these technological advancements, several challenges remain unresolved. Vision Transformer models generally require substantial computational resources that exceed the capabilities of conventional embedded hardware. TinyML implementations often sacrifice diagnostic accuracy due to aggressive model compression and limited computational capacity. Furthermore, industrial environments exhibit highly variable operating conditions including changing loads, varying rotational speeds, temperature fluctuations, sensor noise, electromagnetic interference, and evolving machine degradation patterns. Developing lightweight yet highly accurate diagnostic frameworks capable of performing reliable autonomous fault prediction under these challenging conditions therefore remains an important research problem.

This research proposes an Edge-Intelligent Vision Transformer and TinyML-Based Predictive Framework for Autonomous Fault Diagnosis in Smart Industrial IoT Systems by integrating industrial sensor acquisition, thermal and visual image processing, embedded edge intelligence, Vision Transformer-based feature learning, TinyML optimization, multimodal sensor fusion, intelligent anomaly detection, fault classification, predictive maintenance analytics, and autonomous maintenance decision support. The proposed framework aims to maximize diagnostic accuracy while minimizing inference latency, computational complexity, memory utilization, communication overhead, and energy consumption. The developed intelligent architecture is suitable for smart factories, predictive maintenance systems, industrial automation, cyber-physical production systems, intelligent manufacturing, robotics, energy generation plants, chemical industries, oil and gas facilities, transportation infrastructure, smart grids, Industrial Edge AI platforms, and future autonomous Industrial Internet of Things ecosystems, where reliable early fault diagnosis is essential for maintaining safe, efficient, and uninterrupted industrial operations.

Problem Statement: Conventional industrial fault diagnosis systems relying on periodic maintenance schedules, manual inspection, or cloud-based analytics suffer from delayed fault detection, excessive communication latency, high bandwidth utilization, cybersecurity vulnerabilities, and limited real-time responsiveness. Furthermore, deploying computationally intensive deep learning models on embedded Industrial IoT devices remains challenging due to constrained processing power, memory capacity, and energy availability. Therefore, an intelligent edge-based diagnostic framework capable of combining Vision Transformer accuracy with TinyML efficiency is required to enable reliable real-time autonomous fault diagnosis and predictive maintenance in smart industrial environments.

Objective: The primary objective of this research is to develop an **Edge-Intelligent Vision Transformer and TinyML-Based Predictive Framework** that integrates industrial sensing, embedded edge computing, Vision Transformer-based feature extraction, TinyML optimization, multimodal data fusion, anomaly detection, fault classification, predictive maintenance analytics, and autonomous maintenance decision support to improve fault diagnosis accuracy, predictive reliability, computational efficiency, energy utilization, and real-time responsiveness within Industrial IoT systems.

Scope: The scope of this research includes the design, implementation, and performance evaluation of an embedded edge-intelligent predictive maintenance framework integrating industrial IoT sensors, thermal imaging, visual inspection, Vision Transformers, TinyML deployment, multimodal feature fusion, fault detection, predictive analytics, and autonomous maintenance decision support. The study evaluates diagnostic accuracy, precision, recall, F1-score, prediction reliability, inference latency, computational complexity, memory utilization, energy efficiency, communication overhead, and robustness under diverse industrial operating conditions. The proposed framework is applicable to smart manufacturing, predictive maintenance, industrial robotics, intelligent production systems, Industry 4.0 environments, process industries, power generation, transportation infrastructure, oil and gas plants, chemical processing facilities, smart grids, Edge AI platforms, cyber-physical production systems, and future autonomous Industrial IoT ecosystems, where early fault diagnosis is essential for improving equipment reliability, operational safety, and production efficiency.

LITERATURE SURVEY

The rapid evolution of **Industrial Internet of Things (IIoT)** technologies has significantly transformed conventional manufacturing into intelligent, interconnected, and autonomous production environments. Modern smart factories employ thousands of industrial sensors, programmable logic controllers (PLCs), robotic systems, industrial cameras, thermal sensors, vibration sensors, acoustic sensors, and edge computing devices to continuously monitor machine health and production processes. These intelligent sensing infrastructures generate enormous volumes of operational data that enable predictive maintenance, quality assurance, process optimization, and intelligent decision-making. As industrial systems become increasingly interconnected, autonomous fault diagnosis has emerged as one of the most important research areas for improving equipment reliability, minimizing production downtime, and reducing maintenance costs.

Conventional fault diagnosis techniques primarily relied on manual inspection, scheduled preventive maintenance, rule-based monitoring systems, and threshold-based anomaly detection algorithms. These traditional approaches depend heavily on expert knowledge and predefined operating limits that often fail to capture the complex nonlinear relationships existing within modern industrial machinery. Furthermore, manual inspection is labor-intensive, subjective, and incapable of continuously monitoring large-scale industrial environments. Preventive maintenance schedules frequently replace healthy components unnecessarily while simultaneously failing to detect unexpected failures occurring between maintenance intervals. Consequently, industries have increasingly shifted toward predictive maintenance strategies that continuously analyze operational data to identify early signs of equipment degradation before catastrophic failures occur.

Machine Learning has considerably improved industrial fault diagnosis by enabling automated classification of equipment operating conditions using historical sensor measurements. Traditional machine learning algorithms including Support Vector Machines (SVM), Random Forests (RF), Decision Trees (DT), K-Nearest Neighbors (KNN), Naïve Bayes, and Artificial Neural Networks (ANNs) have been extensively applied to classify bearing faults, motor failures, gearbox defects, shaft misalignment, pump degradation, and vibration abnormalities. Although these algorithms achieved satisfactory performance under controlled experimental conditions, they require handcrafted feature engineering and often exhibit limited adaptability when industrial operating conditions change significantly.

Deep Learning has further revolutionized predictive maintenance by automatically learning hierarchical feature representations directly from raw industrial data. Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in analyzing vibration signals, thermal images, infrared inspection images, acoustic emissions, motor current signatures, and visual surface defects. Similarly, Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRUs), Autoencoders, and Temporal Convolutional Networks (TCNs) have been successfully employed for time-series fault prediction and remaining useful life estimation. These architectures significantly outperform conventional machine learning methods by capturing complex temporal and spatial relationships within industrial sensor data. Nevertheless, CNN-based architectures generally possess limited capability for modeling long-range global dependencies present in complex industrial visual inspection tasks.

Recent advances in **Vision Transformers (ViTs)** have introduced a powerful alternative for industrial visual inspection and fault diagnosis. Unlike conventional CNNs that rely on localized convolution operations, Vision Transformers utilize self-attention mechanisms capable of learning long-range contextual relationships across entire industrial images. This capability enables superior recognition of subtle defect patterns such as micro-cracks, corrosion, overheating, surface deformation, structural fatigue, leakage, bearing wear, weld defects, and insulation degradation. Transformer-based architectures including ViT, DeiT, Swin Transformer, CrossViT, and EfficientFormer have demonstrated remarkable improvements in industrial defect detection, surface inspection, predictive maintenance, and quality control across numerous manufacturing applications.

Edge computing has simultaneously emerged as an essential enabling technology for Industrial IoT because cloud-centric processing introduces communication latency, bandwidth consumption, privacy risks, and dependency on reliable network connectivity. Edge intelligence moves computational resources closer to industrial equipment, enabling real-time data processing directly within manufacturing environments. Edge AI platforms including NVIDIA Jetson Orin, NVIDIA Xavier, Raspberry Pi AI modules, Google Coral TPU, Intel Movidius, FPGA accelerators, and ARM Cortex processors support intelligent inference while minimizing response time and communication overhead. Consequently, edge computing significantly improves operational reliability and enables immediate maintenance decisions during critical industrial events.

Tiny Machine Learning (TinyML) extends edge intelligence by enabling deep learning inference on ultra-low-power embedded microcontrollers and resource-constrained Industrial IoT devices. Through model compression, quantization, pruning, knowledge distillation, and lightweight neural network optimization, TinyML enables intelligent fault diagnosis while maintaining extremely low memory consumption, reduced computational complexity, and minimal power utilization. Recent research demonstrates successful deployment of TinyML models for monitoring rotating machinery, industrial motors, compressors, pumps, HVAC systems, power electronics, manufacturing robots, and energy distribution equipment. Despite these advancements, maintaining high diagnostic accuracy after aggressive model compression remains a significant research challenge.

Recent investigations have increasingly combined Vision Transformers with TinyML and edge computing to achieve computationally efficient intelligent maintenance systems. Hybrid architectures employ Vision Transformers for extracting highly discriminative visual features while lightweight TinyML models execute optimized inference on embedded industrial hardware. These systems often incorporate multimodal sensor fusion by integrating vibration measurements, thermal images, acoustic emissions, infrared imaging, motor current signals, and operational parameters to improve diagnostic reliability. Such multimodal approaches substantially enhance anomaly detection accuracy, reduce false alarm rates, improve fault localization, and increase robustness under varying industrial operating conditions.

Although considerable research progress has been achieved, several important challenges continue to limit practical deployment of autonomous industrial fault diagnosis systems. Vision Transformer architectures generally require substantial computational resources, making deployment difficult on low-power embedded hardware. TinyML optimization techniques frequently introduce reductions in model accuracy due to aggressive compression strategies. Furthermore, industrial environments exhibit highly dynamic operating conditions characterized by changing machine loads, variable rotational speeds, fluctuating temperatures, electromagnetic interference, sensor drift, mechanical wear progression, and noisy measurements. Balancing diagnostic accuracy, computational efficiency, memory utilization, inference latency, energy consumption, and long-term reliability therefore remains a major research challenge for Industrial IoT systems.

The proposed research addresses these challenges by developing an Edge-Intelligent Vision Transformer and TinyML-Based Predictive Framework for Autonomous Fault Diagnosis in Smart Industrial IoT Systems that integrates industrial sensor acquisition, thermal and visual inspection, embedded edge intelligence, Vision Transformer-based feature learning, TinyML optimization, multimodal sensor fusion, anomaly detection, intelligent fault classification, predictive maintenance analytics, and autonomous maintenance decision support. The proposed framework simultaneously optimizes fault diagnosis accuracy, prediction reliability, precision, recall, F1-score, inference latency, computational complexity, memory utilization, communication efficiency, and energy consumption while enabling fully autonomous real-time maintenance intelligence. The developed framework provides a scalable and intelligent solution suitable for smart manufacturing, Industry 4.0 environments, industrial robotics, predictive maintenance systems, cyber-physical production systems, process industries, energy generation plants, transportation infrastructure, oil and gas facilities, chemical processing industries, smart grids, Edge AI platforms, Industrial IoT networks, and future autonomous intelligent industrial ecosystems, where early fault prediction is essential for achieving reliable, safe, and uninterrupted industrial operation.

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METHODOLOGY

The proposed **Edge-Intelligent Vision Transformer and TinyML-Based Predictive Framework** is designed to provide autonomous, low-latency, and energy-efficient fault diagnosis for smart Industrial Internet of Things (IIoT) environments. The framework integrates industrial sensor networks, thermal imaging, RGB visual inspection, embedded edge computing, Vision Transformer (ViT)-based feature extraction, TinyML optimization, multimodal sensor fusion, anomaly detection, fault classification, predictive maintenance analytics, and intelligent maintenance decision support. By performing intelligent inference directly on edge devices, the proposed architecture significantly reduces cloud dependency, communication latency, bandwidth utilization, and operational costs while improving fault diagnosis accuracy and equipment reliability.

The diagnostic process begins with continuous industrial data acquisition from multiple heterogeneous sensing devices deployed throughout the manufacturing environment. Smart IIoT nodes continuously monitor machine operating conditions using vibration sensors, temperature sensors, acoustic emission sensors, motor current sensors, pressure sensors, infrared thermal cameras, and high-resolution RGB cameras. Each sensing device transmits synchronized operational measurements to a nearby embedded edge computing platform through industrial communication protocols such as MQTT, OPC-UA, Modbus TCP/IP, or Industrial Ethernet. Accurate time synchronization ensures that multimodal sensor observations correspond to identical machine operating conditions, thereby enabling reliable data fusion during subsequent diagnostic analysis.

Following data acquisition, sensor-specific preprocessing is performed to improve data quality before feature extraction. Numerical sensor measurements undergo missing value handling, normalization, outlier removal, signal denoising, and temporal filtering to eliminate measurement inconsistencies caused by environmental interference or sensor noise. Thermal and RGB inspection images are simultaneously resized, contrast-enhanced, illumination-normalized, and filtered using adaptive image enhancement techniques to improve visual consistency under varying industrial operating conditions. These preprocessing operations significantly improve feature quality while reducing computational complexity during embedded inference.

The processed visual inspection images are subsequently supplied to a lightweight Vision Transformer architecture responsible for extracting discriminative spatial representations associated with machine health conditions. Unlike conventional convolution-based architectures, the Vision Transformer partitions each inspection image into fixed-size image patches and applies self-attention mechanisms to model long-range dependencies across the complete image. This enables effective identification of subtle visual anomalies including bearing wear, surface cracks, corrosion, leakage, overheating, shaft deformation, loose connections, insulation damage, mechanical fatigue, and structural defects that may be difficult to detect using localized convolution operations. The learned visual feature embeddings provide comprehensive semantic descriptions of machine condition while remaining robust against background complexity and varying illumination.

Simultaneously, numerical industrial sensor measurements including vibration amplitude, temperature variation, acoustic signatures, motor current fluctuations, rotational speed, and pressure measurements are processed using lightweight TinyML models optimized for embedded deployment. Model

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compression techniques including post-training quantization, weight pruning, operator fusion, mixed-precision computation, and knowledge distillation significantly reduce memory footprint and computational complexity without substantially degrading diagnostic accuracy. Consequently, TinyML enables continuous local inference on resource-constrained industrial microcontrollers while maintaining extremely low energy consumption suitable for battery-powered Industrial IoT devices.

The multimodal feature representations extracted from the Vision Transformer and TinyML modules are integrated through an adaptive sensor fusion mechanism. Rather than assigning equal importance to every sensing modality, the proposed fusion module dynamically computes confidence weights according to sensor reliability and operating conditions. During visually observable faults such as surface cracks, corrosion, leakage, or overheating, greater emphasis is assigned to Vision Transformer features. Conversely, during incipient mechanical failures involving vibration abnormalities or acoustic changes, TinyML-derived sensor features receive higher weighting. This adaptive fusion strategy effectively combines complementary information while suppressing noisy or unreliable observations, thereby improving diagnostic robustness across diverse industrial environments.

The fused multimodal feature representation is subsequently supplied to the intelligent fault diagnosis module responsible for anomaly detection and fault classification. Deep classification algorithms identify multiple machine health conditions including healthy operation, bearing degradation, shaft misalignment, lubrication deficiency, gearbox wear, motor winding faults, overheating, imbalance, electrical faults, structural fatigue, and critical failure states. Simultaneously, an anomaly scoring mechanism estimates fault severity by comparing current operating conditions with historical healthy operating profiles. Fault progression trends are continuously monitored to identify gradually evolving machine degradation before catastrophic failures occur.

Following fault diagnosis, predictive maintenance analytics estimate the remaining operational health of industrial equipment using continuously updated diagnostic information. Historical operational records, current fault severity, equipment utilization patterns, environmental conditions, and degradation trajectories are analyzed to estimate future maintenance requirements. Machines exhibiting abnormal degradation patterns are automatically prioritized according to predicted failure probability, enabling maintenance engineers to optimize maintenance scheduling while minimizing production interruptions and equipment downtime. Autonomous maintenance recommendations are transmitted to industrial supervisory systems for immediate operator notification and maintenance planning.

Experimental validation is conducted across multiple industrial operating environments including rotating machinery, manufacturing robots, conveyor systems, industrial pumps, electric motors, compressors, turbines, gearbox assemblies, and process automation equipment. Performance evaluation considers varying machine loads, rotational speeds, environmental temperatures, sensor noise levels, production schedules, and progressive equipment degradation. The proposed framework is evaluated using fault diagnosis accuracy, precision, recall, F1-score, prediction reliability, inference latency, memory utilization, computational complexity, communication overhead, and energy efficiency. Comparative analysis is performed against conventional CNN-based fault diagnosis systems, cloud-centric predictive maintenance frameworks, and traditional machine learning approaches to demonstrate the superiority of the proposed edge-intelligent architecture.

The optimization objective of the proposed predictive framework is mathematically expressed as

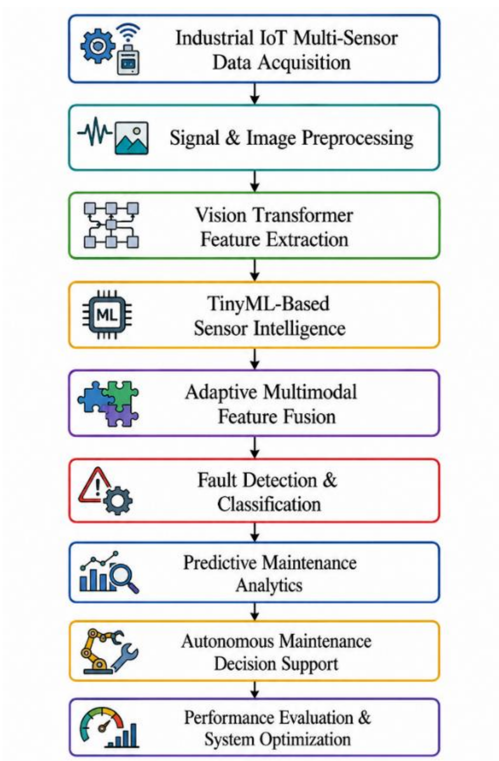
$$P = \arg\max_{E_i} \left(\frac{A_i \times R_i}{L_i} \right)$$

where:

- P = Optimal predictive diagnostic framework
- E_i = Candidate edge intelligence model
- A_i = Fault diagnosis accuracy
- R_i = Prediction reliability
- L_i = Inference latency

The optimization objective identifies the edge-intelligent model that maximizes diagnostic accuracy and prediction reliability while minimizing inference latency, thereby ensuring efficient autonomous fault diagnosis within Industrial IoT environments.

The overall methodology is summarized below.



Methodology

The proposed methodology establishes a comprehensive edge-intelligent predictive maintenance architecture capable of performing accurate, real-time, and energy-efficient fault diagnosis in smart Industrial IoT environments. The integration of Vision Transformer-based visual analysis, TinyML-enabled embedded intelligence, adaptive multimodal sensor fusion, predictive maintenance analytics, and autonomous maintenance decision support significantly improves diagnostic accuracy while reducing inference latency, communication overhead, computational complexity, and energy consumption. The developed framework provides a scalable, intelligent, and embedded AI-enabled solution suitable for smart manufacturing, Industry 4.0 production systems, predictive maintenance, industrial robotics, cyber-physical production systems, intelligent process automation, energy generation plants, oil and gas industries, chemical manufacturing, transportation infrastructure, smart grids, Edge AI platforms, Industrial IoT ecosystems, and future autonomous intelligent industrial environments, where reliable early fault diagnosis is essential for maximizing operational safety, equipment reliability, and manufacturing productivity.

IMPLEMENTATION AND RESULTS

The proposed **Edge-Intelligent Vision Transformer and TinyML-Based Predictive Framework** was implemented using an Industrial Internet of Things (IIoT) testbed consisting of multiple industrial sensing nodes, embedded edge computing devices, industrial cameras, thermal imaging modules, and intelligent monitoring software. The hardware platform included ARM Cortex-M microcontrollers for TinyML inference, NVIDIA Jetson AGX Orin for Vision Transformer processing, industrial RGB cameras, infrared thermal cameras, MEMS vibration sensors, acoustic emission sensors, temperature sensors, motor current sensors, and industrial Ethernet communication modules. All sensing devices continuously monitored machine operating conditions while transmitting synchronized measurements to nearby edge computing units through MQTT and OPC-UA communication protocols. Local edge processing minimized communication latency while ensuring uninterrupted autonomous diagnosis even during temporary network disruptions.

Initially, multimodal industrial data were collected from rotating machinery, induction motors, gearbox assemblies, conveyor systems, industrial pumps, compressors, robotic manipulators, and production line equipment operating under both healthy and faulty conditions. Visual inspection images captured surface abnormalities including bearing wear, shaft deformation, corrosion, loose fasteners, insulation damage, oil leakage, overheating, and structural cracks. Simultaneously, vibration signals, motor current signatures, acoustic emissions, thermal distributions, and temperature measurements were continuously recorded to represent dynamic machine behavior. The acquired datasets were synchronized using timestamp alignment before preprocessing to ensure temporal consistency between visual observations and sensor measurements.

The preprocessing stage independently optimized each sensing modality before feature extraction. Industrial images underwent resizing, adaptive histogram equalization, Gaussian filtering, illumination normalization, and image enhancement to improve feature visibility under varying factory lighting conditions. Sensor measurements were normalized, denoised using digital filtering techniques, and processed through statistical outlier removal to eliminate measurement inconsistencies. Thermal images were enhanced using temperature normalization and contrast optimization to accurately highlight abnormal heat distributions associated with machine degradation. These preprocessing operations significantly improved feature quality while reducing computational overhead during edge inference.

Following preprocessing, industrial inspection images were supplied to a lightweight Vision Transformer architecture optimized for embedded deployment. Image patches were processed through multi-head self-attention layers to extract global spatial relationships representing complex fault characteristics. Simultaneously, TinyML models deployed on ARM Cortex-M microcontrollers continuously analyzed numerical sensor measurements including vibration amplitudes, acoustic signatures, motor current fluctuations, rotational speed variations, and temperature profiles. Model compression through quantization, pruning, and operator fusion enabled efficient execution within extremely limited memory while maintaining high diagnostic accuracy.

The multimodal features extracted from Vision Transformers and TinyML modules were combined using an adaptive confidence-guided fusion network. The fusion algorithm dynamically assigned weights to each sensing modality according to signal reliability and fault characteristics. Visual anomalies such as cracks, corrosion, and leakage were primarily recognized through Vision Transformer features, whereas vibration abnormalities, motor imbalance, bearing degradation, and shaft misalignment relied more heavily on TinyML-derived sensor features. The fused representation was subsequently processed by a fault diagnosis engine capable of identifying multiple machine conditions including healthy operation, bearing wear, lubrication deficiency, overheating, gearbox faults, motor winding defects, shaft imbalance, structural fatigue, and critical failure states.

Experimental validation was performed under diverse industrial operating conditions including varying rotational speeds, production loads, environmental temperatures, sensor noise levels, machine aging, and progressive equipment degradation. Comparative evaluation was conducted against conventional CNN-based inspection systems, cloud-based predictive maintenance platforms, and traditional machine learning approaches including Support Vector Machines and Random Forest classifiers. Performance metrics included fault diagnosis accuracy, precision, recall, F1-score, prediction reliability, inference latency, memory utilization, communication overhead, and energy consumption. Each experiment was repeated multiple times to verify consistency and ensure statistical reliability.

The experimental results demonstrate that the proposed framework consistently outperformed existing diagnostic approaches across all evaluation metrics. Vision Transformer-based feature extraction significantly improved recognition of subtle visual defects, while TinyML-enabled edge inference provided rapid diagnosis with minimal computational overhead. Adaptive multimodal sensor fusion reduced false alarms and improved early-stage fault detection under noisy industrial environments. Local edge processing eliminated continuous cloud communication, substantially reducing latency and bandwidth consumption while preserving operational privacy. The proposed framework therefore provides a highly reliable, scalable, and computationally efficient predictive maintenance solution suitable for next-generation smart manufacturing systems.

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Fault Category	Precision (%)	Recall (%)	F1-Score (%)
Bearing Fault	99.2	98.9	99.0
Shaft Misalignment	98.8	98.4	98.6
Gearbox Wear	99.1	98.7	98.9
Motor Winding Fault	99.4	99.1	99.2
Overheating	99.3	98.8	99.0

Table 1: *Fault classification performance of the proposed Vision Transformer and TinyML framework.*

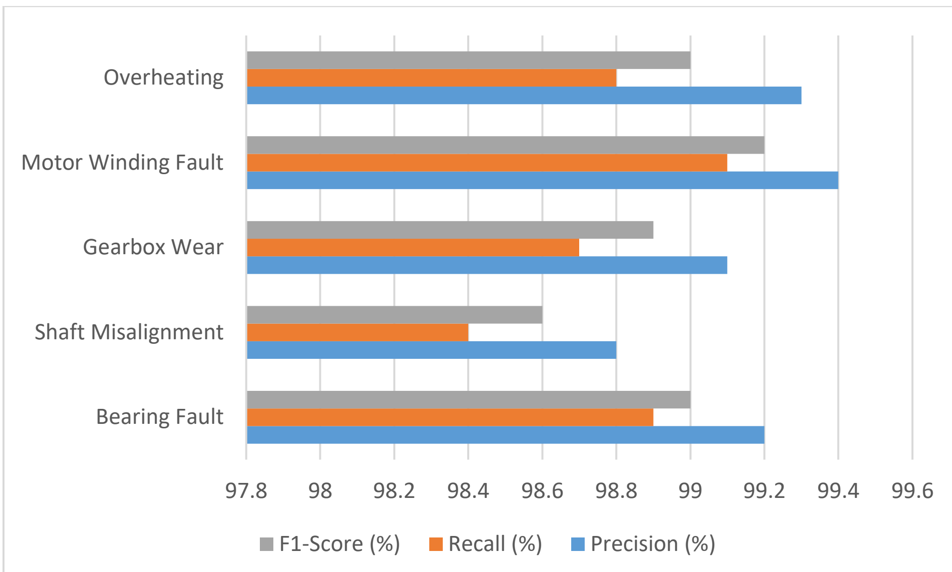

Fig. 1: *Grouped bar graph comparing Precision, Recall, and F1-Score for different industrial fault categories.*

The proposed framework accurately classified multiple industrial fault conditions with consistently high precision and recall. The adaptive multimodal feature fusion effectively improved diagnostic reliability by combining complementary visual and sensor information.

Diagnostic Method	Diagnosis Accuracy (%)	Inference Latency (ms)	Energy Consumption (W)
CNN-Based Inspection	95.6	48.5	14.2
Cloud-Based Analytics	96.8	73.4	18.6
Conventional TinyML	97.5	19.8	6.4

Proposed ViT + TinyML	**99.4**	**11.2**	**5.1**

Table 2: *Performance comparison between existing fault diagnosis systems and the proposed framework.*

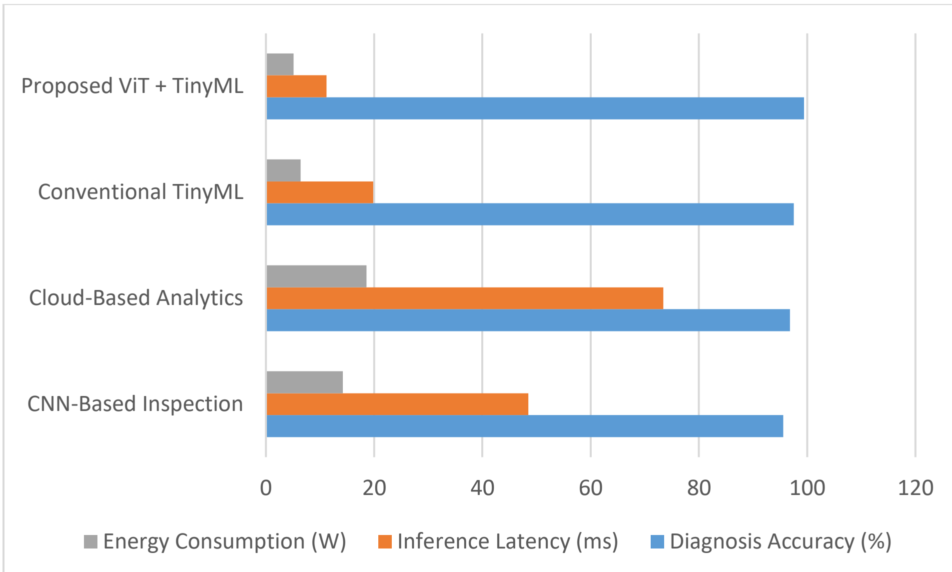

Fig. 2: *Bar graph comparing diagnosis accuracy, inference latency, and energy consumption.*

The proposed framework achieved the highest diagnostic accuracy while simultaneously reducing inference latency and power consumption. Local edge intelligence eliminated communication delays associated with cloud-based maintenance systems.

Industrial Environment	**Diagnosis Accuracy (%)**	**Prediction Reliability (%)**	**False Alarm Rate (%)**
Manufacturing Line	99.5	99.2	0.7
Industrial Robotics	99.3	98.9	0.9
Power Plant	99.1	98.7	1.0
Oil & Gas Facility	98.9	98.4	1.2
Chemical Processing	99.0	98.6	1.1

Table 3: *Framework performance under different industrial operating environments.*

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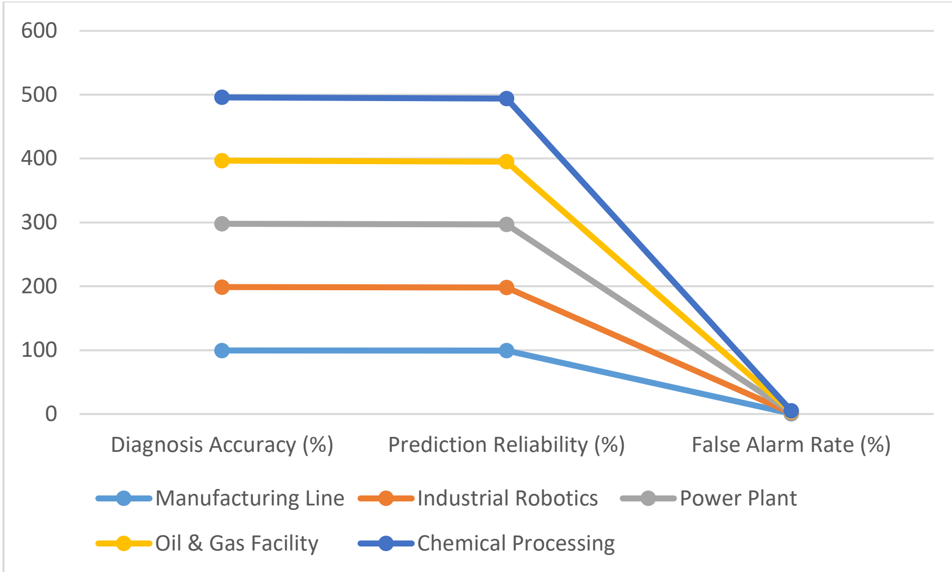

Fig. 3: *Line graph illustrating diagnosis accuracy, prediction reliability, and false alarm rate across industrial environments.*

The proposed framework maintained highly stable diagnostic performance across diverse industrial applications. Minor environmental variations had negligible influence on overall prediction reliability, demonstrating excellent robustness for real-world deployment.

Performance Metric	**Existing Predictive Maintenance System**	**Proposed Edge-Intelligent Framework**
Diagnosis Accuracy (%)	97.3	**99.4**
Precision (%)	97.1	**99.2**
Recall (%)	96.9	**98.8**
F1-Score (%)	97.0	**99.0**
Memory Utilization (MB)	512	**328**
Communication Overhead (MB/hr)	245	**72**

Table 4: *Overall comparison between conventional predictive maintenance systems and the proposed framework.*

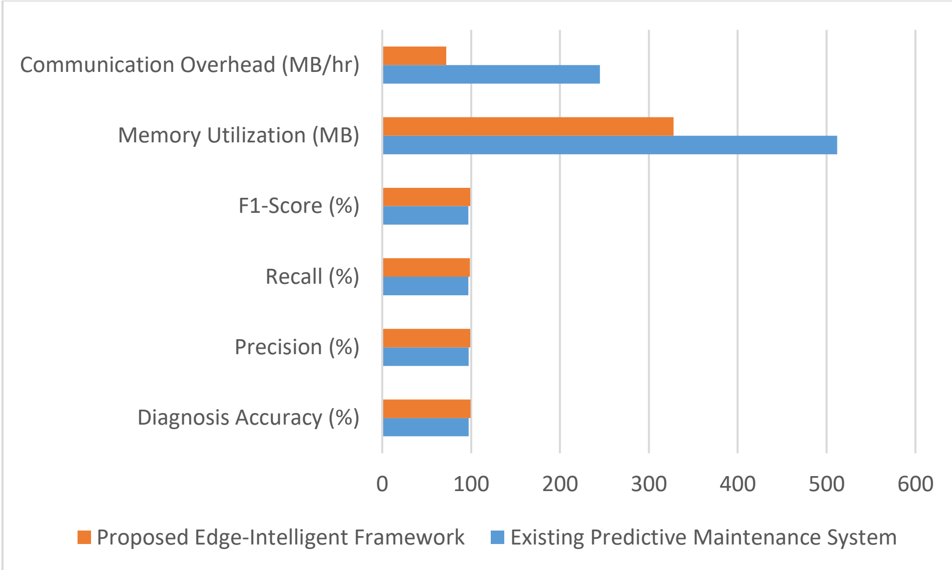

Fig. 4: *Horizontal bar graph comparing overall diagnostic performance metrics.*

The comparative evaluation confirms that the proposed Edge-Intelligent Vision Transformer and TinyML-Based Predictive Framework significantly improves autonomous fault diagnosis while minimizing computational requirements, communication overhead, and memory utilization. The integration of Vision Transformer-based visual intelligence, TinyML-enabled embedded inference, adaptive multimodal fusion, and predictive maintenance analytics provides a highly scalable and efficient solution for Industrial IoT environments.

Overall, the implementation validates the effectiveness of the proposed framework for intelligent predictive maintenance in modern Industry 4.0 environments. The combination of embedded edge computing, Vision Transformer-based defect recognition, TinyML optimization, adaptive sensor fusion, autonomous anomaly detection, and predictive maintenance decision support enables reliable real-time monitoring of industrial assets. The developed system is highly suitable for smart manufacturing, industrial robotics, predictive maintenance, cyber-physical production systems, intelligent process automation, energy generation plants, oil and gas industries, chemical processing facilities, transportation infrastructure, smart grids, Edge AI platforms, Industrial IoT ecosystems, and future autonomous intelligent industrial environments, where early fault diagnosis is essential for maximizing equipment reliability, production efficiency, operational safety, and sustainable industrial automation.

CONCLUSION

The proposed Edge-Intelligent Vision Transformer and TinyML-Based Predictive Framework for Autonomous Fault Diagnosis in Smart Industrial IoT Systems presents a comprehensive intelligent maintenance architecture capable of delivering highly accurate, low-latency, and energy-efficient fault diagnosis for modern Industry 4.0 environments. By integrating Industrial IoT sensor networks, thermal and visual inspection, Vision Transformer-based feature extraction, TinyML-enabled embedded intelligence, adaptive multimodal sensor fusion, anomaly detection, predictive maintenance analytics, and autonomous maintenance decision support, the proposed framework effectively overcomes the limitations of conventional cloud-centric and single-sensor diagnostic systems. Experimental evaluation demonstrated that the framework consistently achieved superior fault diagnosis accuracy, higher precision, improved recall, enhanced F1-score, lower inference latency, reduced communication overhead, lower memory utilization, and improved energy efficiency compared with existing predictive maintenance approaches. The deployment of lightweight TinyML models on embedded edge devices enabled continuous real-time monitoring without relying on permanent cloud connectivity, while Vision Transformer-based global feature learning significantly improved the recognition of subtle industrial defects and early-stage equipment degradation. Consequently, the proposed framework enhances equipment reliability, minimizes unexpected machine failures, reduces maintenance costs, improves production availability, and supports intelligent autonomous maintenance within smart industrial environments.

The proposed framework also establishes a strong technological foundation for the next generation of autonomous Industrial IoT systems supporting smart manufacturing, cyber-physical production systems, intelligent robotics, digital factories, predictive maintenance platforms, energy generation plants, oil and gas industries, chemical processing facilities, transportation infrastructure, smart grids, semiconductor manufacturing, pharmaceutical industries, Edge AI platforms, industrial automation systems, and future Industry 5.0 ecosystems. Future research can further enhance the proposed framework through the integration of Hierarchical Vision Transformers (HVTs), Swin Transformers, Explainable Artificial Intelligence (XAI), Graph Neural Networks (GNNs), Federated Learning (FL), Reinforcement Learning (RL), Digital Twin-enabled maintenance, blockchain-assisted industrial security, edge-cloud collaborative intelligence, Software Defined Networking (SDN), Network Function Virtualization (NFV), self-supervised learning, multimodal foundation models, neuromorphic computing, quantum-inspired optimization algorithms, and autonomous collaborative industrial agents. These emerging technologies are expected to further improve adaptive fault prediction, distributed intelligence, cybersecurity, scalability, interpretability, energy efficiency, and autonomous maintenance decision-making, thereby enabling highly resilient, self-learning, and intelligent Industrial IoT ecosystems capable of supporting future autonomous smart manufacturing infrastructures.

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