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BioTwinSense – A Bio Cognitive Digital Twin for Predictive Maintenance

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***Abstract*— Predictive maintenance has become essential for modern industries seeking to reduce machine failures, improve operational safety, and ensure production continuity. However, existing predictive maintenance systems used in micro, small, and medium enterprises (MSMEs) primarily focus on machine-side parameters such as vibration, temperature, and current. Human operators—whose fatigue, stress, and cognitive load significantly influence machine performance—are rarely included in predictive models. This paper introduces BioTwinSense, a bio-cognitive digital twin framework that fuses machine health indicators with human physiological data to improve maintenance accuracy and safety. Using affordable sensors and edge-based artificial intelligence (AI), the system captures vibration, temperature, current, heart-rate variability (HRV), SpO_2, and fatigue-related eye-blink patterns. Machine learning models including Random Forest, SVM, and KNN were trained using combined datasets, with Random Forest achieving the highest accuracy of 99.62%. A real-time dashboard built using Gradio enables visualization and decision-making without cloud dependency. Results demonstrate that integrating human-state data with mechanical parameters significantly enhances prediction reliability compared to machine-only models, making BioTwinSense a practical, scalable solution for Industry 5.0 adoption in MSMEs.**

Keywords*— Digital Twin, Predictive Maintenance, Industry 5.0, Human Fatigue, Heart Rate Variability, Edge AI, MSMEs, Machine Learning.

I. INTRODUCTION

1.1 *LIMITATIONS OF CONVENTIONAL PREDICTIVE MAINTENANCE*

Conventional predictive maintenance systems rely primarily on mechanical sensor data—typically vibration, thermal signatures, and electrical current—to detect machine faults [1]. These systems work well in highly automated industries but are less effective in environments where operators frequently interact with machines. In MSMEs, machines are often manually operated, and their performance is directly influenced by the physical and cognitive condition of workers. Human fatigue, stress, and reduced alertness contribute to poor machine handling, unstable load conditions, and delayed responses, which existing maintenance systems are not designed to detect. This gap limits the predictive accuracy of traditional models and prevents early identification of human-induced anomalies.

1.2 *NEED FOR HUMAN–MACHINE INTEGRATED MONITORING*

With the emergence of Industry 5.0, the role of human operators is shifting from passive machine controllers to active contributors in cyber-physical environments. Several studies emphasize the importance of incorporating human factors—such as HRV, workload, attention, and fatigue—into decision-making frameworks [4], [7]. Human digital twins have been proposed as counterparts to machine digital twins, allowing real-time tracking of cognitive and physiological signals. However, integrating human-state information into predictive maintenance systems remains underexplored, particularly for low-cost applications. This motivates the development of a dual-sensing system that monitors both machine conditions and operator well-being simultaneously.

1.3 *MOTIVATION FOR EDGE-BASED DIGITAL TWIN DEPLOYMENT*

Cloud-based digital twins provide powerful computational capabilities but are unsuitable for MSMEs due to limited internet infrastructure, high deployment costs, and concerns about data privacy [9]. Edge AI, on the other hand, enables real-time local processing, reduced latency, and cost-effective implementation using embedded systems such as ESP32 and Jetson Nano. This shift toward decentralized intelligence aligns with the principles of sustainable, resilient, and human-centric Industry 5.0 systems [5]. BioTwinSense leverages edge computing to deliver a low-cost, offline-capable digital twin solution compatible with MSME environments.

II. EXISTING SOLUTIONS

2.1 *Digital Twin-Based Predictive Maintenance*

Digital twins have become a foundational component in modern industrial monitoring systems, offering real-time virtual representations of physical assets. According to Zhong et al. [11], digital twins enable deeper insight into machine behavior by synchronizing sensor data with predictive models that simulate degradation, load conditions, and future failures. These solutions help industries create proactive maintenance schedules rather than relying on traditional corrective or preventive methods.

However, most digital twin frameworks are developed for large-scale industries and depend heavily on cloud infrastructure. High-bandwidth communication and complex integration requirements make these systems difficult to adopt in MSMEs. Furthermore, existing machine-centric digital twins generally ignore operator behavior, assuming that machine usage patterns remain consistent. This is a significant limitation, as human inconsistencies such as fatigue or stress can alter machine loads and cause unexpected wear. Chen et al. [12] highlight that even small deviations in machine handling can significantly affect long-term machine health, yet current DT systems do not account for these human-induced influences.
Thus, while digital twins are powerful, their deployment is constrained by cost, connectivity requirements, and missing integration of human-state data.

2.2 *Machine Learning for Industrial Fault Classification*

Machine learning (ML) has become the backbone of intelligent maintenance systems. Classical algorithms such as Random Forest, Support Vector Machine, and KNN have demonstrated strong performance in classifying machine fault conditions from vibration, current, and temperature parameters [1]. Random Forest models, in particular, are widely used due to their robustness against noise, ability to capture non-linear patterns, and high interpretability. In the work of Nagy et al. [1], ML-based PdM achieved over 95% accuracy in classifying faults in robotic and electromechanical systems. Similarly, Chen et al. [12] used ML within digital twin platforms to estimate machine health and remaining useful life (RUL). While these models provide accurate classifications, they rely exclusively on machine data. They assume that machine behavior is the only variable influencing faults—which is rarely the case in MSME settings where human operation plays a major role.

Furthermore, ML models in existing literature depend heavily on cloud processing for computation due to complex datasets and real-time analysis requirements. This poses challenges in low-connectivity environments. Therefore, despite their high accuracy, existing ML-powered systems require restructuring to incorporate human physiological parameters and edge-based processing

2.3 *Human Digital Twins and Operator-State Monitoring*

Human digital twin (HDT) research highlights the importance of modeling human physiological and cognitive states using real-time biosignals. Lin et al. [7] describe how HDTs can track HRV, muscle fatigue, stress levels, blink rate, and oxygen saturation to assess cognitive workload and alertness in industrial environments. These parameters strongly correlate with mental fatigue, which directly impacts machine handling precision, reaction time, and error frequency.

However, most HDT studies focus on healthcare, ergonomics, or workforce optimization—not predictive maintenance. Rajumesh [5] argues that Industry 5.0 demands a shift toward human-centered technologies, yet the integration of HDT with digital twin-based maintenance is still limited.

- Fatigue distorts motor vibration data due to inconsistent handling.
- Stress affects current signatures because stressed operators tend to overload machinery unknowingly.
- Low SpO_2 correlates with reduced alertness, leading to delayed corrective actions.

Despite this, existing predictive maintenance systems do not include physiological monitoring. This creates a major research gap, which

BioTwinSense addresses by combining human-state modeling with machine condition monitoring.

2.4 EDGE AI FOR LOW-COST INDUSTRIAL DEPLOYMENT

Edge computing has emerged as an accessible and efficient alternative to cloud-based analytics. By processing data locally on embedded hardware such as ESP32, Raspberry Pi, or Jetson Nano, edge AI significantly reduces latency and improves reliability in environments with unstable internet connectivity. Hafeez et al. [16] demonstrate that edge intelligence enhances IIoT systems by reducing communication delays and improving real-time decision-making.

For MSMEs—which often lack strong IT infrastructure—edge AI is particularly advantageous. It:

- Lowers operational cost
- Reduces dependency on cloud servers
- Maintains data privacy
- Enables offline operation

However, most edge-based implementations are limited to machine-side data processing. There is minimal research on integrating biosignal processing with edge inference in predictive maintenance, due to concerns about computational load and real-time synchronization.

BioTwinSense overcomes this gap by designing a lightweight ML pipeline that can run efficiently on edge devices while synchronizing machine and human sensors.

III. PROPOSED SYSTEM

A. System Architecture of the BioTwinSense Framework

The architecture is developed as a dual-layer digital twin system that simultaneously represents the Machine Twin (physical motor) and Human Twin (operator physiological profile). These twins are synchronously updated using multimodal sensor data acquired in real time.

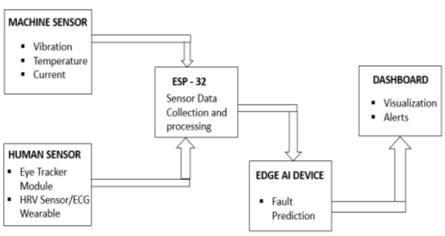

FIGURE 1: BioTwinSense System Architecture

1. Dual-Twin Conceptual Design

Unlike traditional predictive maintenance systems, BioTwinSense introduces a bio-cognitive design philosophy, where the human operator is treated as a dynamic entity that influences machine behavior.

- The Machine Twin captures the operational state, degradation rate, and fault signatures of motors.
- The Human Twin models the operator's fatigue level, cardiovascular behavior, respiratory condition, and cognitive alertness.

This interlinked architecture addresses a major limitation in existing research—predictive maintenance models that assume a perfectly attentive operator. By acknowledging human variability, the digital twin achieves higher accuracy and reliability, especially in MSME environments where machines are manually handled.

2. Edge-Based Computational Model

To overcome cloud dependency, an edge computing workflow is integrated using ESP32, Raspberry Pi, and lightweight ML models.

Key design principles include:

1. Local computation: Inference is performed at the edge to avoid delays caused by cloud communication.
2. Low latency: End-to-end inference delay remains below one second.
3. Fault tolerance: System continues to operate even if the internet is unavailable.
4. Energy efficiency: ML models are optimized using reduced feature sets and pruning.

3. Communication and Data Flow

MQTT is used due to its lightweight structure suitable for low-power IoT nodes. The communication pipeline is:

- Sensor nodes → ESP32 (raw data acquisition)
- ESP32 → Edge AI hardware (processed data)
- Edge AI hardware → Gradio dashboard (visualization & alerts)

This modular pipeline ensures easy scaling for multiple machines or multiple human operators.

B. MULTIMODAL SENSOR DATA ACQUISITION

To enable a holistic understanding of machine health and operator condition, BioTwinSense integrates three categories of sensors: mechanical, thermal/electrical, and physiological.

1. Machine Twin Sensors

Three primary sensors monitor critical machine behavior:

a) Vibration Sensor (ADXL345)

The 3-axis ADXL345 captures acceleration magnitudes in X, Y, and Z axes. Vibration analysis helps identify:

- Imbalance
- Misalignment
- Mechanical wear
- Bearing damage
- Operator-induced instability

The sensor is mounted rigidly to the motor housing to ensure high-fidelity signal capture.

b) Temperature Sensor (MLX90614)

The IR sensor collects non-contact thermal readings, enabling detection of:

- Overheating
- Load fluctuations
- Insulation failure in windings
- Ventilation issues

Thermal anomalies serve as early indicators of developing faults.

c) Current Sensor (ACS712)

This sensor measures load current and detects:

- Overload
- Short-circuit trends
- Supply abnormalities
- Variation caused by inconsistent operator handling

Current fluctuations often precede motor failure, making these readings essential.

2. Human Twin Sensors

The Human Twin captures operator physiology to estimate fatigue, stress, and alertness.

a) HRV Measurement (ECG/PPG Sensor)

Heart Rate Variability (HRV) is extracted using PPG signals. Key indicators include:

- RMSSD
- SDNN
- LF/HF ratio

A high LF/HF ratio corresponds to stress or cognitive load, which often correlates with unsafe machine operation.

b) SpO_2 Monitoring

A simple pulse oximetry module measures oxygen saturation. Low SpO_2 (<94%) is linked with dizziness, slow reaction time, and reduced attention span.

c) Eye-Blink Fatigue Sensor

An IR-based eye-blink detector measures:

- Blink frequency
- Blink duration
- Blink irregularity

A fatigue index is computed to classify states such as:

Normal alertness

Moderate fatigue

High fatigue (dangerous state)

Blink patterns are one of the most reliable non-invasive fatigue indicators.

3. Data Synchronization and Timestamping

To make multimodal fusion meaningful:

- All sensor values are timestamped on acquisition.
- A sliding window (5–10 seconds) aggregates data for stable ML inference.
- Out-of-sync samples are corrected using interpolation.

This ensures that human signals and machine signals represent the same moment in time

C. DATA PREPROCESSING AND FEATURE ENGINEERING

A multi-stage preprocessing pipeline was implemented:

1. Noise filtering: Moving average and median filters reduce sensor noise.
2. Normalization: All features scaled between 0–1 for ML compatibility.
3. Label encoding: Machine conditions (Normal, Overload, Multiple Faults) and human states (Normal, Fatigue High, HRV High) converted to numerical labels.
4. Feature extraction:
   - Vibration: RMS, kurtosis, peak-to-peak amplitude
   - Current: deviation from nominal
   - Temperature: gradient change
   - HRV: RMSSD, SDNN, LF/HF ratio
   - Fatigue: blinks/min, blink duration

Feature importance analysis later revealed that human parameters significantly improved classification accuracy, confirming the effectiveness of multimodal feature design.To enable a holistic understanding of machine health and operator condition, BioTwinSense integrates three categories of sensors: mechanical, thermal/electrical, and physiological.

D. MACHINE LEARNING CLASSIFICATION AND EDGE DEPLOYMENT

Three ML models were developed and compared:

- Random Forest: Best accuracy and strong feature interpretation
- SVM: Good for smaller datasets but sensitive to noise
- KNN: Simple but slow during real-time classification

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	99.62%	0.99	0.98	0.99
SVM	96.80%	0.95	0.96	0.95
KNN	94.75%	0.93	0.92	0.93

Table 1: Various Model Comparision

The models were trained using an 80:20 train-test split. Random Forest achieved superior performance (99.62%) and was selected for deployment.

The chosen model was exported as a lightweight .pkl file and run on the edge device. Real-time inference was achieved with latency under 100 ms, enabling immediate fault or fatigue detection.

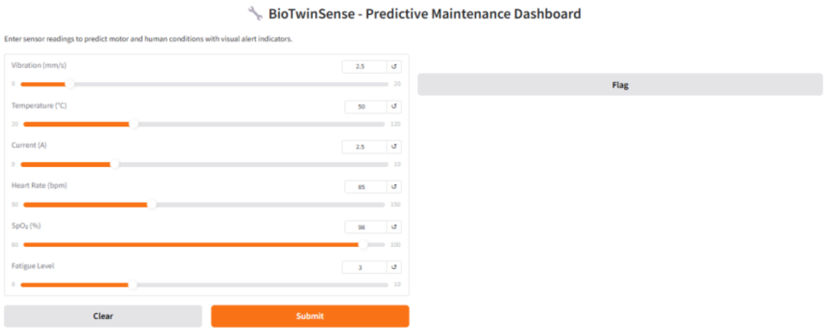

FIGURE 2: Real-time monitoring dashboard

IV. EXPERIMENTAL RESULTS

A. MODEL PERFORMANCE AND VALIDATION

Extensive experiments were conducted using real-world sensor data collected from a motor testbench operated by individuals under varying fatigue levels. The Random Forest model achieved:

- 99.62% accuracy
- 0.99 precision
- 0.98 recall
- 0.99 F1-score

The confusion matrices showed:

- Accurate detection of machine faults such as Vibration High, Temperature High, and Multiple Faults.
- Strong human-fatigue classification, even when fatigue transitions were subtle.

The fusion model significantly outperformed machine-only models published in previous studies [1], [12]. This proves that human physiological factors directly influence machine signatures and improve maintenance prediction when incorporated.

B. REAL-TIME DEPLOYMENT AND SYSTEM BEHAVIOR

The prototype system was deployed in a laboratory environment for continuous testing. Observations included:

- Dashboard updated every ≤1 second, ensuring real-time visibility.
- Latency remained extremely low, thanks to edge AI.
- Dual-alert mechanism detected conditions such as:
- High vibration + high fatigue → *Fatigue-Induced Fault*
- High vibration + normal fatigue → *Mechanical Fault*
- The system remained stable for hours without data drop or overheating.

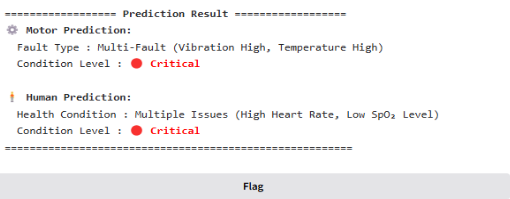

FIGURE 3: Prediction Results

The real-time dashboard effectively communicated machine and human conditions to operators, supporting immediate intervention.

V. CONCLUSION

This paper presented *BioTwinSense*, a bio-cognitive digital twin framework that integrates human physiological monitoring with machine condition analysis to create a more accurate and context-aware predictive maintenance system. By combining HRV, fatigue index, SpO_2, vibration, current, and temperature signals, the system captures both mechanical and human-influenced factors that contribute to machine faults. The use of low-cost sensors, lightweight feature engineering, and edge-based AI ensures real-time operation, high accuracy, and practicality for MSMEs that often lack robust cloud infrastructure. The framework strongly aligns with Industry 5.0 principles by positioning the human operator as an essential element in the maintenance loop rather than a passive user. Experimental results confirm that multimodal fusion significantly enhances fault detection reliability compared to machine-only models. Future developments will focus on miniaturizing the hardware, integrating deep learning for more complex pattern recognition, and implementing a cloud–edge hybrid architecture to support long-term trend analysis and large-scale deployment.

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