Vietnam Journal of Mechanics, Vol. 47, No. 3 (2025), pp. 223 – 234
DOI: https://doi.org/10.15625/0866-7136/22277

EMBEDDED MACHINE LEARNING FOR FAULT DETECTION IN CONVEYOR SYSTEMS USING MULTI-SENSOR DATA AND DISCRETE WAVELET TRANSFORM

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Received: 13 January 2025 / Revised: 15 May 2025 / Accepted: 27 May 2025
Published online: 02 July 2025

Abstract. This study presents a fault detection model utilizing the Seeed Studio XIAO nRF52840 Sense microcontroller development board to identify and diagnose faults in the conveyor belt system of the MPS-PA Bottling Learning System, a component of the Festo Didactic System. The microcontroller is equipped with a 6-axis Inertial Measurement Unit (IMU) and a Pulse Density Modulation (PDM) microphone, enabling it to monitor vibrations and sounds generated during conveyor belt operation. The collected signals are processed using the Discrete Wavelet Transform (DWT) to extract relevant features, which are then used to train an embedded machine learning model designed to detect faults such as bottle obstructions and falls. The conveyor belt transports empty bottles to a dispenser, but a 90-degree turn in the path frequently causes disruptions, resulting in bottle rotation or falls. The IMU captures vibration data, while the PDM microphone records audio signals during these events. The processed DWT features are utilized to train the fault detection model. The model is developed using the TensorFlow Lite framework, incorporating batch normalization to stabilize and accelerate the learning process. Once deployed, the system predicts faults and sends Bluetooth alerts to a host PC when an issue is detected, allowing the process to be halted to prevent further damage. The proposed fault detection model demonstrates promising results, achieving up to 94% accuracy. Additionally, the system's low power consumption, supported by a 200 mAh LiPo rechargeable battery, enhances energy efficiency, contributing to more sustainable manufacturing operations.

Keywords: discrete wavelet transform, sensor fusion, embedded machine learning, fault detection, edge computing.

1. INTRODUCTION

Conveyor belts are essential components in modern manufacturing, facilitating the efficient transport of materials across different stages of production. However, like any mechanical system, conveyor belts are prone to faults and degradation. Common issues include motor overcurrent, dirt accumulation, and belt warping [1]. Additionally, sharp objects transported on the belt may accidentally fall and cause damage [2]. While regularly replacing belts might seem like a practical maintenance strategy, addressing the root causes of these issues and improving system design offer a more sustainable, long-term solution [3].

Recently, data-driven inspection methods based on recorded historical data have become the standard [4]. By analyzing this data, engineers can create preventive maintenance schedules, improving productivity and minimizing unplanned downtime [5].

This study proposes a fault detection method using embedded machine learning with the Seeed Studio XIAO nRF52840 microcontroller kit [6] to monitor the conveyor belt of the Festo MPS-PA Bottling Learning System [7]. This didactic system is designed to simulate industrial conveyor operations, transporting bottles to a water dispensing unit [7]. Over time, the conveyor belt degrades and may eventually fracture. Although the belt can be replaced, recalibration and alignment pose significant challenges, as tuning the belt tension requires manually holding the roller while securing a screw-without a dedicated tuning mechanism.

Furthermore, the system features a 90-degree junction where bottles frequently encounter operational issues. Bottles may rotate in place, causing vibrations in the conveyor frame, and in the worst-case scenario, fall and spill water across the station. While water spills are manageable, transporting corrosive liquids would pose more serious hazards. To address these challenges, the following contributions are aimed to be achieved from this research:

Development of a compact, embedded fault detection system based on the Seeed Studio XIAO nRF52840 Sense microcontroller, leveraging its IMU and PDM microphone sensors to monitor the dynamic behavior of the conveyor belt system in real time.

Implementation of an effective signal processing in a data-driven model: by applying the Discrete Wavelet Transform (DWT) combined with statistical feature extraction, to enhance the characterization of fault signatures from multi-sensor data (vibration and audio) in order to extract features occurring in the error phase (stuck, delay). These features are then used to train a machine learning model, enabling accurate classification of conveyor system anomalies.

Deployment and training of a lightweight and energy-efficient machine learning model, using batch normalization and TensorFlow Lite optimization techniques, to achieve high fault detection accuracy on small and resource-constrained hardware like the XIAO kit, making it a convenient and compact stand-alone device that does not require external hardware.

Demonstration of a real-time fault alert system, capable of detecting and classifying different types of faults within milliseconds after event occurrence, with Bluetooth-based notification to a host PC for immediate response.

Various approaches have been proposed for fault detection in industrial systems using embedded machine learning techniques. For example, Anusha [8] utilized wavelet approximation and a four-layer ANN model with the Edge Impulse tool deployed on an ESP32 microcontroller for conveyor belt maintenance. Moreover, there is also research that has employed discrete wavelet transforms embedded within microcontrollers for real-time anomaly detection in sensor data [9]. Additionally, deep learning methods combined with wavelet transforms have been applied for gear fault diagnosis, demonstrating the effectiveness of such hybrid approaches [10].

When compared to these studies, our work distinguishes itself by integrating statistical feature extraction with DWT for multi-sensor data, specifically tailored for deployment on the compact XIAO nRF52840 microcontroller, making it a stand-alone device without external hardware. While previous works have demonstrated the feasibility of wavelet-based methods and embedded deployments, our approach emphasizes the combination of statistical features and DWT to enhance fault detection accuracy. Furthermore, the use of TensorFlow Lite for model deployment on the XIAO nRF52840 ensures efficient real-time processing suitable for industrial conveyor systems.

2. METHODOLOGY

2.1. Experiment setup

As discussed in the previous section, this study focuses on the MPS-PA Bottling Learning System, with the XIAO nRF52840 kit securely mounted on the conveyor belt frame near the critical 90-degree junction (Fig. 1). This location was selected due to its high vibration levels, which are ideal for capturing fault-related anomalies.

The XIAO nRF52840 kit collects three key types of data: sound, acceleration, and angular velocity. Sound is captured using the onboard microphone, while acceleration and angular velocity are measured through the integrated IMU.

Over the course of the experiment, 100 data samples were collected, each recorded for 20 seconds, and the microcontroller sent all parameter data points every 5 ms. Data

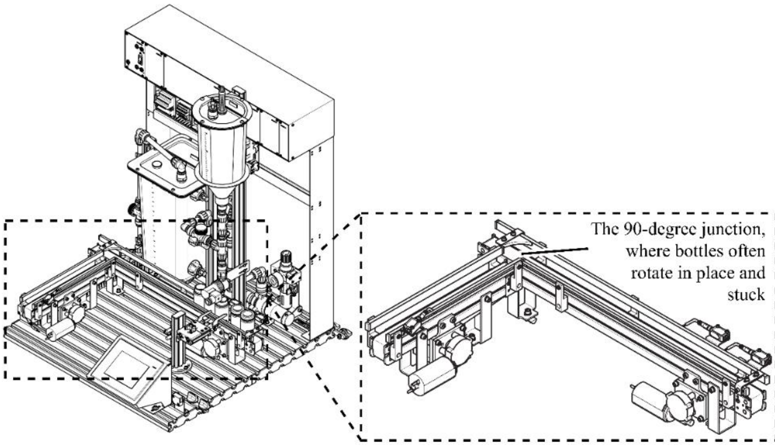

Fig. 1. Festo MPS-PA Bottling Learning System [7]

acquisition took place under both idle and operational conditions of the conveyor belt, capturing a diverse range of operational states to ensure robust analysis.

Fig. 2 illustrates the placement of the XIAO nRF52840 kit on the conveyor frame, highlighting its position near the area identified as experiencing the highest vibration levels. Fig. 3 provides an overview of the experiment setup, including data acquisition, preprocessing workflows, and the integration of the fault detection model.

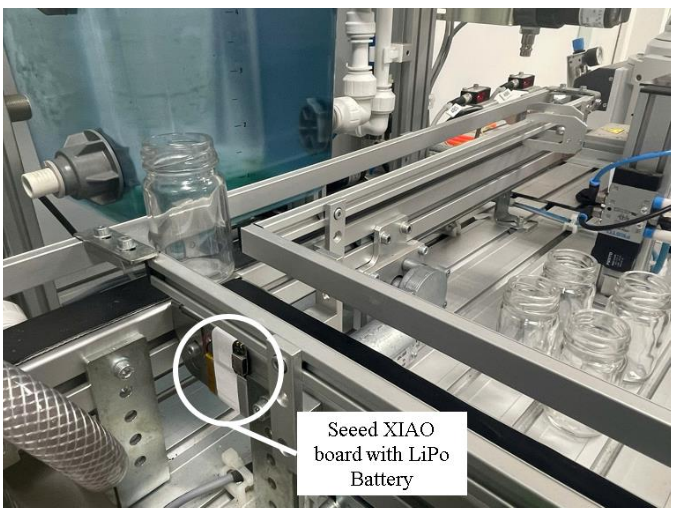

Fig. 2. The XIAO nRF52840 kit is securely mounted on the conveyor frame using double-sided tape, positioned near the junction identified as the area with the highest vibration levels

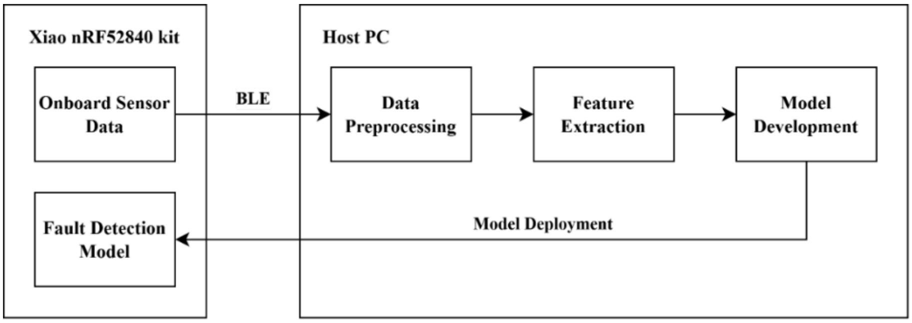

Fig. 3. Experiment overview

2.2. Data preprocessing

For IMU sensor data, the modeling of transverse vibration of conveyor belts in terms of the trough angle shows that the common vibration frequency on conveyors is up to 125 Hz [11], meaning 100 Hz when rounded down. According to the Nyquist Law and the IMU datasheet (LSM6D3), the accelerometer and gyroscope can be configured to sample at 13, 26, 52, 104, 208, 416, 833, 1666, 3332, or 6664 Hz. We decided to choose 208 Hz as a safe sampling rate for the IMU sensor in this case. For the PDM sensor, 16 kHz is the standard sampling output rate. For industrial noises, 5–8 kHz [12] is also an acceptable sampling rate range.

2.3. Feature extraction

Feature extraction is a crucial step in machine learning, converting raw data into a structured format for effective model interpretation [10]. After processing and normalization, relevant features are extracted to train the fault detection model:

- 0 (Normal operation): The idle state.

- 1 (Delay error occurs): Mean that the object velocity is affected by a fault on the conveyor line, resulting in a slight to significant reduction in velocity.

- 2 (Stuck error occurs): The worst scenario in conveyor operation, where the bottle falls and becomes stuck at a fault position on the conveyor line.

These features are extracted from overlapping 0.2-second windows within each sample, with a 50% overlap, ensuring transient events are effectively captured.

2.4. Discrete wavelet transform

Classifying between stuck and fallen bottles, or distinguishing scenarios such as a single bottle stuck, multiple bottles stuck, or multiple bottles fallen, is highly nuanced. To address this complexity, this study investigates the potential of DWT for spectral analysis and feature extraction [10].

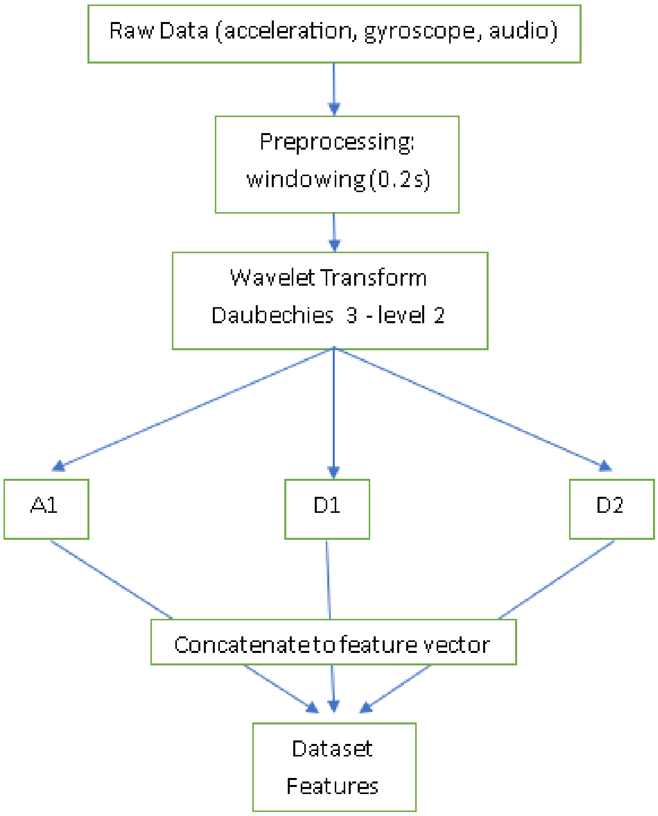

Fig. 4. DWT process to create the dataset

Daubechies wavelets are a family of orthogonal wavelets characterized by their smoothness, compact support, and high vanishing moments, making them well suited for processing discrete signals with gently varying frequencies such as vibration, sound, or rotation.

Daubechies 3 (db3) is a specific variant with three vanishing moments, which balances well between accuracy and computational efficiency. With its asymmetric structure and high smoothness, db3 helps filter noise effectively and preserve necessary details in the signal without increasing computational complexity excessively. Also, in the study by Jha et al. [13], different wavelets were compared for noise filtering and error detection in vibration signals, and it was concluded that Daubechies wavelets, including db3, are capable of retaining important frequency features, which helps in effective error detection.

The DWT process involves decomposing a time-series signal, s, using a pair of filters: a low-pass decomposition filter and a high-pass decomposition filter. These coefficients are then downsampled by a factor of two. The process is repeated by applying the same set of filters to the approximation coefficients (cA_1), generating subsequent levels of approximation and detail coefficients (cD_1, cD_2, etc.). This recursive decomposition can continue for n levels, resulting in a final set of coefficients.

- Approximation coefficients (cA_1), capturing the low-frequency components

$$A1(k) = \sum_{n=0}^{L-1} x[2k-n] \cdot h[n].$$

- Detail coefficients (cD_1 and cD_2), representing the high-frequency components

$$D1(k) = \sum_{n=0}^{L-1} x[2k-n] \cdot g[n],$$
$$D2(k) = \sum_{n=0}^{L-1} A1[2k-n] \cdot g[n],$$

where $x[n]$ is the original signal (raw data); $h[n]$ is the scaling filter (the low-pass filter); $g[n]$ is the wavelet filter (the high-pass filter); and L is the filter length (for DB3: $L = 6$).

2.5. Statistical features

The parameters root mean square, standard deviation, variance, etc. help the model to identify faults by reflecting the level of chaos, rate of change, signal energy, oscillation frequency, deviation, and abnormal peak frequency. These characteristics are also the easiest data preprocessing method for the model to distinguish the three states: Idle, Delay, and Stuck in fault detection.

2.6. Features comparison and analysis

From these data features, it is noticeable that each parameter from these sensors can show differences in the signal if abnormal action occurs on the conveyor: the IMU for vibration movement, and the PDM microphone for the collision sound made by the object and the conveyor. By combining observations from a number of different sensors, a robust and complete description of an environment or process of interest can be provided, which is our purpose in this specific case.

Statistical features

Root mean square demonstrates the overall energy of the vibration. It reflects the overall trend of signal noise, whether an error occurs or not, and its period.

Standard deviation focuses more on the error signal detail, specifically the amount of vibration, which increases markedly when the object starts to lag. However, once the signal noise error is recognized, the standard deviation signal seems to lose detail over time, which makes it still not reliable in terms of accuracy.

Variance tends to be similar to standard deviation but is more sensitive to large amplitudes and tends to demonstrate the highest amplitude in error. However, like the standard deviation, it still lacks detail in terms of time series accuracy.

Discrete wavelet transform

A2 (Approximation): the lowest level of decomposed signal, meaning it reflects the overall trend for the whole operation process and has an effective role in identifying long-term idle states or the overall error trend, similar to the root mean square in statistical features.

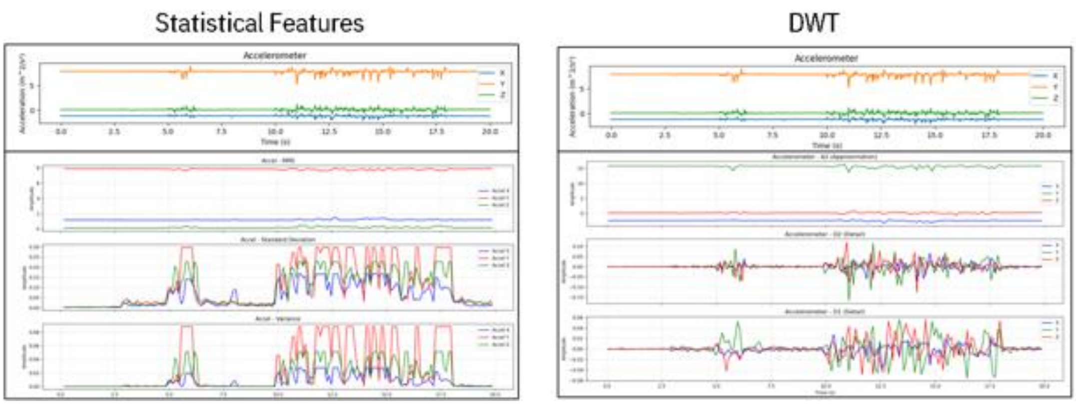

Fig. 5. DWT and statistical features comparison.

In Fig. 5, D2 (Detail level 2) has the role of capturing medium-frequency oscillations, and D1 (Detail level 1) demonstrates the highest frequency for fast collisions and strong vibrations. At first glance, the signal details in these coefficients are highly accurate in time series. When errors happen, the signals are clearly represented by sharp peaks in signal features, indicating the ability to accurately locate the time of the fault. While D2 reflects signs of slight impact, moderate vibration, or changes in the object's state of motion, D1 is particularly effective in detecting faults such as objects becoming stuck due to collisions or abnormal vibrations. The sharp peaks in long-term errors at 11 and 17 seconds in Fig. 5 DWT plot demonstrate the high sensitivity of detail coefficients to these types of faults.

When combined with the A2 approximation coefficient that reflects the long-term trend and background behavior of the system, the wavelet transform provides a comprehensive view of both the overall and detailed characteristics of the signal, which is especially useful in classifying operating states such as idle, delay, and stuck in conveyor systems.

3. MODEL DEVELOPMENT

This study utilizes TensorFlow Lite to develop an embedded fault detection model. The dataset was split into an 80:20 ratio for training and validation, and batch normalization was implemented to stabilize and accelerate training [14]. To handle class imbalance in the dataset, `compute_class_weight()` was used to assign appropriate weights to each class, reducing bias toward the majority class and improving the accuracy of error detection. The model is a multi-layer fully connected neural network built using TensorFlow's Sequential API. It consists of an input layer matching the feature size, followed by three hidden layers:

- **Layer 1**: 256 neurons, ReLU activation, batch normalization, and dropout (0.3).
- **Layer 2**: 128 neurons, ReLU activation, batch normalization, and dropout (0.2).
- **Layer 3**: 64 neurons, ReLU activation.

The output layer has three neurons with a softmax activation function to classify objects into three categories: **idle, delay, and stuck**. The model is trained using categorical cross-entropy loss, optimized with Adam, and evaluated based on accuracy. To prevent overfitting, early stopping halts training if no improvement is observed after 10 epochs, with a maximum of 100 epochs. A batch size of 32 is chosen to balance training efficiency and model performance. After training and evaluating the model, it is saved as a `model.keras` file and then converted to TensorFlow Lite. This conversion ensures that the model fits within the small memory constraints of the XIAO nRF52840 while also enabling faster inference.

4. EVALUATION

Once the datasets are ready, a hybrid model was developed and trained using both statistical features extracted from raw sensor data and features derived from Discrete Wavelet Transform (DWT) coefficients. Table 1 summarizes the evaluation results of these models based on precision, recall, and F1-score.

From Fig. 6, the data points in the stuck group form a relatively separate cluster compared to the rest. This shows that the model has learned the features related to the

Table 1. Model results

	Precision	Recall	F1-score
Normal (0)	0.93	1.00	0.96
Delay (1)	0.99	0.86	0.92
Stuck (2)	0.89	0.95	0.92

phenomenon of objects stuck on the conveyor belt for a long time well. The idle group and delay group tend to have considerable overlap. The difficulty in separating these classes may be due to the fact that the data characteristics between Idle and Delay are not clearly different enough.

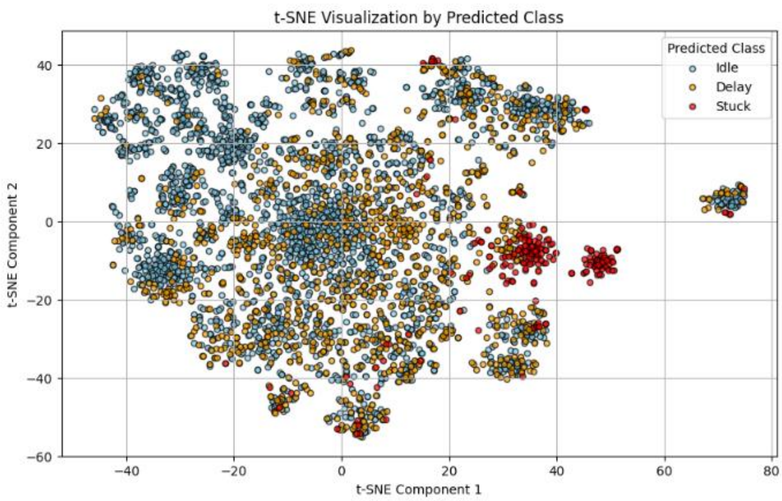

Fig. 6. t-SNE graph of ML model

One main reason is that the current delay labeling rule is not yet optimal. During the collection and labeling process, short delay phenomena are still labeled as delay, while in essence they can be considered normal activities (idle). For the stuck group, the definition is more clear (objects stuck for more than 4 seconds or collision/fall), making it easier for the model to learn and distinguish.

5. DISCUSSION AND FUTURE DIRECTIONS

In summary, this study proposes a fault detection model using TensorFlow Lite on the Seeed XIAO nRF52840 kit and evaluates it with the Festo MPS-PA Bottling Learning System. The model, trained on both statistical features and features derived from wavelet coefficients, reached 94% accuracy.

However, certain challenges were identified during the study. The occurrence of severe cases, such as falling bottles, was extremely rare, making it time-intensive to collect sufficient data to capture this behavior. To address this, implementing an anomaly detection approach, such as K-Clustering Anomaly Detection [15], could be more efficient.

Additionally, the spectral analysis using Discrete Wavelet Transform (DWT) has not been thoroughly explored. Moreover, the current training dataset does not cover all possible scenarios, necessitating the collection of more comprehensive data.

Furthermore, the fault detection alarm should be integrated with the MPS-PA Bottling Learning System's controller to enable immediate system shutdown upon detecting a fault. Using the OPC-UA protocol for this communication would ensure seamless integration and efficient response times [16].

Finally, developing a preventive maintenance framework based on the proposed model would further enhance the system's longevity and operational efficiency. Such a framework would also enrich the learning materials available for automation training using the MPS-PA Didactic System, which already offers extensive educational content. These enhancements would not only improve fault detection but also provide significant educational value.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

ACKNOWLEDGMENT

This research is funded by the Vietnamese-German University Research Funding under grant number DTCS-2023-002.

REFERENCES

[1] I. Elbadawi, M. A. Ashmawy, W. A. Yusmawiza, I. A. Chaudhry, N. B. Ali, and A. Ahmad. Application of failure mode effect and criticality analysis (FMECA) to a computer integrated manufacturing (CIM) conveyor belt. *Engineering, Technology & Applied Science Research*, **8**, (2018), pp. 3023–3027. https://doi.org/10.48084/etasr.2043.

[2] G. Fedorko, V. Molnar, D. Marasova, A. Grincova, M. Dovica, J. Zivcak, T. Toth, and N. Husakova. Failure analysis of belt conveyor damage caused by the falling material. Part I: experimental measurements and regression models. *Engineering Failure Analysis*, **36**, (2014), pp. 30–38. https://doi.org/10.1016/j.engfailanal.2013.09.017.

[3] C. Yan and X. He. Model and dynamic simulation of belt conveyor. In *2010 International Conference on Intelligent System Design and Engineering Application*, IEEE, (2010), pp. 949–951. https://doi.org/10.1109/isdea.2010.331.

[4] E. Ruschel, E. A. P. Santos, and E. d. F. R. Loures. Establishment of maintenance inspection intervals: An application of process mining techniques in manufacturing. *Journal of Intelligent Manufacturing*, **31**, (2018), pp. 53–72. https://doi.org/10.1007/s10845-018-1434-7.
[5] L. Xiao, S. Song, X. Chen, and D. W. Coit. Joint optimization of production scheduling and machine group preventive maintenance. *Reliability Engineering & System Safety*, **146**, (2016), pp. 68–78. https://doi.org/10.1016/j.ress.2015.10.013.
[6] L. Feng and M. Rovai. *XIAO: Big power, small board*. Seeed Studio, (2024). https://files.seeedstudio.com/wiki/XIAO_Big_Power-Board-ebook-photo/XIAO_Big_Power_Small_Board_v20240307.pdf.
[7] Festo. *MPS-PA stations—bottling learning system*, (2019).
[8] P. V. S. Anusha. Edge machine learning-enabled predictive fault detection system for conveyor belt maintenance optimization in industrial settings. *Journal of Electrical Systems*, **20**, (2024), pp. 2031–2041. https://doi.org/10.52783/jes.4003.
[9] J. Pacheco, V. H. Benitez, G. Pérez, and A. Brau. Wavelet-based computational intelligence for real-time anomaly detection and fault isolation in embedded systems. *Machines*, **12**, (2024). https://doi.org/10.20944/preprints202408.1710.v1.
[10] M. Heydarzadeh, S. H. Kia, M. Nourani, H. Henao, and G.-A. Capolino. Gear fault diagnosis using discrete wavelet transform and deep neural networks. In *IECON 2016 - 42nd Annual Conference of the IEEE Industrial Electronics Society*, IEEE, (2016), pp. 1494–1500. https://doi.org/10.1109/iecon.2016.7793549.
[11] P. Bortnowski, R. Król, and M. Ozdoba. Modelling of transverse vibration of conveyor belt in aspect of the trough angle. *Scientific Reports*, **13**, (2023). https://doi.org/10.1038/s41598-023-46534-w.
[12] R. L. Dunn. Understanding industrial noise. *Plant Engineering Magazine*, (2001). https://www.plantengineering.com/articles/understanding-industrial-noise/.
[13] R. K. Jha, P. D. Swami, and D. Singh. Comparison and selection of wavelets for vibration signals denoising and fault detection of rotating machines using neighborhood correlation of SWT coefficients. In *2018 International Conference on Advanced Computation and Telecommunication (ICACAT)*, IEEE, (2018), pp. 1–5. https://doi.org/10.1109/icacat.2018.8933643.
[14] S. Ioffe and C. Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. *arXiv preprint arXiv:1502.03167*, (2015). https://doi.org/10.48550/arXiv.1502.03167.
[15] N. Liao and X. Li. Traffic anomaly detection model using K-means and active learning method. *International Journal of Fuzzy Systems*, **24**, (2022), pp. 2264–2282. https://doi.org/10.1007/s40815-022-01269-0.
[16] P. Vrignat, B. Robles, M. Avila, and F. Kratz. OPC UA: Examples of digital reporting applications for current industrial processes. *DEStech Transactions on Engineering and Technology Research*, (2018). https://doi.org/10.12783/dtetr/ecar2018/26363.