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RHEINISCH WESTFÄLISCHE TECHNISCHE HOCHSCHULE AACHEN
FACULTY OF MECHANICAL ENGINEERING

PROJECT REPORT

INTELLIGENT MONITORING OF THE PRODUCTION SYSTEM

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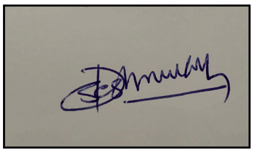
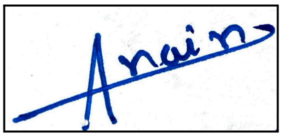
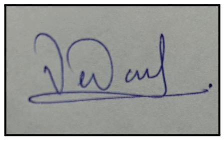
Declaration

We declare to the best of our knowledge that we have written this report by ourselves and only with the help of all references listed in the bibliography.

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Aachen, July 15, 2025

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1 Introduction

1.1. Motivation

Intelligent monitoring is an important part of modern engineering systems. It helps improve dependability, operational effectiveness, and the continuous operation of equipment [1]. By providing real-time data and meaningful insights into system performance, intelligent monitoring makes it possible to detect problems and potential failures at an early stage[2]. This proactive method helps reduce downtime, lowers maintenance costs, and extends the lifespan of equipment by addressing issues before they become serious.[1]

In addition to supporting reliable operations, intelligent monitoring gives engineers and managers the information needed to make better decisions. Having accurate and continuous data makes it easier to manage and optimize systems, as it allows for adjusting parameters to achieve better performance[3]. Real-time monitoring is especially important in high-risk industries like aviation, nuclear power, and manufacturing, where safety cannot be compromised[6]. It ensures that operations stay within safe limits and provides quick warnings about dangerous conditions, which helps maintain overall safety[5].

Another major benefit of intelligent monitoring is its role in meeting industry standards and regulations. Keeping detailed records of system performance and following safety rules helps organizations pass audits and inspections while avoiding legal issues or penalties[1]. Overall, intelligent monitoring in engineering not only improves efficiency, safety, and reliability, but also helps with regulatory compliance and informed management decisions. This makes it possible for organizations to maintain high standards of performance and safety[3].

This project is centred on detecting defects in an assembly line in real time, with the main goal of preventing workflow interruptions. To meet this goal, acceleration data was collected over time using smartphone accelerometers placed at strategic points along the assembly line[2]. This method allowed for comprehensive coverage of the dynamic behavior of the system[1].

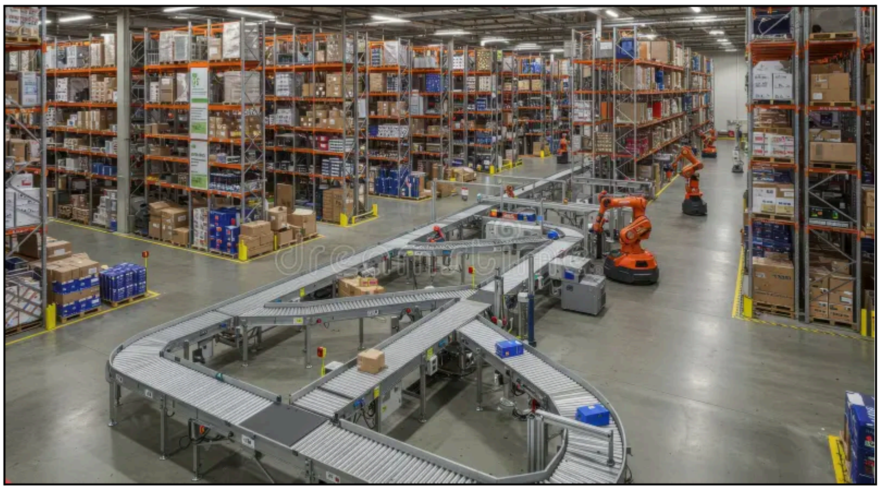


Figure 1- Advanced Material Sorting Warehouse (https://thumbs.dreamstime.com/b/automated-warehouse-conveyor-belts-robotic-arms-efficient-logistics-automated-warehouse-conveyor-belts-353383230.jpg)

The collected acceleration data underwent a series of preprocessing steps, including band-pass filtering and Fast Fourier Transform (FFT) analysis, to isolate and identify critical frequency components associated with potential defects[5]. The extracted features from this preprocessed data served as the foundation for training advanced computational models. Specifically, Random Forest algorithms were employed for the detection of frequency-based defects, while Convolutional Neural Networks (CNNs) were utilized for damping and inclination defect detection[3]. The CNN models were independently optimized using statistical and temporal features derived from the filtered acceleration signals, ensuring robust performance across different defect types[4].

1.2. Division of work and responsibilities

To ensure an efficient and systematic workflow, project responsibilities were clearly distributed among team members as follows:

- Data Collection: Vedant Uddhavrao Chavan, Sumit Deshmukh
- Data Pre-processing: Abhishek Nain, Sumit Deshmukh
- Feature Selection: Neelabh Bhadauria, Abhishek Nain
- Computational Modeling: Abhishek Nain, Vedant Uddhavrao Chavan
- Presentation and Report Preparation: Neelabh Bhadauria, Abhishek Nain

2 Methods

2.1. Signal (pre-)processing

To prepare the dataset for training, acceleration-time data was collected using smartphone accelerometers via the Phyphox app. The raw signals contained noise and baseline drift, so a band-pass filter (25–65 Hz) was applied to isolate the frequency range where mechanical defects were expected, based on domain knowledge and training data characteristics.

After filtering, Fast Fourier Transform (FFT) was conducted on all three axes of acceleration (Ax, Ay, Az). The FFT allowed us to visualize dominant frequency peaks which were then matched against known defect patterns for confirmation. This step was crucial for cases with frequency-specific anomalies.

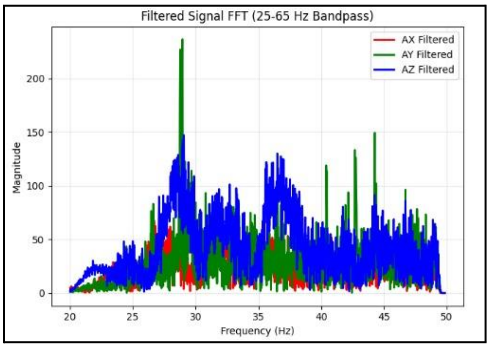
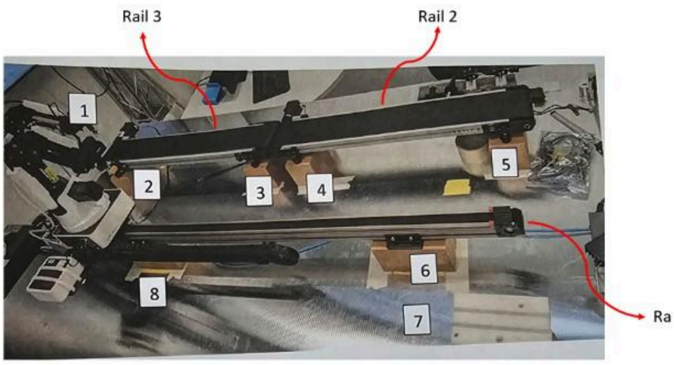


Figure 2: FFT performed on Python



[1]

Figure 3: Assembly Line Setup

The signal was segmented based on timestamp metadata and additionally through a data-driven approach using the 25th percentile (P25) of acceleration values. By analyzing variations in P25 over time, we were able to identify transitions between physical sections of the assembly line automatically. This percentile-based sectioning method provided a robust

---

1

and interpretable boundary mapping aligned with real-world structural changes. Using this segmentation, relevant time-domain and frequency-domain features were extracted.

These included:

- Rolling mean and standard deviation
- Peak frequency
- Spectral energy
- Percentiles (e.g., 25th, 75th) to capture signal shape differences across sections

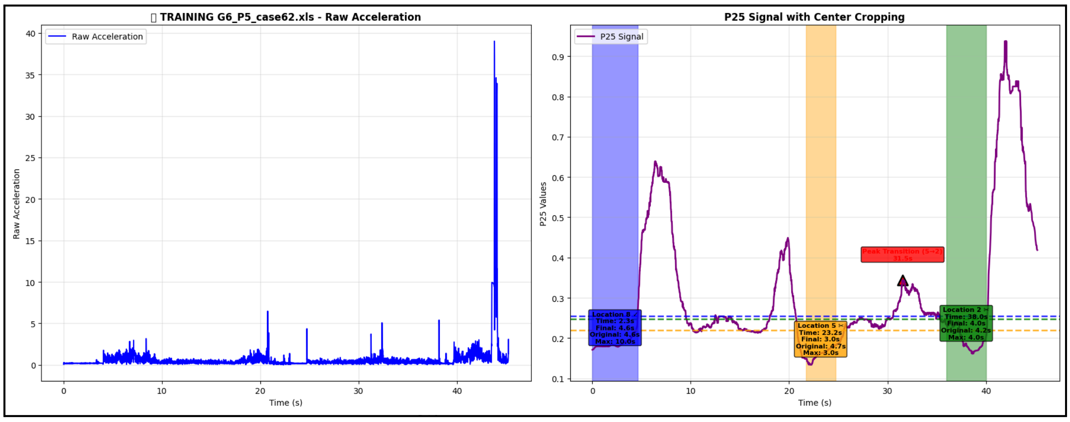


Figure 4:Raw Acceleration Data

Figure 5: P25 w.r.t time

A final feature matrix was compiled for each case, combining the statistical features, raw segment assignment, and timestamp alignment. Labeling was done via a custom Python metadata dictionary, assigning binary labels (1 for defect, 0 for normal) for damping and inclination per timestamp.

2.2. Computational Model

To address different types of defects effectively, our approach divided the modeling pipeline into specialized stages:

Frequency Defect Detection: We used a Random Forest Classifier trained on section-wise FFT-derived features to detect the presence of frequency defects. The model used features such as peak frequency and spectral energy, combined with metadata alignment. Oversampling techniques were applied to address class imbalance. For exact frequency estimation, a Random Forest Regressor was also trained, using the same set of FFT-based features, to provide a more continuous approximation of the dominant frequency. A separate model then predicted the most likely frequency location based on the predicted magnitude distribution.

Damping and Inclination Defect Detection: For damping and inclination, two separate 1D Convolutional Neural Network (CNN) models were trained. These models leveraged time-series sequences of filtered acceleration data (Ax, Ay, Az). No section identifiers were provided as input; instead, defect location was predicted purely from acceleration signal features. Class imbalance was handled using SMOTE for inclination and class weighting for damping.

Each CNN was optimized for its specific task, with separate input pipelines and loss functions for damping and inclination. The input shape included three filtered acceleration signals per timestamp, without section ID.

This modular approach allowed us to fine-tune each model independently, improving generalization across unseen test cases.

2.3. Best performing model

In addition to the CNNs used for damping and inclination, our best-performing model for frequency defect classification was a Random Forest Classifier. This model was trained on FFT-derived features and demonstrated a good trade-off between interpretability and accuracy, achieving an estimated accuracy of around 83% in frequency location prediction (as shown in our test results).

2.3.1. Model architecture

For our machine learning models, the training data consisted of several key inputs: time stamps, accelerations, and filtered segments of data for damping and inclination. Additionally, for frequency modeling, FFT-transformed magnitudes for each section were included. Frequency modeling relied on section-wise magnitude predictions and peak detection.

The frequency prediction model was based on two Random Forest models: one for classifying whether a frequency defect is present, and the other for estimating the exact frequency value. Frequency location was deduced by selecting the section corresponding to the peak predicted frequency magnitude. This multi-stage logic helped separate magnitude estimation from location prediction.

For damping and inclination, we used two dedicated CNN models. These models were trained to predict damping and inclination occurrence using only filtered acceleration sequences. The CNN was structured with two Conv1D layers followed by a Global Max Pooling layer and Dense layers to learn the nonlinear temporal patterns in the vibration signal.

The Conv1D layers extracted local patterns over time, crucial for detecting signal distortions caused by damping or shifts due to inclination. We employed ReLU as the activation function and added dropout layers to avoid overfitting. Our architecture ensured that despite noisy or variable sensor inputs, the models could detect subtle changes in the waveform.

2.3.2. Training parameters

- Optimizer: Adam
- Learning Rate: 0.001 (for CNNs); varied for Random Forest models via grid search
- Batch Size: 64 (CNNs)
- Epochs: 50 (CNNs)
- Validation Split: 0.2
- CNN Loss Function: Binary Cross-Entropy
- Metrics: Accuracy and F1 Score for CNNs; R^2 and MSE for RF Regressor

To prevent overfitting, early stopping was used, and class imbalance was tackled using SMOTE (inclination) and weighted loss (damping). Random Forest models were tuned using cross-validation and bootstrapped ensembles to achieve stable prediction boundaries.This integrated modeling framework enabled modular learning pipelines - RF-based modeling for frequency prediction, and CNN-based detection for dynamic motion-based anomalies.

3 Results

3.1. Cross Validation

To evaluate the internal robustness and performance consistency of our models, cross-validation strategies were applied during training.

Frequency Model (Random Forest): The frequency classification and regression pipelines utilized 5-fold cross-validation on the training set. Each fold preserved the class distribution to handle imbalance and evaluate model generalizability. The classification model was assessed using accuracy and F1 score, while the regression model used Mean Squared Error (MSE) and R^2 score. Average classification accuracy was approximately 87%, and average R^2 score for regression was around 0.92. The standard deviation across folds was low, suggesting stable and consistent performance.

Damping and Inclination Models (CNN): For the CNN models detecting damping and inclination defects, a stratified 80:20 train-validation split was used due to the limited dataset size. In combination with this, each model was trained and validated across three independent runs with different random seeds to verify performance consistency.

To mitigate class imbalance, SMOTE was applied to the inclination dataset, and weighted loss functions were used for damping. Early stopping and learning rate monitoring were employed during training to avoid overfitting.

On the validation set, the CNN model for damping achieved an accuracy of 95.08%(fig.7), but recall for defect cases was only 58.25%(fig.7), with a high number of false negatives. Precision for defect detection was 45.02%(fig.7), and F1 score was 50.79%(fig.7). For inclination, the model performed much better, with validation accuracy of 99.84%(fig.6), recall of 99.89%(fig.6), and precision of 95.74%(fig.6), indicating consistent performance.

These results demonstrate that while the inclination model generalizes well during training, the damping model exhibits limited sensitivity to positive cases, motivating further improvements.

```
--- VALIDATION - INCLINATION DEFECT Performance Metrics ---
Overall Accuracy:  0.9984
Overall Precision: 0.9985
Overall Recall:    0.9984
Overall F1-Score:  0.9985

Per-Class Metrics:
No Inclination Defect  - Precision: 1.0000, Recall: 0.9984, F1: 0.9992
Inclination Defect     - Precision: 0.9574, Recall: 0.9989, F1: 0.9777

Confusion Matrix:
[[51428    81]
 [    2  1820]]
```

Figure 6: Inclination Defect performance matrix

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--- VALIDATION - DAMPING DEFECT Performance Metrics ---
Overall Accuracy:  0.9508
Overall Precision: 0.9576
Overall Recall:    0.9508
Overall F1-Score:  0.9538

Per-Class Metrics:
No Defect  - Precision: 0.9807, Recall: 0.9676, F1: 0.9741
Defect     - Precision: 0.4502, Recall: 0.5825, F1: 0.5079

Confusion Matrix:
[[49350  1655]
 [  971  1355]]
```

Figure 7: Damping Defect Performance Matrix

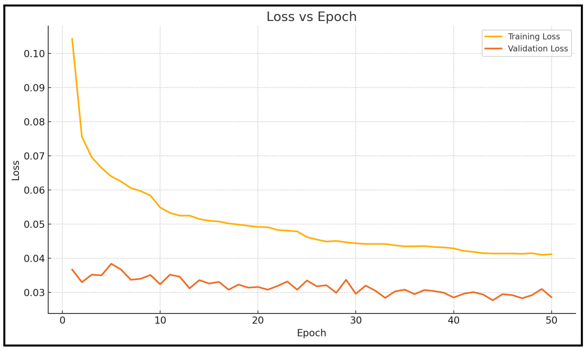

Figure 8: Loss vs Epochs

3.2. Discussion

The trained models were evaluated on five separate test cases. Table 1 presents the CNN model's predictions compared with the actual ground truth provided by the course supervisor.

Test Case	Frequency	Frequency Location	Inclination		Damper	
			Predicted	Actual	Predicted	Actual
1	35Hz	6	Location 4	-	Location 5	-
2	0	-	-	Location 2	-	-
3	40Hz	3	-	Location 6	-	-
4	40Hz	3	Location 4	-	-	Location 5
5	0	-	-	Location 2	Location 6	Location 6

Table 1: Actual and Predicted results

A comparison of the predicted results vs. actual values shows that:

1. Frequency Prediction (Random Forest): Accurate in 5 out of 5 cases for both frequency value and location.
2. Inclination Prediction (CNN): Incorrect in all 3 cases where inclination was present.
3. Damping Prediction (CNN): Partially correct — only 1 out of 2 damping defects were correctly predicted.

3.3. Generalization ability

The frequency detection model exhibited strong generalization, correctly identifying both the presence and location of frequency-related defects across all five test cases. This confirms the robustness of FFT-derived features and the Random Forest pipeline for frequency classification and regression tasks.

In contrast, the CNN models for damping and inclination showed limited generalization to unseen cases. Despite high validation accuracy, performance on the test set was poor. None of the three inclination defects were detected, and one of two damping defects was missed. This indicates the models may have overfit to training data, particularly as the dataset is heavily imbalanced, with most timestamps labeled as non-defective. Consequently, high overall accuracy was misleading — driven primarily by a large number of true negatives — while recall for actual defects was significantly lower (e.g., 58.25% for damping).

The discrepancy between validation and test performance underscores the need for improved data diversity, better feature representation, and model regularization. Enhancing the input representation or expanding the labeled dataset could help build models that generalize better across diverse defect scenarios

4 Conclusion and outlook

4.1. Conclusion

This project set out to design and evaluate a machine learning-based monitoring system for identifying defects within a production assembly line using smartphone accelerometers[7]. The proposed approach combined FFT-based feature extraction with supervised learning pipelines[8]. Random Forest classifiers and regressors were used for detecting frequency-related anomalies, while Convolutional Neural Networks (CNNs) targeted damping and inclination shifts.

The experimental results demonstrated that the frequency model was both robust and effective. In all five test cases, this model consistently identified the frequency and location of anomalies. Cross-validation of the frequency pipeline yielded high classification accuracy (around 87%) and strong regression performance (R^2 approximately 0.92), with low standard deviations, indicating consistent and generalizable behavior.

In contrast, the CNN models for damping and inclination detection struggled to generalize to unseen test cases despite achieving high validation accuracies (over 95% for damping and over 99% for inclination). The variance between validation and test results suggests that these models were overfitting to known training patterns rather than learning features that could be applied to new data[9]. Notably, this limitation stemmed from modeling challenges rather than data quality. For example, differences in sampling rates across sensors made it difficult to create uniformly sized sections required for deep learning input[10]. In addition, the section mapping logic may have not always accurately captured transitions between structural elements, which impacted the model’s spatial learning capabilities.

To address these challenges, a more effective input structure could be adopted. Rather than relying solely on direct timestamped sequences, the use of section-wise statistical features specifically engineered for damping and inclination may reveal more informative patterns. By representing local signal variations more precisely, these features could enhance the model's ability to distinguish between defect and non-defect conditions in various assembly sections.

In summary, while the frequency model demonstrated strong reliability and generalization, the damping and inclination detection models require further tuning in their architecture, improved preprocessing, and the exploration of more suitable feature representations.

4.2. Outlook

Looking forward, improving the performance of the CNN models should be a primary focus. This can be achieved by refining the input features—engineering section-specific statistical features such as signal energy, envelope variation, and intensity within selected frequency bins. Such features could make it easier for the models to detect localized patterns associated with damping and inclination defects. Establishing a more robust preprocessing pipeline to align sampling rates across all sensors will also contribute to greater input consistency and model reliability.

Further, hybrid model architectures that integrate CNNs with attention mechanisms or recurrent layers may prove helpful, especially in capturing subtle signal transitions that are typical of certain defects.

The adaptability and accuracy of the frequency model suggest a promising application in real-time industrial monitoring. With minimal additional computation, this classifier could serve as a live anomaly detector, allowing operators to identify and address issues proactively. Timestamp-level predictions would also contribute to detailed traceability, supporting predictive maintenance efforts.

This project opens several avenues for further research and application:

- Optimizing section mapping algorithms to more reliably detect transitions in complex mechanical assemblies.
- Studying model robustness under different load conditions, noise environments, and equipment types.
- Expanding the dataset to include more assembly lines, supporting the training of models that generalize across broader industrial settings.
- Investigating model interpretability techniques to better understand which features are most influential, guiding both future sensor data collection and feature engineering.

Overall, while the project achieved reliable results for frequency-related defect detection, continued work on input feature design, model architecture, and preprocessing alignment will be essential to improve the detection of damping and inclination anomalies. With these improvements, machine learning-based monitoring solutions such as the one presented here can play a significant role in advancing predictive maintenance practices for modern manufacturing systems.

5 References

[1] Lee, J., Lapira, E., Bagheri, B., & Kao, H.-A. (2013).
Recent advances and trends in predictive manufacturing systems in big data environment.
Manufacturing Letters, 1(1), 38–41.
https://doi.org/10.1016/j.mfglet.2013.09.005

[2]Zhao, R., Yan, R., Chen, Z., Mao, K., Wang, P., & Gao, R. X. (2019).
Deep learning and its applications to machine health monitoring.
Mechanical Systems and Signal Processing, 115, 213–237.
https://doi.org/10.1016/j.ymssp.2018.05.050

[3] Bharathi, N., & Sarma, D. V. S. (2019).
Defect Detection in Manufacturing Systems Using Sensor Data and Machine Learning Approaches.
In *Proceedings of the 2019 International Conference on Intelligent Manufacturing and Automation*, pp. 212–217.

[4] Li, X., Ding, Q., & Sun, J. Q. (2018).
Remaining useful life estimation in prognostics using deep convolution neural networks.
Reliability Engineering & System Safety, 172, 1–11.
https://doi.org/10.1016/j.ress.2017.11.021

[5]Randall, R. B. (2011).
Vibration-based Condition Monitoring: Industrial, Aerospace and Automotive Applications.
John Wiley & Sons.

[6]Widodo, A., & Yang, B.-S. (2007).
Support vector machine in machine condition monitoring and fault diagnosis.
Mechanical Systems and Signal Processing, 21(6), 2560–2574.
https://doi.org/10.1016/j.ymssp.2006.12.007

[7] Kim, J., Lee, J., Park, Y., & Lee, J. (2018). "Smartphone-Based Data Acquisition and Real-Time Monitoring for Industrial Machines." Sensors, 18(1), 206.

[8] Hastie et al., 2009
Hastie, T., Tibshirani, R., & Friedman, J. (2009). The Elements of Statistical Learning. Springer.

[9] Goodfellow et al., 2016
Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.

[10] Smith, S. W. (2007). The Scientist and Engineer's Guide to Digital Signal Processing. California Technical Publishing.