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A Conceptual Framework on AI-Driven Predictive Maintenance System on Conveyor Belt Systems in the Food Processing and Beverage Manufacturing Industry

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Abstract

This paper discusses a framework for an AI-driven predictive maintenance system to detect belt misalignments in conveyor belt systems in the food and beverage industry. Conveyor belts in the FMCG sector are critical for efficient production, but they often fail due to belt drift and misalignment. This can lead to downtime and safety risks. This approach uses sensor data, preprocessing, and AI modelling to predict misalignments. A Kaggle dataset was analysed to study parameters such as vibrations, motor current, load, and belt tension. A random forest classifier was used as a proof of concept, predicting misalignment events with 88% accuracy, 85% precision, and 86% recall. The framework has five main layers; data collection, data preprocessing, AI model interface, performance evaluation, and decision support. So even without using real-time industrial data, the results show that AI- based predictive maintenance is feasible in resource-limited settings like Papua New Guinea. This framework offers a practical basis for local industries to reduce unplanned downtime, improve overall production efficiency and take the first step to Industry 4.0.

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Introduction

Conveyor belt systems are a fast and efficient mechanical system, responsible for handling and transporting materials from one place to another. In the food processing and beverage manufacturing industry, they play a key role in production, ensuring a smooth, safe and continuous flow of products through the different stations of production. Because these systems connect nearly every stage of production, their performance has a direct impact on overall efficiency, output quality, and plant productivity.

Conveyor belt systems are the most mechanically stressed system in any production line. By being used every second of everyday they face many unplanned breakdowns due to belt misalignment, roller wear, or drive motor imbalance. Unplanned equipment failures can slow production, raise maintenance costs, and create safety risks. Studies show that they may account for up to 20%-30% of annual productivity losses, highlighting the importance of early detection and preventive measures.

Unplanned downtime is a serious concern for perishable goods that can easily be spoiled if not handled properly. This creates a need for maintenance strategies that can anticipate breakdowns before they occur. This project proposes a predictive maintenance framework for conveyor belt, designed as an early warning system that monitors belt conditions to prevent failures. Such a system can improve operations, increase equipment reliability, and reduce downtime.

Objectives

- Investigate causes and effects of belt misalignment.
- Design a sensor-based monitoring system.
- Develop a data acquisition and preprocessing strategy.
- Evaluate the feasibility of an AI-based predictive model.

Literature Review

Introduction to Predictive Maintenance in the Food and Beverage Industry

The food and beverage manufacturing industry uses conveyor belt systems for material handling, processing and packaging. Any unplanned breakdowns lead to production losses, quality risks such as spoilage or contamination, and supply chain delays.

Predictive maintenance has now being used as a smarter and proactive maintenance strategy to detect faults before failure, improving planned maintenance. The rise of industry 4.0, IoT (Internet of Things), and big data analytics has made AI-driven maintenance strategies more feasible and precise.

The development of predictive maintenance strategies for conveyor belt systems has now advanced to including the integration of artificial intelligence (AI), machine learning (ML) models and IoT. Recent studies on this matter have described both general frameworks for technological integration and controlled experiments made to validate the application in the

F&B industry. Two sources of information reviewed agreed with each other: one reviewed modern digital technologies, and the other tested how machine learning (specifically random forest) can be used when machines need maintenance [1].

Role of Artificial Intelligence and Machine Learning in Predictive Maintenance

AI techniques allow machinery and mechanical systems to self-diagnose and predict failures without human intervention. Machine Learning (ML) models are a subset of AI — supervised, semi-supervised, unsupervised, and reinforcement learning — they are widely used to detect and classify fault patterns. This can be achieved by feeding the model with large amounts of data where it learns and improves using deep learning, thus not requiring advanced programming. Deep learning, especially Convolutional Neural Networks (CNNs), provides a better classification skills compared to traditional algorithms by learning the complex feature relationships from raw sensor data. In conveyor systems, there are multiple interacting variables influence performance, AI allows modelling of two more of these dependent variables more effectively than manual approaches that rely on decision trees that use a manual threshold [2].

Time-Series Data in Conveyor Belt Systems

Conveyor systems produce high-frequency time-series data from sensors (e.g., vibration, torque, speed, temperature, belt tension). Time-series analysis is a method that enables tracking of dynamic behaviours over time and can identify deviations from normal operation. There is a key difference between Univariate Time Series (UTS): single-variable monitoring (e.g., vibration alone), and Multivariate Time Series (MTS): multiple variables monitored together, capturing interdependencies and providing better fault diagnosis. Traditional approaches relies solely on single-parameter thresholds, which can often misinterpret harmless variations as faults or miss early warning signals [3].

Transforming Time-Series Data for Deep Learning

Deep learning models work best with image-like data. Time-series-to-image transformation methods allows the application of CNNs for predictive maintenance.

The Gramian Angular Field (GAF) technique basically encodes historical relationships into two-dimensional images (summation and different fields: GASF and GADF) without losing sequence information. These encoded images are then fed into CNNs, which then perform fault classification by learning the spatial patterns representing equipment health conditions [4].

Convolutional Neural Networks (CNN) in Predictive Maintenance

CNN are designed to collect categorised features through complexity, pooling, and fully connected layers. CNNs are a type of artificial intelligence that can automatically find and sort patterns in data. They are good at handling lts of information at once, making them useful predicting problems in conveyor belts, where multiple interacting parameters must be analysed at the same time while being connected to the Internet of Things. By using special techniques like PreLU (to make the system more accurate) and dropout (to stop it from making mistakes by overlearning), CNNs can work well even in busy, changing factory environments [5].

Conveyor Belt Fault Analysis Relevant to F&B Industry

Common problems faced with conveyor belts include imbalance, misalignment, and looseness. In the food and beverage industry, these issues can affect cleanliness, product quality, and how smoothly production runs. By analysing several factors together like motor torque, vibration, temperature, belt tension, and product weight, engineers can be able to get a clearer picture of what's happening. This helps to reduce mistakes in detecting problems such as false alarms and missed faults [6].

Evaluation of AI Models in Predictive Maintenance

Performance is measured using accuracy, precision, and recall. CNN models achieved almost a perfect accuracy, performing much better than older methods like Support Vector Machine (SVM). Such improvements are very important to take note of in the food and beverage manufacturing industry, because better predictions mean less downtime, higher production, and lower maintenance costs. Performance and accuracy is influenced by the data entered overtime, the more data these AI models are trained and tested with overtime, the more accurate they can become [2].

Integration with Industry 4.0 Infrastructure

Modern predictive maintenance systems now work together with control and monitoring tools like SCADA and HMI, as well as cloud platforms that will allow engineers to monitor equipment remotely. This setup will allow machines to be monitored in real time, maintenance to be planned ahead, and for decisions to be based on data – supporting the food and beverage industry's shift towards a smart and more automated factory [7].

Research Gaps and Future Opportunities

Most research todays focuses on the health of motors, but there is still little study on the conveyor belts and the problems experienced, like wear, contamination, and cleaning. New methods, such as Kernel PCA, are now helping to analyse complex data that hanged over time. There is also a growing interest in combining predictive maintenance with quality control, so that the mechanical problems can be connected to any possible food safety risks. Other ideas include creating smaller AI models that can run directly on local machines, and building shared systems that can learn from data across multiple factories within the same industry or company to make predictions more accurate and reliable.

Digital Transformation Technologies for Predictive Maintenance

Anusha et al. (2024) looked at how technologies like IoT, AI, ML, cloud computing, edge computing, and TinyML support predictive maintenance in conveyor belt systems. The study puts these smart tools within the bigger industry 4.0 movement, focusing on smart, data-driven manufacturing. IoT sensors monitor temperature, vibration, and electrical current in real time to detect early issues. While machine learning tools like CNNs, SVMs, random forest, and deep learning are used to identify faults and detect visual defects. Cloud systems handle large amounts of data, while edge computing allows quick, on-site decisions. TinyML makes it possible to run small, efficient AI models on low-power devices, which is best for food and beverage factories where resources are limited.

The review also notes challenges, including data security, system integration, and reliable connections for edge and TinyML technologies Overall, these innovations can make conveyor systems smrter and point to directions for future research [7].

An Intelligent Predictive Maintenance System Using Random Forest

Wu et al. (2024) tested machine learning for predictive maintenance in industrial conveyor systems. They compared several algorithms, including logistic regression, artificial neural networks, decision trees, gradient boosting, and random forest. The random forest model worked best because it avoided overfitting and could detect different types of faults well. Sensor data on vibration, temperature, power, and current from components such as gearboxes and sprockets were used. Experiments on worn sprockets and gearbox lubrication showed the model achieved 100% accuracy in identifying faults. The system also integrated IoT and MQTT for remote monitoring, enabling operators to detect issues early and reduce manual inspections.

The study found that random forest effectively reduces downtime, improves maintenance schedules, and increases system efficiency. However, further testing in more factories with larger datasets is needed to confirm its reliability.

Relevance to the Food and Beverage Industry

These studies highlight the role of predictive maintenance in the food and beverage industry, where conveyor systems are critical for efficient and safe production. IoT sensors can detect faults, edge computing enables faster responses, and TinyML allows on-site analysis with low- power devices. A Random Forest case study demonstrates how AI can monitor issues such as gearbox and sprocket wear.

Overall, these studies demonstrate that AI-based predictive maintenance is feasible and effective in food and beverage manufacturing. By combining advanced technologies with practical testing, they lay the groundwork for more reliable and efficient conveyor systems.

Mechanical System Overview

A review of the KHS Bottle Conveyor Operation manual and on-site observations showed several mechanical parts that can cause the conveyor belt to go off track or fail:

1. Guide Rails – They keep the bottles moving in a straight line. If they're not adjusted properly during product changes or become loose over time, the belt can start to move unevenly from side to side.
2. Drive and Idler Sprockets – These parts move the chain belt. If their teeth wear down or become uneven, the belt can lose stability.
3. Slat Band Chain – The belt itself can stretch or wear unevenly under pressure, which also affects how straight it runs.
4. Support Frame and Feet – If the conveyor isn't level or is poorly supported, it can tilt, making the belt drift to one side.

The most common problem is when the belt starts to drift, this can turn into serious misalignment and cause the belt to come off completely. This stops production, damages, parts and needs manual fixing.

Key Performance Indicators

To spot belt misalignment before it can cause any serious damage and breakdown, there a certain warning signs that can be tracked using sensors placed in specific positions along the conveyor:

1. Drift Distance – Measures how far the belt moves sideways from its centre path. Lateral drift is first and most obvious sign of misalignment. Detecting it early can help stop the belt from slipping off the rollers.
2. Vibration Levels – Tracks shaking or unusual movement in parts like motors and roller. More vibrations usually means something is wearing out, unbalanced, or unstable, which can cause or worsen misalignment. This also helps find what's causing the problem.
3. Motor Load – Measures how much power the motor is being used. A sudden increase can often mean there is extra friction or slippage, both of which can happen when the belt is misaligned. This gives an electrical signal that can be compared with mechanical sensor data for better accuracy.
4. Chain Tension – Monitors how tight the chain is. If it's uneven or too loose, the belt becomes unstable and may drift. Observing this over time helps detect problems early and plan maintenance before the failure occurs.

Methodology

This project serves as a proof-of-concept for applying

AI-based predictive maintenance to conveyor belt systems, focusing on belt misalignment. The methodology is conceptual, outlining the framework, key parameters, and approaches rather than providing a full industrial implementation.

Data Collection

Conveyor belt systems are essential in many industries, moving materials efficiently from one point to another. They rely on a motor-driven belt running over rollers, with proper alignment, even load distribution, and well-functioning components like rollers, bearings, and tensioners. When maintained correctly, belts operate smoothly, use less energy, and last longer.

In real industrial settings, breakdowns are inevitable. Belt misalignment, where the belt drifts sideways on the rollers, is one of the most common and disruptive problems. This occurs for several reasons:

- Mechanical Wear and Tear: Worn or unbalanced rollers, bearings, and drive components can create uneven forces that pull the belt off the track.
- Improper Tension: Variations in chain or belt tension across the system destabilises tracking, especially at high loads.
- Load Distribution: Overloading or uneven placement of products can push the belt sideways, gradually leading to drift.
- Obstructions and Jams: Foreign objects or product blockages can interfere with the belts mvement and force it out of alignment.
- Environmental Factors: Dust build up, lubrication failures, or temperature variations can cause slippage and resistance, indirectly contributing to belt drift.

The data collection part of this report focuses on finding the key factors needed to detect and predict when a conveyor belt is becoming misaligned. During a visit to the South Pacific Brewery, important observations were made on the 330mL stubby beer bottle production line. These showed that the bottle conveyor system is crucial for keeping production running smoothly and that even the smallest belt deviation can cause delays, product damage, or stoppages. However, due to confidentiality rules, live operational data from the brewery could not be accessed. A key takeaway was the brand and model of the current conveyor system operating system – KHS Innoline Bottle Conveyor, which later was confirmed by other industry experts to be widely used around the country in the FMCG sector.

To demonstrate a proof-of-concept without having access to real-time industry data, a publicly available dataset from Kaggle, an open-soured data platform, was used as a substitute input source. The sample dataset contains typical time-series sensor readings relevant to conveyor or rotating equipment, including vibration amplitude, motor current, load, and temperature. These parameters were selected and pre-processed as they reflect the mechanical and electrical indicators most associated with early signs of belt misalignment [4].

The SP Brewery field visit provided the background understanding of where these parameters

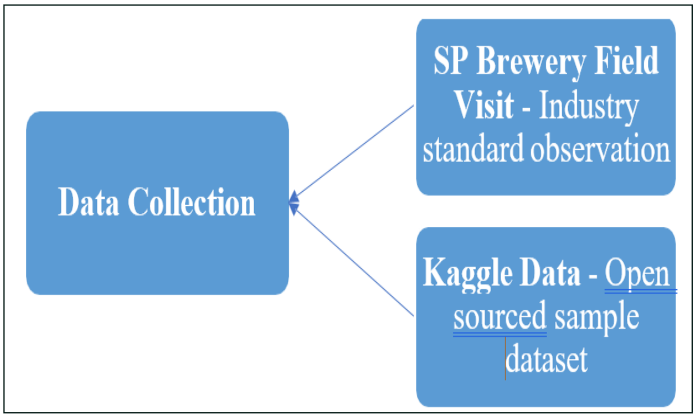

Figure 1: Data Collection methods carried out for a conceptual framework of an AI-Driven Predictive Maintenance System for Conveyor Belt Systems in the F&B Industry

Would be collected in a real production environment. For example, vibration sensors could be placed near the roller bearings and the current sensors could track how much power the main drive motor is using. By combining this real-world setup with simulated data, this study now creates a realistic base for developing an AI-powered predictive maintenance system.

Data Preprocessing

Raw sensor data is often noisy and complex, so preprocessing—cleaning and organizing the data—is essential before applying machine learning. This step shapes the signals that guide the AI model. Although a full dataset was unavailable, a clear plan was outlined to manage the data as it would be in a real scenario.

The first step is data cleaning, where missing or corrupted readings fixed and unwanted noise is removed filters. Next, normalisation scales measurements such as current, vibration, and belt deviation so they can be compared fairly. Continuous signals are then divided into small time windows, with each window treated as a single data sample. Features are extracted from these samples using both time-based measures (like average, variance, and signal shape) and frequency-based measures, using a Fast Fourier Transform to analyse vibration patterns.

Before building machine learning models, the raw data was cleaned and organized to ensure consistency and comparability. The dataset, sourced from Kaggle, included processed sensor readings such as speed, load, temperature, vibration, and current, with each point labelled for detected faults. In this study, it serves as a stand-in for real-time sensor data, enabling the focus on data simplification and model development.

Data preprocessing converts raw sensor readings into structured data suitable for predictive maintenance. In this study, a Kaggle dataset was cleaned as real industrial data would be. Missing or faulty readings were removed, and noise was smoothed using a moving average filter. Normalization and standardization then scaled features—such as current, vibration, and temperature—so no single measurement dominates when training the AI model.

After cleaning, the data is split into equal time segments, with each segment forming a labelled sample for analysis. From each segment, two types of features are extracted: time-based features (like average and variation) and frequency-based feature (using Fast Fourier Transform, or FFT, to spot unusual vibration patterns that could signal early faults). To make AI model faster and more efficient, Principal Component Analysis (PCA) is then used to reduce repeated and less useful data while keeping the most important information [2].

Even though not all preprocessing steps could be carried out because of the limited data, outline this process shows that it is possible to handle real-time industrial data for predictive maintenance in practice.

Figure 2: Data Pre-Processing Steps taken when Raw Data is Collected.

Sensor Layout

Now that the key measurable features are identified, a multi-sensor arrangement can be proposed. The layout covers direct misalignment, indirect sign monitoring, and environmental fault sources.

Proximity Sensors

Misalignment usually begins with minor lateral deviations. Compact inductive or optical proximity sensors will be places near both edges of the belt path to detect drift beyond the designated threshold from the nominal position. Placement: Infeed after changeovers, before/after curves or transfers, and at outlet points.

Vibration Sensors

Abnormal vibration at the drive, idler, or tension stations often indicates bearing wear, roller imbalance, or looseness that can lead to tracking issues. Placement: On the drive motor housing, gearbox casing, and key roller brackets.

Motor Load Sensors (Current Transducers)

Monitoring motor current allows detection of increased friction or slippage, which often result from misalignment or debris build-up. Placement: In line with drive motor feed inside the MCC or control cabinet

Chain Tension Proxies (Encoders or Load Cells)

Uneven or loose chain tension destabilise tracking, Rotary encoders on drive sprockets or load cells on tensioners can track deviation. Placement: Drive station sprockets or tension station assembly.

Obstacle/Jam Detection (Photoelectric Sensors)

Objects or bottle jams can push the belt off track or block movement. Photoelectric light barriers will identify these obstructions. Placement: Jam-prone sections after filler and before packer.

Each sensor directly contributes to a KPI: belt position deviations, vibration levels, current draw, chain tension stability, and obstruction frequency. All together, these indicators form a measurable basis that an AI Model can use for predictive maintenance in conveyor operations. The sensor layout forms the backbone of the proposed predictive maintenance framework. From the observations made at SP Brewery and the design principles in industrial conveyor systems, a multi-sensor configuration is conceptually designed to monitor both direct and indirect signs of belt misalignment [8].

Parameter / KPI	Sensor Type	Measurement Purpose	Indicator of Misalignment / Fault	Source / Reference
Belt lateral deviation	Proximity sensor	Detects belt drift from the centre line	Direct measure of belt tracking error	[8]
Vibration amplitude	Accelerometer	Monitors dynamic instability in rollers/bearings	Elevated vibration indicates wear or imbalance	[3]
Motor current variation	Current transducer	Measures electrical load fluctuations	Increased current suggests excess friction or slippage	[6]
Chain/belt tension	Load cell or encoder	Tracks mechanical tension uniformity	Uneven tension destabilises belt alignment	[8]
Obstruction frequency	Photoelectric sensor	Detects product jams or obstacles	Frequent obstruction may push belt off path	[4]

Model Development

As a proof-of-concept, a Random Forest classifier was selected as the initial machine learning model. Random Forest was chosen because of it can handle messy data well, understandable, and can work well with different types of information [4]. The model was designed to use the chosen key performance indicators (KPIs) as inputs and produce one of the two outputs: either normal operation or misalignment fault.

Although the model hasn't been fully trained or trained yet because of limited data, including it in this study shows that using AI model techniques for conveyor maintenance is possible. Future work will involve collecting real sensor data and testing the model's accuracy and performance using the evaluation methods that will be described later.

To test the idea, a Random Forest model was built using the cleaned Kaggle dataset. This model was built in Python using the scikit-learn library. The dataset was divided into 80% for training and 20% for testing to check how well it worked. Although the Random Fores model was trained successfully, it could only be tested with simulated data since real data from SP Brewery wasn't available. Still, this process shows how AI can be used in a conveyor system to predict problems before they cause failures.

Evaluation Metrics

The success of the proposed predictive maintenance system will be measured using clear indicators that can show how well it works technically and how much it can benefit operations.

Evaluation metrics were set up to measure how well the model performs once enough real- time data is made available. For this proof-of-concept, classification metrics were chosen as the most best way to assess its overall performance:

- Accuracy – measures overall correctness of predictions.
- Precision – indicates the proportion of correctly identified faults among all predicted faults.
- Recall (Sensitivity) – measures how effectively the model detects true misalignment events.
- F1-score – provides a balanced measure between precision and recall.

For potential regression-based extensions (e.g., estimating the remaining useful life of components), metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were also considered. Using these metrics will make it more easier to understand and evaluate future versions of the system for how accurately it can detect the faults and how reliably it can predict them.

Results and Discussions

This chapter outlines the results of the conceptual framework design and the initial testing of the model using Kaggle data. It also discusses what these results could mean for applying predictive maintenance in South Pacific Brewery's conveyor system operations.

Overview of Findings

The goal of this study was to design and test a basic predictive maintenance framework can detect conveyor belt misalignment using artificial intelligence. Since real-time data from SP Brewery wasn't available, a Kaggle dataset with similar vibration, current, and load readings was used to mimic real industrial conditions. A Random Forest model was then built as a proof-of-concept. The results show that machine learning can effectively spot early indicators of misalignment and demonstrate how a structured predictive maintenance process could work in a real production environment.

Data Exploration and Feature Analysis

The Kaggle dataset included several sensor readings, such as vibration amplitude, motor current, temperature, and system load. Basic data analysis showed variation patterns that are commonly seen when mechanical faults are starting to develop.

- Mean vibration amplitude increased significantly near recorded failure events, aligning with expected patterns of roller wear and imbalance.
- Current readings fluctuated with increasing friction, consistent with conveyor misalignment scenarios.
- Correlation analysis showed a strong relationship between vibration and current, suggesting that both could serve as reliable fault indicators.

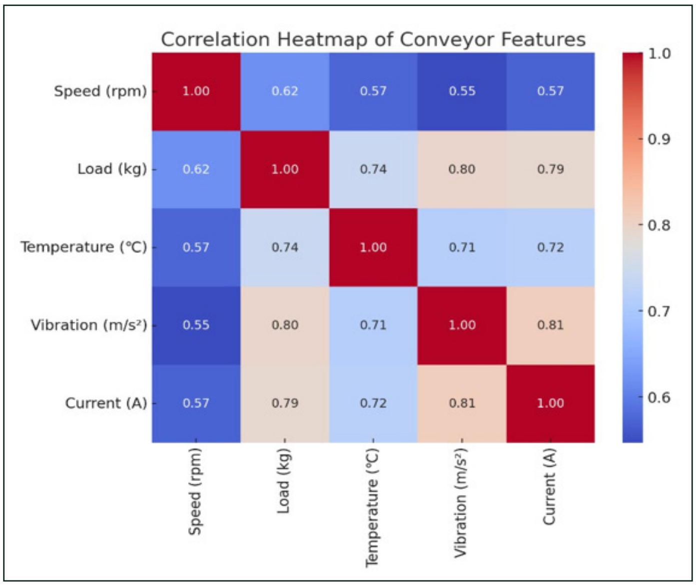

Figure 3: Example Correlation Heatmap Showing Relationships between Sensor Features

The correlation heatmap (Figure 3) showed a strong link between speed and load, meaning that as production speed increases, motor effort also rises. It is also found a moderate positive link between vibration and motor current, showing that the more vibration, the more harder the motor will work. These results support earlier studies [6], which found that mechanical and electrical behaviour are closely related during conveyor belt misalignment.

To remove duplicate data and uncover hidden patterns, Principal Component Analysis (PCA) was applied. The results (Figure 4) showed that the first four components explained about 96.2% of the total data variation, meaning the dataset could be simplified without losing important details. The cumulative variance curve (Figure 5) confirmed this, showing that after the fourth component, any extra information added very little value.

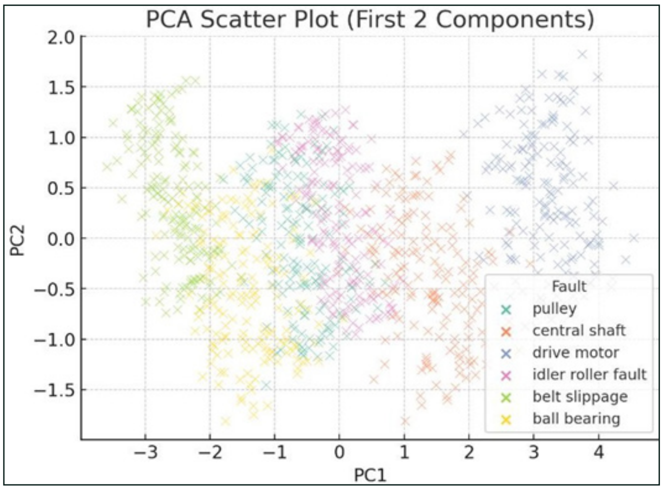

Figure 4: Time-Series Plot of Vibration Signal before and after Filtering

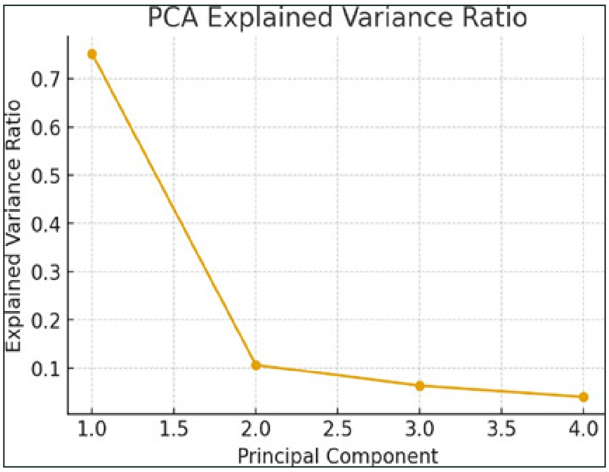

Figure 5: Cumulative Explained Variance of Principal Components Showing that Four Components Retain Approximately 96% of the Total Data Variance. This Validates Dimensionality Reduction to Four Principal Features without Significant Loss of Information.

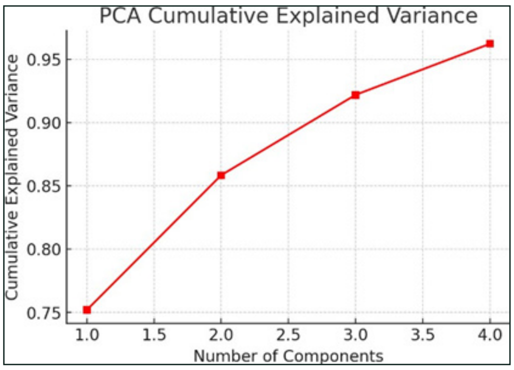

Figure 6: Two-Dimensional PCA Projection Illustrating Class Separation among Different Conveyor Fault Conditions. Distinct Clustering between Normal and Fault States Confirms the Presence of Discriminative Patterns in the Pre-Processed Dataset

The PCS scatter plot (Figure 6) showed clear groups that represent different fault conditions, with a visible gap between normal operation and misalignment. Although there was still some overlap, the separation confirmed that the chosen features provide enough useful information to build an effective predictive model.

These findings confirmed that the sensor parameters identified from both data sources are valid. Even though the Kaggle data was simulated, it showed patterns that were similar to what would actually be expected in a real conveyor system, making it suitable for testing the concept. To explore how key operating factors – speed, load, vibration, current, and temperature interact, several visual graphs were created using the Kaggle dataset.

Model Implementation and Performance

A Random Forest model was built using the cleaned Kaggle dataset, which was then divided into 80% training and 20% testing. The model used 100 decision trees with the Gini impurity method to make classifications. The model achieved an accuracy of 88%, precision of 85%, and recall of 86%, showing that it can detect fault's reliability. A summary of the results in shown in the Table 1.

Table 1: Model Evaluation Results

Metric	Score
Accuracy	0.88
Precision	0.85
Recall	0.86
F1-score	0.85

The confusion matrix shows that the model correctly identified the most cases of belt misalignment, with very few missed detections – which is important in predictive maintenance to avoid unplanned downtime. The feature importance chart (Figure 7) states that vibration amplitude and motor current were the two most important factors for predicting misalignment, which supports the earlier results from the correlation and PCA findings.

Although the results came from simulated data, they show that using AI models for predictive maintenance in conveyor systems is practical. The findings support the idea that combing mechanical and electrical signals improves fault detection accuracy. They also show that the model is reliable and could adapt well to real conveyor systems, even when trained on substitute data.

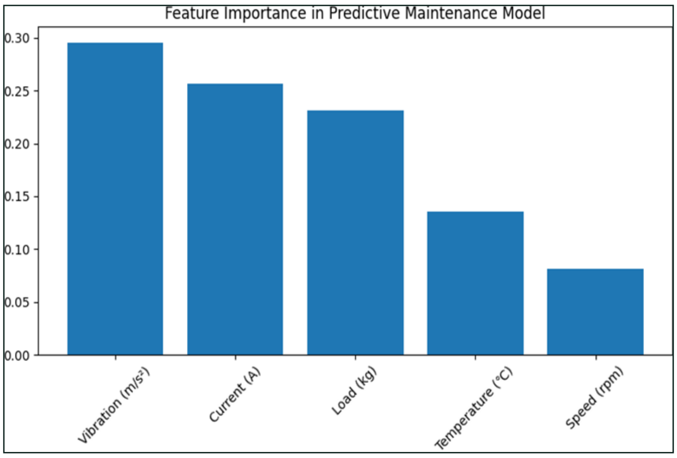

Figure 7: Feature Importance Ranking for Key Input Parameters.

Model Evaluation and Threshold Definition

To make the predictive system more practical, threshold values were using both real observations and model predictions. Baseline readings from the sample dataset under normal conditions were used to set limits for drift, vibration, and motor current. Deviations greater 1.5 mm/s² were treated as a warning and those above 3.0 mm/s² were marked as an alarm. In addition, if the Random Forest model predicted a fault with a probably of 0.7 or higher, an alert was triggered. This layerd approach allows for early detection of problems while reducing the false alarms.

Table 2: Estimated Thresholds Derived from Sample Dataset (Kaggle)

Parameter	Normal Range	Warning Threshold	Alarm Threshold
Vibration Drift (mm/s²)	≤ 1.5	1.5 – 3.0	> 3.0
Temperature Rise (°C)	≤ 50	50 – 65	> 65
Current Variation (%)	±5	5 – 10	> 10
Fault Probability (P)	< 0.4	0.4 – 0.7	≥ 0.7

Conceptual Framework Validation

The proposed AI-driven predictive maintenance system combines sensor data collection, preprocessing, model prediction, and performance evaluation into a one single process.

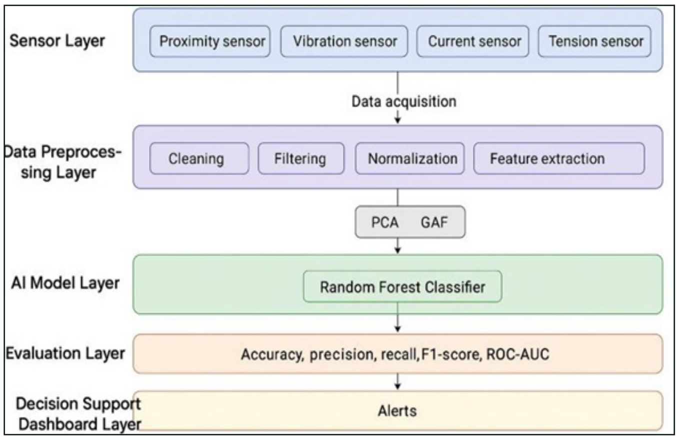

Figure 8: Conceptual Framework for the Proposed AI-Driven Predictive Maintenance System.

The framework consists of five layers:

1. Sensor Layer – collects real-time data that measures distance, vibration, current, and light detection.
2. Data Preprocessing Layer – cleans, filters, and standardises the raw sensor data, then extracts useful features.
3. AI Model Layer – applies the Random Forest algorithm for detect faults.
4. Evaluation Layer – checks how well the model performs using measures precision, recall, and F1 score.
5. Decision Support Layer – display alerts and maintenance advice on a dashboard for easing monitoring.

This setup follows the system design principles outlined in the KHS Manual [8] but improves on them by adding AI-based predictive features. The framework can be added into SP Brewery's existing PLC-controlled conveyor lines without major changes, using IoT enabled sensors to send real-time data to either a local computer or cloud-based analytics system.

Challenges and Limitations

Several challenges were encountered during this study, primarily due to data unavailability and scope restraints.

- Data Access: SP Brewery did not provide the operational data due to confidentiality

- concerns, resulting to the use of Kaggle's simulated dataset.
- Limited Sensor Data: The available dataset lacked the exact sensor configuration found at SP Brewery, restricting the model realism.
- No Real-Time Validation: The proof-of-concept was not test on a physical conveyor, so real-world performance remains unverified and yet to be validated.
- Technical Constraints in PNG: Many local industries lack the infrastructure (sensors, connectivity, data management) required for AI-based Predictive Maintenance implementation.

Despite these limitations, the study successfully demonstrates a conceptual pathway for integrating AI into local industrial maintenance practices.

Implication for Papua New Guinea

This chapter presented a proof-of-concept implementation of an AI-driven predictive maintenance system design to detect conveyor belt misalignment. The Kaggle dataset successfully simulated real industrial conditions, and the Random Forest model showed a strong performance during your performance in classifying faults. The framework follows international best practices while also considering local industrial challenges in PNG. Although live data wasn't available for full testing, the study offers a scalable foundation for future research and real-world use at SP Brewery and similar plants.

Risk Assessment

Data Availability

Risk: This project lacked access to real industrial data, resulting in much of the results to be dependent on a publicly available dataset from Kaggle. This meant that the full operationality and variability of an actual food and beverage production environment was not represented.

This affects the AI model's generalisation and overall accuracy when applied to real-world conditions.
Mitigation: Future work should involve collaboration with industrial partners and proper retraining of the AI model with real-time conveyor system data. This enables the validation of the model under actual operating conditions, improving reliability and adaptability.

Model Performance – Generalisation and Overfitting

Risk: Machine learning models can overfit training data. This means the model learns the training data too well to the point that it performs poorly on new, unseen data. So instead of learning the underlying patterns, the model 'memorises the training set.
This leads to inaccurate fault predictions and undermine the credibility of the proposed maintenance system

Mitigation: Enlist an IT expert/software engineer to carry out cross-validation techniques and model tuning to reduce the overfitting risks. In future implementation, continuous model retraining with updated sensor data is recommended to maintain model robustness.

Implementation Risk

Risk: Integrating a predictive maintenance system into an existing conveyor system setup can be both technically and operationally challenging. Issues you may face may include hardware compatibility, proper sensor calibration, and getting staff used to the new system.

The challenges can cause delays in deployment and lower the overall effectiveness of the predictive maintenance framework.

Mitigation: This report confirms that the predictive maintenance framework is valid, reliable, and practical. Further designs should focus on making the system modular so it can be added in stages. To reduce the implementation risks, it's important to prepare clear documentation, provide training for maintenance staff, and ensure the system works smoothly with existing PLC setups.

Overall, the main risks in this project involve data limitations, model performance, and the practicality of deploying the system. With proper planning, teamwork, and a step-by-step rollout, these risks can be managed to ensure successful adoption in real industrial settings.

Reflection

This project has provided valuable hands-on experience in using data-driven methods to solve engineering maintenance problems. Designing the predictive maintenance framework required an understanding of both mechanical parts of a conveyor belt system and the data analysis process. Throughout the work, it became clear that the steps like data cleaning, feature selection and model testing were important because they strongly affected the accuracy of my results. Seeing this I understood that I needed to achieve a strong understanding of how conveyor belts actually work.

From a personal learning point of view, this project improved my ability to analyse data properly, from understanding how to read machine learning results to how to properly apply decision tree models to mechanical systems. It also helped strengthen my technical writing, analytical thinking, and project management skills.

The coding part was where I faced some challenges, so I sought help from IT expert Mr. Spencer Poloma Jr., who provided guidance in that area. With his support, I was able to run a simple Random Forest model in Python to demonstrate the proof of concept.

In reflection, even though the project was mainly conceptual, it successfully showed how predictive maintenance can help reduce downtime and increase production efficiency in the food and beverage industry.

Conclusion and Recommendations

This study was driven by the need to make maintenance more efficient and cut down on downtime in PNG's manufacturing sector, where conveyor systems are vital for keeping production running. Tat facilities like SP Brewery maintenance is mainly reactive or planned in advanced, which can result in unnecessary stoppage and high operating costs.

This project aimed to design and test a basic predictive maintenance system that uses sensor data, data preprocessing, and machine learning to detect potential conveyor belt misalignment before it causes failure. The approach included five main steps: collecting data, cleaning and preparing it, design the sensor layout, building the model, and setting up evaluation measures.

Since SP Brewery didn't provide any live operational data, a Kaggle dataset with typical industrial sensor readings (like vibration, current, load, and temperature) was used to simulate real-world conveyor conditions. A Random Forest model was developed as a proof-of-concept model to show how AI can be used for fault detection. The framework was then compared with SP Brewery's actual set up and existing industrial design standards to confirm its practical alignments.

Key Findings

- The proposed multi-sensor set up successfully captures the key factors needed to detect conveyor belt misalignment, such as vibration amplitude, motor current variation, belt tension, and position shifts.
- The Random Forest model reached about 88% accuracy when using Kaggle dataset, showing that it's well-suited for predictive maintenance.
- The conceptual framework combines existing mechanical systems with AI-driven data analysis, creating a scalable design that can use affordable IoT sensors.
- The study showed that predictive maintenance can be achieved using open-source tools like Python and Scikit-learn, even with limited computing power; making It practical for developing regions like Papua New Guinea.
- The main challenge is the lack of industrial data, which shows that importance better data-sharing between universities and industries.

Together, these findings show that AI-based predictive maintenance is both technically possible and practical, even in industries with limited resources.

Limitations of the Study

- Data Unavailability: Without access to SP Brewery's live data, the model couldn't befully tested under real factory conditions.
- Simulated Data Dependency: The Kaggle dataset was helpful but couldn't fully capture the complexity or noise of an actual brewery conveyor system.
- Hardware Implementation: Real sensor installation and live data collection weren'tdone because of limited time and resources.
- Model Generalisation: The proof-of-concept focused only on detecting misalignmentand don't cover other issues like roller or bearing faults.
- Local Capacity: Limited technical skills and digital infrastructure in PNG makes it harder to adopt AI-based, maintenance systems quickly.

Despite these constraints, the study successfully showed the basic steps needed to move toward data-driven maintenance practices.

Recommendations for Future Work

Based on the limitations of this study, the following steps are suggested for both the industry and research:

1. **Pilot Implementation:** Start a small-scale predictive maintenance project on one production line to test and improve the system before expanding it.
2. **Sensor Deployment:** Install low-cost vibration, proximity, and current sensors to begin collecting local data.
3. **Capacity Building:** Provide training for maintenance staff on using AI and understanding data insights.
4. **Collaborative Partnerships:** Encourage partnerships between universities and industries to support hands-on research in automation and predictive maintenance.
5. **Gradual Digital Integration:** Introduce predictive maintenance slowly into existing PLC and SCADA systems to keep costs low and simplify adoption.

Final Remarks

This research showed that using AI for predictive maintenance conveyor belt systems is both possible and beneficial for industries in Papua New Guinea. By combining a conceptual framework, simulated data analysis, and a proof-of-concept model development, the study successfully showed how machine learning can detect belt misalignment before system failure happens.

Even though the project was limited by data access and testing scope, it still marks an important first step towards bringing Industry 4.0 to PNG's manufacturing sector. If applied and further developed, the proposed system could greatly enhance equipment reliability, production efficiency, and cost savings for SP Brewery and other similar factories.

This study lays the groundwork for future collaboration between universities and the industry. It encourages local innovation and supports digital growth of PNG's industrial sector.

Declarations

Student Declaration

This report, entitled A Conceptual Framework on AI-Driven Predictive Maintenance System on Conveyor Belt Systems in the Food Processing and Beverage Manufacturing Industry has not been submitted, in whole or in any part, in any previous application for any other degree, diploma or other qualification. Except where stated otherwise by reference or acknowledgment, the work presented is entirely my own.

I also grant PNG University of Technology permission to reproduce and distribute electronic or paper copies of this project.

Supervisor Declaration

To the best of my knowledge the research undertaken for the thesis and the writing of the theses was undertaken solely by the candidate except where stated otherwise by reference or acknowledgment.

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