Machine Learning Techniques for Improving Multiclass Anomaly Detection on Conveyor Belts

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Abstract. *Industrial conveyor belt systems are essential for material transport due to their efficiency. Regardless, they are prone to various kinds of failures such as idler anomalies, belt tears, and misalignment, which can cause significant disruptions in the production process. Preemptive maintenance of such systems is a challenging task due to the rarity of comprehensive anomaly detection datasets in the area. Current monitoring systems only evaluate the conveyor or idle belt's condition at the installation point. Our study introduces a comparative of machine learning techniques, such as a Hybrid Transformer model tailored for multiclass anomaly detection with limited data, merging domain-specific augmentations with a convolutional-transformer hybrid architecture. Furthermore, specific machine learning approaches for time series such as models based on feature extraction, Catch22, Minirocket Arsenal, Hivecote2 and Time Series Forest were tested and impressive results were achieved with a maximum accuracy of 94% with a Multirocket Arsenal. This research demonstrates a promising advancement in predictive maintenance for industrial conveyor systems.*

1. Introduction

Industrial conveyor belt systems are essential in the transport of materials such as ores and stones [Farhat et al. 2023], but despite their robustness are still prone to damage, with common faults including mistracking, slippage, tear, deviation, and idler faults [Farhat et al. 2023, Nienhaus et al. 2015, Matos et al. 2023]. Detection and maintenance of such damage are crucial for the efficiency of the transporting system, as well as the safety of workers involved. Traditionally, the maintenance approach for these systems has been reactive instead of preemptive, primarily due to challenges in accurately monitoring the system's health.

To address the problems associated with conveyor belts, there are various solutions available such as mechanical systems, ultrasonic and acoustic sensors, vibration analysis, and computer vision. However, mechanical systems only partially mitigate the problem, and ultrasonic and acoustic sensors can only monitor a few idlers. Moreover, optical systems are heavily influenced by environmental conditions. The industrial environment is characterized by dust, rain, and poor lighting conditions, which directly affect image processing accuracy [Nienhaus et al. 2015]. Additionally, most solutions only evaluate the belt or the idler's belt condition at a single point. The current solutions for conveyor belts are not very effective because most belts travel long distances, which makes their efficient operation challenging.

Therefore, developing methods to inspect and monitor conveyor belts is interesting to the mining industry. The proposed work aims to evaluate the health of a conveyor belt by utilizing an Inertial Measurement Unit (IMU) coupled to the belt. We created a dataset based on [Matos et al. 2023], in which we collect reference and anomalous IMU data. We tested a reduced-scale conveyor belt in different work scenarios, including correct performance and idlers' structural anomalies. Hence, we analyzed the measured data to evaluate its health.

To classify the conveyor belt health, our study suggests the comparison of various machine learning techniques. For instance, we introduces a Hybrid Neural Network model (HNN) in response to these challenges. This model combines convolutional neural networks (CNNs) and transformer architectures to process sensor data from conveyor systems effectively. It receives the time series features, creating intermediate features through the CNN. In its sequential form, this data is then classified by a final transformer section, allowing for accurate prediction of specific anomaly classes in the sensor data.

Besides the Hybrid Neural Network, we implemented other machine learning models. For example, we developed Random Forests models to classify the conveyor belt health. Moreover, we used machine learning approaches for time series such as models based on feature extraction, such as Catch22, Minirocket and multrocket Arsenal, and Time Series Forest.

This paper will discuss the development and efficacy of the aforementioned machine learning techniques in a multiclass anomaly detection for conveyor belt systems, representing a significant advancement in preemptive maintenance and system health analysis.

2. Problem Description

Misalignment is the anomaly that most impacts the availability of conveyor belts, in terms of both occurrence frequency and the duration of maintenance interventions. Considering the replacement, execution, and repair time, this failure is responsible for significant operational losses and increased production costs. Often, depending on the type of misalignment, it can not only cause material spillage but also force the belt beyond its physical limit, leading to its rupture and, consequently, severe accidents. Another important factor is that, with their rupture, production comes to a halt, resulting in financial losses [Nienhaus et al. 2015].

This failure can occur due to various factors, such as misalignment of supports, misaligned brackets, wind action, and decentralized feeding, among others [Otto and Katterfeld 2015]. Another factor that may lead to a belt misalignment is problems on the belts idlers and brackets. Figures 1 and 2 compare a belt in a normal position and a misaligned belt due to a misaligned bracket.

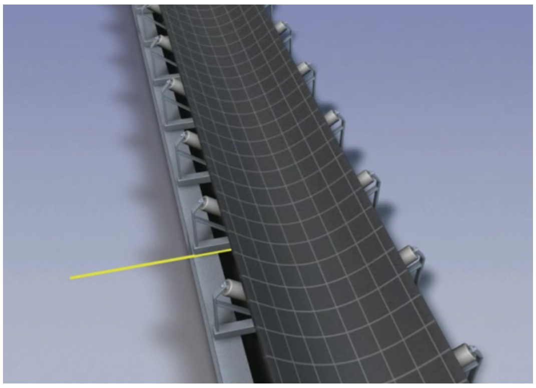

Figure 1. Aligned Conveyor belt.

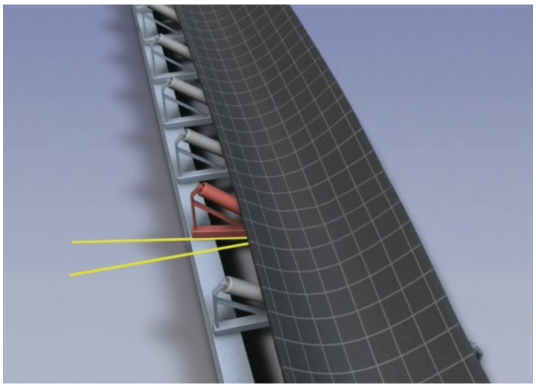

Figure 2. Conveyor belt misalignment due to bracket and idlers problems.

Current anomaly detection methods in this context are primarily limited to single-observation detections, which fail to consider the sequential nature of the sensor data, leading to insufficient predictive capabilities. Additionally, multiclass anomaly detection, crucial for accurately identifying specific types of roller issues, is notably absent in existing approaches, specifically with regards to industrial health monitoring scenarios. The lack of accuracy in current approaches when dealing with time-series require a more robust solution capable of handling the nuances of different anomaly types.

Regarding data availability, existing datasets, such as timeeval.github.io and the UCI time series repository for anomaly detection, often do not cater to the specific needs of industrial conveyor systems. These datasets are typically one-dimensional, lacking the multi-faceted approach required for 3D space sensor data interpretation. Furthermore, they are often limited in size and scope, posing challenges in training models for diverse and large-scale industrial applications. Another challenge lies in the variability of data quality and frequency. Sensor data often comes in different sampling frequencies, necessitating interpolation for standardization before analysis. This adds an additional layer of complexity to model training and accuracy.

The necessity for multiclass anomaly detection in conveyor belts cannot be overstated. Each type of anomaly requires a specific response; for example, a roller slightly out of place may have a higher level of concern than a roller that does not have contact with the belt. Accurately identifying these nuances is crucial for effective maintenance, as it directly impacts the decision-making process for repairs and replacements. Thus, a model capable of precise multiclass anomaly detection is essential for operational efficiency in industrial environments.

3. Related Works

Mechanical devices, like switches, are commonly installed next to conveyor belts to detect when they deviate from their normal path. However, these devices can only partially solve the problem by alerting or turning off the equipment when a misalignment is detected. This may not be enough to monitor or prevent a conveyor belt fault completely. [Nienhaus et al. 2015].

Some researchers have focused on monitoring conveyor belts as a part of their work. In Reference [Farhat et al. 2023], the proposed analysis of the motor current signature of the conveyor belt (MCSA) is based on the fact that belt attrition, caused by mistracking, increases the motor load, resulting in current alterations. In Reference [Ericeira et al. 2020], the condition of idlers was evaluated using ultrasonic sensor data. Different machine learning algorithms were applied to differentiate between problematic and non-problematic idlers.

In Reference [Nienhaus et al. 2015], thermographic cameras using Long Wave Infrared (LWIR) were employed to monitor conveyor belts during feeding. The data acquired through this process was utilized to optimize the belt feeding system to prevent misalignment or to correct existing deviations in the belt's trajectory.

In Reference [Chamorro et al. 2022], a method was proposed to monitor the condition of a conveyor belt. The method uses a series of sensors to estimate the misalignment of the belt, which is achieved through machine vision techniques. The captured images are sent to a computer, where they are processed to evaluate the behavior of the belt. In reference [Žvirblis et al. 2022], strain gauges data and long short-term memory (LSTM) and Transformer neural network models were used for the classification of different conveyor belt conditions (loaded and unloaded).

[Kirjanów-Błażej et al. 2022] presents a method to evaluate the thickness measurement of conveyor belts. The method was based on using several ultrasonic sensors installed on conveyor belts. [Cieplok 2023] study provides a study about dynamic damper applied for vibration analysis of the conveyor belts. The dynamic damper improves the vibration studies through anti resonance effect to achieve a significant decrease in vibration amplitude and forces transmitted to the foundation. The [Cieplok 2023] focuses on vibration analysis, while this paper studies misalignment caused by several reasons, not just because of vibration issues.

A monitor system based on UHF RFID sensor response is used for structural health monitoring in reference [Zohra et al. 2021]. However, the belt material affects the sensor performance because of the dielectric properties and rubber thickness. A study with a similar approach [Salim et al. 2021] is about a monitory system based on UHF

RFID sensor, which can provide a safer monitoring of the conveyor belt through data collected via RSSI (Received Signal Strength Indicator) from the sensors.

The Reference [Zimroz et al. 2023] presents prospects of the IMU use to monitor conveyor belts. They did experiments in a reduced-scale conveyor belt with a coupled IMU. It was verified that idlers defects diagnostics and straightforward interpretation are signals of z acceleration and gyroscope in the Y direction. IMUs were also used in reference [Yasutomi and Enoki 2020]. A method to estimate the position of the IMU on a conveyor belt is proposed. A Deep Convolutional LSTM neural network was implemented to detect features that may inform position. Despite using IMUs to monitor conveyor belts, the aforementioned works do not measure inertial data during anomaly conditions.

In our previous work [Matos et al. 2023], we have used IMUs installed at the lateral extremities of the belt to evaluate its health along its route. Various tests were conducted on the conveyor belt, including its correct performance, structural anomalies, and misalignment under different work scenarios. However, we only used similarity analysis techniques to evaluate the conveyor belt's conditions. The comparison of the related works can be seen in Table 1.

In our current work, we propose a more advanced analysis, using the previous experiment's methodology, that utilizes machine learning techniques such as a hybrid transformer architecture and random forests models alongside other temporal series feature extractors like Catch22, Minirocket, and TSforest.

Table 1. Comparison of the related works.

Study	Current Signature Analysis	Ultrasonic Sensor	Camera	RFID	Strain Gauge	IMU	Anomaly detection
[Farhat et al. 2023]	✓	✗	✗	✗	✗	✗	✓
[Ericeira et al. 2020]	✗	✓	✗	✗	✗	✗	✓
[Nienhaus et al. 2015]	✗	✗	✓	✗	✗	✗	✓
[Chamorro et al. 2022]	✗	✗	✓	✗	✗	✗	✓
[Žvirblis et al. 2022]	✗	✗	✗	✗	✓	✗	✓
[Kirjanów-Błażej et al. 2022]	✗	✓	✗	✗	✗	✗	✓
[Salim et al. 2021]	✗	✗	✗	✓	✗	✗	✓
[Zohra et al. 2021]	✗	✗	✗	✓	✗	✗	✓
[Yasutomi and Enoki 2020]	✗	✗	✗	✗	✗	✓	✗
[Zimroz et al. 2023]	✗	✗	✗	✗	✗	✓	✗
[Matos et al. 2023]	✗	✗	✗	✗	✗	✓	✓

4. Background and Proposed Architecture

In this section, we discuss the machine learning and feature extractor techniques used to classify conveyor belt behavior. In this study, we experimented hybrid transformers models, random forests models, and models based on time series feature extraction such as Catch22, Minirocket Arsenal, Multirocket Arsenal, and TSforest.

4.1. Random Forest

It is widely employed for solving large data regression and classification problems. A Random Forest algorithm consists of an ensemble of decision trees, each generated randomly [Breiman 2001]. We used 100 trees for the random forest models and the time series subsequences as input without feature extraction.

4.2. Feature extraction-based models

Feature extraction-based classification, instead of using raw numerical data points as input, uses extracted statistical and domain characteristics from the raw data and uses these processed values as features. Examples of possible characteristics to extract are the mean, standard deviation, skewness, slope, and peak positions. However, features can also be extracted through more sophisticated methods. The following feature extractors algorithms were implemented and tested on our data:

4.2.1. Catch22

The Canonical Time-series Characteristics is a set of 22 features designed for the analysis of time-series data [Lubba et al. 2019]. These features capture various aspects of temporal patterns, including regularity, complexity, and periodicity. The term "Canonical" emphasizes their standardized applicability across different domains. Researchers and practitioners leverage Catch22 for diverse applications, such as signal processing, financial analysis, and healthcare. The reference [Lubba et al. 2019] serves as a source for more detailed information on the Catch22 feature set.

4.2.2. Rocket algorithm family

In our study, we adopted an ensemble approach, utilizing both MiniRocket [Dempster et al. 2021] and MultiRocket [Tan 2022]. These algorithms represent modified versions of the Rocket algorithm, enhancing their efficiency and effectiveness in specific feature extraction scenarios for time series data. Both are convolution-based feature creation models, coupled with subsequent application of linear classifiers, forming a robust methodology for predictive modeling and classification tasks. The ensemble strategy incorporating MiniRockets and MultiRockets contribute to improved model performance by leveraging the strengths of both algorithms. For further details on the optimization and implementation of these algorithms, refer to the original papers [Dempster et al. 2021, Tan 2022].

4.2.3. Time Series Forest (TSF)

The TSF algorithm is an adaptation version of the Random Forest classifier [Breiman 2001] designed to handle sequential temporal data [Deng et al. 2013]. It divides time series into segments and employs decision trees to build models within each segment. The final class of the time series is determined by aggregating individual tree predictions through a voting mechanism. This approach enables TSF to effectively capture intricate temporal patterns, making it a versatile tool applicable to various temporal data scenarios. For more details on TSF's methodology and applications, refer to the foundational works [Breiman 2001, Deng et al. 2013].

4.3. Hybrid Neural Network architecture

We propose the use of a hybrid architecture, fusing a 1D convolutional neural network (CNN) as input layer and a transformer architecture as output layer for processing the time series data and classifying the different anomalies.

1D Convolutional Layers: The 1D CNN consists of 3 sequential convolutional layers, each with 256 kernels. These layers are responsible for compressing the multi-dimensional time series data into a more manageable form, extracting temporal features and contextual relation of each multidimensional features, which are statistically dependent on each other.

Transformer Architecture: Following the convolutional layer, we employ a transformer architecture [Vaswani et al. 2023] with 32 attention heads and 4 layers. The transformer architecture takes as input the intermediate features processed by the CNN, so it receives the condensed time series data and uses the attention mechanisms to classify the processed sequences.

The hybrid nature of the model offers several advantages. Firstly, it provides a level of interpretability [Ferry et al. 2023], with the convolutional layers offering context-aware data processing and the transformer providing insights into sequence relationships. Secondly, this architecture has shown superior performance in multiclass anomaly detection tasks, particularly in distinguishing individual anomalies with a high degree of accuracy, as evidenced by its 98% ROC score. Moreover, its training speed is highly efficient, requiring on average 2 to iterate 500 epochs with a batch size of 64 series. To train the model, we used a learning rate of 1e-3, and the Adam Optimizer [Kingma and Ba 2017]

5. Methodology

The laboratory experiments were conducted using a reduced-scale conveyor belt and an NGIMU sensor from X-io Technologies. The NGIMU sensor was positioned at the extremities of the belt to monitor its behavior. To understand how the sensor axes work, imagine the belt as a flat surface, the X axis is along the length of the belt, the Y axis is perpendicular to the belt, and the Z axis is vertical, perpendicular to the plane of the conveyor belt. The NGIMU, an inertial measurement unit, transmitted data via Wi-Fi and User Datagram Protocol (UDP). The conveyor belt used in the experiment had 5 pairs of idlers, each measuring 110 cm in length and 25 cm in width.

We have developed several work scenarios for the conveyor belt. Initially, we gathered accelerometer and gyroscope data while the belt was operating under normal conditions, as depicted in Figure 3. These data serve as Ground Truth or references for the other scenarios' data. Then, we created abnormal scenarios, specifically on the belt's idlers. For the idler anomaly, we raised the third idler's position, first on the left and then on the right. Figure 4 displays the elevated idler on the left. The other anomaly scenario generated was more drastic. We removed the left and then the right idler to simulate a severe anomaly.

To study this phenomenon, IMU data was collected for each scenario, with the conveyor belt speed set at 2.25 m/s and the acquisition frequency varying from 100Hz to 500 Hz for both accelerometer and gyroscope. The final processed dataset has a total of 156 experiments, with different time series sizes. Each experiment was interpolated to a size of 500 observations, with 6 features (one for each dimension and sensor type, such as X-axis gyroscope data for example).

Analyzing the raw measurement data can be difficult due to the noisy and un-

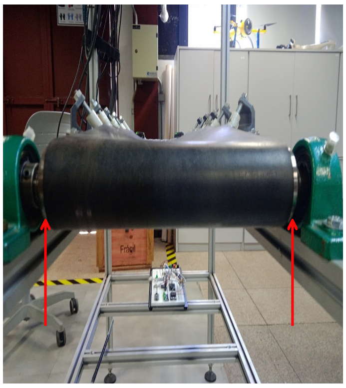

Figure 3. Aligned Conveyor belt.

Figure 4. Pin elevated on the left.

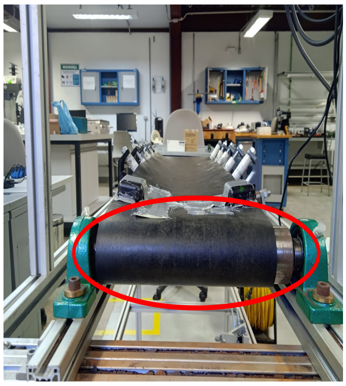

Figure 5. Misaligned conveyor belt.

synchronized signal of the IMU. To address this issue, we have developed an algorithm that utilizes previously collected raw measured data. This algorithm is designed to detect data within the range of interest (ROI) by identifying signature data that occurs when the sensor moves from the superior to the inferior side of the belt. By doing so, it retrieves only the measured data taken when the NGIMU was on the superior side, that is, when the sensor is in contact with the belt's idlers. This approach helps to ensure that the data collected is accurate and reliable.

Before classifying the time series, we had to split up the series we received from collecting the signals on the model. To do this, we used the peaks generated by the gyroscope's Y axis to separate the signals collected only on the upper part of the belt, because the anomalies generated were all on the rollers that support the belt, so the data from the lower part was removed along with the signals from the end of the belt, when the sensor reverses position. We also applied a moving average to smooth out the series and make the task of separating the signals easier. After dividing the time series we interpolated with a linear spline so that all the series to be classified have the same number of points.

To validate each model, we used Leave-One-Out Cross-Validation (LOOCV), a cross-validation technique in which each data point in the set is used as a test set exactly once. The model is trained with the other points for each data point and evaluated on the point left out. Performance is evaluated for each iteration, and the results are averaged to estimate the model's performance. Although it can be computationally costly, LOOCV is useful on small data sets, maximizing the use of data for training. This technique was chosen because our dataset is small, 150 examples, and the computational cost was not excessive. For the HNN model we used *hold-out* for both validation and testing, with a train-test split of 80% of the original dataset. This decision was made due to the computational cost that arises of training multiple transformer instances if the validation were to be performed using LOOCV as well.

6. Results

The Hybrid Transformer model showcased commendable performance in anomaly detection on our test conveyor belt system. Key performance metrics are as follows: an accuracy, precision, recall, and F1-score all around 93.55%. These figures are significant as they demonstrate the model's overall effectiveness. Accuracy indicates the proportion of total predictions that were correct, while precision and recall provide insight into the model's ability to correctly identify positive instances. The F1-score, being the harmonic mean of precision and recall, offers a balance between the two. Moreover, a ROC AUC score of 0.9857 highlights the model's superior capability in distinguishing between normal and anomalous states.

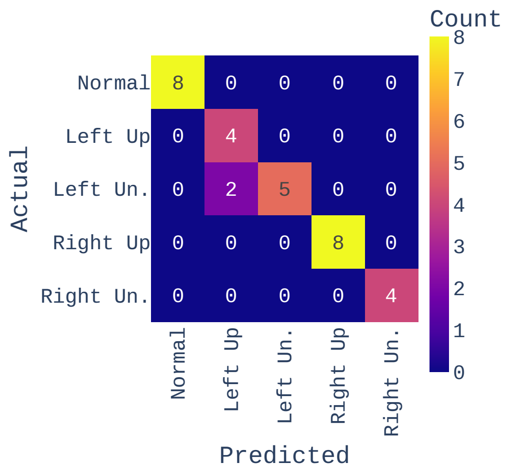

Figure 6. Confusion Matrix on test dataset

Figure 7. ROC curve on test dataset, averaged over all classes

Notably, the model exhibited a marginally lower performance in detecting anomalies on the left side of the conveyor belt. This outcome suggests a potential sensitivity to the sensor's orientation, indicating that incorporating multiple sensors could enhance detection capabilities in future iterations. Addressing the challenges posed by the limited dataset size, particularly the tendency to overfit, was achieved through careful hyperparameter tuning and the implementation of regularization techniques such as early stopping. These strategic adjustments, especially the reduction in batch size, were key in elevating the model's accuracy to approximately 93.5% on the test data.

Model	Accuracy (%)	AUROC (%)	Training Time (hours)
HNN	93.55	98.5	0.033
Multirocket Arsenal	92.30	96.59	0.037
Mini Rocket Arsenal	89.74	95.45	0.006
TSforest	82.05	90.37	0.001
Random Forest	76.92	87.48	0.001
Catch22 + Random Forest	74.35	87.50	0.004

Table 2. Comparison of Model Performance

Models based on feature extraction performed well in terms of accuracy, especially ensemble strategies such as Multirocket and Minirocket Arsenal. Of particular note is the minirocket, which has a much shorter training time than the HNN and multirocket.

The others performed less well, but they are simpler models that don't use the ensemble strategy or even extract features like RF. One observation is that catch22, a feature extractor, performed worse than RF without feature extraction. However, Time Series Forest, which extracts features from subsequences, proved to be a more interesting way of classifying our time series, with better results than RF, classifying the series with features extracted from the whole series with catch22 and also RF classifying the series with the raw data. In summary, the Hybrid Transformer model's performance underscores its potential as a robust tool for predictive maintenance in industrial conveyor belt systems, demonstrating a marked advancement over existing anomaly detection methods.

In summary, the Hybrid Transformer model's performance underscores its potential as a robust tool for predictive maintenance in industrial conveyor belt systems, demonstrating a marked advancement over existing anomaly detection methods.

7. Conclusions and Future Research

This paper proposed a method for evaluating the health of conveyor belts using two inertial sensors and machine learning applied to a time series. We tested diverse approaches to classify the conveyor belt behavior. Machine learning techniques such as Random Forest, hybrid transformers, and models based on feature extraction were experimented.

In an experiment, we installed IMUs in a reduced-scale conveyor belt and collected reference and anomalous data by altering the device structure. We used machine learning multiclass classification models to classify the conveyor belt health. On the comparison of each algorithm, the hybrid transformers model obtained a 95.55% accuracy, higher than the other experimented models.

Using the developed model, we could detect the conveyor belt's idler anomalies on both sides, even utilizing only one side IMU data therefore solving our initial problem of improving on existing multiclass anomaly detection algorithms. As part of our future research, we aim to collect a bigger database on an industrial conveyor belt and implement the machine learning strategies mentioned in this study.

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