WHITE PAPER

UTILIZING AI TECHNIQUES TO DETECT ANOMALIES FOR PREDICTIVE MAINTENANCE IN THE MINING INDUSTRY

Abstract

Artificial intelligence (AI) and Machine Learning (ML) can be essential in improving efficiency and reducing the cost of operations in the mining industry. Unlike traditional reactive methods, AI and ML-based techniques enable a proactive approach that uses sensor data and historical information to predict equipment failures. This helps prevent costly equipment downtime.

This paper delves into the application of AI and ML techniques, particularly in anomaly detection, to enhance safety and efficiency in the mining industry. It explores various anomaly detection methods, including statistical, rule-based, machine learning, and deep learning approaches, highlighting their strengths and weaknesses. It presents an ML-based approach and underlines the pivotal role of the audience's domain expertise and good quality data in its successful implementation. The paper also showcases various use cases of anomaly detection that Infosys has successfully implemented in this industry using AI/ML techniques, demonstrating the end users integral role in these advancements. It also shares the benefits realized through these implementations, such as improved efficiency, enhanced safety, and reduced costs, further validating the end users expertise.

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INTRODUCTION

The mining industry operates in a dynamic and fluctuating environment characterized by resource price volatility, fluctuating resource fields, and managing large-scale projects throughout their life cycles. The emergence of smart mining, using technologies like the Internet of Things (IoT), AI, ML and automation, presents numerous opportunities, including heightened safety measures, enhanced operational efficiency and substantial cost savings. Jung (2021) conducted a systematic review of ML applications in mining, revealing that over the past three years, approximately 53% of the research undertaken in the last decade focused on exploration, exploitation and reclamation [1]. This paper delves explicitly into utilizing AI techniques like anomaly detection in mining operations.

Li (2020) and Liu (2021) concentrated on underground mining, employing image processing techniques to identify anomalies in electrical equipment and detect transformer oil leakage. Meanwhile, Liu proposed a multi-sensor data anomaly detection method based on edge computing [2][3]. Extending this research to excavators, Zhou (2019) explored anomaly detection applications, and Bharadwaj (2020) successfully implemented similar techniques on Haul Trucks, achieving high anomaly detection accuracy through ML methods [4][5]. Suzuki (2014) contributed to this field by presenting an anomaly detection system tailored for advanced maintenance services, integrating maintenance expertise with data mining technology [6].

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These studies underscore AI's potential to enhance safety and efficiency within the mining industry. Harnessing data-driven insights into mining operations can lead to the following benefits:

1. **Increased efficiency:** Predictive maintenance helps avoid unplanned downtime, improving overall efficiency.
2. **Improved safety:** Early warnings can prevent hazardous situations and injuries.
3. **Reduced cost:** Detecting anomalies early reduces maintenance costs and extends the machinery's lifespan.

In this paper, a few use cases have been elaborated on, where Infosys has implemented AI solutions for its mining clients using different ML and anomaly detection methods. The paper highlights the business problems that were addressed, the Infosys approach, and the challenges, benefits, and learnings that were gained when implementing these solutions. These solutions are spread across different mining processes ranging from asset management to process monitoring, where historical data can be used to learn about the problems and train ML models that were then deployed to assess real-time data and provide insights to business users about impending risks that may arise to their operations.

In the past, the maintenance approach was predominantly reactive. It involved addressing equipment issues only after breakdowns, leading to costly downtime, safety hazards and reduced productivity.

Descriptive & Diagnostic analytics

The shift to condition-based maintenance is an improvement, utilizing sensor data to monitor equipment health and predict failures. However, this method has its limitations. It relies heavily on human analysis and is restricted to issues detectable by specific sensors. Despite its advancements, it remained reactive, responding only after an event.

Traditionally, statistical and rule-based techniques are used to define thresholds and alert anomalous activity in the data. The operations team then needs to investigate the system behavior leading to the alert and take necessary actions. This can be typically time-consuming for the user, and the number of alerts sometimes can be excessive as there could be many sensors for a given process or asset. Typically, they address 'what happened' and 'why did an event happen.' Moreover, the recurring human effort is high and needs highly skilled labor to analyze the data, understand it, and recommend action. Such techniques rely on rudimentary dashboards and reports.

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Predictive & Prescriptive analytics

With the advent of AI and ML, the industry is transforming by scrutinizing vast datasets to pinpoint anomalies that might evade human inspectors. These technologies predict failures more accurately and unveil patterns to forestall future issues, ushering in a proactive maintenance paradigm that revolutionizes the mining sector.

Implementing AI-driven predictive maintenance solutions enables organizations to minimize downtime, reduce maintenance costs and enhance safety across operations. By utilizing performance data from mining equipment and learning from it, we ensure smoother operations and a safer working environment. These techniques will address 'what and when an event will occur.' Under Prescriptive Analytics, it can also suggest 'what a user must do' based on the repository of knowledge, which can be updated as time progresses depending on mistakes and the preciseness of the prediction. These methods require more initial effort. However, the recurring human effort is significantly less. Moreover, the skill needed to understand is also low compared to Descriptive & Diagnostic Analytics. These proactive techniques do not wait until an event occurs, thus saving the user time, effort, and cost. These techniques utilize predictive models with or without an advisory system.

Figure 1 indicates the improvement in Business Value as the maturity of decision support systems increases. For Predictive and Prescriptive models to work well, there must be a good Descriptive foundational layer of "what happened," i.e., good data and records of past events and decisions.

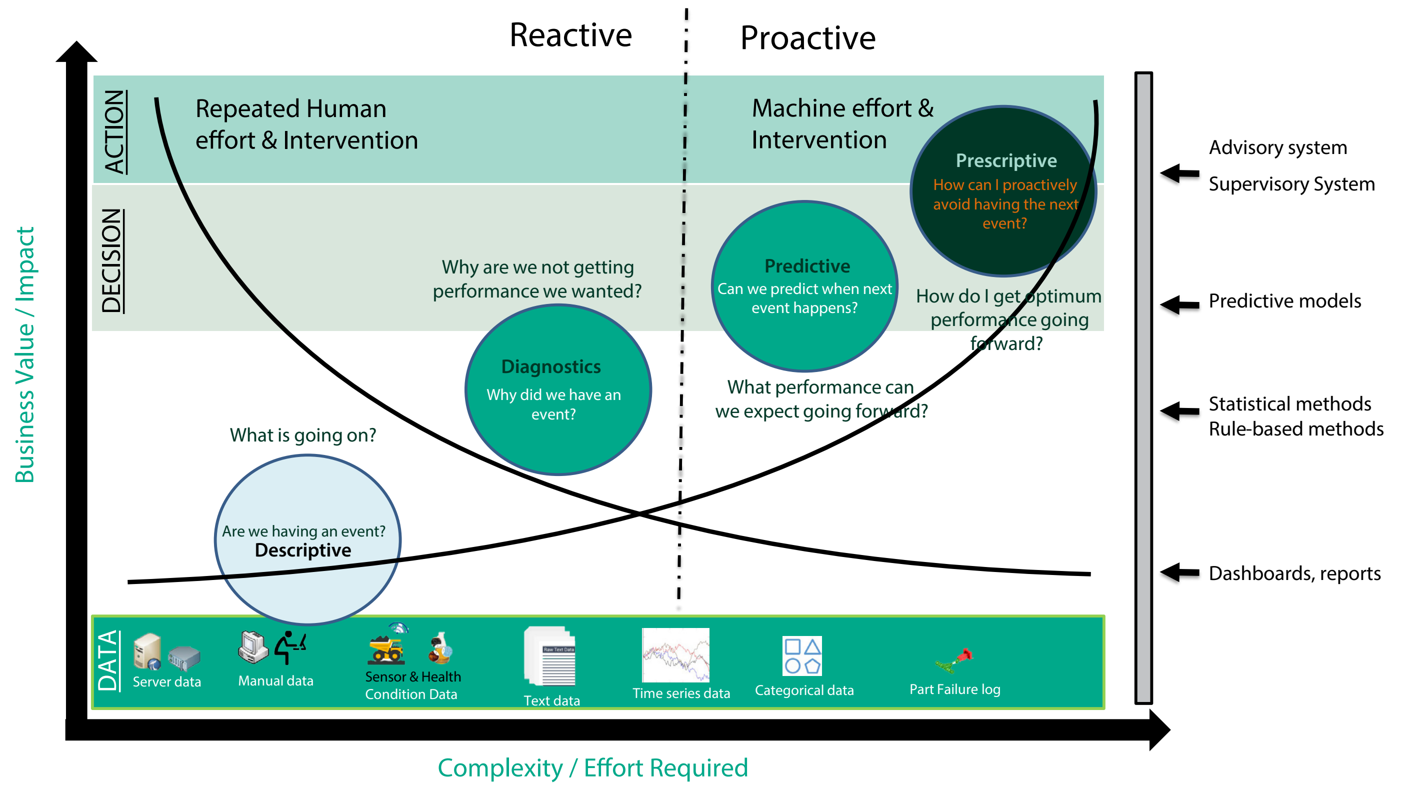
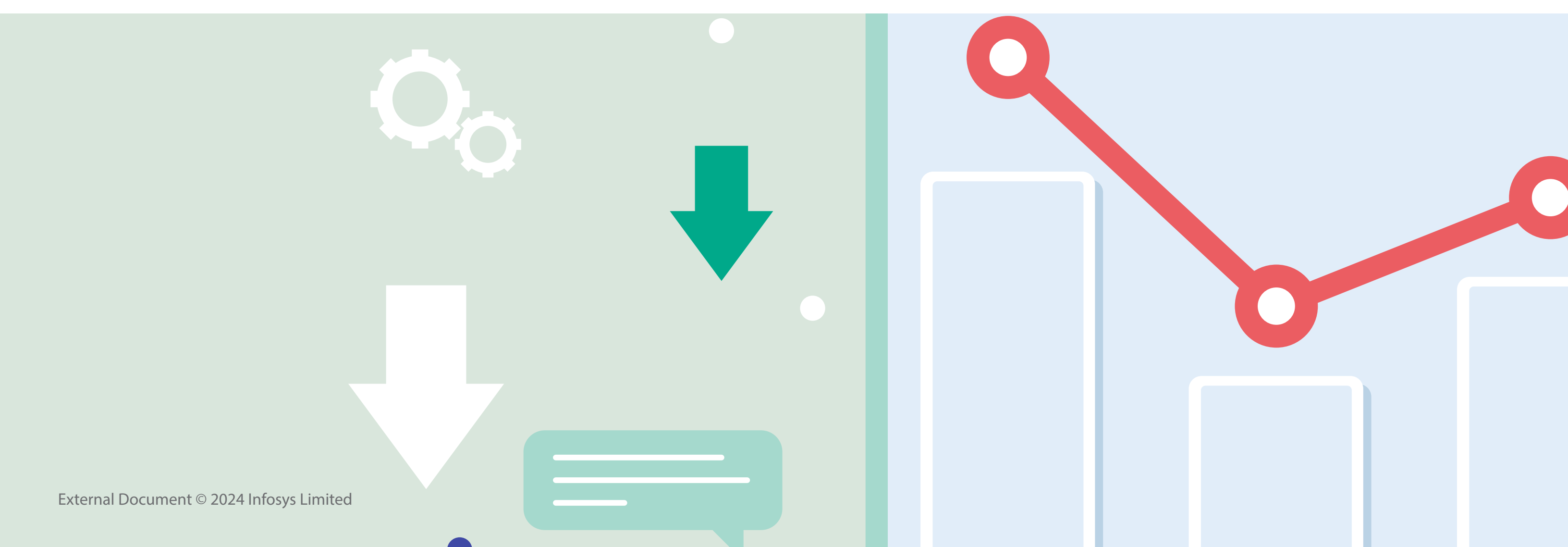


Figure 1: Business value of various decision support systems



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The following section discusses the various methods and algorithms that can help improve decision-making and business value.

OVERVIEW OF ANOMALY DETECTION METHODS

In the mining industry, a variety of anomaly detection techniques are employed:

Descriptive & Diagnostic analytics

- *Statistical methods:* Statistical formulas analyze data, detecting unusual patterns and anomalies
- *Rule-based methods:* Predefined rules based on expert knowledge identify anomalies

Predictive & Prescriptive analytics

- *ML algorithms:* Historical and real-time data train ML models for anomaly detection
- *Deep learning methods:* Neural networks and large datasets detect complex anomalies

Each technique has strengths and weaknesses; the optimal approach depends on the specific application and available data.

Statistical Methods for Anomaly Detection

Statistical techniques detect anomalies by comparing data to established statistical models or distributions. These methods identify unusual patterns by assessing deviations from expected behavior. Common statistical techniques include Z-scores, Grubbs' test, and the Chi-Square distribution. While offering model interpretability and a solid foundation for understanding data, they may need help with complex patterns and large, high-dimensional datasets. These techniques are more reactive, answering what is happening in the system and why an event happened. These are commonly used to analyze machine performance data to detect abnormal behavior or to monitor environmental factors like temperature, humidity, and pressure to ensure safety.

Rule-based Methods for Anomaly Detection

Rule-based methods detect anomalies by comparing events to predetermined thresholds or rules. They provide transparency and control, particularly in safety, maintenance and production applications. However, they can be complex to develop, struggle with unknown anomaly types, and require frequent updates. Just like the statistical method, this is also reactive.

ML Algorithms for Anomaly Detection

ML algorithms detect anomalies without explicit rules, learning normal and abnormal behavior patterns from data. Widely used algorithms include Neural Networks, Support Vector Machines (SVM) and Decision Trees. While offering adaptability and early warning capabilities, they may lack interpretability and necessitate large, labeled datasets. ML algorithms are extensively used in mining to detect production, maintenance, real-time monitoring, and risk analysis anomalies. Unlike the above approaches, these techniques are more proactive, which helps predict when the next event can occur and proactively recommends how to avoid an event.

Deep Learning Approaches for Anomaly Detection

Deep learning methods excel in pattern recognition, prediction, and anomaly detection, utilizing techniques such as Autoencoders, Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). They shine in handling complex patterns and large datasets but may require massive, labeled datasets and can lack interpretability while risking overfitting. These techniques are extensively used for recognizing anomalies in product quality, analyzing machine health data to prevent failures, and autonomous vehicles for safe navigation. Just like the ML approach, this, too, is proactive.

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AI/ML-BASED IMPLEMENTATION APPROACH TO ANOMALY DETECTION.

Some critical success factors for developing an ML model that provides good results and accuracy that business teams can rely on for their decision-making processes include understanding the business domain, availability of good quality data, proper processes, skillset and experience. The data science team needs to work closely with business SMEs at each stage of the process to get relevant inputs and feedback as the model is being developed and validated. Once the model is validated and ready to use, it is piloted for use in production for a certain duration, where the results are closely monitored, and regular feedback is obtained from SMEs on the performance. The model typically gets fine-tuned in this stage and improved continuously so business teams can use insights reliably.

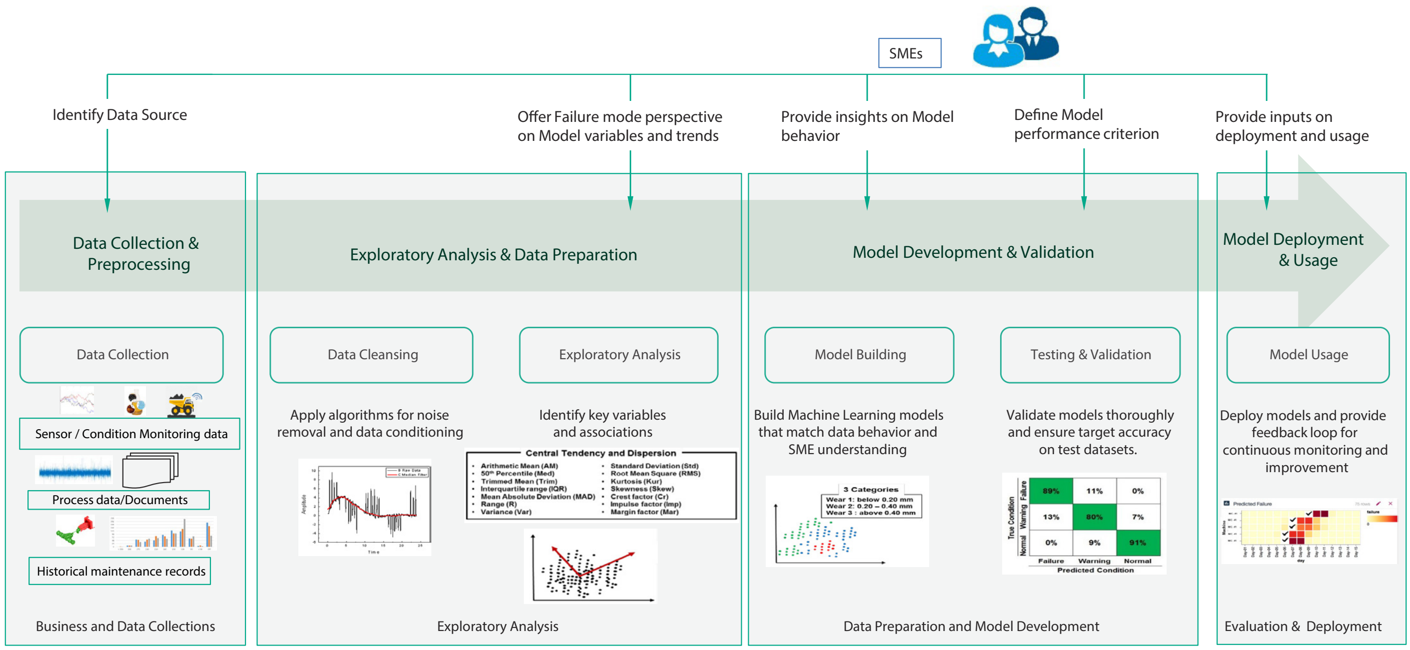

Figure 2 Activities involved in anomaly detection approach

1. Data Collection and Preprocessing – Once the business problem is defined, this is the first step to start the engagement, where different data sources are identified that can be used for developing the model. These typically include:

- Sensor data stored in a historian
- User/process logs
- Technical documentation on the process/equipment
- Maintenance work orders and corrective actions, FMEA reports
- Existing alarms configured based on business rules.

Once the required data is identified and collected, preprocessing combines the data from different sources into a format that can be used to explore it better. This includes handling any missing data and removing irrelevant or inconsistent data.

2. Exploratory Analysis and Data Preparation – This is a crucial step in developing an ML model. It involves analyzing and visualizing the dataset to understand its characteristics, identify patterns, and gain insights to inform feature selection, data preprocessing, and model selection. Some common techniques used in exploratory analysis include:

a) Summary statistics: Calculating basic statistics, such as mean, median, mode and standard deviation, to understand the central tendency and dispersion of the data.

b) Data visualization: Creating plots, such as histograms, box plots, scatter plots and pair plots, to visualize the distribution of individual features and relationships between features and identify outliers or trends.

c) Correlation analysis: Calculating correlation coefficients between features to identify linear relationships and potential multicollinearity issues.

d) Feature engineering: Exploring potential transformations or combinations of features to create new meaningful variables that may improve model performance.

e) Class distribution analysis (for classification problems): Analyzing the distribution of classes to understand class imbalances and decide on appropriate strategies such as resampling techniques.

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f) Dimensionality reduction: Applying techniques such as PCA (Principal Component Analysis) or t-SNE (t-distributed Stochastic Neighbor Embedding) to visualize high-dimensional data and identify clusters or patterns.

g) Outlier detection: Identifying outliers that may adversely affect the model's performance and deciding on appropriate treatment, such as removal or transformation.

By conducting a thorough exploratory analysis, we can better understand the dataset's characteristics, which helps make informed decisions throughout the ML model development process.

3. **Model Development and Validation:** In this stage, a training pipeline is created to train and test the ML model. Different models are trained and tested to check which fits the dataset well. Classification models are evaluated based on metrics like accuracy, precision, recall, F1 score and area under the ROC curve. For anomaly detection models, training data is selected based on normal operating conditions. Once the model is trained, the prediction error is checked against the original dataset to evaluate the model fit and against the past known events. The alerting threshold is then set based on metrics like Hotelling T2.

Once the best-fit model is identified, its parameters are fine-tuned to improve performance. The model is then further tested using cross-validation techniques to verify its robustness and generalization ability. Model explainability is also very important so business users can interpret the model results and make informed decisions. Techniques like (LIME), SHapley Additive exPlanations (SHAP) and feature importance analysis are often implemented, and output from these is added to the model predictions.

4. **Model Deployment and Usage**: Once the model performance arrives at a satisfactory level, it's then deployed for real-world usage. Scoring pipelines are created in this stage so that the model can evaluate new real-time data and make predictions. A dashboard is often created for easy consumption of model results, where the results can be presented to users as a web application. Additional charts have also been developed to help users with problem diagnosis. Automated emails are also configured so that new alerts can be sent to users to take prompt action. Feedback from users is collected using the web application, periodic performance reviews of the model are done to assess how well the model performs in the real world, and opportunities are identified where the model needs further improvement. MLOps is typically used to manage the complete process and automate the model monitoring, retraining and deployment activities.

Over time, the model prediction could drift. Maintaining the effectiveness of predictive maintenance models is crucial for accurate prediction. This process involves **Model Monitoring**, where the model's performance on new data is tracked to identify any degradation in accuracy. If a decline is observed, **Model Re-training** becomes necessary. This involves feeding the model with fresh data, potentially including new anomalies encountered, to improve its ability to detect issues. Finally, the retrained model is **re-deployed** into production to resume its predictive maintenance duties. This cyclical process ensures that the predictive models remain optimized and continue to provide valuable insights to prevent equipment failures.

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ANOMALY DETECTION USE CASES IN THE MINING INDUSTRY.

This section describes various anomaly detection use cases that Infosys implemented for clients in the mining industry.

Safe Mining Operations - Mine Water Monitoring for Underground Mining

Business Context

Water management in underground mines is a critical and challenging activity. Excess water accumulating from unknown sources is always a risk, interrupting regular activities and being a safety issue. Two major incidents have occurred in the Garson Mine, which shut down regular mining operations for a long time. The main aim of this use case is to use the available information and design a soft sensor that can detect such incidents in advance so that proper actions can be taken to avoid them.

Solution Approach

The solution approach involves assessing the data and developing the solution. This included:

- Developing an anomaly detection model using PCA and T2/SPE scores
- Developing a dashboard to show model results and any other useful information to operators
- Automating the manual process of analyzing data from PI and generating alerts based on the model
- Working with mine reliability engineers to validate the alerts and improve the model
- Deploying the model to Azure platform

Business Benefits

Some of the business benefits realized are -

1. Automated daily alerts for the mine engineers so that they could focus on the investigation/remediation and reduce efforts to analyze the data.
2. Reduced safety related incidents by prompting engineers to take early actions.
3. Helped scale up to different mines across the business thanks to the generic nature of the solution setup.

Predictive Maintenance of Mining Haul Truck and Scoops

Business Context

The operating costs of mining haul trucks are approximately USD 550 per hour per truck, so extending their Mean Time Between Failure (MTBF) can help reduce operating costs and maximize profitability. In addition, repair and maintenance costs are significant, and any unplanned maintenance event may increase these costs by up to 30%.

Solution Approach

The solution approach involved analyzing the data, feature engineering, and building and deploying the model. The details of the approach are as follows:

- Collect alarm data from vehicle telemetry, oil sample analysis, and historical failure data
- Perform feature engineering to identify the significant parameters that can be used to predict the failure
- Clean, merge, and label the data to create input data for model training
- Validate the predictive model with the test data and field data
- Use a combination of supervised (xgboost) and unsupervised (KNN) models to address end-of-life and premature failure modes in the components
- Use LIME and radar charts to explain model results by analyzing if the important parameters from the oil sample analysis are outside or within limits

Infosys also published a joint paper with the client for this solution, where the approach is covered in more detail **[5]** on completion and deployment of the predictive model. The customer has acknowledged Infosys' efforts in an open forum (Linked-in)**[7]**

Business Benefits

The primary business benefits include:

1. Increase the engine life from 23K to 26K hours.
2. Predict premature failure to reduce the downtime and maintenance costs.
3. Prioritize component replacement to maximize the useful life and uptime simultaneously.
4. Provide early alerts for part procurement – minimize the inventory of parts.

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Outcome

- **$ 1.6 M** savings from reliability improvement
- **$ 151K** savings due to reduction in unscheduled downtime of trucks
- **6.6%** increase in machine reliability
- **50% decrease from the previous year's downtime hours on engine problems**

Rotational Equipment Health Monitoring in Mining Processing Plants

Business Context

Unplanned failures of critical equipment can be very costly for the mining processing plant operations. For example, the unplanned failure of a single autoclave agitator was estimated to cost $10M. Vibration sensors are installed to monitor equipment health, where the raw waveform data gets processed by proprietary software and different trend parameters like velocity and acceleration are generated, providing insights into the onset of various failure modes. This analysis is done periodically using the software where alerts are configured for each parameter. There is an opportunity to do this analysis in real-time by integrating the online data into PI Historian and then using ML techniques to perform more dynamic analysis by integrating the process data with the vibration data.

Solution Approach

The solution approach involved assessing the data and developing the solution, which included:

- Develop an anomaly detection model using PCA and T2/SPE scores
- Develop a dashboard to show model results and any other useful information to operators
- Automate the manual process of analyzing data from PI and generate alerts based on the model
- Work with mine reliability engineers to validate the alerts and improve the model
- Deploy the model to the Azure platform

Business Benefits

1. Automated daily alerts for the reliability engineers so that they can focus on the investigation/remediation and reduce efforts to analyze the data.
2. Generic setup to be scaled to different assets across the business.

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CONCLUSION

Considering the nature of the industry, AI and ML provide an immense opportunity to improve productivity, safety and efficiency. As illustrated in the use cases, adopting AI and ML techniques effectively for anomaly detection offered significant business benefits. Anomaly detection is just one application area, but these techniques can also be effectively harnessed and expanded to realize benefits in other application areas. With the onset of new technologies like Generative AI, many new use cases will evolve and help transform mining operations.

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