Good morning everyone,

Today, I would like to talk about the importance of anomaly detection in asset management programs and how machine learning techniques can be used to predict potential failures in critical assets such as machinery, motors, and pumps.

As we all know, the reliability and availability of critical assets are essential for smooth operations in heavy industries. Failure of these assets can lead to significant financial losses. Asset management programs are put in place to ensure the integrity and reliability of these assets. Anomaly detection plays a critical role in the Asset Management program, as it allows for the early detection of anomalies in equipment behavior, mitigating risks and preventing unplanned downtime.

In this study, we proposed using anomaly detection techniques to detect anomalies in the sensor readings of a pump and predict potential failures. We used machine learning algorithms to develop an anomaly detection model that can detect anomalies in real-time and provide timely alerts to maintenance personnel. The dataset used in this study is the Pump Sensor Data, which is a time-series dataset collected from a sensor attached to a pump in an industrial setting.

Two models were used in this study for anomaly detection: autoencoders and deep neural networks. The autoencoder was implemented using Pytorch Lightning, a high-level interface for Pytorch that simplifies the training and deployment of deep learning models. The deep neural network was implemented using TensorFlow. The neural network architecture consisted of two hidden layers with 200 and 40 neurons, respectively, and a single output neuron with a relu activation function.

The results showed that the deep learning model yielded highly promising results in detecting anomalies in the sensor data. By predicting whether a machine is going to break down in the next 20 minutes, the model achieved zero false negatives, indicating that it can accurately predict potential failures. The confusion matrix obtained from the model also supports its efficacy in detecting anomalies with high precision and recall values.

However, the Autoencoder model did not perform well in detecting anomalies in the sensor data. Although the model showed promising results during training, it did not generalize well on the test data. One possible reason for this is the lack of negative samples used in training the model. Since the autoencoder was only trained on positive data, the reconstruction error for negative examples was not significantly different from normal data, making it difficult for the model to detect anomalies accurately.

In conclusion, the deep learning model is a promising solution for detecting anomalies in industrial machinery, which can ultimately reduce the risk of unplanned downtime and mitigate financial losses. Further investigation is required to determine the optimal threshold for detecting anomalies using the Autoencoder model.

Thank you for your attention.