Title: A Case Study in Anomaly Detection using Vibration Sensor Data

Introduction:

In our exploration of predictive maintenance, we delved into the realm of anomaly detection using vibration sensor readings from the NASA Acoustics and Vibration Database. The goal of our study was to employ deep learning techniques, specifically Long Short-Term Memory (LSTM) neural networks, to predict potential bearing failures before they occur.

Dataset Overview:

Our dataset comprised 1-second vibration signal snapshots recorded at 10-minute intervals from four bearings run to failure under constant load. Each file contained 20,480 sensor data points per bearing, sampled at 20 kHz. The data was organized into two zip files, requiring extraction and combination into a single data directory for analysis.

LSTM Networks for Anomaly Detection:

Inspired by the work of Dr. Vegard Flovik, we opted for LSTM neural network cells in our autoencoder model. Unlike traditional supervised learning, our approach was unsupervised, aiming to model normal behavior and identify anomalies as deviations from the norm. LSTMs, being a subtype of recurrent neural networks, were ideal for analyzing temporal data, making them suitable for sequential sensor readings.

Data Exploration and Pre-processing:

We began by plotting the training set sensor readings to observe the trending pattern over time. As we progressed through the test set, anomalies manifested as pronounced changes in vibration patterns, particularly near the failure point. To prepare our data for LSTM networks, we normalized it to a range between 0 and 1 and reshaped it into a 3-dimensional tensor format [data samples, time steps, features].

Autoencoder Neural Network Architecture:

Our chosen architecture, the autoencoder neural network, functions as an ''identity'' learner. It compresses input data to its core features and learns to reconstruct the original data. In the context of anomaly detection, the model is trained on normal data, and anomalies are identified through increased reconstruction errors when the model encounters data outside the norm.

Threshold Determination for Anomaly Identification:

By plotting the distribution of calculated loss in the training set, we identified a suitable threshold for anomaly detection. This threshold ensures that anomalies are distinguished from noise, preventing false positives. The neural network's ability to flag impending bearing malfunctions well in advance demonstrates its efficacy in detecting deviations from normal operational values.

Conclusion:

Our study showcases the power of neural networks, particularly LSTMs, in predictive maintenance through anomaly detection. By leveraging the unique capabilities of autoencoder architectures, we successfully identified anomalies in vibration sensor data, paving the way for early prediction of bearing failures. This approach not only enhances equipment reliability but also minimizes downtime and maintenance costs, underscoring the practical applications of deep learning in industrial settings.

Title: Integrating Prophet Library for Anomaly Detection: Unveiling Patterns in Sensor Data

Introduction:

In our quest for comprehensive anomaly detection, we seamlessly incorporated the powerful Prophet library into our analysis. By leveraging Prophet's automatic identification of trends and seasonality, we streamlined our workflow, eliminating the need for explicit input of these parameters. Our focus was on utilizing the average sensor values as the 'y' column, allowing Prophet to autonomously decipher patterns in the data.

Prophet Visualization:

To further enhance our analytical capabilities, we harnessed Prophet's built-in visualization tools. These visualizations offered a clear and intuitive representation of the identified trends, seasonality, and anomalies. The seamless integration of these visualizations into our workflow not only facilitated result interpretation but also provided valuable insights into the temporal dynamics of our sensor data