PREDICTIVE MAINTENANCE SOLUTIONS INC.

AI-Powered Predictive Maintenance

Presented by the Data Science Team, showcasing innovative AI solutions.

Unexpected Failures

Unexpected machine failures pose a **significant threat** to operational efficiency, resulting in an average cost of **$5,117 per incident** and potential downtime of up to **24 hours**. These failures lead to reactive maintenance issues, causing not only financial losses but also productivity setbacks. Addressing these challenges is crucial for maintaining smooth operations and reducing unplanned downtime across the facility.

Our Mission: Achieving Operational Excellence

Operational Risk

We aim to minimize and manage **potential risks** effectively.

Predict Failures

Our goal is to leverage data to **anticipate issues** before they arise.

Cost Avoidance

Our focus is on preventing unnecessary **expenditures and downtime**.

Data Overview

The dataset comprises **10,000 records** that capture IoT sensor readings, enriched with features like timestamps and cost metrics. This diverse data pool provides a robust foundation for our predictive maintenance model. By analyzing the data, we can uncover patterns that lead to better **operational insights** and more effective failure predictions, ultimately driving improvements in maintenance strategies.

96.6%
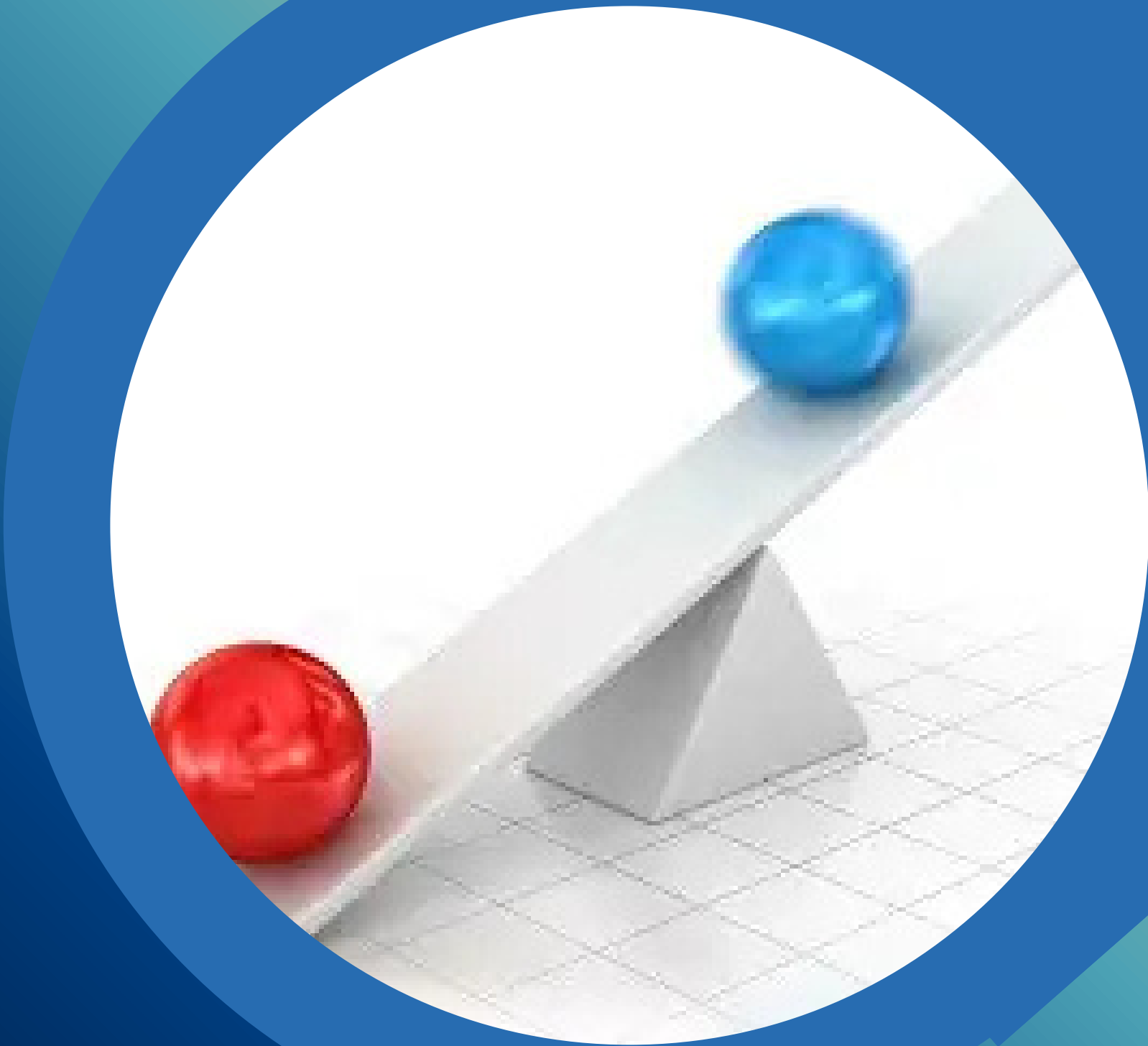
Normal Operations

3.4%

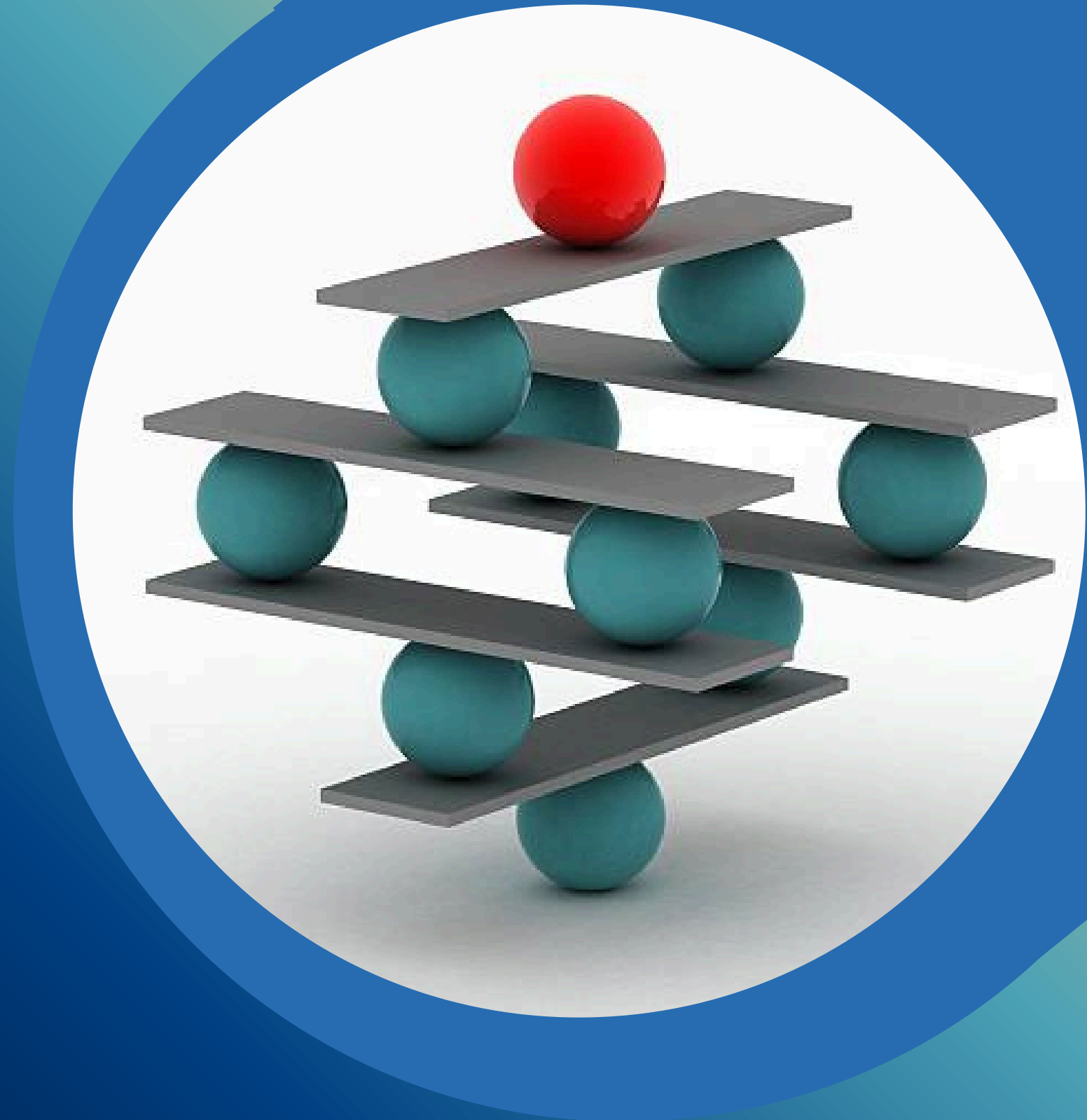Failure Incidents

5

Types of Failures

Imbalanced Data

One of the primary challenges we faced was the **imbalanced data problem**. With 96.6% of our dataset representing normal operation and only 3.4% indicating failures, the model was at risk of becoming biased. This imbalance can lead to poor predictive performance, making it crucial to implement strategies that ensure a balanced representation of both normal and failure instances.

Applying SMOTE

The **Synthetic Minority Over-sampling Technique (SMOTE)** enhances model reliability by tackling class imbalance. By generating synthetic samples from the minority class, SMOTE ensures a balanced dataset, which significantly improves the detection and prediction of rare failures. This approach not only boosts model accuracy but also enhances the overall performance in predicting maintenance needs, reducing unplanned downtimes effectively.

$5,117

Average cost per failure

30%

Cost variance impact

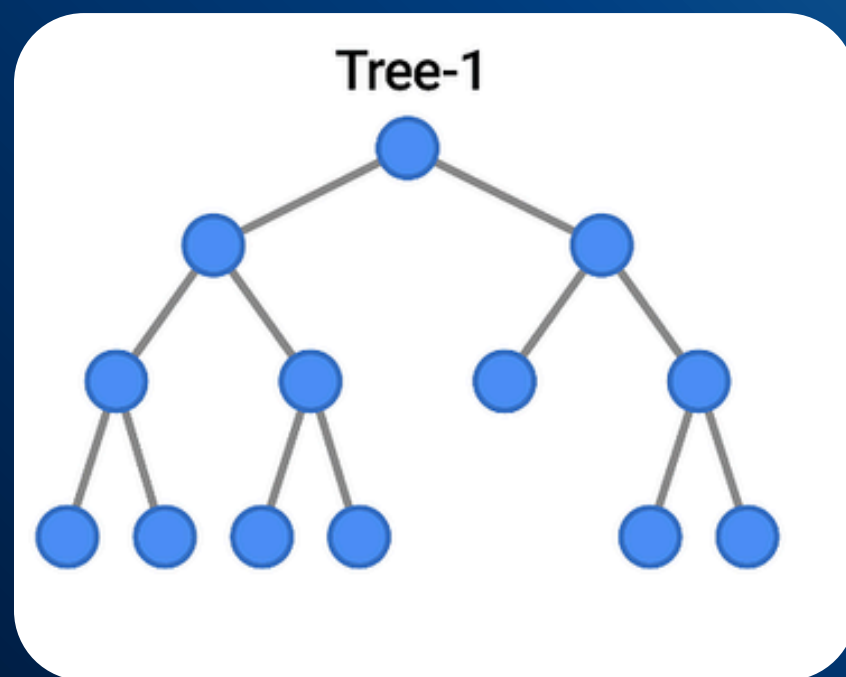**24 hours**

Maximum downtime experienced

Building Intelligence

To create an effective predictive maintenance model, we focused on **transforming raw data** into actionable insights. This involved meticulous feature engineering, where we cleaned the data to remove noise and enrich key attributes. By preparing the data in a structured pipeline, we set the foundation for machine learning algorithms to learn effectively and generate accurate predictions for equipment failures.

Model Performance Comparison: RF, XGBoost, LightGBM

Random Forest

Baseline model for performance comparison.

XGBoost

Strong contender with robust performance metrics.

LightGBM

The strongest performer with highest accuracy.

99%

Accuracy of LightGBM

95%

Precision Rate Achieved

90%

Recall Rate Observed

Meaning of Metrics

Understanding the metrics is crucial for our project's success. With **95% correct alerts**, the model effectively catches **9 out of 10 failures**, minimizing false alarms. This translates into timely interventions and reduced downtime. By leveraging these metrics, we can ensure that our predictive maintenance system not only identifies potential issues but also enhances operational efficiency across the board.

Dashboard Deployment

The transition from model to real tool is crucial for effective predictive maintenance. Our **interactive dashboard** provides real-time diagnostics and predictive insights to operational teams. With user-friendly interfaces and cost estimation features, the dashboard enables swift decision-making, ultimately improving machine reliability and minimizing downtime. This tool transforms complex data into actionable insights, ensuring a proactive maintenance strategy.

Predictive Maintenance in Action

In this example, we detected rising torque levels in a machine, which indicated a potential failure type known as OSF (Overheating Shaft Failure). By utilizing our predictive maintenance model, we were able to take proactive measures, thereby avoiding costly downtime and preventing significant operational disruptions. This scenario exemplifies the tangible benefits of our AI-powered approach.

UX Complexity

The **user experience (UX)** of our dashboard initially faced significant complexity issues. Early designs were cluttered and confusing, making it difficult for users to interpret vital information quickly. By simplifying the layout and enhancing visual clarity, we transformed the interface, allowing users to engage with the dashboard more effectively and make informed decisions faster.

UI Improvements

We greatly enhanced user experience by refining the dashboard's layout. With a focus on **clarity and simplicity**, the updated design reduces clutter and improves readability. This transition allows users to navigate the interface with ease, leading to faster decision-making and more efficient monitoring of predictive maintenance metrics. A clean interface directly contributes to better operational outcomes.
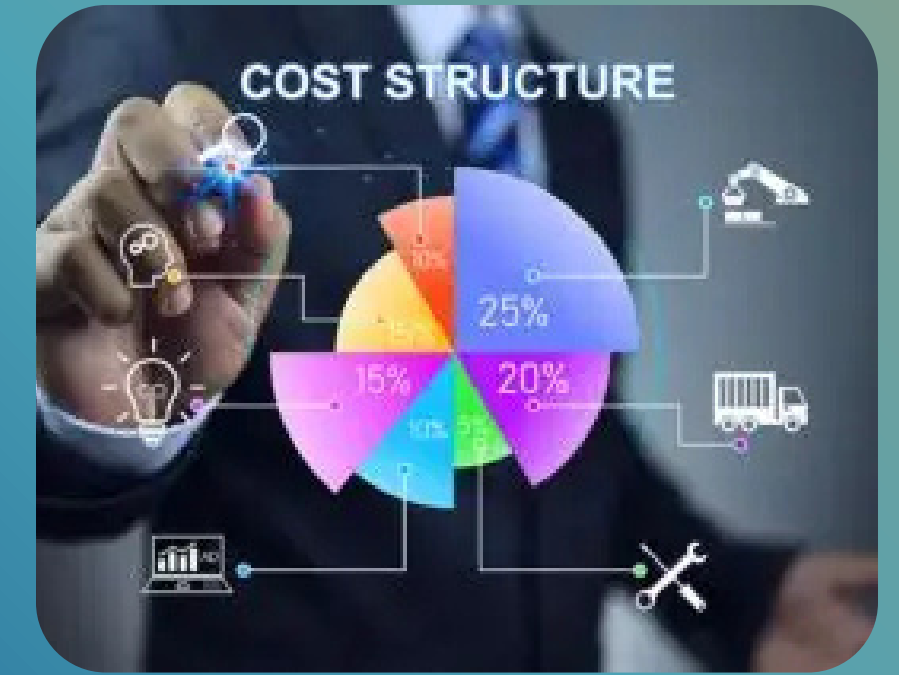
Key Deliverables from Our Journey

Model

An accurate model for predicting failures.

Dashboard

A user-friendly interface for real-time insights.

Cost Analytics

Detailed analysis of cost savings achieved.

Business Impact

The implementation of our AI-powered predictive maintenance model has led to significant cost savings and efficiency improvements. By avoiding unplanned downtime and reducing maintenance costs, we project savings of up to **$5,000 per failure**. This proactive approach not only enhances operational performance but also positions the organization to better allocate resources and invest in future innovations.

System Architecture

The **system architecture overview** illustrates the seamless integration of data pipelines, machine learning models, and user interfaces. It highlights how data flows from IoT sensors to the predictive maintenance model and culminates in the user-friendly dashboard. This framework ensures real-time monitoring, predictive insights, and effective decision-making, thereby optimizing operational efficiency and minimizing unexpected downtimes.

Overcoming Challenges

01 **Imbalance**

The data imbalance significantly impacted our model's ability to accurately predict rare failure events.

02 **Cost Variance**

Variability in costs made it challenging to assess the true financial implications of machine failures.

03 **Model Tuning**

Continuous adjustments and testing were necessary to optimize model performance and enhance prediction accuracy.