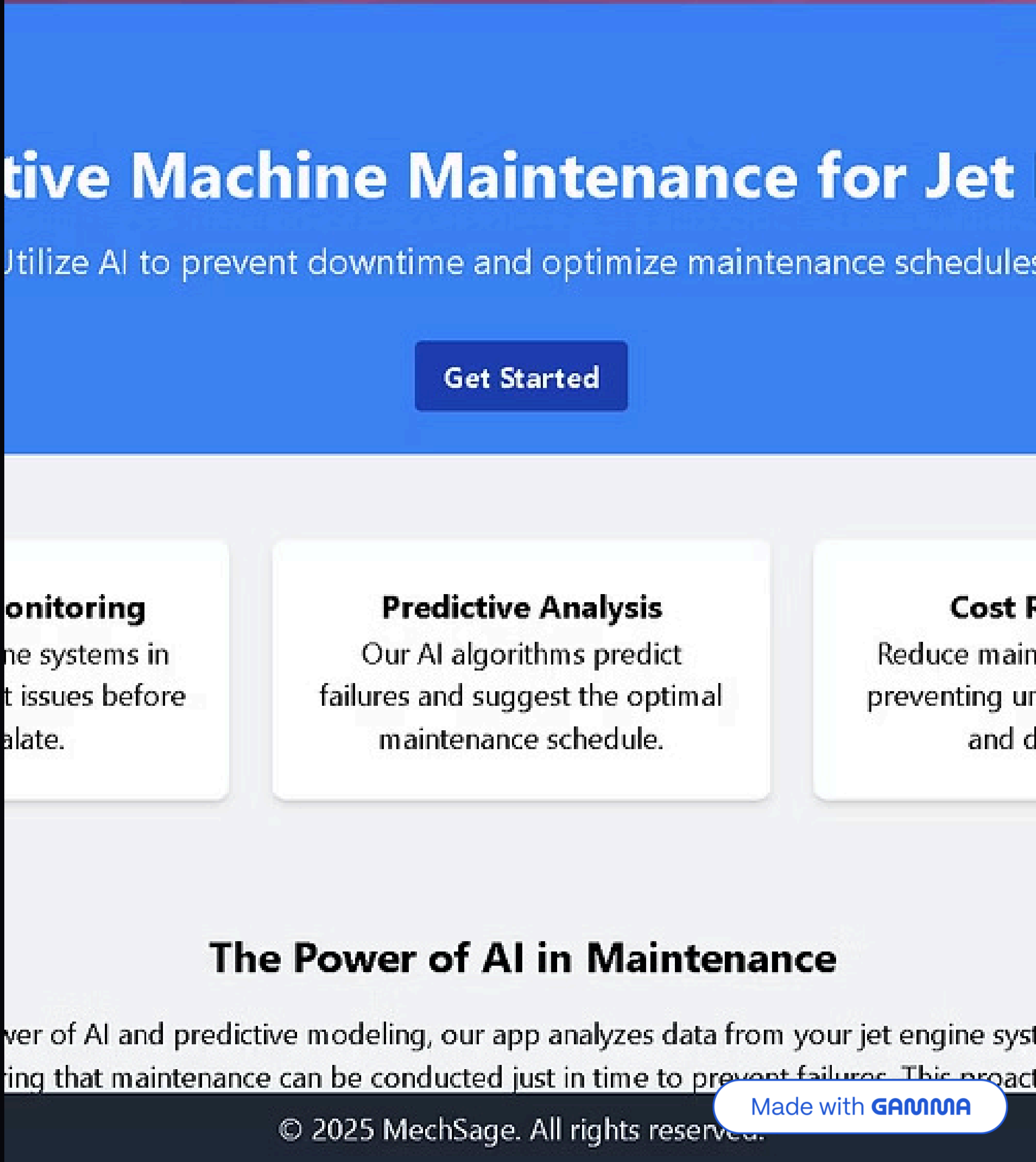
Predictive Maintenance for Industrial Equipment

A machine learning solution for predicting equipment failures and enabling proactive maintenance scheduling to minimize industrial downtime.



The Challenge

Problem Statement

Industrial equipment failures lead to costly unplanned downtime, production losses, and safety risks. Traditional reactive maintenance approaches are inefficient and expensive.

Our Approach

Leverage machine learning to predict equipment failures before they occur, enabling proactive maintenance scheduling and optimizing operational efficiency.

Project Objectives

Develop ML Solution

Build a robust predictive maintenance system tailored for industrial equipment monitoring and analysis.

Predict Failures

Accurately forecast equipment failures and maintenance needs in advance using historical sensor data.

Enable Proactive Planning

Facilitate proactive maintenance scheduling to minimize downtime and maximize equipment lifespan.

Dataset Foundation

NASA CMAPSS Jet Engine Data

Our model is trained on NASA's Commercial Modular Aero-Propulsion System Simulation (CMAPSS) dataset, a comprehensive collection of multivariate time series data.

Key characteristics:

- Multiple engines of the same type
- Run-to-failure sensor recordings
- Realistic operating conditions and degradation patterns
- Industry-standard benchmark for RUL prediction

Data Preprocessing Pipeline

Feature Reduction

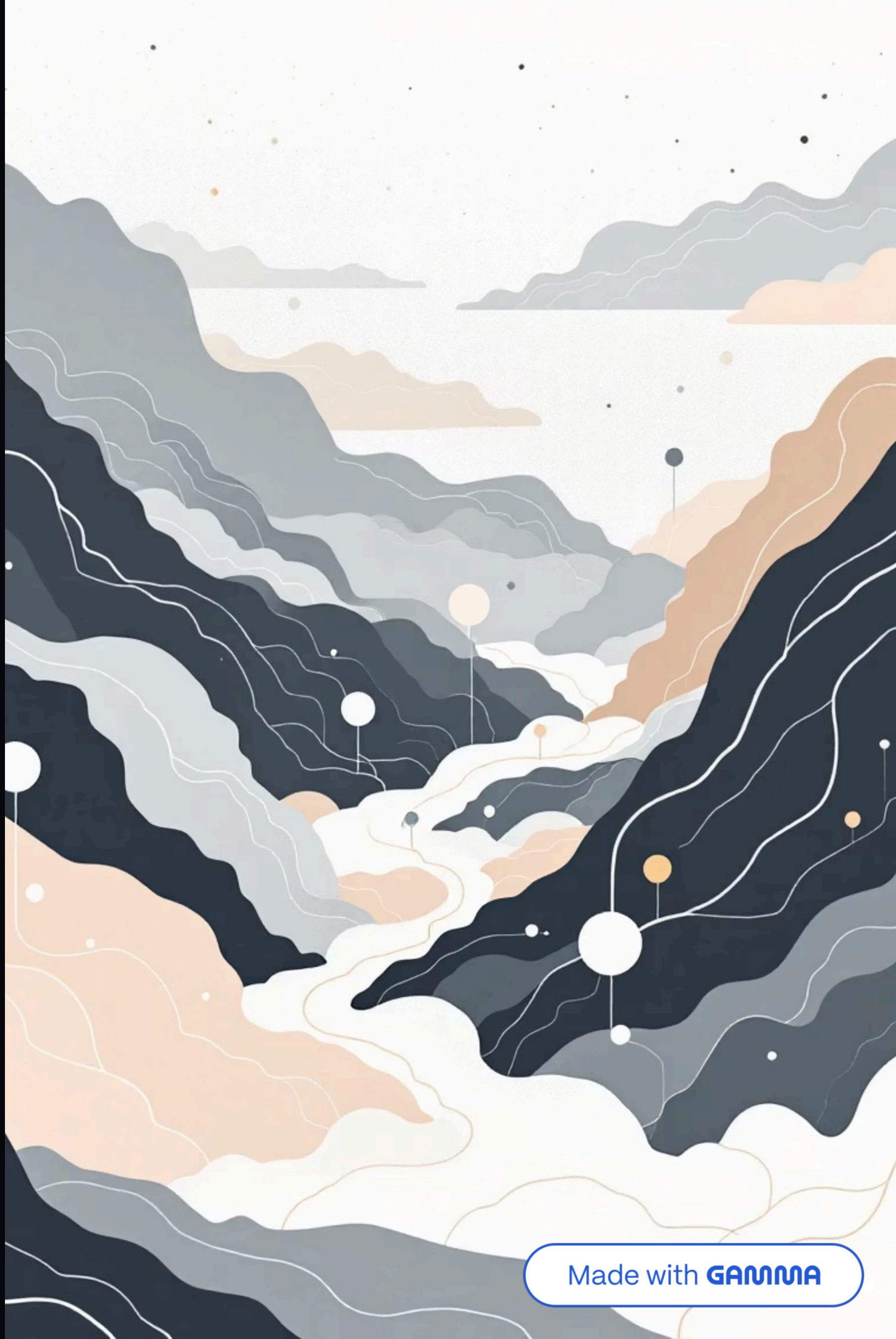
Identify and retain the most relevant sensor features while eliminating noise and redundant variables.

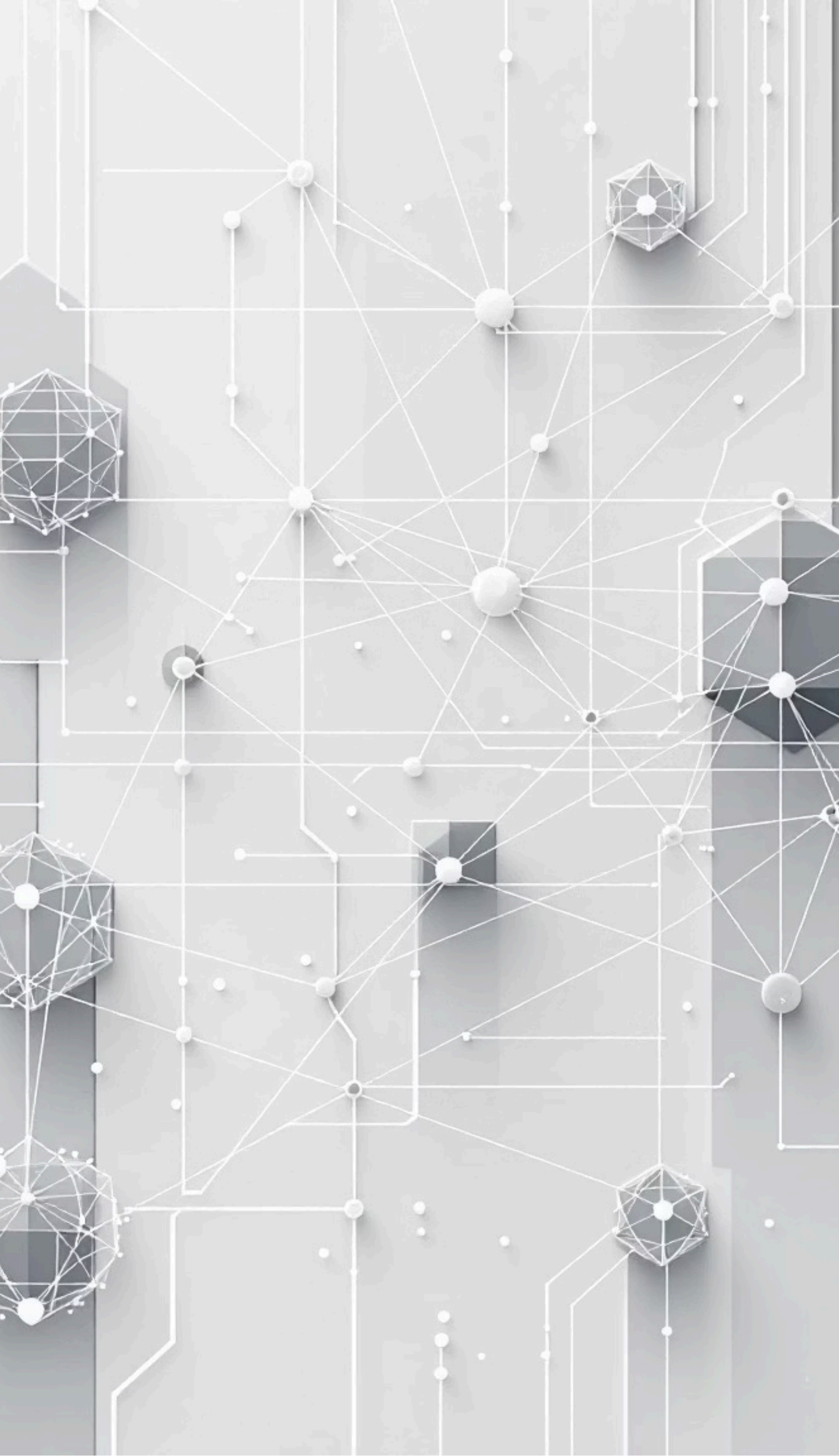
Handling Missing Values

Apply imputation techniques to address gaps in sensor readings and ensure data completeness.

Min-Max Scaling

Normalize features to a consistent range, improving model convergence and prediction accuracy.





Machine Learning Models for RUL Prediction

1

XGBoost

Gradient boosting algorithm optimized for performance and accuracy. Achieved the highest R^2 score of 0.65, demonstrating superior predictive capability for remaining useful life estimation.

2

Random Forest Regressor

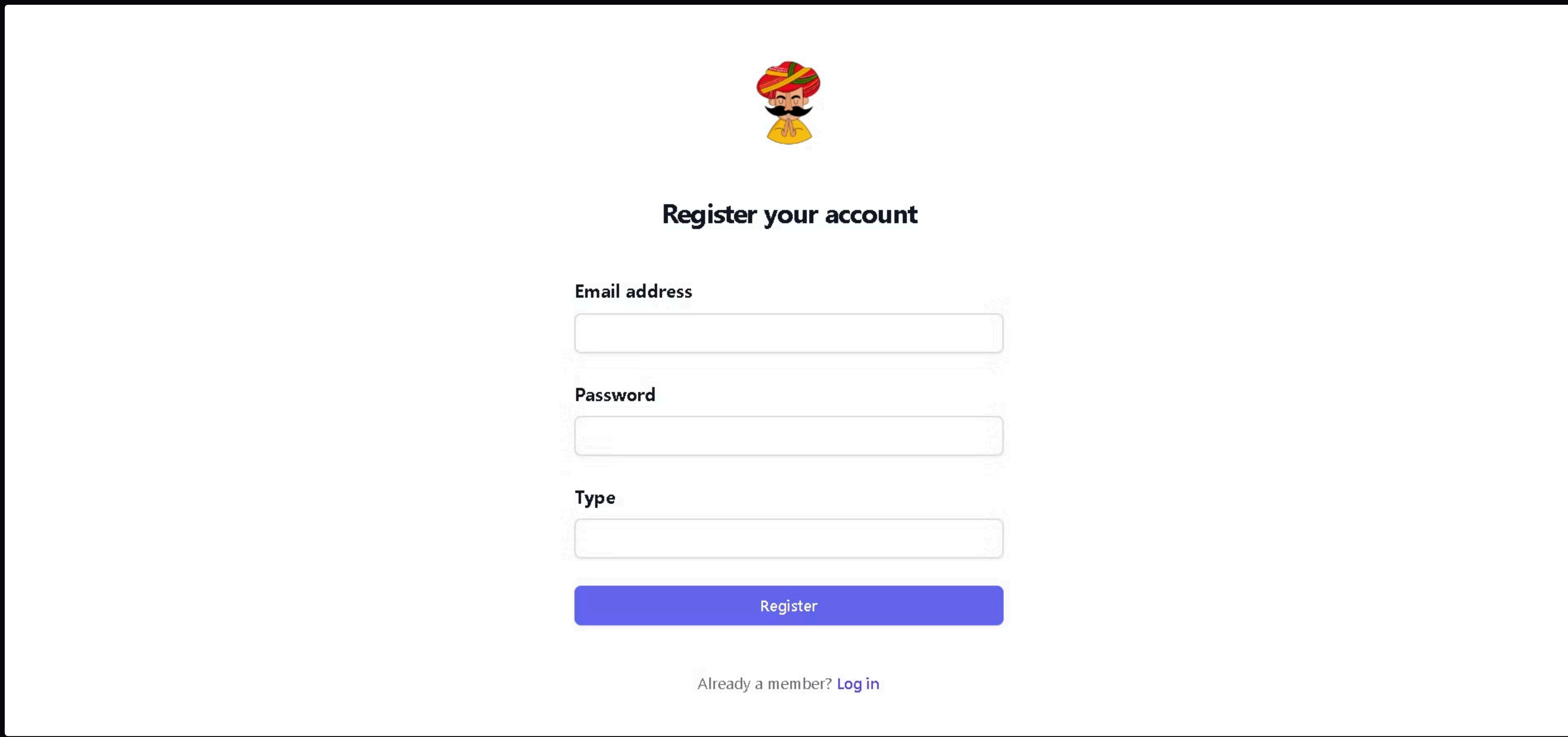
Ensemble learning method combining multiple decision trees to reduce overfitting and improve generalization across diverse operating conditions.

3

Decision Tree Regressor

Baseline model providing interpretable decision rules for maintenance predictions, useful for understanding feature importance and failure patterns.

Interactive Web Application Features



Authentication & Access Control

Secure user management system ensuring authorized access to sensitive equipment data and predictions.

Real-time Monitoring & RUL

Live sensor data visualization with instant remaining useful life predictions for proactive decision-making.

Multi-channel Alerts

Intelligent notification system delivering critical alerts through web browser and Telegram for immediate response.

Maintenance Scheduling

Personalized calendar integration for planning and tracking maintenance activities based on predictions.

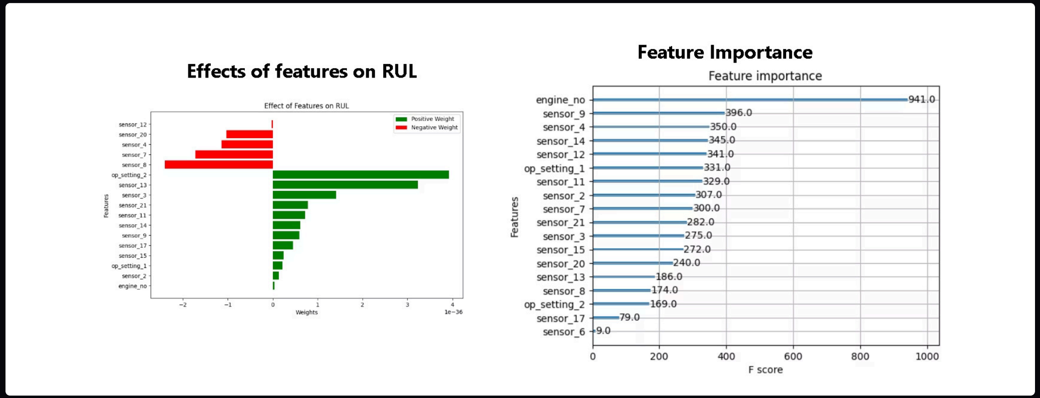
Analytics Dashboard

Comprehensive static plots and interactive dashboards providing insights into equipment health trends.

Feedback & Reporting

Built-in mechanisms for user feedback collection and detailed maintenance report generation.

Technology Stack



Modern Architecture

- **React.js:** Dynamic frontend for interactive user experiences
- **Flask:** Python backend serving ML models and APIs
- **MongoDB:** NoSQL database for flexible sensor data storage
- **Node.js:** Server-side runtime for real-time operations
- **Telegram API:** Instant mobile notifications
- **Chart.js:** Beautiful data visualizations and graphs

Model Performance Results

0.65

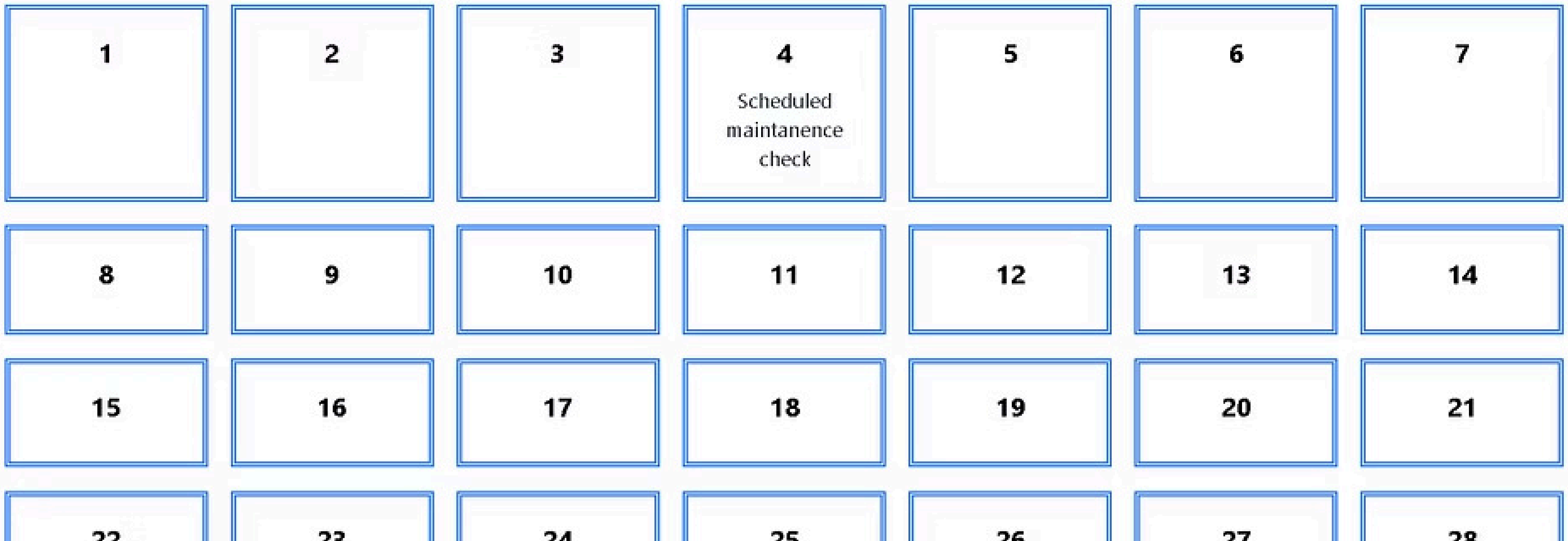
R^2 Score

XGBoost model performance

Leading Predictive Capability

XGBoost achieved the highest coefficient of determination ($R^2 = 0.65$), significantly outperforming baseline models and demonstrating strong predictive capability for remaining useful life estimation.

This performance enables reliable maintenance forecasting, reducing false alarms while ensuring critical failures are predicted with sufficient lead time.



Key Outcomes & Future Directions

Superior Model Performance

XGBoost demonstrated the highest predictive capability with R^2 score of 0.65, validating the effectiveness of ensemble learning for RUL prediction.

Comprehensive Web Platform

The React-based application delivers real-time monitoring, intelligent alerting, maintenance scheduling, and actionable insights in a unified interface.

Continuous Improvement

Ongoing refinement through user feedback integration and model retraining ensures the system evolves to meet changing industrial requirements and improves prediction accuracy over time.