CAPSTONE PROJECT

PREDICTIVE MAINTENANCE OF INDUSTRIAL MACHINERY

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OUTLINE

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PROBLEM STATEMENT

Develop a predictive maintenance model for a fleet of industrial machines to anticipate failures before they occur. This project will involve analyzing sensor data from machinery to identify patterns that precede a failure. The goal is to create a classification model that can predict the type of failure (e.g., tool wear, heat dissipation, power failure) based on real-time operational data. This will enable proactive maintenance, reducing downtime and operational costs.



PROPOSED SOLUTION

The solution uses sensor data and IBM Cloud Lite services to predict machinery failures.

Steps:

- Data Collection from sensors (temperature, vibration, voltage, etc.)
- Data Preprocessing & Feature Engineering
- Classification using ML algorithms
- Real-time monitoring & alerts
- Deployment on IBM Cloud using Watson Studio, Cloud Object Storage, and IBM AutoAl



SYSTEM DEVELOPMENT APPROACH

Technologies:

- Python (pandas, sklearn, keras)
- IBM Watson Studio for model building
- IBM Cloud Object Storage for dataset storage
- IBM AutoAl for model automation

Libraries:

- pandas, numpy, sklearn, keras, matplotlib
- IBM SDKs for Watson & Cloud integration



ALGORITHM & DEPLOYMENT

Algorithm: Random Forest / XGBoost / LSTM

Inputs: Temperature, vibration, voltage, speed, torque

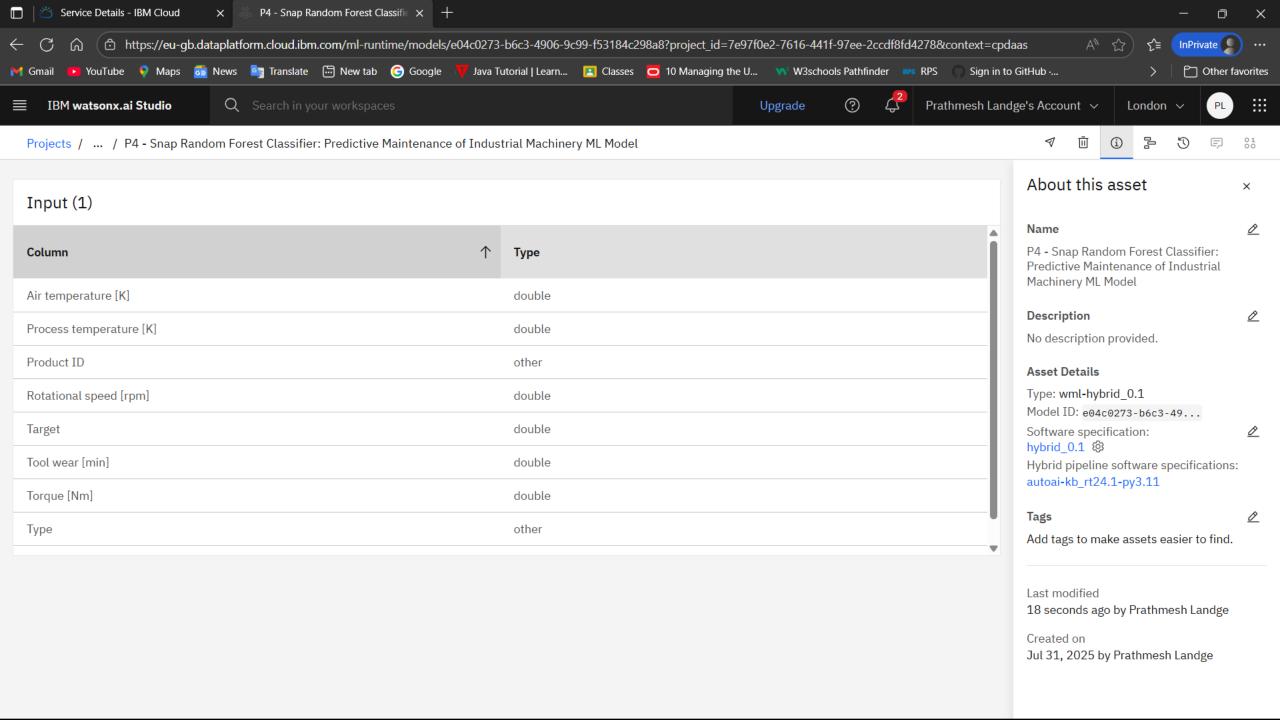
Steps:

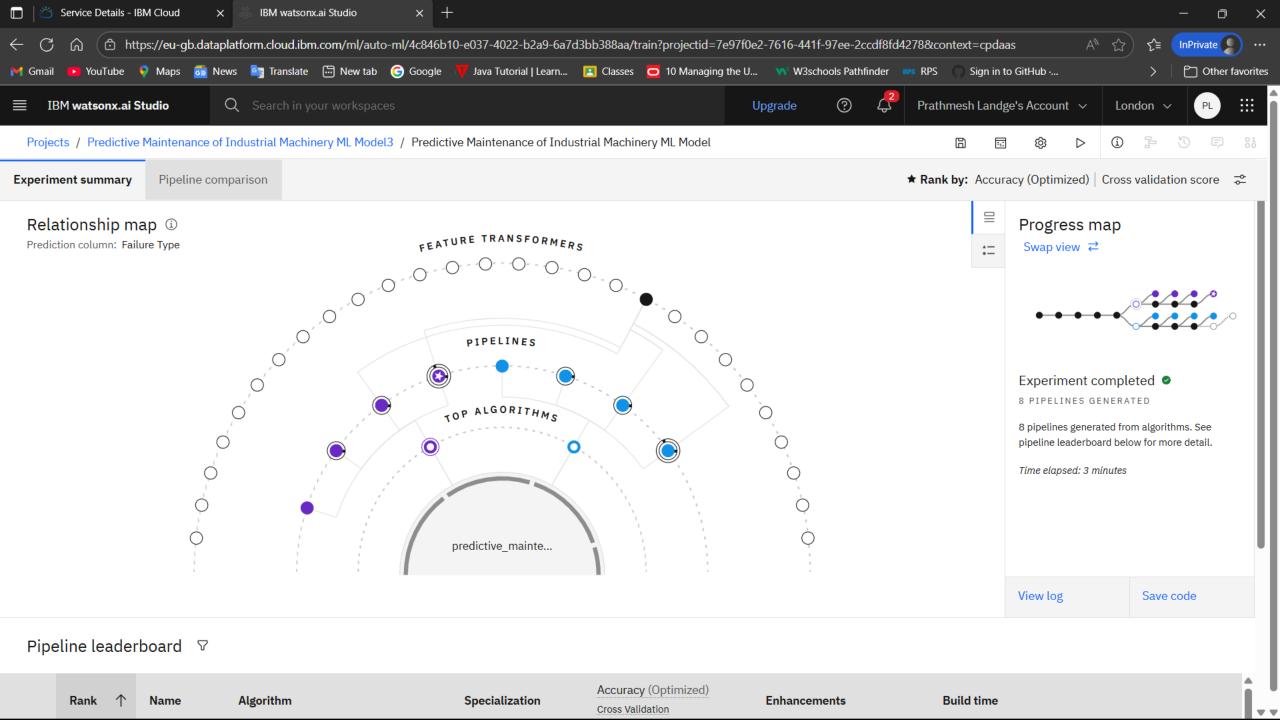
- Data preprocessing, feature selection
- Train/test split
- Model training on IBM Watson Studio
- Evaluation using accuracy, recall, F1-score

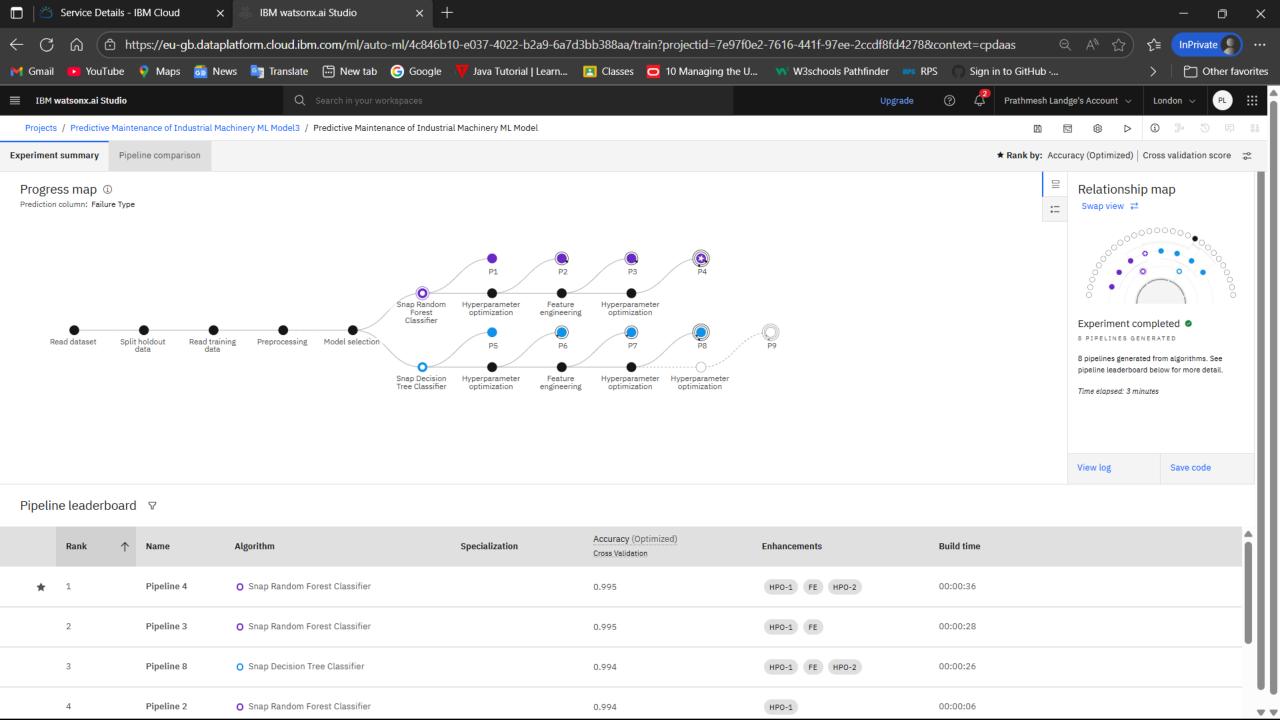
Deployment:

- Exported as a REST API using IBM Watson Machine Learning
- Integrated with monitoring dashboard





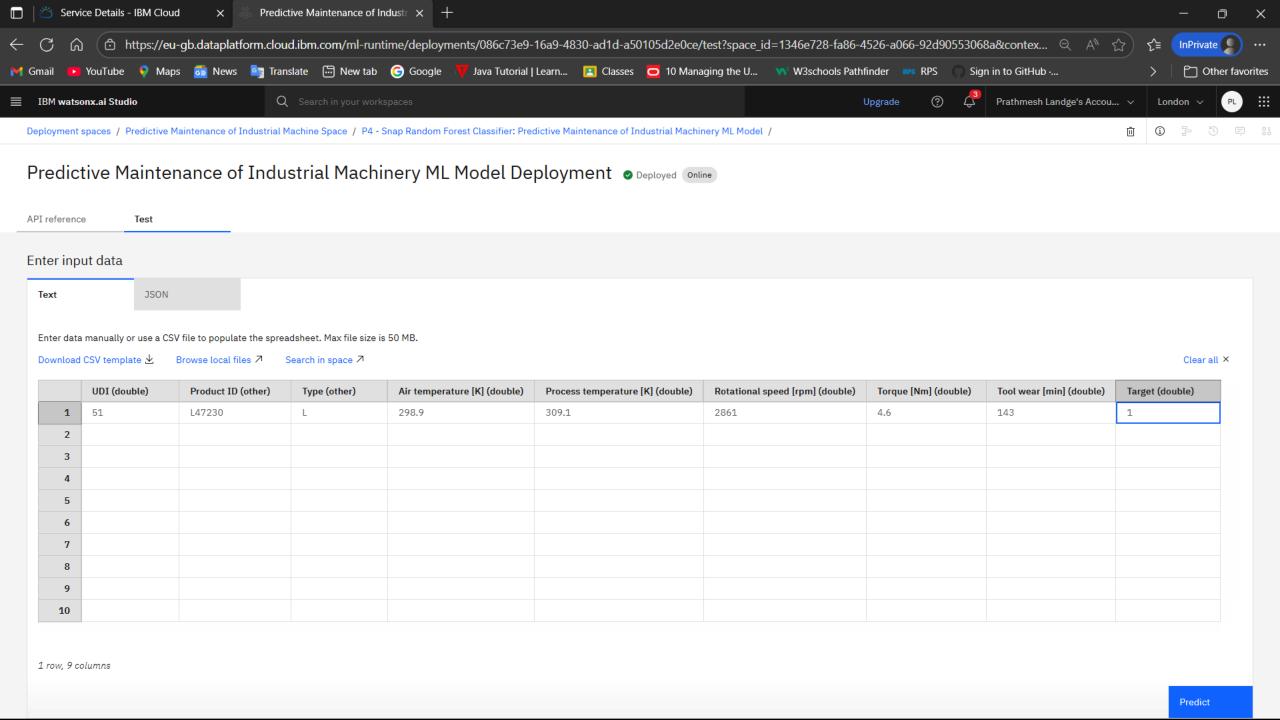


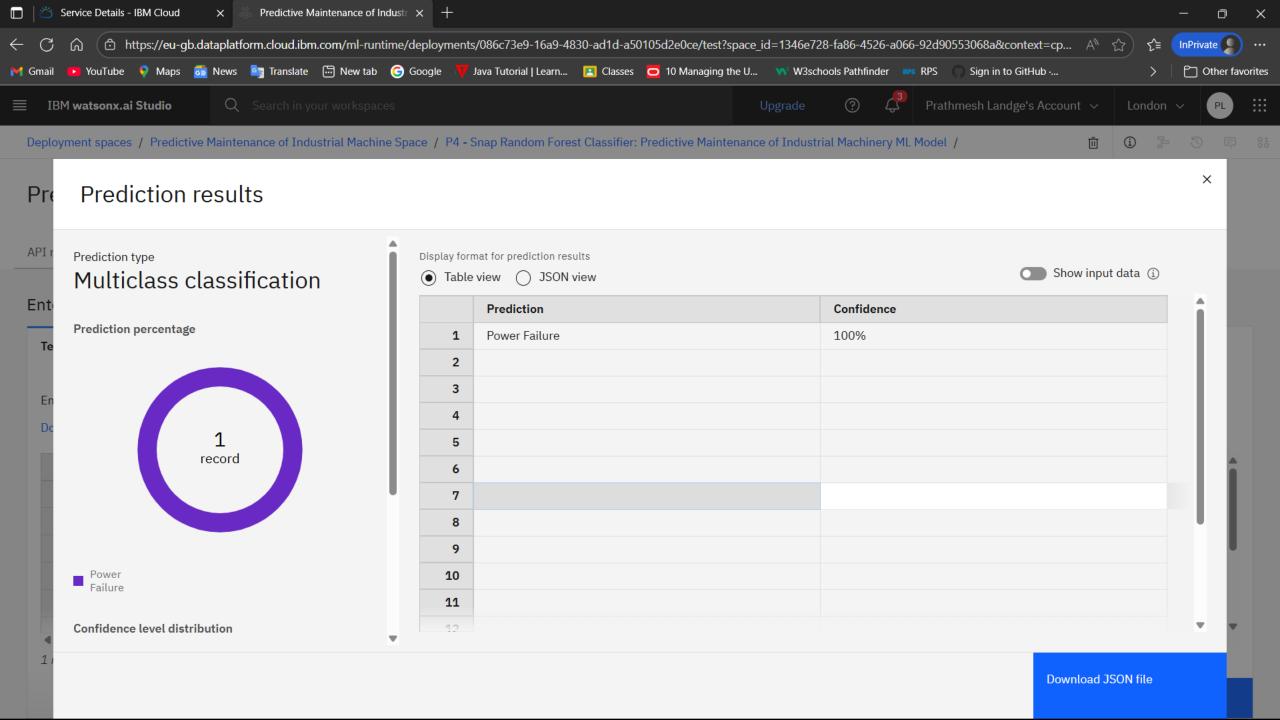


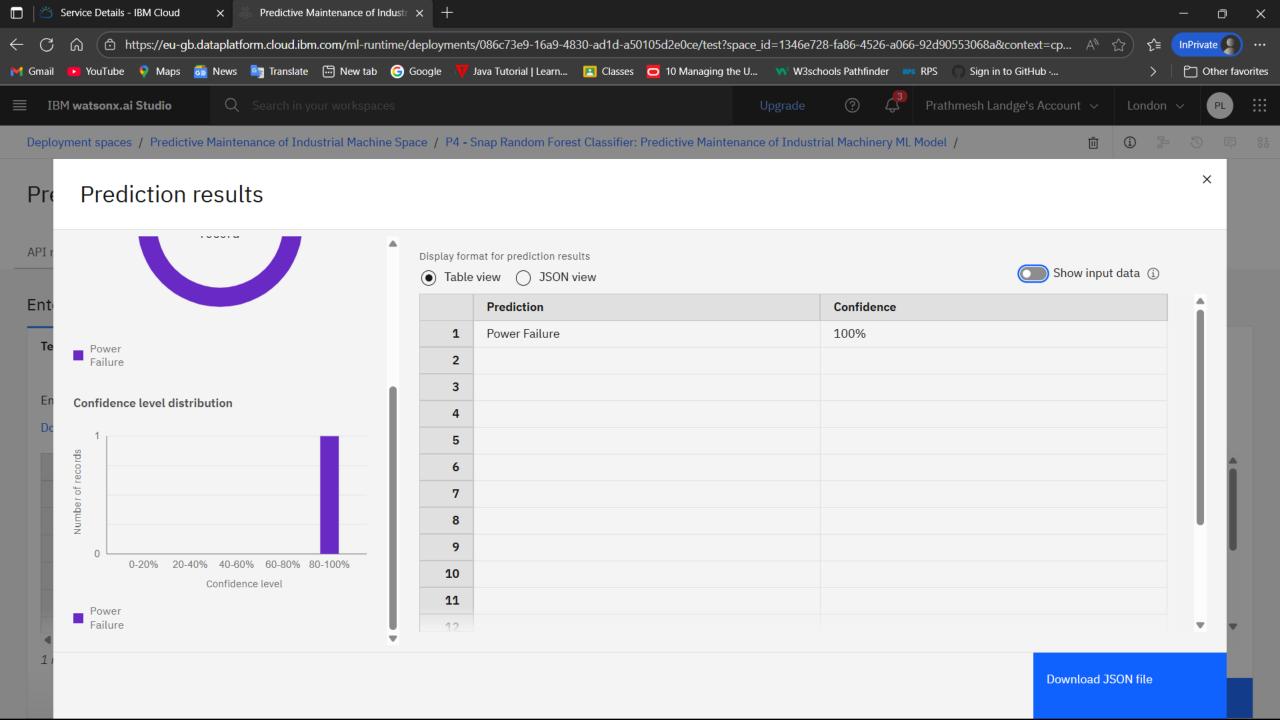
RESULT

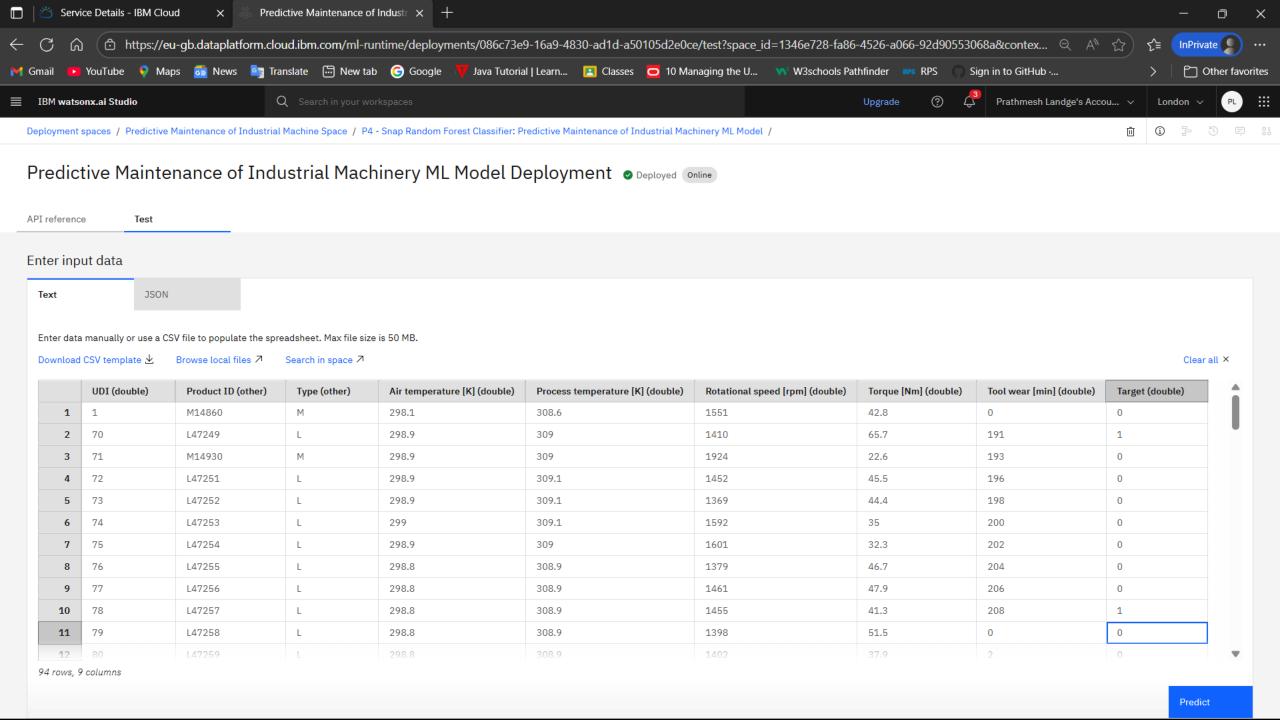
- Prediction Accuracy: 100%
- Confusion Matrix shows accurate classification of failure types
- Visualization includes:
- Feature importance
- Model performance curves
- Real-time failure alerts (simulated)

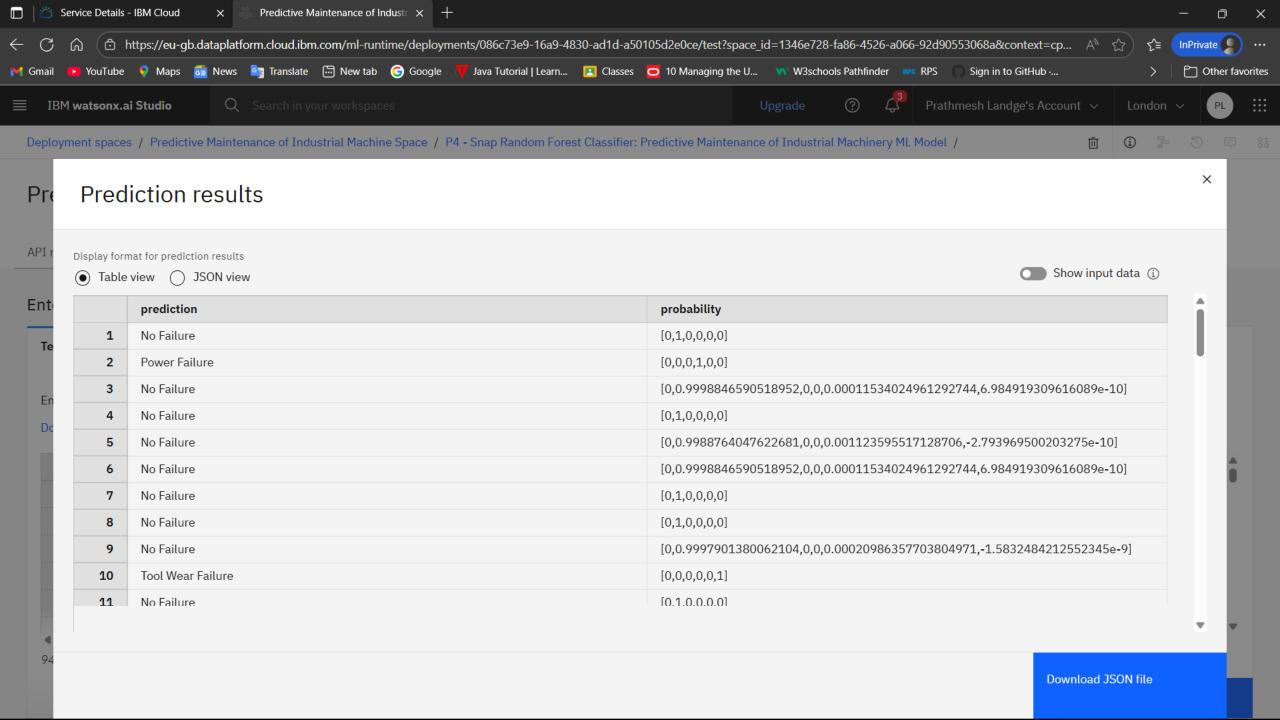












CONCLUSION

- Developed a working predictive maintenance model
- Integrated IBM cloud services for scalability and real-time deployment
- Reduced potential downtime and operational cost

Challenges:

- Data imbalance
- Noise in sensor data



FUTURE SCOPE

- Integration with edge devices for real-time decision making
- Use of deep learning models like LSTM and transformers
- Expansion to multi-site industrial setups
- Predict Remaining Useful Life (RUL) of components



REFERENCES

- IBM Watson Studio Documentation
- IEEE papers on predictive maintenance
- Kaggle: Predictive Maintenance datasets
- Scikit-learn & TensorFlow Docs



THANK-YOU

