

# **SYNOPSIS**

## **TITLE**

### **Bosch Production Failure Detection**

#### **1. Title of the Project**

Bosch Production Failure Detection is a machine learning system that predicts manufacturing line failures using sensor data from Bosch production processes. The system processes 200 key numeric sensors from 20K+ parts to classify production failures with an XGBoost model achieving AUC 0.646. A Streamlit web app provides live failure probability predictions for maintenance decisions.app.py+1

#### **2. Statement of the Problem**

Manufacturing lines experience costly downtime from equipment failures, with Bosch production challenged by imbalanced datasets (1.2% failure rate) and 970+ high-dimensional sensor readings requiring automated detection. Manual quality checks cannot handle real-time prediction across 200 sensors per part. The project addresses this with a predictive classifier enabling proactive maintenance to minimize production losses.Bosch-Production-Failure-Detection\_fixed.ipynb

#### **3. Significance of the Project Present State of the Art**

Industry 4.0 leverages ML for predictive maintenance, with XGBoost established for sensor-based classification on imbalanced industrial data. Current Bosch operations use reactive maintenance while advanced factories employ real-time sensor analytics. This project advances the field by deploying a production-ready predictor with feature selection (top 200 varying sensors) and interactive dashboard, bridging research to practical manufacturing insights.app.py+1

## **4. Objectives of the Project**

1. Preprocess Bosch production datasets by cleaning and selecting top 200 varying sensors
2. Train XGBoost classifier targeting AUC >0.60 on 200K production parts
3. Validate model performance with 80/20 train/test split and ROC-AUC metrics
4. Export trained model (bosch\_model.json) for production deployment
5. Develop Streamlit dashboard for live sensor input and failure predictions
6. Demonstrate high-risk scenarios with sensor readings >150 triggering alertsBosch-Production-Failure-Detection\_fixed.ipynb+1

## **5. Scope of the Project**

The project analyzes Bosch's Kaggle production dataset focusing on numeric sensors for binary failure prediction (Response 0/1). Scope includes data cleaning, model training, evaluation, and web deployment using 200K samples  $\times$  200 features. Excludes categorical features, real-time streaming, and multi-class failure types for focused implementation with production-ready deliverables.Bosch-Production-Failure-Detection\_fixed.ipynb

## **6. Hardware and Software Specifications**

### **Hardware Requirements**

- Processor: Intel i5 or above
- RAM: Minimum 16 GB (200K $\times$ 200 data processing)
- Storage: 500 GB SSD
- Display: Standard monitor with browser supportBosch-Production-Failure-Detection\_fixed.ipynb

## **Software Requirements**

- Operating System: Windows/Linux/MacOS
- Python: 3.12+
- Libraries: Pandas, NumPy, XGBoost, Scikit-learn, Streamlit
- Development Environment: Jupyter Notebook, VS Codeapp.py+1

## **7. Data Collection and Methodology**

### **Data Collection**

Sourced from Kaggle Bosch Production Line Performance dataset containing 200K+ parts with 970 numeric sensors plus Response labels (1.2% positive failures).Bosch-Production-Failure-Detection\_fixed.ipynb

### **Methodology**

1. Load train\_numeric.csv (200K rows, safe nrows sampling)
2. Fill NaN→0, drop >99% zero variance columns
3. Select top 200 std-dev sensors (L3S29F346, L3S29F347 stations)
4. 80/20 train/test split, fit XGBoost (n\_estimators=100)
5. Evaluate AUC 0.646, save bosch\_model.json
6. Deploy Streamlit app for 3-sensor live prediction demoapp.py+1

## **8. Algorithm**

1. Start
2. Load train\_numeric.csv → 200K rows
3. Clean: drop zero columns → Xclean.csv (200K×200), yclean.csv
4. Train/test split (80/20, random\_state=42)
5. Train XGBoost model (n\_estimators=100)
6. Evaluate: predict\_proba → AUC 0.646

7. Save model → bosch\_model.json
8. Deploy Streamlit: live sensor inputs → failure probability
9. Endapp.py+1

## 9. Limitations Constraints of the Project

- Limited to static Kaggle dataset; no live factory sensor feeds
- Excludes categorical features for numeric focus
- Imbalanced classes (1.2% failures) limit precision/recall
- Fixed 200-sensor selection; full 970+ possible with more compute
- Manual 3-sensor demo; full 200-input scaling needs optimizationapp.py+1

## 10. Conclusion and Future Scope

### Conclusion

The Bosch Production Failure Detection system successfully transforms complex sensor data into actionable maintenance predictions with AUC 0.646. The Streamlit dashboard provides intuitive failure probability display (e.g., >50% triggers MAINTENANCE NOW alerts), demonstrating practical Industry 4.0 predictive maintenance. Bosch-Production-Failure-Detection\_fixed.ipynb+1

### Future Scope

- Hyperparameter optimization/ensemble models for AUC >0.70
- Include categorical features and full 970-sensor dataset
- Real-time IoT sensor integration via APIs
- Multi-class failure type prediction
- Cloud deployment (AWS/Heroku) with auto-scalingBosch-Production-Failure-Detection\_fixed.ipynb

## **11. References Bibliography**

1. Kaggle: Bosch Production Line Performance Dataset (2016)
2. XGBoost: eXtreme Gradient Boosting Documentation
3. Streamlit: Deploy ML Apps in Minutes
4. Scikit-learn: ROC-AUC Metrics Documentation