ABSTRACT:

Machine learning models deployed in real-world environments often degrade over time due to changes in data distribution and user behaviour. This project proposes a Model Failure Forecaster that monitors model behaviour and input data characteristics to identify early signs of reliability loss before observable performance decline. By analyzing prediction confidence, uncertainty, and data drift trends, the system forecasts potential model failure without relying on immediate ground-truth labels. The approach is demonstrated using a time-evolving dataset as a case study. The proposed framework enables proactive model maintenance and improves long-term trustworthiness of deployed machine learning systems. Additionally, the methodology is domain-agnostic and can be applied across various applications such as energy systems, financial transactions, and user behaviour analysis. Early failure prediction helps reduce system downtime, incorrect decisions, and operational risks in dynamic environments.

Domain:
Machine Learning, Data Analytics

Keywords:
Web Server Logs, Traffic Analysis, Anomaly Detection, Machine Learning, Unsupervised Learning, Feature Engineering, Bot Detection, Network Traffic Monitoring