AI-BASED LEAD-TIME FORECASTING AND ANOMALY DETECTION IN SUPPLY CHAIN USING CNN-BILSTM AND LSTM-AUTOENCODER

Case Study- Intelligence System In Production (Group B)

Phase 2 Progress Presentation

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REAL INDUSTRIAL PROBLEM

- Unpredictable **supplier lead times** cause:
  - Production delays
  - Stockouts and excess inventory
  - Customer dissatisfaction and cost overruns
- ERP systems record data but **do not forecast or detect risk**.
- **Automotive and spare-parts industries** face these issues most critically.
- **AI-driven forecasting and anomaly detection** help:
  - Predict potential supplier delays early
  - Improve planning accuracy
  - Enable proactive, data-driven decisions

SUMMARY OF KEY APPROACHES FROM LITERATURE

Approach Type	Main Perspective & Assumptions	Advantages	Limitations / Gaps	Representative Papers
Machine Learning	Learns nonlinear feature relationships (supplier, transport, region); assumes independent records and static behaviour.	Flexible with structured ERP data; interpretable and faster to train.	Ignores sequential time patterns; weak at forecasting long-term dependencies.	Roy et al., 2015 – Stock Market Forecasting Using LASSO Regression
Deep Learning (**LSTM / BiLSTM**)	Models' long-term dependencies in sequential ERP or time-series data; assumes large data availability.	High forecasting accuracy; learns temporal trends automatically.	Misses short-term variations; heavy computational requirements.	Siami-Namini et al., 2019 – Performance of LSTM and BiLSTM in Time Series Forecasting
Hybrid Deep Learning (**CNN–BiLSTM**)	Combines CNN (short-term features) + BiLSTM (long-term memory) for improved forecasting.	Captures both local and global dependencies; superior to standalone models.	Limited real-world deployment; often used in research environments.	Amellal et al., 2023 – Combined CNN–LSTM for Lead-Time Forecasting
Hybrid Anomaly Detection (**LSTM-AE + OCSVM**)	Learns normal supplier behaviour via LSTM Autoencoder; OCSVM defines anomaly boundaries.	Unsupervised, robust anomaly detection adaptable to new suppliers.	Computationally intensive; requires tuning for real-time use.	Nguyen et al., 2021 – LSTM Autoencoder for Supply Chain Anomaly Detection

RESEARCH GAP & POSITIONING

- Most research focuses on **demand or price forecasting**, not **lead-time forecasting**.
- Few studies combine **forecasting and anomaly detection** in one framework.
- Existing ERP tools are **reactive**, not **predictive**.
- Our project extends *Amellal et al. (2023)* by:
- Building a **deployable hybrid AI system**.
  - Integrating **CNN–BiLSTM** for lead-time forecasting.
  - Adding **LSTM-AE + OCSVM** for supplier anomaly detection.
  - Developing a **real-time dashboard** (FastAPI + Streamlit) for industry use.

TOOLS AND METHODS COMPARISON

Aspect	Prior Work	Our Approach	Key Advantage
Forecasting	ARIMA, Random Forest, LSTM	CNN–BiLSTM	Captures both short-term and long-term patterns
Anomaly Detection	Isolation Forest, Autoencoder	LSTM-AE + OCSVM	Unsupervised, robust anomaly classification
Data Type	Static, tabular	Sequential ERP data	Reflects real supplier timelines
Deployment	Offline models	FastAPI + Streamlit	Real-time, interactive dashboard

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WHY WE CHOSE OUR APPROACH

- **CNN–BiLSTM**
  - CNN extracts short-term temporal features (local delivery patterns).
  - BiLSTM captures long-term dependencies (supplier trends).
  - Together → High forecasting accuracy and low RMSE.
- **LSTM Autoencoder + One-Class SVM**
  - Learns “normal” supplier behavior → detects deviations automatically.
  - OCSVM defines clear mathematical boundaries for anomalies.
- **FastAPI + Streamlit Integration**
  - Converts the model into a **real-time operational system**.
  - Enables visualization, alerts, and decision-making in one dashboard.

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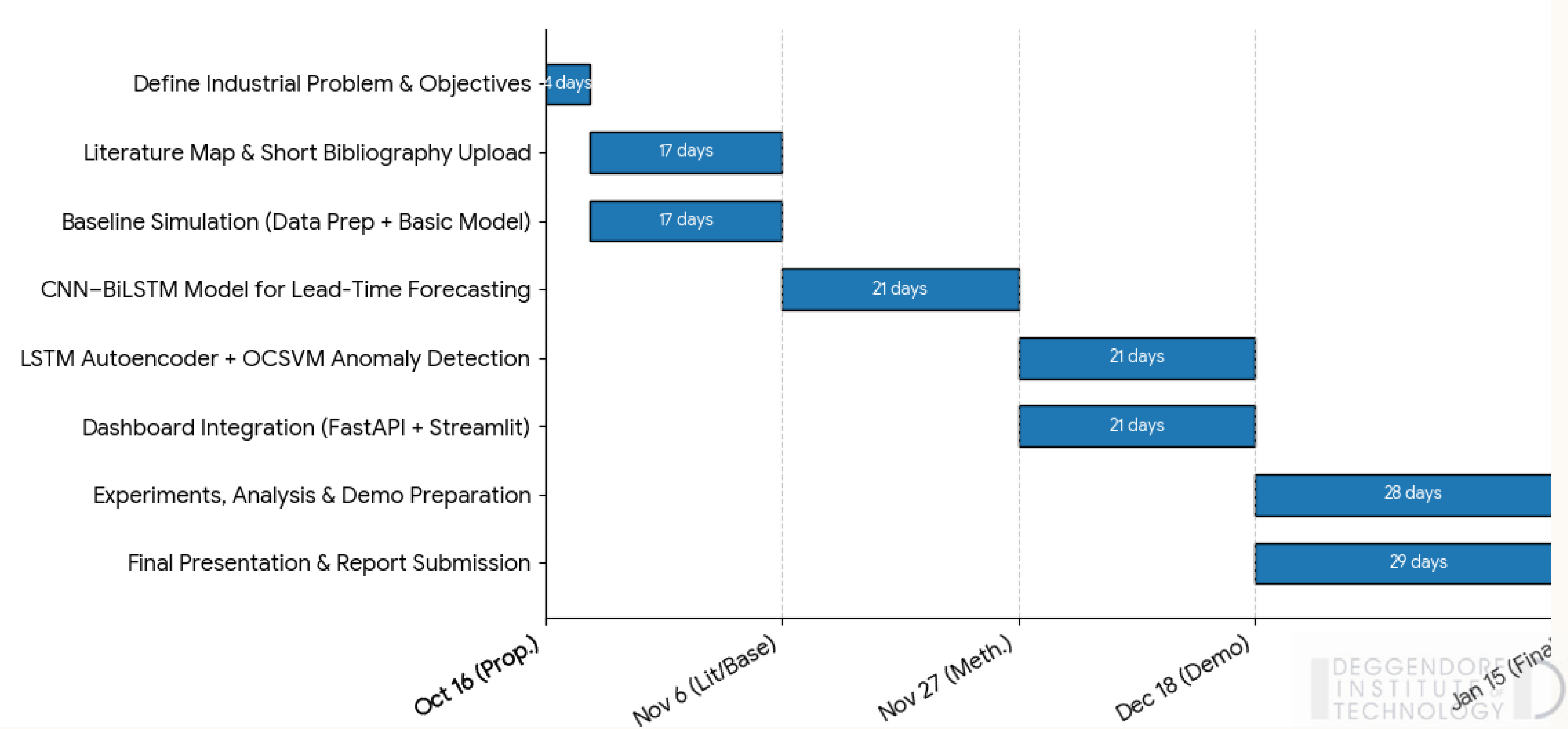
METHODOLOGY STEPS

1. Data Cleaning & Feature Engineering
2. CNN–BiLSTM for Lead-Time Forecasting
3. LSTM-AE + OCSVM for Anomaly Detection
4. Dashboard Integration & Evaluation

PROJECT TIMELINE



PROGRESS

COMPLETED:

DATA PREPROCESSING & FEATURE EXTRACTION

CNN–BILSTM MODEL TRAINING

IN PROGRESS:

ANOMALY DETECTION PIPELINE SCAFFOLDED

DASHBOARD UI DEVELOPMENT (FASTAPI + STREAMLIT)

ANOMALY EVALUATION (PRECISION, RECALL, F1)

INTEGRATION AND DOCUMENTATION

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THANK YOU

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