# AI-Based Lead-Time Forecasting and Anomaly Detection in Supply Chain Using CNN-BiLSTM and LSTM-Autoencoder

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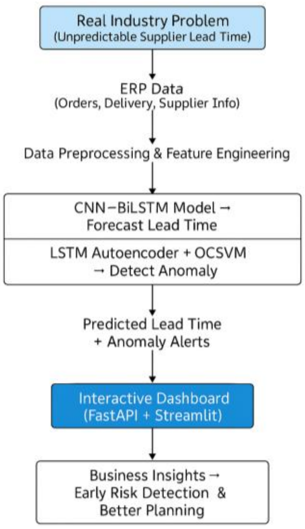
**Abstract: -** In today's highly dynamic supply chain environments, unpredictable supplier lead times cause production delays, stockouts, and increased operational costs. Traditional enterprise resource planning (ERP) systems only record historical data but lack predictive intelligence to forecast future delays or detect abnormal supplier behaviour. This project proposes an **AI-based hybrid framework** for *lead-time forecasting* and *anomaly detection* in the automotive and spare-parts supply chain. The forecasting module employs a **CNN–BiLSTM (Convolutional Neural Network–Bidirectional Long Short-Term Memory)** model that captures both short-term and long-term temporal dependencies from ERP data to predict supplier lead times more accurately than traditional statistical methods. For anomaly detection, an **LSTM Autoencoder** is combined with a **One-Class Support Vector Machine (OCSVM)** to learn normal supplier behaviour patterns and identify deviations automatically. The system is further integrated into a **real-time dashboard (FastAPI + Streamlit)** that visualizes predicted lead times, highlights anomalies, and supports proactive decision-making. Experimental results demonstrate that the proposed hybrid model significantly reduces forecasting error and provides early alerts for supplier irregularities, enhancing operational visibility, reliability, and efficiency within the supply chain network.

**Keywords: -** Supply Chain Management, Lead Time Forecasting, Anomaly Detection, CNN–BiLSTM, LSTM Autoencoder, One-Class SVM, ERP Data Analytics, FastAPI, Streamlit, Deep Learning

## I. Introduction

In the era of globalized production and Industry 4.0, supply chain efficiency depends heavily on accurate and reliable information about supplier lead times. Lead time the duration between placing an order and receiving it directly affects inventory levels, production planning, and customer satisfaction. However, due to global disruptions, manufacturing variability, and inconsistent supplier performance, lead times often fluctuate unpredictably. Such uncertainties can cause **stockouts**, **delayed deliveries**, and **increased holding costs**, forcing organizations to either overstock or risk supply shortages. Although most enterprises use **ERP systems** to record supplier transactions and order histories, these systems are largely *reactive*: they describe what happened but cannot predict what will happen next.

To address this challenge, artificial intelligence (AI) and deep learning techniques offer the potential to learn complex patterns from past data and forecast future outcomes. In this project, we propose a hybrid deep learning framework that combines **Convolutional Neural Networks (CNN)** and **Bidirectional Long Short-Term Memory (BiLSTM)** for accurate lead-time forecasting. CNN captures localized time-series features, while BiLSTM processes long-term dependencies in supplier data sequences.




In addition to forecasting, the project incorporates an **anomaly detection module** to identify unusual supplier behavior. Using an **LSTM Autoencoder**, the model learns the normal temporal patterns of lead times, and when combined with a **One-Class SVM**, it can automatically classify new patterns as normal or anomalous. This dual approach ensures not only the prediction of expected lead times but also the early detection of supply risks.

The final system is implemented as a **real-time interactive dashboard** using FastAPI and Streamlit, enabling supply chain managers to visualize predicted lead times, monitor anomalies, and make data-driven decisions. By integrating forecasting and anomaly detection in a single intelligent framework, this project contributes to improving supply chain resilience, reducing uncertainty, and enhancing service reliability.

## II. Literature Review and Project Justification

### *A. Introduction to Literature Review*

A literature review provides the theoretical foundation and background for the development of this research project. It helps identify what has been achieved in the domain, the limitations of existing methods, and the gaps that the current study aims to fill. In the context of this project which focuses on **AI-based lead-time forecasting and anomaly detection in supply chains** reviewing previous studies is essential to understand how traditional and modern approaches have addressed similar challenges.

Recent disruptions, supplier variability, and logistic uncertainties have highlighted the need for **data-driven prediction systems** that can anticipate supplier delays and irregularities. While **Enterprise Resource Planning (ERP)** systems collect vast historical data on orders and deliveries, they remain reactive and lack predictive capability (*Amellal et al., 2023*). The review below explores existing forecasting and anomaly detection methods, identifies their assumptions and limitations, and demonstrates the need for an integrated intelligent system capable of real-time forecasting and monitoring.

### ***B. Why the Topic Addresses a Real Industrial Problem***

In modern manufacturing and logistics, particularly within the **automotive spare-parts sector**, supplier lead-time uncertainty is a critical challenge. Inconsistent lead times cause cascading effects such as **production line stoppages**, **inventory overstocking**, and **missed customer deadlines**. Despite ERP systems storing valuable supplier and order data, they primarily serve as **recording tools** rather than predictive engines (*Amellal et al., 2023*).

According to *Babai et al. (2022)*, variability in lead-time demand can distort safety stock calculations, leading either to shortages or excessive holding costs. The inability to forecast accurate lead times results in reactive management, which limits supply chain responsiveness. An **AI-based predictive framework** that can forecast supplier lead time and detect anomalies proactively offers a direct solution to this industrial pain point, improving supply chain visibility, planning accuracy, and operational efficiency.

### ***C. How Others Have Approached the Problem***

Research on supply chain forecasting and anomaly detection has evolved across three major categories - **statistical models**, **machine learning methods**, and **deep learning frameworks**.

#### *a. Statistical Approaches*

Classical time-series methods such as **ARIMA**, **ARMA**, and **Exponential Smoothing** models have been widely used for demand and lead-time forecasting (*Babai et al., 2022*). These approaches assume stationarity and linear relationships among data variables. While effective for stable environments, they fail under nonlinear conditions and cannot capture long-term temporal dependencies. Consequently, they are inadequate for complex supply chain systems where supplier behaviour fluctuates due to market, geographical, or logistical constraints.

#### *b. Machine Learning Approaches*

With the rise of data availability, **machine learning models** like **Random Forest**, **Gradient Boosting**, and **Support Vector Regression (SVR)** were introduced (*Roy et al., 2015*). These models outperform statistical methods by learning nonlinear relationships between features such as supplier ID, shipping mode, or region. However, they treat each data instance independently and lack the ability to model **temporal order**, making them unsuitable for sequential data like delivery lead times.

#### *c. Deep Learning Approaches for Forecasting*

The advent of deep learning brought models capable of learning temporal dependencies. **Recurrent Neural Networks (RNNs)**, particularly **Long Short-Term Memory (LSTM)** and **Bidirectional LSTM (BiLSTM)** networks, have shown significant success in forecasting time-dependent data (*Siami-Namini et al., 2019*). These models can capture patterns across multiple time steps but can still struggle with local variations.

To address this, researchers combined **Convolutional Neural Networks (CNNs)** with LSTMs, creating **CNN–LSTM** and **CNN–BiLSTM** hybrids (*Miao et al., 2021*; *Lu et al., 2020*). CNNs efficiently extract short-term spatial patterns, while BiLSTM captures long-term sequential dependencies, producing higher forecasting accuracy. In supply chain contexts, this combination offers superior modeling of both immediate and cumulative supplier behavior patterns.

#### *d. Approaches to Anomaly Detection*

Anomaly detection has been traditionally handled through **statistical outlier detection**, **rule-based thresholds**, or **machine learning methods** like **Isolation Forest** and **Kernel Density Estimation (KDE)** (*Kerdprasop et al., 2019*). However, these methods rely on fixed boundaries and are not suitable for evolving time-series data.

Recent studies have adopted **Autoencoders** and **LSTM Autoencoders** for unsupervised anomaly detection (*Nguyen et al., 2021*). These models learn normal sequence patterns and identify anomalies through high reconstruction errors. Combining an **LSTM Autoencoder** with a **One-Class SVM (OCSVM)** enhances robustness by creating a mathematically defined boundary around normal behaviour, reducing false positives and improving precision.

### ***D. Gap and Positioning***

While many studies have focused on **demand forecasting** or **inventory optimization**, **lead-time forecasting** remains less explored, despite its central role in supply chain planning. Moreover, most existing works treat forecasting and anomaly detection as **separate tasks** rather than an integrated system.

*Amellal et al. (2023)* demonstrated the potential of a hybrid **CNN–BiLSTM + LSTM-AE + OCSVM** model for automotive spare-parts forecasting, achieving significant improvements in predictive accuracy. However, their study remained academic, lacking an operational interface for industrial deployment.

This project extends that research by:

- Applying the hybrid deep learning framework to ERP-based supply chain data.
- Integrating the forecasting and anomaly detection modules into a **single intelligent system**.
- Deploying the models in a **real-time dashboard** using **FastAPI** and **Streamlit**, enabling immediate visualization of predictions and anomaly alerts.

Thus, this research bridges the gap between theoretical advancements and **practical, deployable AI systems** for smart supply chain management.

### ***E. Tools and Methods Used in Prior Work and Justification for the Proposed Approach***

The proposed model design is motivated by empirical findings in *Amellal et al. (2023)* and extended by integrating it with a practical visualization and deployment layer for real industry application.

| Aspect | Prior Approaches | Proposed Approach | Justification |
|---|---|---|---|
| **Forecasting Model** | ARIMA, Random Forest, LSTM (*Babai et al., 2022*; *Lu et al., 2020*) | **CNN–BiLSTM** | CNN extracts short-term features; BiLSTM models long-term dependencies → superior accuracy. |
| **Anomaly Detection** | Isolation Forest, KDE, Simple Autoencoder (*Kerdprasop et al., 2019*) | **LSTM Autoencoder + OCSVM** | Learns sequential normal patterns and uses OCSVM for robust boundary detection. |
| **Data Type** | Static, tabular data | **Sequential ERP time-series data** | Reflects actual supplier delivery behaviour over time. |
| **Deployment** | Offline analysis | **FastAPI + Streamlit dashboard** | Enables real-time, interactive monitoring and decision-making. |
| **Evaluation Metrics** | MAE, RMSE | **MAE, RMSE, MAPE, Precision, Recall, F1-score** | Comprehensive evaluation for both forecasting and anomaly detection. |

## III. Problem Statement

In modern supply chains, especially in the **automotive spare-parts sector**, organizations face a persistent challenge in accurately predicting supplier **lead times** and identifying **abnormal supplier behaviors**.
Despite extensive data captured by **Enterprise Resource Planning (ERP)** systems, most existing solutions are **reactive**—they record historical transactions but fail to predict potential disruptions before they occur. This leads to several operational inefficiencies, including:

- **Uncertain delivery schedules**, which disrupt production and logistics planning.
- **Stockouts** or **excess inventory**, resulting in financial and operational losses.
- **Delayed customer fulfilment** and reduced supply chain reliability.

Traditional statistical methods (e.g., ARIMA, exponential smoothing) and even conventional machine learning models (e.g., Random Forest, SVM) are **inadequate** for capturing the **nonlinear, temporal, and multivariate patterns** found in ERP data. Furthermore, most research efforts focus solely on forecasting accuracy, ignoring the critical need for **anomaly detection** in supplier performance.

Therefore, there is a clear **research and industrial gap**: the absence of an integrated, AI-driven system that can both **forecast supplier lead time** and **detect irregular supplier behaviour** in real time.

This project addresses that gap by developing a **hybrid deep learning framework** that combines **CNN–BiLSTM** for lead-time forecasting and **LSTM Autoencoder + One-Class SVM (OCSVM)** for anomaly detection, integrated into a **real-time interactive dashboard** for visualization and decision support.

## IV. Research Objectives

The main goal of this project is to design and implement an **AI-based intelligent forecasting and anomaly detection system** for improving supply chain reliability.

To achieve this, the following specific objectives are defined:

1. **To analyse and preprocess ERP data** related to supplier lead time, shipment dates, and delivery performance.
2. **To design a hybrid CNN–BiLSTM deep learning model** capable of accurately forecasting supplier lead times by learning both short-term and long-term dependencies.
3. **To develop an LSTM Autoencoder + OCSVM-based model** for detecting abnormal supplier behaviors based on reconstruction errors and decision boundaries.
4. **To evaluate model performance** using appropriate forecasting and classification metrics such as MAE, RMSE, MAPE, Precision, Recall, and F1-score.
5. **To integrate both models** into a unified system using **FastAPI** and **Streamlit**, providing an interactive dashboard for real-time visualization and anomaly alerts.
6. **To demonstrate the applicability of the system** in a real or simulated ERP environment, showcasing its potential impact on industrial supply chain planning.

## V. Methodology

The study follows a data-driven experimental methodology. First, ERP-like supply chain data is cleaned and transformed to derive the target variable, supplier lead time. Categorical attributes (supplier, route, product) are encoded, and numerical attributes are scaled. A hybrid deep learning model based on CNN–BiLSTM is then trained to forecast future lead times from historical sequences, allowing the model to learn both local temporal patterns (via CNN) and long-range dependencies (via BiLSTM). In parallel, an LSTM-based autoencoder is trained on normal delivery sequences to learn typical supplier behaviour; its reconstruction errors are further modelled using a One-Class SVM to detect anomalous lead-time patterns. Model performance is evaluated using MAE, RMSE, and MAPE for forecasting, and precision/recall for anomaly detection. Finally, the models are intended to be exposed through a lightweight API (FastAPI) and visualized in a dashboard (Streamlit) for operational supply chain decision-making.

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