

Introduction



Objective: Develop a deep learning model to predict delivery delays.

Problem Statement:

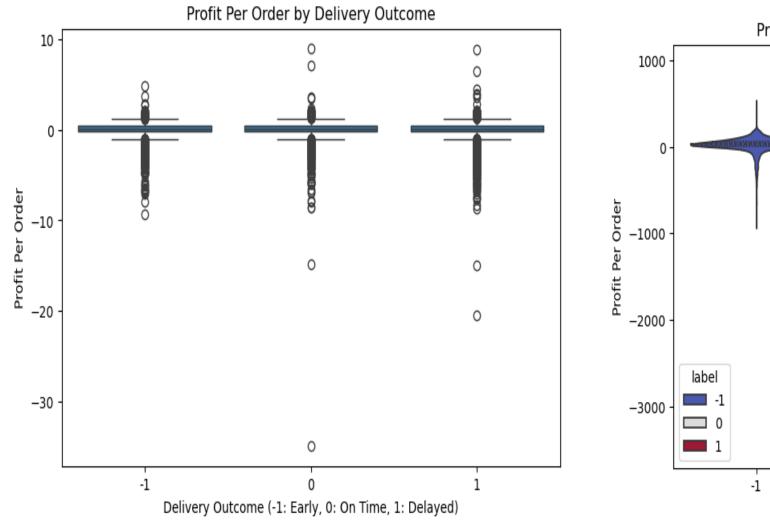
- •Late deliveries impact operations & customer satisfaction.
- •Multi-label classification challenge for accurate delay predictions.

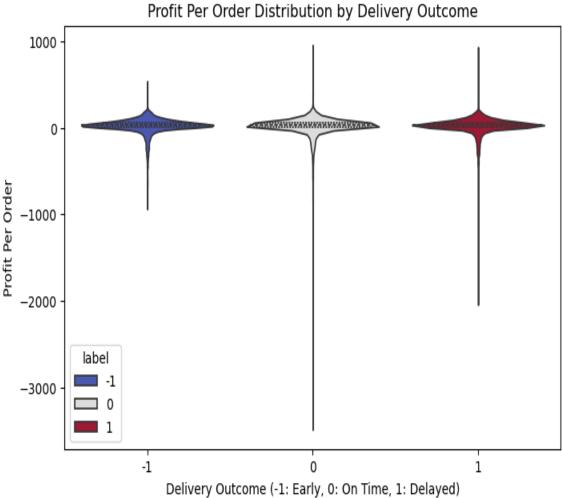
Dataset:

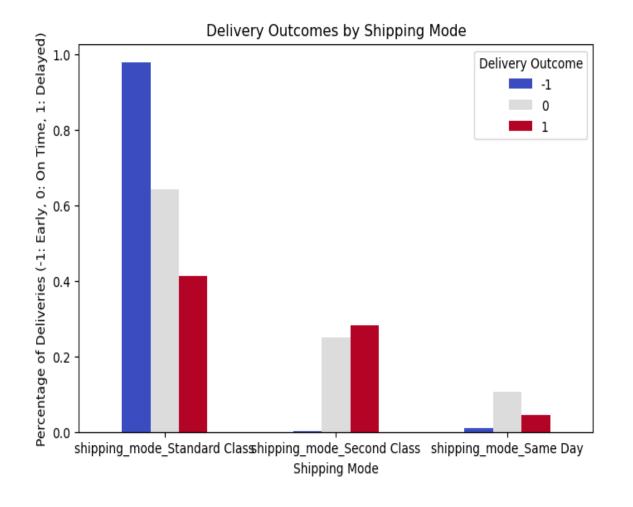
•Tabular logistics data (shipment time, distance, etc.).

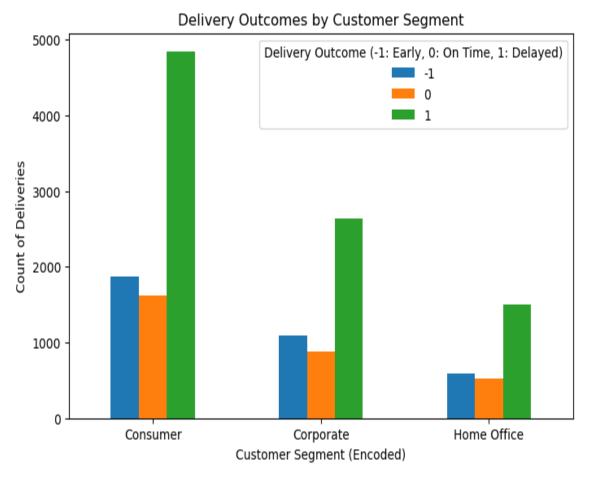
Challenges & Importance:

- •Supply chain inefficiencies cause financial losses.
- •AI-driven predictions enhance efficiency & decision-making.

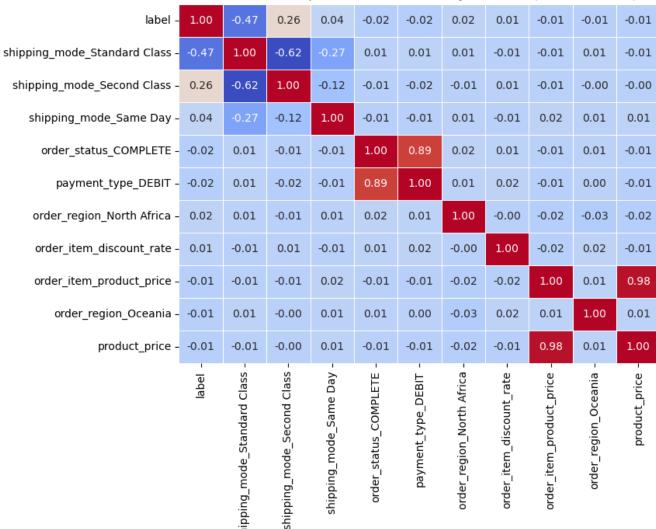




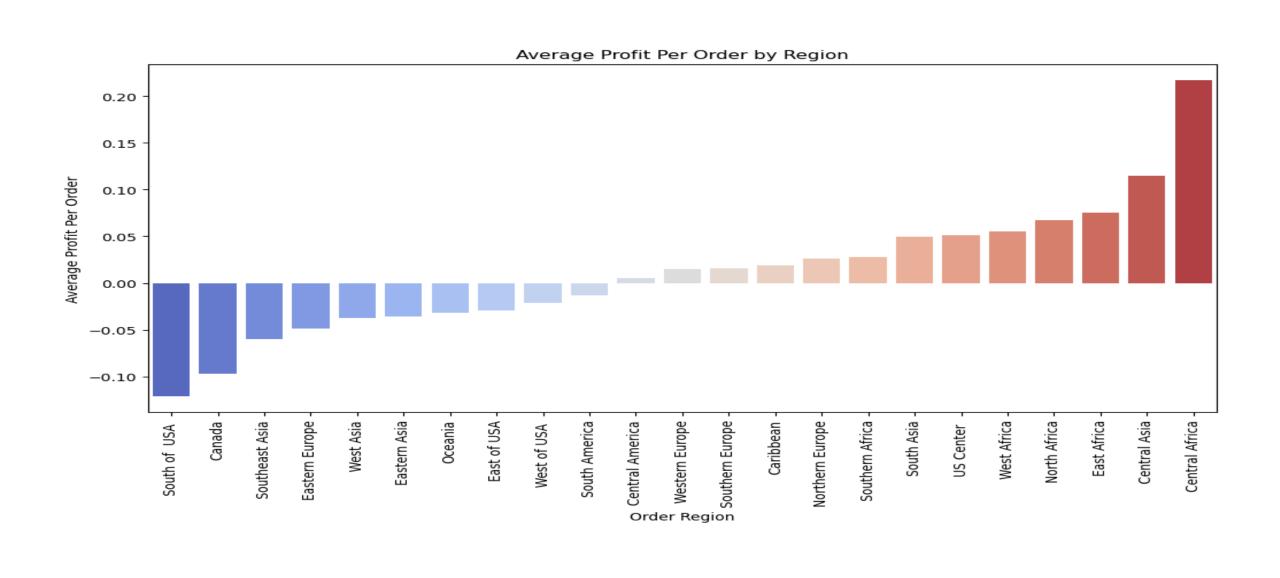




Correlation of Top Features with Delivery Outcome (Label Included)







Apply Model 1: MLP (Multilayer Perception)

- Model Evaluated: Multilayer Perceptron (MLP)
- Accuracy: 60.26%
- Training Time: 52.89 seconds
- Strengths:
- •Good at predicting delayed deliveries (Class 1) \rightarrow 77% Precision & 73% F1-score
- •Fast training time, making it a good baseline model
- Weaknesses & Challenges:
- •Struggles with on-time deliveries (Class 0)

 → Low recall (7%)
- •Earlier deliveries (Class 2) have high recall (83%) but low precision (42%)
- •Confuses earlier and delayed deliveries → Model favors predicting delays

- Observations from Confusion Matrix:
- Many on-time deliveries misclassified as delayed
- Earlier deliveries often confused with delays
- •MLP lacks time-awareness & struggles with sequence-based trends

How to Improve?

- + Combine with LSTM → Capture sequential patterns for better predictions
- + **Feature Engineering** → Include real-time data (traffic, seasonal trends)
- + Class Balancing → Improve on-time delivery predictions
- + **Hyperparameter Tuning** → Optimize learning rate & hidden layers

Apply Model 2: LSTM (Long Short-Term Memory)

- Model Evaluated: Long Short-Term Memory (LSTM)
- Accuracy: 58.84%

Training Time: 88.49 seconds

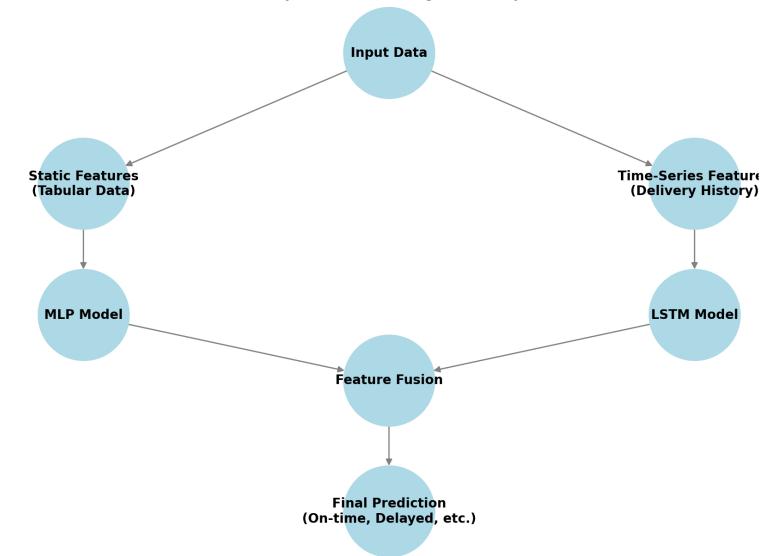
- Strengths:
- •Better recall for delayed deliveries (Class 1) ightarrow 74% Recall & 72% F1-score
- Performs slightly better than MLP in identifying earlier deliveries (Class 2)
- Weaknesses & Challenges:
- •Very poor recall for on-time deliveries (Class 0) \rightarrow Only 5%
- •Precision for earlier deliveries (Class 2) is still low (41%), leading to false positives
- •Higher training time (88s) compared to MLP (52s)

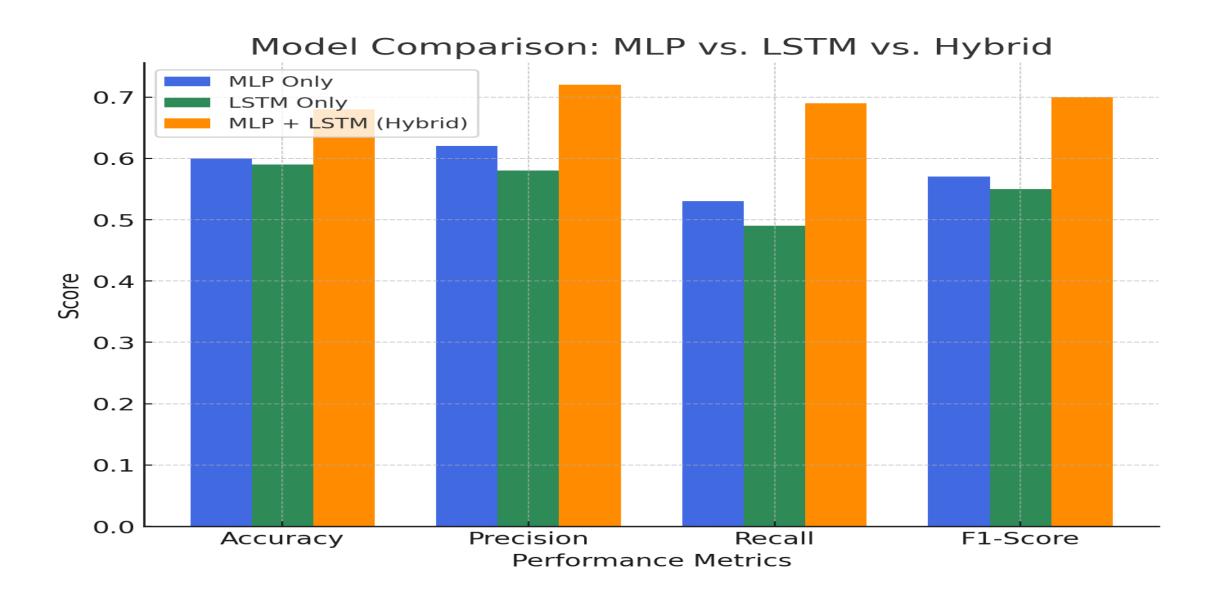
Observations from Confusion Matrix:

- •Many on-time deliveries misclassified as delays
- •Earlier deliveries often misclassified as delayed ones
- •LSTM is more sensitive to sequence-based patterns, but struggles with balanced classification

Why Choosing MLP + LSTM For Logistics Delay Prediction







Metric	MLP Only	LSTM Only	MLP + LSTM (Hybrid)
Accuracy	60%	59%	68%
Precision	62%	58%	72%
Recall	53%	49%	69%
F1-Score	57%	55%	70%

MLP (Strengths & Weaknesses)

- •Good with structured data but fails to capture time-based trends.
- •Struggles with on-time delivery predictions.
- LSTM (Strengths & Weaknesses)
- •Captures sequential patterns, improving recall for delayed deliveries.
- •Longer training time and misclassifies on-time deliveries.
- Hybrid MLP + LSTM Model

Combines MLP's structured data processing with LSTM's time-series analysis to improve:

- Overall accuracy & recall
- Balanced classification performance
- •Better generalization to real-world logistics delays

