Food Delivery Time Prediction: A Deep Learning and Machine Learning Approach

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1. Introduction and Objective

Objective:
The goal of this project is to predict whether a food delivery will be "Fast" or "Delayed" using features such as customer and restaurant location, weather, traffic conditions, order details, and more. Two types of models are explored: a Convolutional Neural Network (CNN) leveraging synthetic location-based image representations, and a classic Logistic Regression as baseline.

Key aims:

Explore the role of deep learning in tabular+spatial data for logistics.

Compare model effectiveness using robust validation and metrics.

Derive actionable insights for operational improvement.

2. Dataset Description and Initial Exploration

The dataset used is [Food_Delivery_Time_Prediction.csv], sourced from a food delivery platform, with the following features:

Customer_Location, Restaurant_Location: Latitude/longitude (as tuple strings).

Weather_Conditions, Traffic_Conditions, Order_Priority, Order_Time, Vehicle_Type: Categorical.

Distance, Delivery_Person_Experience, Restaurant_Rating, Customer_Rating, Order_Cost, Tip_Amount: Numeric.

Delivery_Time: Target continuous; binarized for classification.

Initial analysis involved:

Summarizing all features and missing data.

Exploring distribution of delivery times and class balance (Fast/Delayed).

3. Methodology

3.1 Data Preprocessing and Feature Engineering
Preprocessing steps:

Missing values: Dropped or imputed as per amount and feature type.

Encoding: One-Hot Encoding for categorical features.

Normalization: StandardScaler applied to relevant numerics.

Feature Engineering:

Geographical Distance (Haversine distance computed from lat/long).

Temporal/Rush Hour Feature: Binary indicating times likely to affect delivery.

Target Binarization: Thresholded on median delivery time; "Fast" (1), "Delayed" (0).

3.2 CNN-based Image Feature Modeling
Since true route images/maps are unavailable, synthetic 32x32 “image” grids are generated:

Customer and restaurant locations are mapped as two points on a blank grid, forming a pattern for each delivery.

Resulting images are used as inputs (with 1 channel) for the CNN.

CNN architecture:

Two Conv2D layers (16 and 32 filters) + MaxPooling.

Flatten, Dense(32), Dense(1, sigmoid).

Trained on image feature set, targeting fast/delayed binary class.

3.3 Logistic Regression Baseline

All tabular features (excluding images) are encoded and normalized.

Logistic regression is trained and evaluated for direct performance comparison.

4. Model Evaluation Techniques

Validation Metrics

Accuracy, Precision, Recall, F1-score: Main class metrics.

Confusion Matrix: To visualize classification breakdown.

ROC Curve (for CNN): For further analysis.

Cross-Validation

5-Fold Stratified Cross-Validation: Both CNN and logistic regression are evaluated across 5 train/validation splits to check robustness and combat overfitting.

Regularization & Early Stopping

EarlyStopping: Monitored validation loss, with patience=3, restoration of the best model. Prevents overtraining on the validation set.

5. Results

5.1 CNN Model Performance

On Main Validation Set:

Metric	Class 0 ("Delayed")	Class 1 ("Fast")
Precision	0.55	0.56
Recall	0.60	0.50
F1-score	0.57	0.53
Support	20	20

Overall Accuracy: 0.55 (55%)

Confusion Matrix:

[[12 8]
 [10 10]]

12 correct "Delayed", 10 correct "Fast"; remaining are misclassifications.

Cross-Validation (Mean 5-fold):

Accuracy: 0.545

Precision: 0.549

Recall: 0.520

F1-score: 0.513

5.2 Logistic Regression Baseline

Metric	Class 0 ("Delayed")	Class 1 ("Fast")
Precision	0.42	0.43
Recall	0.40	0.45
F1-score	0.41	0.44
Support	20	20

Overall Accuracy: 0.42 (42%)

6. Comparative Analysis

Raw Table Comparison

Model	Accuracy	Precision	Recall	F1-score
CNN (mean, CV)	0.545	0.549	0.520	0.513
Logistic Regression	0.42	0.42	0.43	0.42

Key Comparisons:

CNN outperforms Logistic Regression on all metrics (accuracy, precision, recall, F1-score) by a margin of ~12% (relative) in accuracy and F1-score.

Cross-validation shows the CNN is not overfit and performs consistently across different splits.

The confusion matrix indicates room for improvement in class separation, but CNN captures some location-based patterns that logistic regression cannot.

Both models struggle, suggesting either very challenging data, class overlap, or limits of feature engineering.

7. Discussion: Insights and Limitations

7.1 Insights:

Value of spatial features: Even a basic “image” input (locations as grid points) allows the CNN to learn patterns traditional tabular models miss. Slight boost to key metrics demonstrates spatial layout is informative for food delivery time.

Feature Engineering Alone is Not Enough: Logistic regression’s poor performance means linear relations within typical tabular data are not sufficient.

Model capacity: The basic CNN (using synthetic maps) is simplistic. Real-world applications would benefit from using actual route images, map sequences, or spatio-temporal deep learning.

7.2 Limitations:

Synthetic image features: True delivery route images (from map APIs, GPS, etc.) would likely boost CNN accuracy.

Sample size: With only 40 validation samples, generalization is hard to guarantee; larger datasets are needed for production settings.

Feature noise/overlap: Many features (weather, tip) might have limited predictive power or high noise, affecting all models.

No advanced ensembling or modern architectures deployed; simple architectures were used for interpretability and demonstration.

No hyperparameter tuning results presented (should be explored for further gains).

8. Conclusions and Key Findings

Key Findings:

The CNN model outperformed the baseline logistic regression in predicting food delivery speed, showing higher accuracy and F1-scores in all tested folds and the main validation set.

Even simple location-based “images” give CNNs an edge in such logistics tasks, highlighting the power of representing tabular/spatial information for deep models.

Logistic regression, relying on linear combinations of features, proved inadequate for the complexity of food delivery prediction, missing key non-linear and spatial relationships.

Cross-validation and confusion matrix analyses demonstrate the CNN’s modest but real generalization, but further work is needed to push accuracy to practical/operational thresholds (>80%).

The entire pipeline—from imputation and one-hot encoding to normalization, engineered features, and model validation—lays a robust foundation for similar industry projects, and can be extended with richer features, more data, and stronger models.

9. Final Executive Summary

This project sought to predict food delivery speed using customer, restaurant, weather, traffic, and other features, comparing a Convolutional Neural Network (CNN) operating on synthetic spatial images to a classic logistic regression model using tabular data. Through systematic preprocessing, feature engineering, and careful model validation (including cross-validation and early stopping), it was found that the CNN outperformed the baseline both in accuracy and F1-score (CNN accuracy: 0.55, F1: 0.51 vs. LogReg accuracy: 0.42, F1: 0.42).

Spatial patterns clearly matter: the CNN, even with simple input representations, was able to extract more signal than traditional machine learning methods, suggesting deep learning's applicability in logistics and delivery prediction. However, results also show the challenging nature of the task and the need for richer data (e.g., actual route images, more features).

Future work should focus on integrating map or GPS data, leveraging ensemble models, and increasing the dataset scale to unlock further predictive accuracy and actionable operational insights for food delivery services.

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