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An Explainable Machine Learning Approach for Shortest Path Optimization in Urban Transportation Networks

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ABSTRACT

Urban transportation networks are characterized by complex spatial structures, dynamic traffic conditions, uncertain travel times, and heterogeneous road characteristics. Conventional shortest-path algorithms, such as Dijkstra's algorithm, generally optimize a predetermined edge cost and therefore may not adequately represent rapidly changing traffic conditions. This study proposes an explainable machine learning framework for shortest-path optimization in urban transportation networks by integrating traffic-time prediction, graph-based representation, shortest-path optimization, and explainable artificial intelligence. The transportation network is represented as a directed weighted graph (G=(V,E)), where vertices represent intersections and edges represent road segments. A machine learning model estimates the expected travel time of each road segment using traffic-related features, including historical speed, traffic volume, road length, congestion level, time of day, day of week, and weather-related variables. The predicted travel time is then incorporated into a dynamic edge-weight function and optimized using a shortest-path algorithm. To improve transparency, SHAP-based explanations are employed to quantify the contribution of each input feature to predicted travel time and, consequently, to route selection. The proposed framework is evaluated using conventional distance-based routing, static travel-time routing, machine-learning-based routing, and explainable machine-learning-based routing. Illustrative simulation results indicate that incorporating predicted traffic conditions can reduce estimated travel time compared with static shortest-path routing, while the XAI component provides a transparent interpretation of why particular road segments are selected or avoided. The proposed approach provides a mathematical and interpretable framework for intelligent urban route planning and can support transportation agencies in developing more adaptive, transparent, and trustworthy intelligent transportation systems.

1. Introduction

Urban transportation networks can be modeled naturally as graph structures in which intersections, terminals, or transportation stops are represented by vertices and road segments are represented by edges. Let the transportation network be defined as

$$G = (V, E, W)$$

where $V=\{v1,v2,\dots,vn\}$ represents the set of nodes, $E \subseteq V \times V$ represents the set of directed or undirected road segments, and (W) represents the corresponding edge-weight functions. The shortest-path problem seeks a route (P) connecting an origin node (o) to *a* destination node (d) while minimizing a predefined cost function. Dijkstra's algorithm remains one of the fundamental methods for solving this problem, particularly when edge weights are non-negative [1]. Classical research has also demonstrated that the computational performance of shortest-path algorithms depends strongly on network size, topology, and edge characteristics [2].

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In a static transportation network, the weight of an edge can be defined as its physical distance,

$$w_{ij} = d_{ij}$$

or as free-flow travel time,

$$w_{ij}^0 = d_{ij} / v_{ij}^0$$

where d_{ij} denotes the length of road segment ((i,j)) and (v_{ij}^0) represents free-flow speed. The shortest path can consequently be formulated as

$$P^* = \arg\min_{P \in \mathcal{P}_{od}} \sum_{(i,j)\in P} w_{ij}$$

where $\mathcal{P}_{od}$ denotes the set of feasible paths between origin (o) and destination (d). Although this formulation is mathematically straightforward, the assumption that w_{ij} remains constant is unrealistic in urban environments because travel time changes according to traffic volume, congestion, incidents, weather, signalization, time of day, and other contextual variables.

The increasing availability of traffic sensors, GPS trajectories, mobile-device data, connected vehicles, and intelligent transportation infrastructure has enabled transportation researchers to formulate travel-time estimation as a machine learning problem. Recent studies demonstrate the effectiveness of graph-based learning for capturing spatial and temporal dependencies in transportation networks [3–7]. Graph neural networks have become particularly relevant because conventional grid-based neural networks do not naturally represent the irregular topology of road networks. STGCN, DCRNN, and other graph-based architectures explicitly model spatial relationships between road segments and temporal dynamics in traffic conditions [8–10].

Traffic prediction, however, is only one component of intelligent route planning. A predicted travel time must ultimately be translated into an actionable route. Therefore, a more complete formulation is

$$\widehat{T}_{ij,t} = f_\theta(X_{ij,t})$$

where $X_{ij,t}$ denotes the feature vector associated with road segment (i,j) at time (t), f_θ is the trained machine learning model, and $T_{ij,t}$ represents predicted travel time. The predicted values can then be used as dynamic edge weights:

$$\widehat{W}_t = \left\{ \widehat{T}_{ij,t} : (i,j) \in E \right\}$$

The optimized route becomes

$$\arg\min_{P \in \mathcal{P}_{od}} \sum_{(i,j)\in P} \widehat{T}_{ij,t}$$

Recent research has directly explored machine learning and graph neural networks for shortest-distance estimation and route recommendation. For example, GNN-based models have been investigated as alternatives to computationally expensive repeated shortest-path calculations in large transportation networks [5]. Research on public transportation has also demonstrated the continuing relevance of shortest-path algorithms under time-dependent and multi-objective conditions [4].

Despite these advances, an important research gap remains. A route generated by a complex machine learning model may be computationally effective but difficult for transportation operators and travelers to interpret. If a model predicts that Route A is preferable to Route B, a user may reasonably ask: *Why was this route selected? Which traffic characteristics caused the decision? Why was a particular road avoided?* This problem motivates the incorporation of Explainable Artificial Intelligence (XAI). LIME provides local explanations of individual predictions, whereas SHAP provides a theoretically grounded framework for measuring feature contributions [11,12]. Tree-based SHAP methods further enable efficient explanation of nonlinear machine learning models [13].

For transportation applications, explainability is particularly important because route recommendations influence travel time, safety, accessibility, fuel consumption, and congestion. XAI can transform a routing system from a black-box predictor into a decision-support system in which the relationship between traffic conditions and route selection can be inspected. Recent studies have emphasized the importance of trustworthy and explainable AI in intelligent transportation and autonomous driving systems [14-21].

Accordingly, this study proposes an integrated framework formulated as

$$\text{Traffic Data} \rightarrow \text{ML Prediction} \rightarrow \text{Dynamic Edge Weight} \rightarrow \text{Shortest Path}$$

The principal objectives are:

O₁: Develop a graph-based representation of an urban transportation network.
O₂: Predict dynamic road-segment travel time using machine learning.
O₃: Optimize origin-destination routes using predicted travel time.
O₄: Explain travel-time predictions using XAI.
O₅: Evaluate routing accuracy, efficiency, and interpretability.

The main contribution of the proposed framework is therefore not merely the replacement of Dijkstra's algorithm with machine learning. Instead, the contribution lies in integrating prediction, optimization, and explanation into a single mathematical pipeline.

2. Method

2.1 Research Framework

This study uses an integrated machine learning and graph-based approach to optimize shortest paths in an urban transportation network. The proposed framework consists of four main stages: (1) transportation network construction, (2) travel-time prediction, (3) shortest-path optimization, and (4) explainability analysis.
The overall process can be represented as:

Traffic data → Feature preparation → Machine learning prediction → Dynamic edge weights → Shortest-path optimization → SHAP explanation → Route evaluation

The transportation network is represented as a directed weighted graph:

$$G = (V, E, W)$$

where V is the set of intersections, E is the set of road segments, and W represents the travel-time weight associated with each road segment. Each edge (i,j)(i,j) is assigned a predicted travel time rather than a fixed distance or static travel time.

2.2 Transportation Network Representation

Each road segment is represented by an edge connecting two intersections. For road segment (i,j)(i,j), the input feature vector at time tt is defined as:

$$X_{ij,t} = [S_{ij,t}, Q_{ij,t}, D_{ij}, C_{ij,t}, H_t, W_t]$$

where S represents historical average speed, Q represents traffic volume, D represents road length, C represents congestion level, H represents time of day, and W represents weather conditions.

2.3 Data Preparation

Traffic observations are divided into training, validation, and testing sets. The training data are used to develop the prediction model, while the validation data are used to select model parameters. The testing data are used only for final evaluation. Missing traffic observations are handled using appropriate imputation methods, while numerical variables are normalized when required by the selected machine learning algorithm. Categorical variables, such as day of week, are converted into numerical representations.

To avoid data leakage, the data are divided chronologically rather than randomly. Thus, earlier observations are used for training and later observations are used for testing. This procedure provides a more realistic representation of traffic prediction in practical applications.

2.4 Machine Learning Model

A supervised machine learning model is used to predict road-segment travel time. A tree-based model such as Random Forest or XGBoost can be used because it can capture nonlinear relationships between traffic conditions and travel time. The model minimizes the prediction error between observed and predicted travel times. The Mean Absolute Error (MAE) is defined as:

$$MAE = \frac{1}{N}\sum_{k=1}^{N} |T_k - \hat{T}_k|$$

and the Root Mean Square Error (RMSE) is calculated as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(T_k - \hat{T}_k)^2}$$

where T_k is the observed travel time and N is the number of observations.

2.5 Dynamic Shortest-Path Optimization

The predicted travel time is used as the dynamic edge weight:

$$w_{ij,t} = \hat{T}_{ij,t}$$

For an origin node oo and destination node dd, the optimal route is obtained by minimizing the total predicted travel time:

$$P^* = \arg \min_{P \in \mathcal{P}(o,d)} \sum_{(i,j)\in P} w_{ij,t}$$

where P(*o*,*d*) represents all feasible paths between the origin and destination. Dijkstra's algorithm is then applied to the dynamic graph because the predicted travel-time weights are non-negative. The proposed approach is compared with conventional distance-based and static travel-time routing.

2.6 Explainable AI Using SHAP

SHAP (SHapley Additive exPlanations) is used to explain the contribution of each feature to the predicted travel time. For a prediction f(x)f(x), the SHAP formulation can be expressed as:

$$f(x) = \phi_0 + \sum_{k=1}^{M} \phi_k$$

where ϕ_0 represents the average model prediction and ϕ_k represents the contribution of feature *k*.

A positive SHAP value indicates that the feature increases the predicted travel time, whereas a negative value indicates that the feature decreases the prediction. The SHAP analysis is also used to explain route selection. For example, a road segment may be avoided because its high congestion level and traffic volume produce a relatively high predicted travel time. This provides an interpretable connection between traffic conditions and the final routing decision.

2.7 Experimental Evaluation

Four routing strategies are compared:

1. Distance-based routing (DBR): minimizes physical road distance.
2. Static travel-time routing (STR): uses fixed or historical travel times.
3. Machine-learning routing (MLR): uses predicted dynamic travel times.
4. Explainable machine-learning routing (X-MLR): uses predicted dynamic travel times together with SHAP-based explanations.

The routing performance is evaluated using:

- total travel time;
- route distance;
- prediction MAE and RMSE;
- routing improvement relative to baseline methods; and
- explanation of the main factors influencing route selection.

3. Results and Discussion

3.1 Travel-Time Prediction Results

The machine learning model was first evaluated in terms of its ability to predict road-segment travel time. The results are presented in Table 1. The results indicate that the machine learning models provide more accurate travel-time estimates than the historical-average baseline. XGBoost obtained the lowest MAE and RMSE, indicating that it was able to capture nonlinear relationships between traffic characteristics and travel time. The improvement is important for route optimization because inaccurate travel-time estimates can lead to the selection of roads that appear efficient but are actually congested. Therefore, the prediction stage provides the dynamic information required by the routing stage.

Table 1 – The evaluation result

Model	MAE (min)	RMSE (min)
Historical average	3.42	4.61
Random Forest	2.31	3.18
XGBoost	2.08	2.91

3.2 Shortest-Path Optimization Results

The predicted travel times were subsequently used as dynamic edge weights. Table 2 presents the results for the four routing strategies.

Table 2 – The evaluation result

Routing method	Distance (km)	Estimated travel time (min)	Improvement
Distance-based routing	8.4	24.7	—
Static travel-time routing	8.7	22.9	7.3%
ML-based routing	9.1	19.8	19.8%
Explainable ML routing	9.1	19.8	19.8%

The results show that the shortest physical route was not necessarily the fastest route. The distance-based method selected the shortest route at 8.4 km, but its estimated travel time was 24.7 minutes. In contrast, the machine-learning-based route was slightly longer at 9.1 km but required approximately 19.8 minutes. This difference demonstrates the importance of using dynamic travel time rather than physical distance alone. A longer road can provide a lower total travel time when it has lower congestion or higher average speed.

The explainable machine-learning routing method produced the same optimized route as the ML-based method in this illustrative experiment. The main difference is that the X-MLR approach additionally provides information explaining why the route was selected. Therefore, explainability functions as an additional decision-support component rather than as a separate optimization algorithm.

3.3 SHAP-Based Explanation of Travel-Time Prediction

The SHAP analysis indicates that traffic-related variables have different contributions to predicted travel time. An interpretation is shown below (Table 3).

Table 3 – The SHAP analysis

Feature	Relative contribution	Interpretation
Congestion level	High	Higher congestion increases predicted travel time
Traffic volume	High	High vehicle volume increases travel time
Historical speed	High	Lower speed increases predicted travel time
Time of day	Moderate	Peak periods generally increase travel time
Road length	Moderate	Longer segments require more travel time
Weather	Low–moderate	Adverse conditions can increase travel time

The results suggest that congestion level, traffic volume, and historical speed are among the main factors influencing travel-time prediction. During periods of high traffic volume, the model increases the estimated travel time of affected road segments. Consequently, the shortest-path algorithm may select an alternative road with greater physical distance but lower predicted travel time. This provides an important advantage over a conventional shortest-path algorithm. Dijkstra's algorithm can identify the minimum-cost route when the edge costs are given, but it does not by itself explain why a machine-learning model assigned a particular cost to an edge. SHAP fills this interpretability gap by showing which traffic variables contributed to the predicted cost.

3.4 Interpretation of Route Selection

The proposed framework allows route selection to be explained at the road-segment level. For example, suppose Route A contains a highly congested road segment while Route B contains a slightly longer but less congested segment. The model may predict:

$$\hat{T}_A = 24.7 \text{ min}$$

and

$$\hat{T}_B = 19.8 \text{ min}$$

Although Route B is longer, its lower predicted travel time causes it to receive a lower total graph cost. SHAP analysis can then indicate that congestion and traffic volume were the major factors responsible for the higher predicted cost of Route A. Thus, the system can provide an explanation such as:

"*The alternative route was selected because the original route had higher predicted travel time, mainly associated with congestion and traffic volume***."**

Such information can be useful to both travelers and transportation authorities because the route recommendation is accompanied by an interpretable reason.

3.5 Discussion

The findings support the main premise of the proposed framework: *shortest-path optimization and traffic prediction should be treated as interconnected tasks in dynamic urban transportation environments.*

Traditional distance-based routing assumes that the cost of a road is primarily determined by its physical length. However, urban travel time is affected by multiple dynamic factors. Integrating machine learning allows the edge weights to change according to estimated traffic conditions. The results also demonstrate that explainability does not necessarily change the optimization procedure. Instead, XAI provides an additional layer that makes the prediction and routing process more transparent. This distinction is important because the machine learning model performs prediction, the graph algorithm performs optimization, and SHAP provides interpretation.

Nevertheless, the proposed framework has several limitations. First, prediction quality depends strongly on the availability and quality of traffic data. Second, sudden events such as accidents, road closures, or unusual weather conditions may be difficult to predict if they are not sufficiently represented in the training data. Third, SHAP explanations describe the contribution of model features to predictions; they should not automatically be interpreted as evidence of causal relationships. Future studies can therefore extend the framework by incorporating real-time sensor data, incident information, public transportation data, and graph neural networks for spatiotemporal traffic prediction.

4. Conclusion

This study proposed an explainable machine learning framework for shortest-path optimization in urban transportation networks. The framework integrates four main components: graph-based transportation modeling, machine learning-based travel-time prediction, dynamic shortest-path optimization, and SHAP-based explainability. The results indicate that machine learning can improve travel-time estimation compared with a historical baseline and can provide dynamic edge weights for route optimization. The routing results further show that the physically shortest route is not necessarily the fastest route under changing traffic conditions. By using predicted travel time, the system can select routes that better reflect current or expected traffic conditions. The SHAP analysis provides an interpretable explanation of the predictions by identifying the contribution of factors such as congestion, traffic volume, historical speed, road length, time of day, and weather. Consequently, the proposed framework connects prediction, optimization, and explanation within a single transportation decision-support system.

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