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TAXI DEMAND PREDICTION IN REAL TIME

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Abstract - *The research paper introduces a novel model for accurately forecasting future taxi demand in various neighbourhoods. By analysing the relationship between past behaviour and subsequent taxi demand, this model effectively predicts future demand patterns. Utilizing an advanced sequence learning This study presents a model for predicting future taxi demand in various neighbourhoods based on current demand and relevant information. The model examines the relationship between past behaviour and subsequent taxi demand to effectively predict future demand. A person who calls a taxi to go shopping, for example, may need another taxi to get home a few hours later. Through its gating mechanism, the model effectively collects and stores important information for later use, exploiting the idea of long-short-term memory (LSTM), an effective sequence learning strategy. The study goes on to explain the methodology employed, which includes dividing the city into distinct areas and predicting demand in each area. The efficiency of this approach is assessed using a dataset comprising taxi requests in New York. The findings indicate that the suggested technique outperforms alternative prediction methods like pre-neural networks. The chapter also discusses research on how results change when additional information such as weather, time, and departure locations are added. By taking these variables into account, the predictive accuracy of the model can be increased, resulting in more accurate demand estimates, better fleet management and shorter waiting times. Overall, the chapter highlights the value of accurate taxi demand forecasting, presents a sequence of learning model using LSTM, demonstrates the effectiveness of the proposed strategy compared to other approaches, and argues the potential benefits of incorporating more relevant data in forecasting process. Taxi demand forecasting, time series forecasting, recurrent neural networks and mixed density networks are some of the index terms.*

***Key Words*: Real-time, Demand prediction, Time series forecasting, Sequential data.**

1. INTRODUCTION

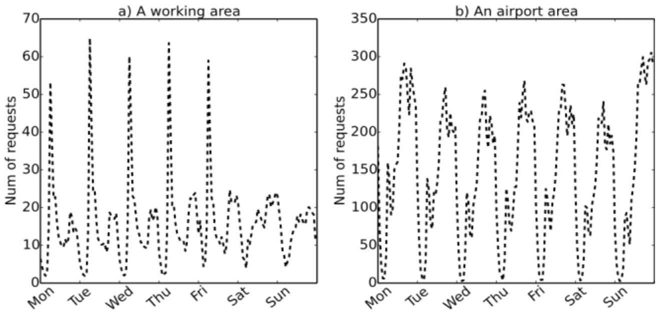
We've all had problems when it's hard to get a taxi, especially in a busy area. This often happens because taxi drivers do not know the ideal places to wait for passengers. But a tool that directs drivers to the best waiting areas or helps them find consumers would effectively alleviate this problem.

1.1 Overview

Efficiently dispatching taxis and minimizing wait times for both drivers and passengers is essential. However, taxi drivers face challenges in determining the best locations to wait for passengers, as they lack knowledge of passenger locations and intended destinations. To address this issue, a smart taxi centre equipped with predictive capabilities is necessary, especially considering the future integration of self-driving taxis. Accurately forecasting future demand across the entire city requires advanced technology due to the vast amount of data involved. Historical taxi trip data collected through Global Positioning System can provide valuable insights into predicting demand patterns.

1.2 Problem Definition

A sample of the taxi request patterns in two locations is shown below.



Predicting the demand for taxi services in specific urban districts at certain times can be achieved by analysing historical data. In this study, a real-time approach is proposed to estimate taxi demand across different sections of a large city. By dividing the city into smaller divisions, the total number of taxi requests within short time intervals (e.g., 20 minutes) is recorded for each division based on previous data. Subsequently, a long-short-term memory recurrent neural network is trained using this sequential information. To predict the future demand for taxis, a recurrent LSTM neural network model is employed. This model takes into account both the current taxi demand and other relevant data as inputs, allowing it to store essential information needed for accurate predictions. Taxi demand forecasting involves tackling complex time series analysis problems, similar to those encountered in natural language processing and unsegmented handwriting generation tasks that utilize sequence learning models like LSTMs. These models make use of key mechanisms to retain vital data in memory, thereby enabling them to capture long-term dependencies within the dataset.

Due to advancements in taxi demand prediction, it is now possible to estimate the number of individuals who will request a taxi after attending an event. For instance, if a certain number of people are observed requesting taxis to arrive at a concert, this information can be used to predict that a similar quantity of individuals will require transportation from the concert venue to other locations hours later. However, accurately predicting real-valued numbers poses challenges as relying solely on population means often yields unreliable results. Additionally, the LSTM network becomes confused when encountering previously unseen patterns. To address these issues and enhance predictions, Mixed Dense Networks have been incorporated into LSTM models. Instead of generating precise demand values, MDN produces mixed distributions representing potential demand levels. By sampling from this probability distribution function, one can determine expected taxi demand effectively.

1.3 Objectives

An efficient taxi dispatch system is crucial in minimizing wait-times for both drivers and passengers. With limited information about passenger locations and destinations, drivers often struggle to optimize their routes and availability. To address this challenge, a smart taxi center can be established that utilizes predictive modeling techniques to forecast future demand across the entire city. By effectively managing the fleet of taxis and efficiently allocating resources based on predicted demand patterns, waiting times can be significantly reduced while serving more customers within shorter timeframes.

1.4 Methodology

Data preprocessing: The dataset collected from the Kaggle source may contain missing values, negative values, or errors. To clean the dataset, we remove incomplete records. Once the cleaned dataset is obtained, it needs to be prepared for further analysis. Recurrent Neural Network: In this study, a RNN model is used for taxi demand prediction. The input of the network consists of current taxi demand and other relevant information, while the output represents the predicted demand in the next time-step. Using a recurrent neural network allows us to store and analyze sequential data effectively, which is essential for predicting future outcomes in a time series forecasting problem like taxi demand prediction. Among various types of RNNs available today, Long Short Term Memory networks are commonly employed due to their effectiveness and ability to capture long-term dependencies efficiently. Long short-term memory networks, a type of recurrent neural network, are effective in capturing long-term dependencies through their gating mechanism. The goal is to accurately predict taxi demand in small areas, enabling drivers to know precisely where they should be located. Our system is trained using a dataset and uses LSTM for future demand prediction. For presenting the predictions and results, we generate a graph that displays the projected crowded area for the next time slot based on our Neural Network model. This model utilizes data from previous observations to forecast high-demand areas within a city. By directing drivers to these identified locations, we aim to address anticipated demands effectively.

Flow Chart of the system used in this project:

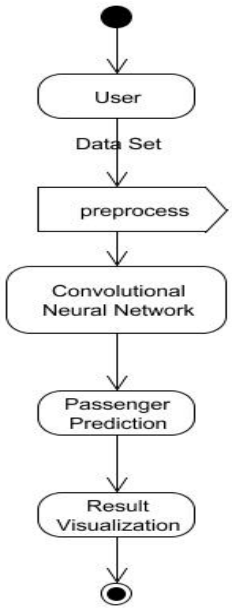


Figure 1.1 Flowchart of the system used in this project

2. LITERATURE SURVEY

2.1 Related Work

Previous research on forecasting taxi demand has been limited. One approach by Zhang et al. involves developing a passenger hotspot recommendation system for taxi drivers, where past taxi data is analyzed to identify popular hotspots and assign them a score based on their popularity. At each time step, the k most popular hotspots are recommended to drivers based on predicted hotspots and driver location. Another study by Zhao et al focuses on maximizing predictability of taxi demand at the street block level. They demonstrate the predictability of taxi demand by measuring the entropy of previous demand cycles and utilize three forecasting techniques to support their hypothesis regarding maximum predictability in this context.

The proposed architecture by Moreira-Matias et al. utilizes three distinct forecast models. The projected demand for each time step is determined based on weighted estimates from these models. To update the ensemble weights in the sliding window, previous time steps' individual prediction results are taken into consideration. This framework can accurately predict short-term demand for 63 taxi stands in Porto, Portugal. Davis employs a time series modeling approach to anticipate and predict the demand for taxi rides in Bengaluru, India. Drivers have access to this valuable information through a mobile application which provides insights about high-demand locations

The dispatch center in other cases utilized historical and current taxi data for simulation. Zhang et al. proposed a system that promptly assigns taxis based on two categories of passengers: those who have already departed and those who will soon arrive. The dispatch center can simulate passenger arrivals and departures by utilizing real-time GPS tracking information from each taxi. Hidden Markov chains were incorporated with the Dmodel demand inference model to capture changes in the state of departing and arriving passengers. Miao et al., on the other hand, suggest implementing a shipping system to balance the supply of taxis across the city while also minimizing unnecessary gaps between demand and supply. Their approach involves calculating future taxi demand through repeated sampling from historical data to determine an average value for the next time interval.

2.2 Existing System

In order to minimize response time and maximize efficiency, taxi drivers must strategically determine their waiting locations to quickly pick up customers. Similarly, passengers also desire the convenience of finding a taxi promptly when in need. The control center for the taxi service plays a crucial role in making decisions regarding centralizing operations within highly congested areas. In scenarios where there is no specific high-demand location based on time factors (e.g., airports, commercial districts, school districts, railway stations), taxis may be dispersed across a broader geographic area at times. Furthermore, the model's effectiveness can be attributed to its three components: firstly, by calculating the root mean square error between individual prediction outputs and actual values allows precise focus on each unique requirement.

Based on the information provided in these sources, an important element is the calculation of root mean square error to compare the accuracy between joint predictions and true values. Additionally, a more accurate forecast can be achieved by combining independent and common features from both questions. This involves calculating the root-mean-square error between the output of a single forecast module and that of a parallel forecast module. The first section consists of two individual demand prediction modules, one for rising demand patterns and another for declining demand patterns, using only one form of input and output each.

The time feature embedding module is the second component which utilizes the tf encoder to extract time features associated with taxi demand. These features are derived from a pre-trained taxi demand classifier. In order to predict two requests simultaneously, the third component known as the combined joint prediction module integrates all input data and temporal functions. This module has potential for expansion by incorporating additional factors such as weather conditions or major events that may impact typical taxi pick-up and drop-off patterns.

2.3 Limitation of Existing System

The efficient management of a taxi fleet is crucial for serving crowded areas. It involves optimizing resource utilization to minimize passenger waiting time and maximize the number of customers served within a short period.

2.4 Proposed System

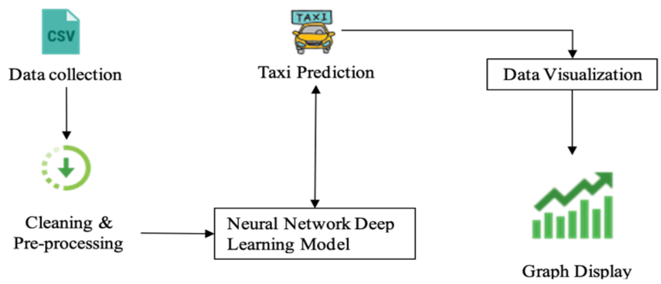
The preceding discussions on taxi demands have sparked interest in predicting future taxi demand using historical trip data. Many studies employ weighted methods or time series fitting models to forecast taxi demand. However, these techniques face challenges when dealing with large and continuous data sequences. Moreover, the application of a time series fitting model differs across different locations, requiring separate training for each site.

Our study distinguishes itself from previous research by its ability to capture long-term correlations in sequences that are widely

A key distinction between our study and previous works is the ability of our model to capture long-term correlations in sequences occurring at significant temporal intervals. By harnessing adequate processing power, it becomes feasible to extend this capability to span periods as extensive as a month or even a year. During training, we employed sequences spanning up to one week. An advantage of our approach lies in its capacity for simultaneous prediction across all neighborhoods, facilitating the transfer of LSTM patterns from one domain to another. Furthermore, rather than deterministic forecasting of request quantities per location, our model predicts the probability distribution encompassing taxi demand on an overall scale. This strategy offers greater precision by accounting for forecast uncertainty.

3. METHODOLOGY

3.1 Architecture



The dataset obtained from the Kaggle source may contain errors, negative values, or missing values. In order to preprocess the data, it is necessary to clean and remove incomplete records. Once the cleaned dataset is prepared, it needs to be properly formatted for input into subsequent algorithms. The current taxi demand and other pertinent data serve as inputs for the network, with the output being a prediction of future demand at a specified time interval. Recurrent neural networks are employed in this context due to their ability to retain important information and forecast forthcoming events accurately. Moreover, predicting taxi demand involves complex time series analysis techniques that need to be applied effectively.

LSTM networks have become the most commonly used type of RNN for forecasting taxi demand. They are capable of capturing long-term dependencies due to their unique input method. In order to provide accurate guidance for drivers, it is necessary to predict taxi demand in small geographical regions. By training our system on a dataset, we are able to make future predictions.

Using LSTM and neural networks, we can forecast the next time slot and identify areas with high demand. Drivers will be directed to wait in these identified areas as determined by the system's prediction model for future demand in the city.

3.2. Sequence Diagram

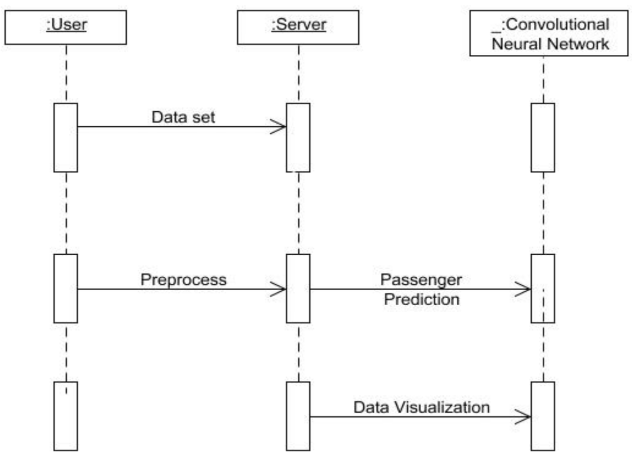


Figure 3.2: Sequence Diagram

4. TOOL DESCRIPTION

4.1 Hardware Requirements

- Hard disk: 500 GB and above.
- Processor: i3 and above. Choose a processor with sufficient power and multiple cores to run search algorithms and text data processing.
- Ram: 4GB and above. Allocate enough RAM to store and process text data efficiently.
- GPU (Graphic Processing Unit): Consider GPUs for compute-intensive tasks such as natural language processing or machine learning-based ingest systems.
- Redundancy and scalability: For high availability and scalability, consider redundant hardware components such as servers or storage devices.

4.2. Software Requirements:

- Operating System : Windows 7 and above (64-bit).
- Python : 3.6 [libraries: SciPy, NumPy, pandas)].

5. IMPLEMENTATION

This section first describes the methodology employed to convert high-resolution GPS data into the count of taxi requests in each local city. Additionally, a concise overview of how recurrent neural networks are mathematically represented is provided.

A. GPS Data Encoding:

To accurately anticipate taxi demand in specific areas, it is important to divide the city into smaller regions. However, predicting taxi demand in these limited areas can be challenging. Therefore, it is crucial to choose a range that drivers can easily evaluate and that provides accurate results. In this study, the Geohash library was utilized to precisely partition a geographic region into smaller subregions by employing a hierarchical geographic data structure known as Geohash geocoding system. This creates grid-like containers within the given space for more efficient analysis and forecasting of taxi demand patterns. The dimensions of the grid are determined by the length of the geohash code. In our study, we utilized NYC taxi data collected from January 1, 2013 to June 30, 2016. After applying data filtering techniques, we obtained a dataset containing over 600 million recorded taxi trips. Each record in the dataset includes a timestamp and GPS location for both pick-up and drop-off events. For our analysis purposes, we partitioned New York City into approximately 6,500 zones using Geohashing with a resolution of level seven. At this resolution level no zone exceeds dimensions of 153 x 153 meters (approximately). The demand for taxis at each step is then computed based on historical taxi data specific to that particular zone. This information is used as input for training an LSTM model which aims to learn sequential patterns within the data.

B. Recurrent Neural Networks:

Given the sequential nature of taxi demand data, it is important to utilize a model that can effectively handle time series. Recurrent neural networks have emerged as popular models for processing sequential input due to their ability to store and utilize meaningful information from previous inputs in order to predict future outcomes. Unlike feedforward neural networks which can only generate output based on current input, RNNs possess a memory component that enables them to retain crucial details about past inputs. This feature proves especially valuable in tasks such as language modeling where predictions made at earlier time steps impact subsequent ones. The name "recurrent" stems from the fact that RNNs perform the same calculations on each element of a given sequence and base their conclusions on prior computations

- The transmission of data from one phase to the next involves utilizing shared weights across multiple time-steps. To train these weights, we visualize an unrolled network for a specific number of time-steps, as illustrated in Figure 3.

- When the network is unfolded, it becomes more apparent how information is propagated forward and why it is utilized for sequential learning. The computation at each time step can be expressed as follows:

- The hidden state at time-step t, denoted as h_t, is determined by the previous hidden state and the current input. This calculation involves applying a non-linear function to the sum of three terms: $W_{xh}x_t$ (representing the influence of the current input), W_{hh}ht−1 (representing the influence of the previous hidden state), and b_h (a bias term). The typical choice for this non-linearity is hyperbolic tangent.
- The output at a given time step, denoted as y_t, can be customized based on the specific task. For instance, when predicting the next word in a sentence, y_t could represent a probability distribution across the vocabulary options available.
- Each time-step that has been unrolled shares all of the parameters Wxh, Whh, and Why. As a result, the network really executes the same computation at each time-step while using a distinct set of inputs (xt). As a result, the network's total number of parameters is significantly decreased, and overfitting on smaller datasets is prevented. The key characteristic of RNNs is their hidden state. It functions as a network memory that stores important data about what occurred during each previous time step.

- LSTMs have emerged as the most commonly used type of RNNs. With their distinct gating mechanism, LSTMs possess the ability to capture and learn long-term dependencies. Initially introduced by Hochreiter & Schmidhuber, these networks have undergone continuous refinement and gained considerable popularity over time through contributions from various researchers.

Flow chart of the implementation:

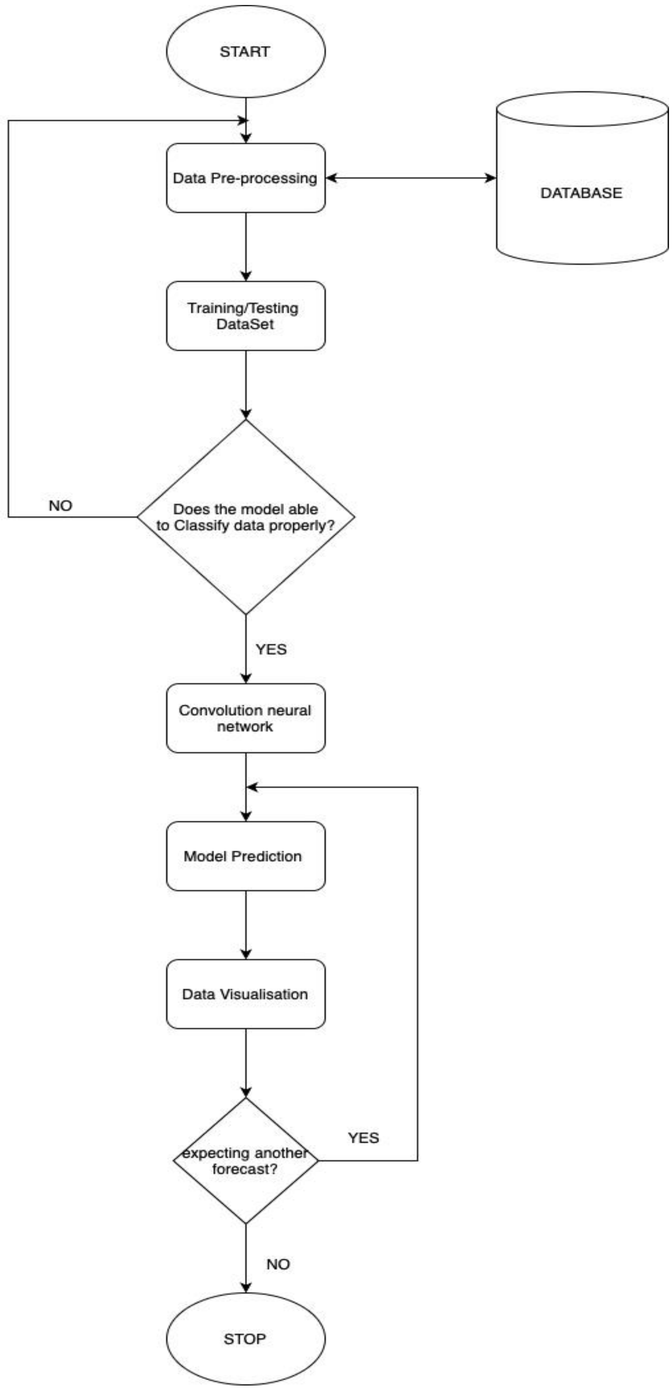


Figure 5.1 Implementation

6. RESULTS AND ANALYSIS

6.1. Result Discussion and Analysis

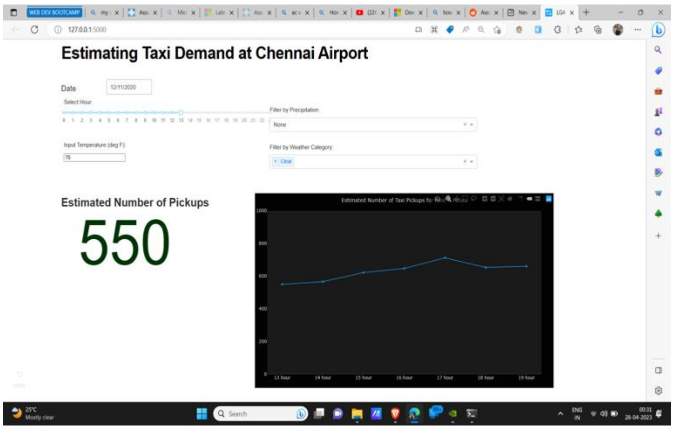


Figure 6.1 Result and Analysis

7. CONCLUSIONS AND FUTURE SCOPE

7.1 Conclusions

The research findings suggest that a hybrid model combining recurrent neural networks and fuzzy density networks can successfully predict taxi demand in various areas of a city. The proposed LSTM model effectively utilizes past taxi demand patterns to make accurate forecasts. Experimental results reveal that the LSTM model achieves an impressive accuracy rate exceeding 83 percent

The chapter focuses on the advantages of using the proposed strategy in situations where there is high demand in some areas and taxi drivers have to compete for customers in other neighborhoods. By accurately forecasting demand, the app can optimize taxi sharing and reduce the time drivers spend waiting for passengers. As a result, those who need cabs stand to gain significantly from this, saving them crucial time and enhancing their whole experience.

Furthermore, putting in place such a predictive system may save a lot of gasoline. Taxis now frequently use needless amounts of gasoline looking for customers. The approach can minimise unused fuel usage, benefiting the environment and saving money for taxi companies by properly forecasting demand and effectively allocating cabs to locations with high prospective demand.

In conclusion, the proposed recurrent neural network-based sequence learning model demonstrates its usefulness in predicting taxi demand. Its use can lessen rivalry among taxi drivers, save time for customers, and consume less gasoline, thus helping the environment and the transportation system.

7.2 Future Work

- Improved Model Architectures: Researchers can explore and develop more advanced RNN architectures or variants, such as Gated Recurrent Units (GRUs), Transformer-based models, or attention mechanisms, to enhance the model's ability to capture long-term dependencies and complex patterns in taxi demand data. Investigating the use of advanced architectures may lead to improved accuracy and better performance.

- Incorporating External Factors: Currently, many taxi demand prediction models primarily rely on historical demand data. Future work can focus on incorporating additional external factors that influence taxi demand, such as weather conditions, traffic patterns, events happening in the city, or even social media data. By incorporating these factors, the prediction model can provide more accurate and context-aware demand forecasts.

- Real-Time Data Streaming: Existing models often assume the availability of complete historical data to make predictions. However, in real-time scenarios, it is crucial to process streaming data and provide immediate demand forecasts. Future work can explore techniques for handling streaming data in RNN models, allowing them to update predictions in real-time as new data becomes available.

- Spatial-Temporal Modeling: Taxi demand is influenced by both spatial and temporal factors. Future research can focus on developing models that effectively capture the spatial-temporal dynamics of taxi demand. This can involve integrating techniques like graph neural networks (GNNs) or spatio-temporal modeling approaches to better understand the relationship between different locations and how demand patterns evolve over time.

- Uncertainty Quantification: Providing uncertainty estimates along with demand predictions is valuable for decision-making and resource allocation. Future work can investigate methods for quantifying and representing the uncertainty in taxi demand predictions using RNN models. Bayesian approaches, ensemble methods, or Monte Carlo sampling techniques can be explored to estimate prediction uncertainties.

- Deployment and Scalability: It is essential to consider the practical aspects of deploying and scaling up real-time taxi demand prediction systems. Future research can focus on developing efficient and scalable architectures that can handle large-scale datasets and real-time prediction demands, allowing for the practical implementation of the models in real-world taxi dispatching systems.

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