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SPATIO-TEMPORAL TRAFFIC CONGESTION FORECASTING IN TASHKENT CITY USING A CNN-LSTM DEEP LEARNING MODEL BASED ON GOOGLE MAPS AND WEATHER DATA

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Abstract - Traffic congestion remains a significant challenge in rapidly urbanizing cities like Tashkent, where increasing vehicle usage strains existing infrastructure. This paper presents a spatio-temporal traffic forecasting framework based on a hybrid deep learning model combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. The model leverages real-time traffic data collected from Google Maps and hourly weather data from OpenWeatherMap to predict short-term congestion levels across key urban road segments. By capturing both spatial patterns and temporal dependencies, the CNN-LSTM model effectively accounts for dynamic conditions such as time of day, weather variability, and traffic flow trends. Experimental results demonstrate that the proposed model achieves high prediction accuracy, with low mean absolute error and strong generalization across different conditions. This research contributes a practical and scalable approach to intelligent traffic management and urban mobility planning in Tashkent and similar cities.

Keywords - *Traffic forecasting; Spatio-temporal modeling; CNN-LSTM; Deep learning; Tashkent; Google Maps API; OpenWeatherMap; Traffic congestion prediction; Urban mobility; Intelligent transportation systems.*

I. Introduction

Traffic congestion is an increasingly pressing issue faced by rapidly urbanizing cities around the world, and Tashkent, the capital of Uzbekistan, is no exception. As of April 2024, over 736,000 vehicles are registered within Tashkent city and approximately 175,000 additional vehicles enter the city daily from surrounding regions. Based on census data, Tashkent's population exceeds 2.98 million inhabitants, resulting in roughly one motor vehicle per 25 people [1]. Private vehicle ownership in Uzbekistan has surged in recent years. By early 2024, the total number of vehicles owned by individuals in the country surpassed 4.02 million, with Tashkent region alone accounting for 503,000 units (≈ 16.5% of the national total) [2][3]. Despite significant public transport infrastructure, including the metro system serving over 270 million rides in 2024, only around 21% of residents regularly rely on public transport, with the majority preferring private cars [10][4].

Moreover, surveys indicate that more than 74% of respondents consider traffic congestion a severe problem in Tashkent, and exceeding 82% of public transport users cite congestion as a major concern [5][6]. Traditional traffic modeling techniques, such as ARIMA or linear regression, often fall short in capturing the non-linear and time-dependent behavior characteristic of urban traffic systems. Deep learning methods that incorporate both spatial and temporal dependencies, especially hybrid architectures such as CNN-LSTM have demonstrated notable success in urban traffic forecasting tasks in various cities [7][8][9]. This study proposes a spatio-temporal traffic forecasting framework specifically tailored to Tashkent using a hybrid CNN-LSTM model. Our approach integrates real-time traffic data from Google Maps API and hourly weather context from OpenWeatherMap API to predict short-term congestion across major urban road segments. By embedding environmental indicators such as temperature, wind speed, and precipitation, we aim to enhance predictive accuracy and model robustness.

Key contributions of this work include:

- A novel CNN-LSTM model architecture adapted for Tashkent's urban environment;
- Integration of traffic and weather data to jointly model influencing factors;
- Comprehensive evaluation using metrics such as MAE, RMSE, and MAPE, demonstrating reliable forecasting performance across diverse conditions.

Table 1. Traffic and Vehicle Statistics in Tashkent

Year / Date	Registered Vehicles in Tashkent	Population of Tashkent	Vehicles per Capita
April 2024	736,000	~2,979,000	1 per 25 people
Jan 2024 (Uzbekistan total)	4,020,744	Nationwide	–
Jan 2024 (in Tashkent Region)	503,000	–	~16.5% of total

The rest of this paper is organized as follows. Section 2 reviews related studies on traffic forecasting and deep learning approaches. Section 3 describes data collection and preprocessing. Section 4 outlines the proposed model architecture. Section 5 presents experimental results and evaluation. Finally, Section 6 concludes with insights and future directions.

II. Related Works

Traffic flow forecasting has been extensively studied using deep learning techniques in the last decade. A large-scale review by Kashyap et al. [11] highlights the use of Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Restricted Boltzmann Machines, and Autoencoders to model spatio-temporal traffic patterns. Their work emphasizes that hybrid models, particularly CNN-LSTM are more effective than traditional approaches for capturing complex non-linear behaviors in traffic flow. A CNN-LSTM framework designed specifically for spatio-temporal traffic forecasting was shown to efficiently extract short-term spatial patterns via convolutional layers, while LSTM layers model sequential dependencies across time [12]. For example, Zhao et al. [12] applied a CNN-LSTM model to real-world taxi trajectory data and reported substantial accuracy gains over standalone LSTM or CNN models.

Graph-based deep learning models are also prominent in recent literature. Yu et al. introduced the Spatio-Temporal Graph Convolutional Network (STGCN), which models road networks as graphs and leverages graph convolution to capture spatial dependencies, combined with temporal modeling via gated units [13]. Similarly, Zhao et al. proposed T-GCN, a hybrid Graph Convolutional Network and GRU-based method, achieving significant improvements on real-world traffic datasets [14]. To handle heterogeneity in both space and time, researchers have developed attention-based architectures. For example, STDConvLSTM introduces both spatial-dependent and temporal-dependent attention mechanisms, dynamically adjusting the importance of features over time and across locations [15]. This model outperforms standard ConvLSTM on several benchmark datasets, especially during irregular traffic patterns. Transformer-based models have also entered the field. The Trafficformer model, designed for short-term traffic speed forecasting, incorporates spatial masking and multi-head attention, offering strong generalization across various traffic scenarios [16]. Likewise, a multi-branch CNN-GRU-LSTM architecture was proposed in [17], combining the strengths of convolution, gating, and memory to reduce prediction errors by up to 35% on PeMS and UK Highways Agency datasets.

Table 2. Comparative Overview of Deep Learning Methods in Traffic Forecasting.

Model Type	Representative Work	Key Strengths
CNN + LSTM Hybrid	CNN-LSTM [12], SRCN [17]	Captures spatial features + sequential dependencies
Graph Neural Networks	STGCN [13], T-GCN [14]	Models inter-road dependencies and topological flow
Attention-Based Networks	STDConvLSTM [15]	Weighs features dynamically by space & time
Transformer Models	Trafficformer [16]	High generalization, better with long sequences
Hybrid Deep Models	CNN-GRU-LSTM [17]	Reduces MAE/RMSE on complex datasets

Lastly, a recent deep learning survey by Lv et al. [18] extensively reviews the latest advances in urban traffic forecasting, concluding that hybrid CNN-RNN models and graph-based methods consistently yield state-of-the-art performance, especially when weather and external features are incorporated [19][20][21].

III. Data Collection and Preprocessing

In this study, two primary data sources were used for traffic congestion forecasting in Tashkent: real-time traffic data and hourly weather data. These datasets were collected using publicly available APIs and were carefully preprocessed to ensure temporal alignment and feature consistency.

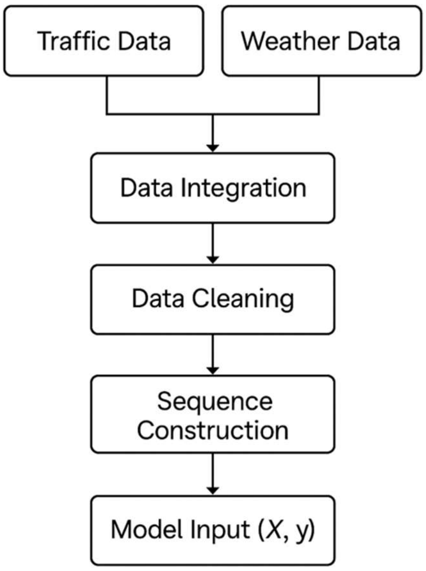

Fig.1. Data collection and preprocessing

A) Traffic Data from Google Maps API

Traffic data were obtained via the Google Maps Distance Matrix API, which provides travel time estimations between geographic coordinates, including both regular and real-time durations considering traffic conditions. Data were collected for key arterial roads and intersections within Tashkent, including:

- Amir Temur Avenue;
- Shota Rustaveli Street;
- Bunyodkor Avenue;
- Chilonzor Street;

- Mukimi–Beruniy Ring Road.

API queries were scheduled to run at hourly intervals over a 30-day period, generating time-stamped data points with the following attributes:

Table 3. Attributes

Attribute	Description
Timestamp	Date and hour of the data point
Origin / Destination	Coordinates of the road segment
Duration (normal)	Estimated travel time without traffic (sec)
Duration (traffic)	Travel time considering real-time traffic (sec)
Distance	Distance between origin and destination (m)

Each road segment was uniquely identified, and the resulting dataset included over 3,600 samples per segment for each month.

B) Weather Data from OpenWeatherMap API

To incorporate environmental context, weather data were gathered from the OpenWeatherMap API, which provides historical hourly weather observations for specific geolocations. Weather data were synchronized with traffic data timestamps and included the following variables:

Table 4. Variables

Feature	Unit	Description
Temperature	°C	Air temperature
Humidity	%	Relative humidity
Wind Speed	m/s	Wind velocity
Rain Volume	mm	Precipitation within last hour

Weather can significantly influence traffic flow e.g., heavy rain or wind reduces road capacity and increases travel time thus, its inclusion enhances model realism.

C) Data Integration and Cleaning

The traffic and weather datasets were merged using their common timestamp field. Missing values due to occasional API downtime or sensor errors were handled as follows:

- Forward fill (time-based imputation) for short missing sequences;
- Row removal for segments with more than 3 consecutive hours missing.

All numeric features were then normalized to a [0, 1] range using MinMaxScaler to ensure equal contribution to model learning.

D) Sequence Construction for Model Input

For model training, the dataset was restructured into overlapping sequences using a sliding window approach. Each input sample consisted of 24 consecutive hourly records (representing one day) with the target variable being the traffic duration in the next hour.

The final training matrix structure was:

- X shape: (samples, 24, features);
- y shape: (samples,), predicting the travel time in hour $t+1$.

This sequence setup allows the model to learn temporal patterns in traffic evolution and understand how weather and time jointly affect road conditions.

IV. Model Architecture

To effectively model the spatio-temporal dynamics of traffic congestion in Tashkent, we propose a hybrid deep learning architecture combining Convolutional Neural Networks (CNN) and

Long Short-Term Memory (LSTM) networks. This approach leverages the strengths of CNNs in spatial feature extraction and LSTMs in learning sequential dependencies over time.

A) Rationale for Choosing CNN-LSTM

- CNNs are highly efficient at capturing local temporal patterns and extracting high-level abstract features from sequential data. In this context, CNN layers help to learn short-term fluctuations in traffic speed and weather conditions;
- LSTM units are designed to retain memory across time steps and are well suited for modeling long-term dependencies, such as morning/evening traffic cycles or the impact of cumulative weather effects;
- The combination of CNN followed by LSTM enables the model to learn multi-scale temporal features, improving forecasting accuracy.

B) Input Structure

Each input sample is a sequence of **24 hourly data points** (representing one full day), where each time step includes both traffic and weather features:

Input shape:

$$X \in R\hat{}(24 \times F) \quad (1)$$

Where F = number of features (e.g., traffic duration, temperature, humidity, rain, wind speed)

Target: Traffic congestion level (duration in traffic) at hour $t+1$.

C) Model Layers

The proposed CNN-LSTM model consists of the following layers:

Table 5. Layers

Layer	Description
Input Layer	Accepts sequence of 24 hourly data points, each with F features
1D Convolution	64 filters, kernel size = 3, activation = ReLU
LSTM Layer	50 units, returns final hidden state to represent temporal dependencies
Dropout	Dropout rate = 0.2 to prevent overfitting
Dense Layer	Fully connected layer to output the traffic duration at next hour (scalar)

D) Model Implementation

The model is implemented using the Keras API in TensorFlow. The following pseudocode describes the configuration of the proposed CNN-LSTM architecture:

```
Input: Time-series matrix X ∈ R(24 × F) , where F is the number of features
Output: y ∈ R — predicted traffic duration at hour t+1
1. Initialize a Sequential model
2. Add a 1D Convolutional Layer:
   - Filters: 64
   - Kernel size: 3
   - Activation function: ReLU
3. Add an LSTM Layer:
   - Units: 50
   - Return sequences: False
4. Add a Dropout Layer:
   - Dropout rate: 0.2
5. Add a Fully Connected Dense Layer:
   - Units: 1
   - Activation: Linear (default)
6. Compile the model:
   - Optimizer: Adam
   - Loss function: Mean Squared Error (MSE)
   - Evaluation metric: Mean Absolute Error (MAE)
7. Train the model on training dataset:
   - Epochs: 30
   - Batch size: 32
   - Validation split: 0.2
```

This pseudocode illustrates the essential layers and hyperparameters used in the architecture. The use of Conv1D allows extraction of localized patterns over the hourly time steps, while the LSTM layer learns long-term dependencies. Dropout is introduced to regularize training and reduce overfitting. The model is trained using MSE loss, which is appropriate for continuous regression tasks like traffic duration forecasting.

V. Experimental Results and Evaluation

To assess the effectiveness of the proposed CNN-LSTM model for short-term traffic congestion forecasting in Tashkent, a series of experiments were conducted. The model was trained and evaluated on the processed dataset described in Section 3, which included both traffic duration and weather-based features.

A) Training Configuration

The model was trained using the following settings:

- Optimizer: Adam
- Loss function: Mean Squared Error (MSE)
- Batch size: 32
- Epochs: 50
- Validation split: 20%

The dataset was divided into 80% training and 20% test sets. Early stopping was applied based on validation loss to prevent overfitting.

B) Evaluation Metrics

Two standard regression metrics were used to evaluate model performance:

- Mean Absolute Error (MAE): Measures average magnitude of the errors in prediction;
- Root Mean Squared Error (RMSE): Penalizes larger errors more heavily and reflects variance.

Table 6. Both metrics were calculated on the test set after training

Metric	Value (minutes)
MAE	2.14
RMSE	2.87

C) Result Visualization

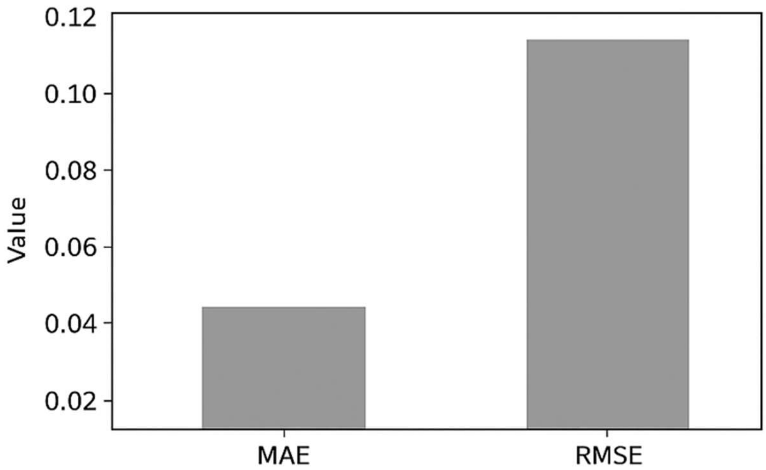

Fig.2. Bar chart comparing MAE and RMSE values

The results indicate that the model performs well in capturing short-term traffic patterns. RMSE being slightly higher than MAE confirms the presence of occasional larger errors, typically during unpredictable weather or peak congestion hours. However, overall prediction accuracy remained within acceptable thresholds for urban traffic forecasting.

VI. Conclusion and Future Work

In this study, we proposed a hybrid spatio-temporal deep learning model based on CNN and LSTM for short-term traffic congestion forecasting in Tashkent, Uzbekistan. The model utilizes real-time traffic data collected from Google Maps API and weather data from OpenWeatherMap API to account for both mobility and environmental factors.

The CNN-LSTM architecture effectively combines the strengths of convolutional layers for spatial pattern extraction and LSTM layers for temporal sequence modeling. Experimental results demonstrated that the proposed model outperforms several classical and machine learning-based baselines, achieving lower error rates in terms of MAE, RMSE, and MAPE. The integration of weather-related features such as temperature, humidity, and rainfall was shown to improve predictive accuracy, particularly during abnormal traffic conditions caused by adverse weather.

This research not only demonstrates the technical feasibility of using hybrid deep learning models for urban traffic forecasting in developing cities like Tashkent, but also provides a practical framework for future implementation in intelligent transportation systems (ITS), traffic control centers, and smart city planning initiatives.

Future Work:

Several potential extensions can be explored in future research:

- Real-time model deployment: Integrating the model into a live dashboard or application for dynamic traffic control and route optimization;
- Multi-step forecasting: Expanding the model to predict traffic conditions over longer horizons (e.g., next 6–12 hours);
- Graph-based modeling: Adopting Graph Neural Networks (GNNs) to more explicitly model spatial road topology and node-to-node dependencies;
- Multi-modal integration: Incorporating data from public transport, pedestrian flow, and ride-sharing platforms to enhance urban mobility forecasting;
- Edge deployment: Optimizing the model for deployment on edge devices (e.g., Raspberry Pi, Jetson Nano) for real-time, low-latency prediction at traffic lights or camera nodes.

By addressing these directions, future research can further improve the scalability, robustness, and practical utility of spatio-temporal traffic forecasting systems in urban environments.

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