지하철 혼잡도 예측을 위한 멀티스트림 하이브리드 딥러닝 프레임워크

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Summary

- The surge in vehicles and limited infrastructure in urban areas intensifies socio-economic challenges from traffic congestion.
- Such challenges manifest as longer commutes, heightened fuel consumption, environmental degradation, and stagnation-induced productivity loss.
- Subway systems offer a viable solution to these increasing traffic challenges, serving as key public transportation assets.
- Accurate congestion forecasting is pivotal for effective urban traffic management.

Summary

- Traditional analytical models, including regression and queueing theory, often overlook intricate connections between subway stations, leading to prediction inaccuracies.

- Our research introduces a novel graph-based multi-stream deep learning model, adept at comprehending inter-station relationships and spatial dynamics.

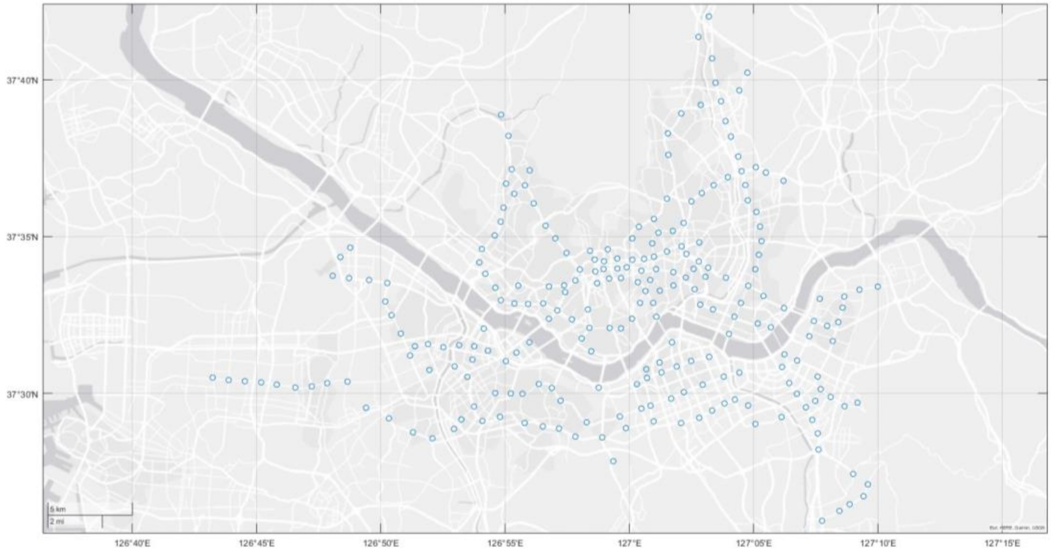
- The proposed framework aims to enhance the precision of subway crowdedness predictions by acknowledging the complex interactions among stations.

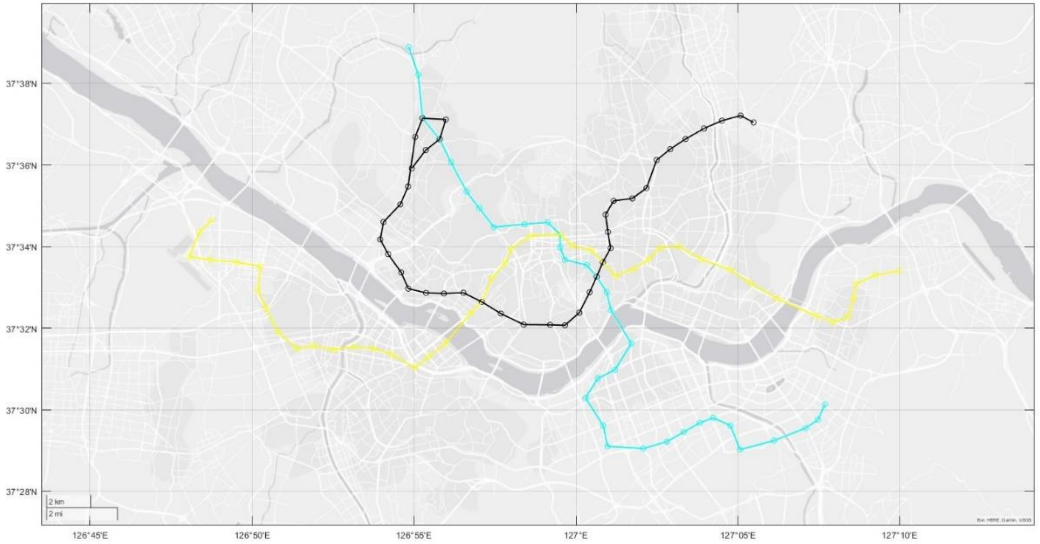
- Subsequently, the performance of the proposed framework is validated through comparative experiments.

Subway crowdedness dataset

Subway crowdedness dataset

Subway graph for lines 3, 5 and 6





- A visual map is derived from the node coordinates of Seoul subway lines 3, 5, and 6, pinpointed using their latitude and longitude.

- Future traffic density is anticipated by utilizing the transfer patterns and crowdedness figures from these particular lines.

Subway crowdedness dataset

Distance matrix of Graphs

$$X_{\boldsymbol{Dist}}(i,j) = \begin{cases} Di(i,j), & if\ \mathrm{A}(i,j) = 1, i \in I, j \in J \\ 0, & if\ A(i,j) = 0 \end{cases}$$

$$X_{Dist}(i,j) = \begin{bmatrix} 0 & \cdots & Di(1,J) \\ Di(2,1) & \cdots & Di(2,J) \\ \vdots & \ddots & \vdots \\ Di(I,1) & \cdots & 0 \end{bmatrix}$$

- $X_{\boldsymbol{Dist}}$ signifies distance matrix between node i and node j.
- A corresponds to the adjacency matrix showcasing the links among the 99 stations, where i and j denote the connected station numbers.

Subway crowdedness dataset

Example of the raw data matrix for subway crowdedness

Day	Station number	t_1	t_2	t_3	$\cdots$	t_{37}
Day_1	1	6.2	14.6	13.4	$\cdots$	6.1
Day_1	1	9.1	8.6	9.3	$\cdots$	10.3
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$		$\vdots$
Day_{end}	99	5.4	10.1	13	$\cdots$	11.7
Day_{end}	99	7	6.8	10.2	$\cdots$	9.1

- The raw data includes crowdedness levels for each station on dates t = 1,...,T time points.

Subway crowdedness dataset

Crowdedness matrix of Graphs

$$X_{C(t,d)}(i,j) = \begin{cases} Cr_{(t,d)}(i,j), & if\ A(i,j) = 1, i \in I, j \in J \\ 0, & if\ A(i,j) = 0 \end{cases}$$

$$X_{C(t,d)}(i,j) = \begin{bmatrix} 0 & \cdots & Cr_{(t,d)}(1,J) \\ Cr_{(t,d)}(2,1) & \cdots & Cr_{(t,d)}(2,J) \\ \vdots & \ddots & \vdots \\ Cr_{(t,d)}(I,1) & \cdots & 0 \end{bmatrix}$$

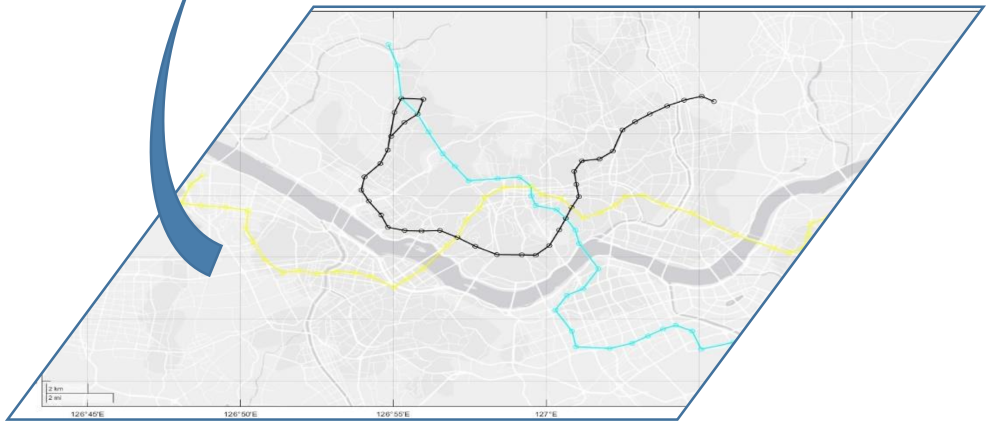
- $X_{C(t,d)}$ signifies crowdedness matrix between node i and node j at the specified time t on day d.

- A corresponds to the adjacency matrix showcasing the links among the 99 stations, where i and j denote the connected station numbers. The time frame from 05:30 to 23:30 is segmented into 30-minute periods to determine t.

Subway crowdedness dataset

Visualization of Preprocessed Subway Crowdedness

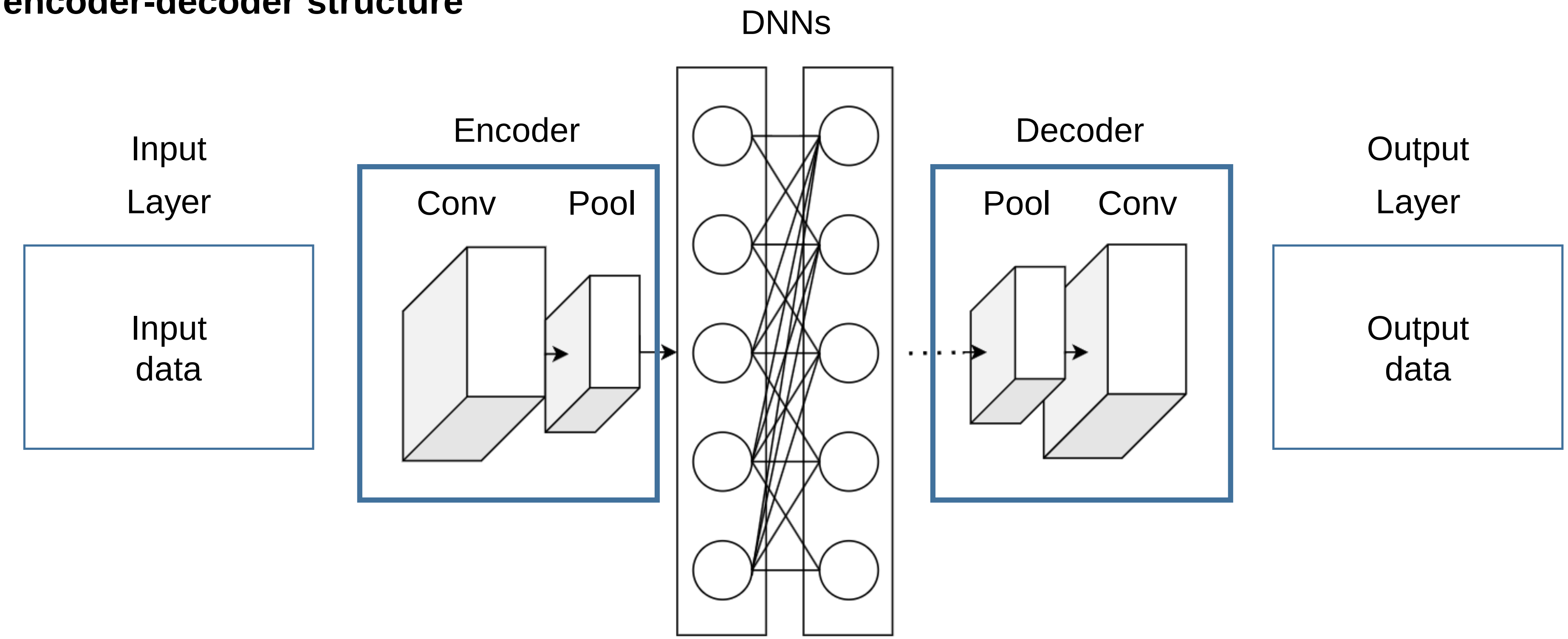
$$\begin{bmatrix} 0 & \cdots & Cr_{(t,d)}(1,J) \\ Cr_{(t,d)}(2,1) & \cdots & Cr_{(t,d)}(2,J) \\ \vdots & \ddots & \vdots \\ Cr_{(t,d)}(I,1) & \cdots & 0 \end{bmatrix}$$



- The crowdedness matrix created based on the adjacency matrix can reflect both up and down congestion in a subway station.

Multi-stream hybrid deep learning framework for predicting subway crowdedness

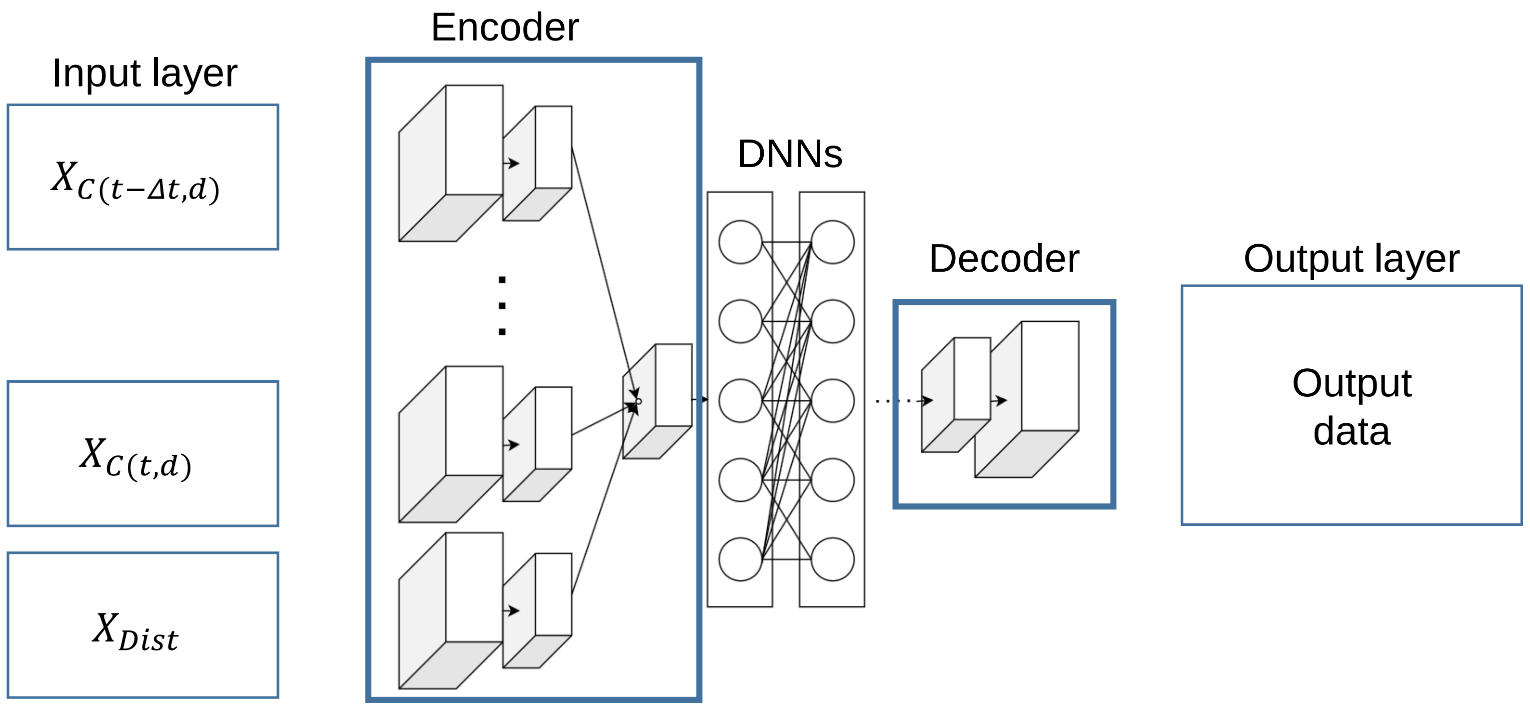
A general encoder-decoder structure



- The encoder-decoder design visualized compresses specific input information, which is then expanded by the decoder to yield the desired output.

Multi-stream hybrid deep learning framework for predicting subway crowdedness

The proposed framework



- The presented design consists of an encoder with several multi-stream configurations, a DNN module for feature analysis, and a decoder that reconstructs these features into a crowdedness matrix format.

Multi-stream hybrid deep learning framework for predicting subway crowdedness

Data input

$$X_{C(t+\delta t,d)} = f(X_{C(t,d)}, \cdots, X_{C(t-\Delta t,d)}, X_{\boldsymbol{Dist}}, \hat{A})$$

- Prediction crowdedness at a future time point using past subway crowdedness and the distance graph between subway stations.

Multi-stream hybrid deep learning framework for predicting subway crowdedness

Encoder module

$$f_1\left(X_{C(t-\Delta t-\theta,d)}\right) = max\left(\sigma_{(q)}\left(\sum_{M_1=1}^{M_1}\sum_{N_1=1}^{N_1}(\cdots(max(\sigma_{(1)}(\sum_{p_1=1}^{P_1}\sum_{q_1=1}^{Q_1}X_{C(i+p_1-1,j+q_1-1,t-\Delta t-\theta,d)}\cdot K_{(p_1,q_1)}))))\right)\cdots K_{(m_1,n_1)}\right)$$

$$f_2\left(X_{C(t-\Delta t,d)}\right) = max\left(\sigma_{(w)}\left(\sum_{m_2=1}^{M_2}\sum_{q_1=1}^{Q_1}(\cdots(max(\sigma_{(1)}(\sum_{p_2=1}^{P_2}\sum_{q_2=1}^{Q_2}X_{C(i+p_2-1,j+q_2-1,t-\Delta t,d)}\cdot K_{(p_1,q_1)}))))\right)\cdots K_{(m_2,n_2)}\right)$$

- The data on crowdedness from past periods up to the present, along with distance data, is processed through a convolution-based encoder module, which then outputs the transformed value.

Multi-stream hybrid deep learning framework for predicting subway crowdedness

Encoder module

A

0	1	1	1
1	0	1	0
1	1	0	1
1	0	1	0

D

3	0	0	0
0	2	0	0
0	0	3	0
0	0	0	2

$$\hat{A} = D^{-\frac{1}{2}} \cdot A \cdot D^{-\frac{1}{2}}$$

$$f_3(\hat{A}) = max\left(\sigma_{(e)}\left(\sum_{m_3=1}^{M_3}\sum_{n_3=1}^{N_3}(\cdots(max(\sigma_{(1)}(\sum_{p_3=1}^{P_3}\sum_{Q_3=1}^{Q_3}\hat{A}_{(i+p_3-1,j+q_3-1)} \cdot K_{(p_3,q_3)}))))\right)\cdots K_{(m_3,n_3)}\right)$$

$$f_4(X_{Dist}) = max\left(\sigma_{(r)}\left(\sum_{m_4=1}^{M_4}\sum_{n_4=1}^{N_4}(\cdots(max(\sigma_{(1)}(\sum_{p_4=1}^{P_4}\sum_{q_4=1}^{Q_4}X_{Dist(i+p_4-1,j+q_4-1)} \cdot K_{(p_4,q_4)}))))\right)\cdots K_{(m_4,n_4)}\right)$$

Multi-stream hybrid deep learning framework for predicting subway crowdedness

Concatenation and DNN module

$$f_{concat}(f_1, f_2, f_3, f_4) = f_1 + f_2 + f_3 + f_4$$

$$f_{DNN}(f_{concat}) = \sigma_{(k)}\left(\sum_{u=1}^{U}(\cdots \sigma_{(1)}(\sum_{b=1}^{B} f_{concat} \cdot W_{(1,b)}\right) \cdots W_{(k,u)}))$$

- Values outputted through the encoder module are integrated and fed into the DNN, allowing it to abstract combined features and learn intricate patterns.

Multi-stream hybrid deep learning framework for predicting subway crowdedness

Decoder module

$$f_{De}^{(n)}(i,j) = \sigma_{(n)}(\sum_{l=1}^{L_{(n)}} \sum_{h=1}^{H_{(n}} f_{De}^{(n-1)}(v_n \cdot i + L_n - l, v_n \cdot j + H_n - h) \cdot K^{(n)}(l,h))$$

$$f_{De}^{(1)}(i,j) = \sigma_{(1)}(\sum_{l=1}^{L_{(1)}} \sum_{h=1}^{H_{(1)}} f_{DNN}(v_1 \cdot i + L_1 - l, v_1 \cdot j + H_1 - h) \cdot K^{(1)}(l,h))$$

- $f_{De}^{(n)}$ denotes the output of the n th transposed convolution and $K^{(n)}$ represents the filter for the n th operation.
- As in Equation, when n equals 1, the input feature map f_{DNN} is used.

Multi-stream hybrid deep learning framework for predicting subway crowdedness

Decoder module

$$Z(i,j) = \sum_{s=1}^{S} \sum\nolimits_{r=1}^{R} f_{TC}^{(g)}(i+s-1, j+r-1) \cdot K(s,r)$$

Energy function

$$E = \frac{1}{I \cdot J} \sum_{i=1}^{I} \sum_{j=1}^{J} (Y_{(i,j)} - Y_{(i,j)}^{pred})^2$$

- f_{out} signifies the decoder module's concluding result, indicating the forecast for subway crowdedness.
- The proposed framework utilizes Mean Squared Error(MSE) for its energy function E. By doing so, it aims to reduce the variance between the real subway crowdedness value $Y_{(i,j)}$ and its estimated counterpart $Y_{(i,j)}^{pred}$, facilitating both the assessment and enhancement of the model's effectiveness.

Multi-stream hybrid deep learning framework for predicting subway crowdedness

Backward

$$DE_{a,b}^{i}{}' = DE_{a,b}^{i} - \eta \cdot \frac{\partial E}{\partial DE_{a,b}^{i}}$$

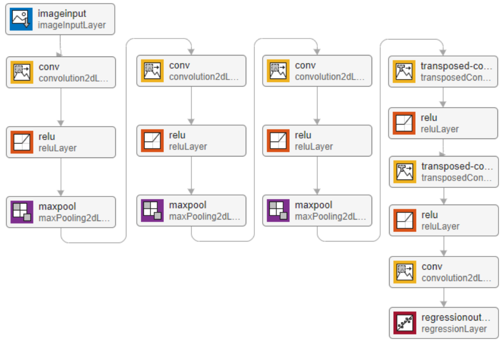
$$W^{v,u\prime} = W^{v,u} - \eta \cdot f\left(\frac{\partial DE}{\partial W^{v,u}}\right) \cdot \frac{\partial E}{\partial Z}$$

$$S_n^{l\prime} = S_n^{l} - \eta \cdot \frac{1}{n} \cdot \frac{\partial h}{\partial S_n^{l}}$$

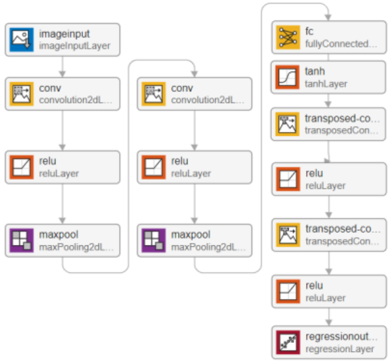
- Parameters in the decoder module are updated using the learning rate and the partial derivative of the energy function, influencing the learning of $DE_{a,b}^{i}{}'$.
- The weight update for the DNN module is determined, where weights connecting different DNN layers are modified through an activation function applied to their partial derivatives and the energy function's partial derivative.
- The encoder's backpropagation distributes the error from the deep learning process among input flows, updating each encoder's convolution filter.

Multi-stream hybrid deep learning framework for predicting subway crowdedness

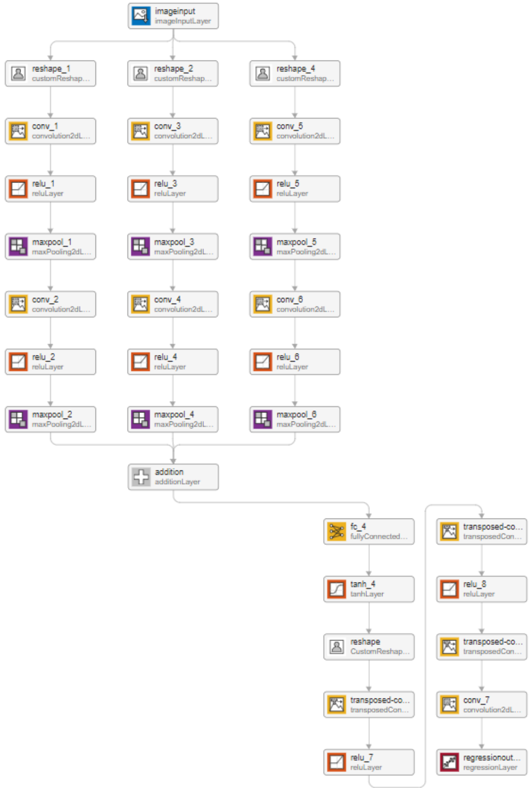
Comparisons models



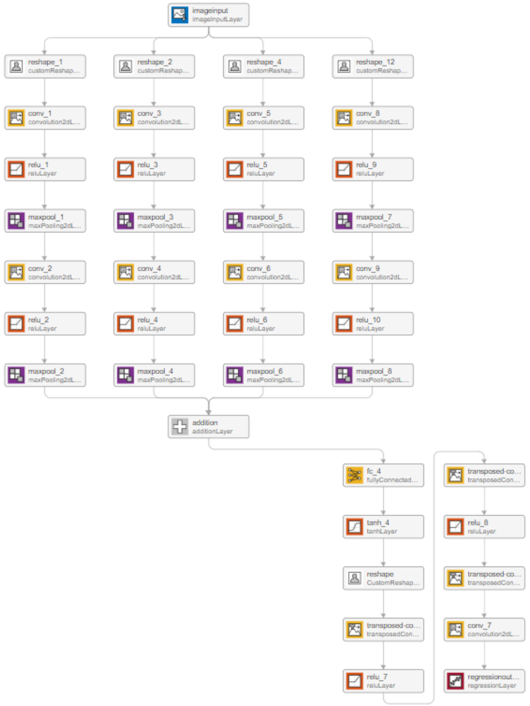
(a)



(b)



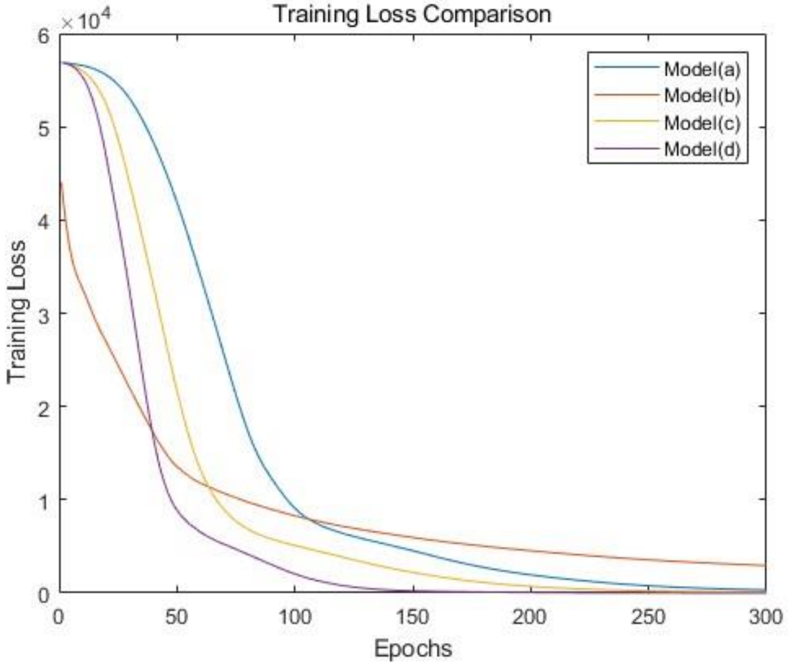
(c)

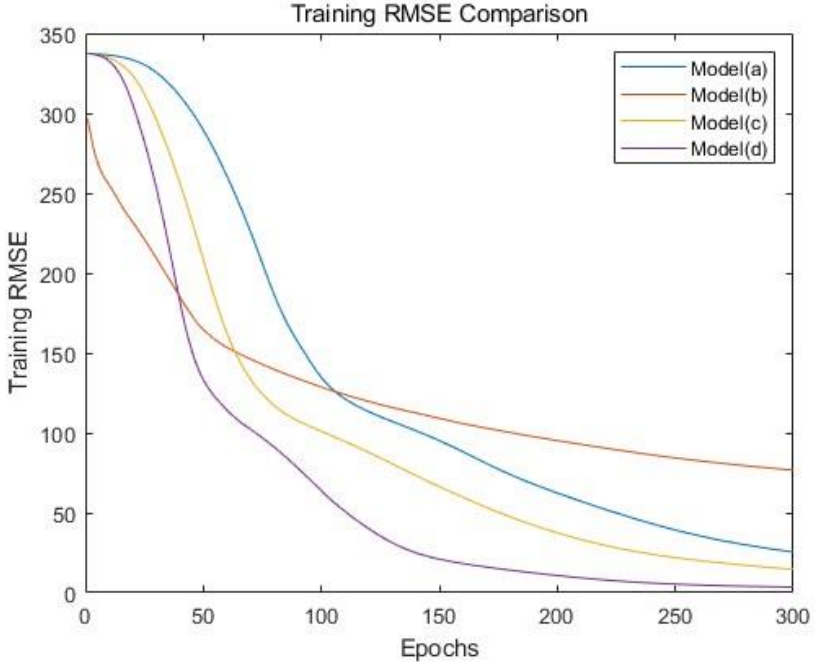


(d) Proposed framwork

Multi-stream hybrid deep learning framework for predicting subway crowdedness

Comparisons analysis





Models	(a)	(b)	(c)	(d)
Test RMSE	0.2549	0.7674	0.1463	0.0355

Multi-stream hybrid deep learning framework for predicting subway crowdedness

Implementation information and experiment environments

Classification	Items	Specification
Implementation	Implementation language	MATLAB
	Deep learning library	Deep learning toolbox
	OS information	Windows 10
Training options	Optimizer	Adam
	Learning rate	0.001
	Maximum epochs	300
Hardware specification	CPU	Intel Xeon E-2136 3.30 GHz
	RAM	64G
	GPU	GeForce GTX 1080

Conclusions

- This research introduces a multi-stream, graph-based deep learning approach tailored for subway crowdedness forecasting.
- It integrates past and present crowdedness data, inter-station distances, and interchange station insights to enhance prediction accuracy.
- This method aims to refine subway operations and enhance commuter experiences.
- In testing, our method outperformed both traditional single-input and certain multi-input models that overlook transfer station factors.
- The dataset in our research focuses solely on several subway lines within one city, emphasizing the need for broader validation across different cities and routes.
- By diversifying the multi-stream input data, this model can potentially adapt to predict crowdedness in urban railways based on a myriad of events.
- Envisioning its advancement, there's potential to craft a refined prediction tool that factors in elements like climatic conditions, significant happenings, and shifts in regulations.

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