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Poster Session at Graduate School Information Fair
Predicting Traffic Congestion in Transportation Networks
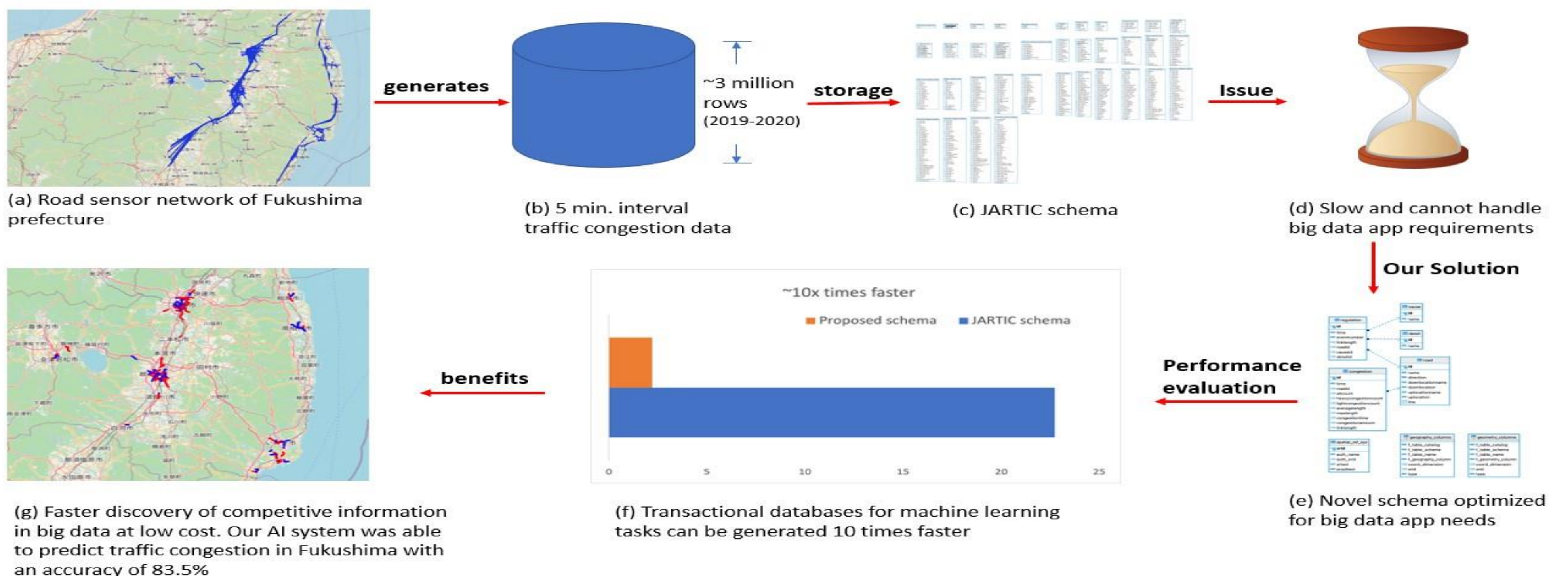
Importance

Predicting traffic congestion is crucial to achieve the following:

1. Sustainable Developmental Goals
2. Autonomous driving
3. Saving lives
4. Smart Cities and
5. Disaster management

Challenges

1. How to store big congestion data effectively?
2. Which is the best model to predict traffic congestion?
   1. Several models exist to predict traffic congestion
   2. Each model has its own selection bias
   3. Selecting a right prediction model is an open-research problem.
   4. Our research aims to address this open-research problem by evaluating various existing prediction models

Addressing Challenge-1: Efficiently Storing the Big Congestion Data

(a) Road sensor network of Fukushima prefecture

generates

(b) 5 min. interval traffic congestion data

~3 million rows (2019-2020)

storage

(c) JARTIC schema

Issue

(d) Slow and cannot handle big data app requirements

Our Solution

Performance evaluation

(e) Novel schema optimized for big data app needs

benefits

~10x times faster
- Proposed schema
- JARTIC schema

(f) Transactional databases for machine learning tasks can be generated 10 times faster

(g) Faster discovery of competitive information in big data at low cost. Our AI system was able to predict traffic congestion in Fukushima with an accuracy of 83.5%

Figure 1: Proposed novel data warehouse schema to store traffic congestion data. Our schema allows us to create train-test datasets 10 times faster than the state-of-the-art.

Addressing Challenge-2: Predicting Traffic Congestion

Train and **test** dataset. (80% – 20%)

Time	Road 1	Road 2	Road 3	Road4	Road5	Road 6	...
00:00	100	200	75	134	40	0	
00:05	150	250	50	134	0	0	
00:10	200	150	50	123	0	0	
00:15	0	0	160	145	158	130	
00:20	0	0	170	56	231	168	
00:25	0	123	180	79	167	200	
00:30	175	90	0	74	0	70	
...							

input → **ML/DL algorithms** → output

Algorithms studied:
- LSTM
- Seq2Seq
- Transformer

Predicted results

Time	R1	R2	R3	R4	R5	R6
00:35	100	200	75	134	40	150
00:40	130	200	45	134	0	160
00:45	0	150	50	123	0	0
00:50	0	190	0	156	0	175
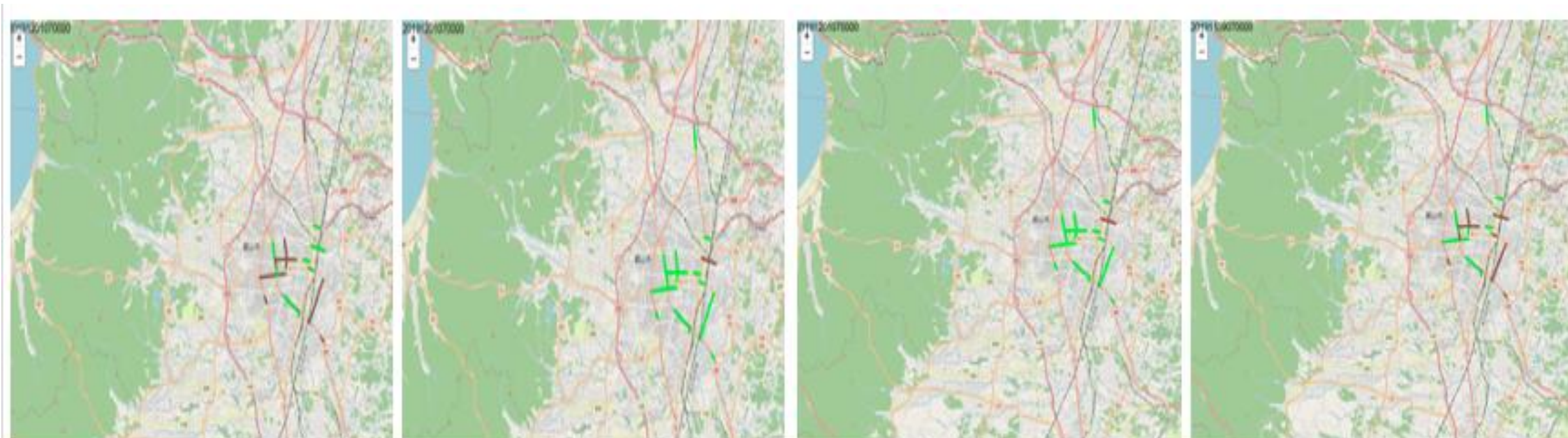
	Ground truth	LSTM Pred.	Seq2Seq Pred.	Transformer Pred.
RMSE		0.124-0.389	0.072-0.361	0.174-0.540
Model building time		Quick	Quick	Slow (30 min/road)

- LSTM
- Seq2Seq(no attn)
- Transformer

rmse