Towards Prediction of Bus Arrival Time using Multi-layer Perceptron (MLP) and MLP Regressor

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PRESENTATION OUTLINE

INTRODUCTION

- Public transportation in developing countries often suffers from over-crowding and inconsistent travelling frequency, leading to poor service quality.
- The advent of IoT and tracking technologies has made it possible to track bus fleets in real-time, providing greater certainty to commuters.
- However, the estimated time of arrival (ETA) may not accurately reflect the true representation of the actual arrival time, causing delays and decreasing the quality of service.

Bukit Bintang Kuala Lumpur (Malaysia)

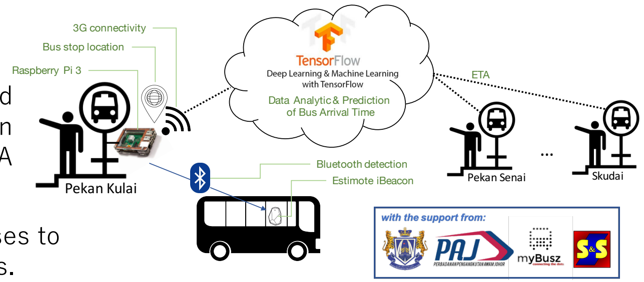
Tampoi, Johor (Malaysia)

ASEAN IVO PROJECT

An IoT-based Data Collection and Analytics Framework using Bluetooth Proximity Beacons

ASEAN IVO 2022

Introduction :



Tracking of public bus location requires a GPS device to be installed, and many bus operators in developing countries do not have such a solution in place to provide an accurate estimated time of arrival (ETA). Without ETA information, it is very difficult for the public to plan their journey effectively.

This project proposes an innovative IoT solution to track the location of buses to collect transportation data without requiring the deployment of GPS devices. It uses Bluetooth Low Energy (BLE) proximity beacon to track the journey of a bus by deploying an *Estimote* proximity beacon on the bus. BLE detection devices are installed at selected bus stops along the bus route to detect the arrival of buses. Once detected, the location of the bus is submitted to a cloud server to compute the bus ETAs and perform analytics.

With the data collected, the project will build deep-learning models to learn about the journey duration during peak and non-peak period. With an accurate predictive model and fleet monitoring dashboard, this will enable the municipal councils to monitor traffic flow and predict congestions in the future.

Project Members :

Members	Affiliation
Sharul Kamal bin Abdul Rahim (Project Leader), Abu Sahmah bin Md Supa'at, Jafri bin Din, Mohd Adib bin Sarijari, Omar bin Abdul Aziz, Olakunle Elijah, Siti Fatimah bte Ausordin, Muhammad Zairil bin Muhammad Nor	UTM, Malaysia
Sye Loong Keoh, Chee Kiat Seow, Qi Cao	UGS, Singapore
Somnuk Phon-Amnuaisuk, Md Saiful bin Haji Omar, Soon-Jiann Tan, Haji Idham Maswadi bin Haji Mashud	UTB, Brunei

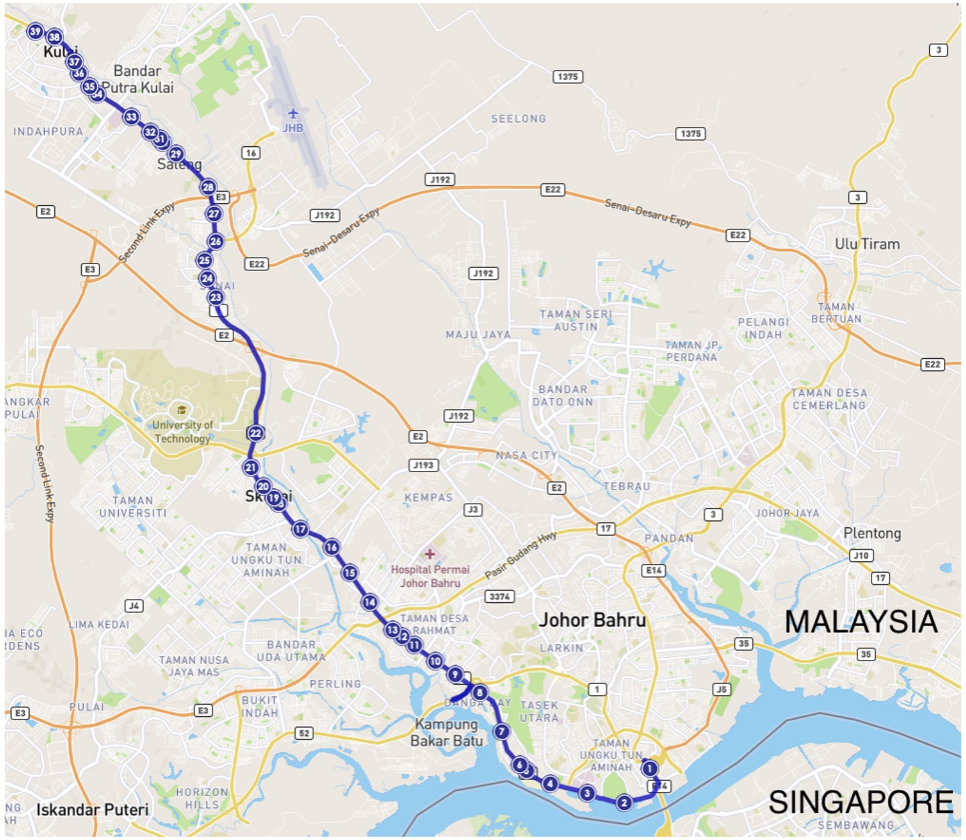
Members	Affiliation
Achmad Basuki, Adhitya Bhawiyuga, Eko Setiawan, Agung Setia Budi	UB, Indonesia
Yung-Wey Chong, Mohd Najwadi Yusoff, Noor Farizah binti Ibrahim	USM, Malaysia
Kok Chin Khor, Mau Luen Tham	UTAR, Malaysia

MOTIVATIONS AND AIM

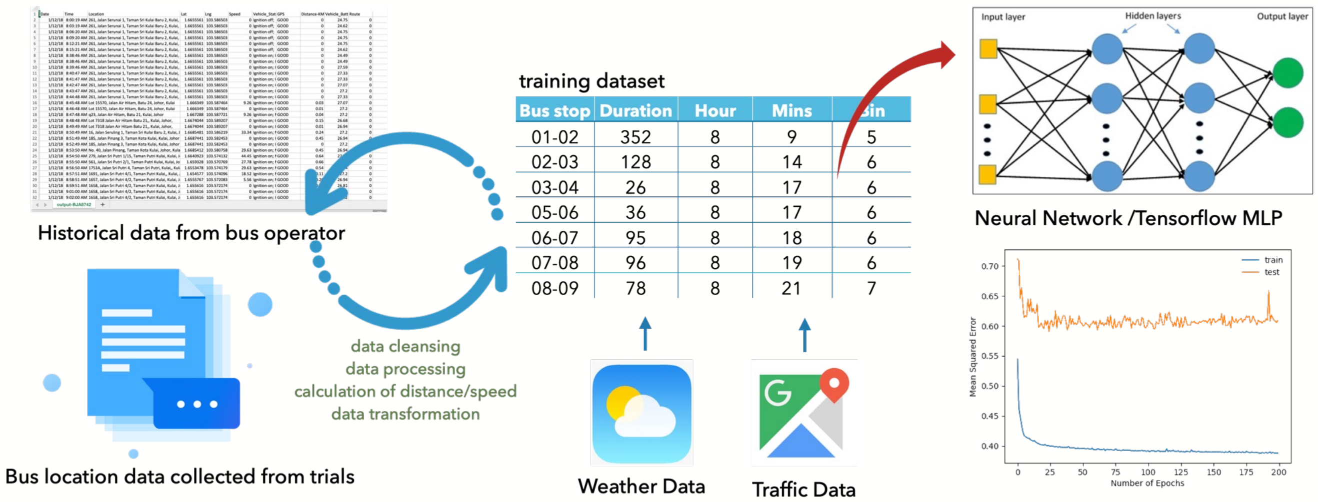
- Previous studies have shown the feasibility of using machine learning techniques to predict bus arrival times
- However, many of these studies have focused on developed countries with advanced transportation systems and infrastructure, and may not be directly applicable to developing countries.
- We aim to enhance service quality and passenger satisfaction in a developing country's public bus network by building a prediction model that considers smaller datasets.

BUS SERVICE ROUTE
(Kulai ⇔ Johor Bahru Sentral)

- Stage bus service between Kulai and Johor Bahru Sentral in Malaysia.
- 40 bus stops and 34.1 km.
- Journey time typically takes 50 – 70 mins depending on the traffic condition.
- Historical GPS dataset obtained from the Malaysian bus operator.



METHODOLOGY

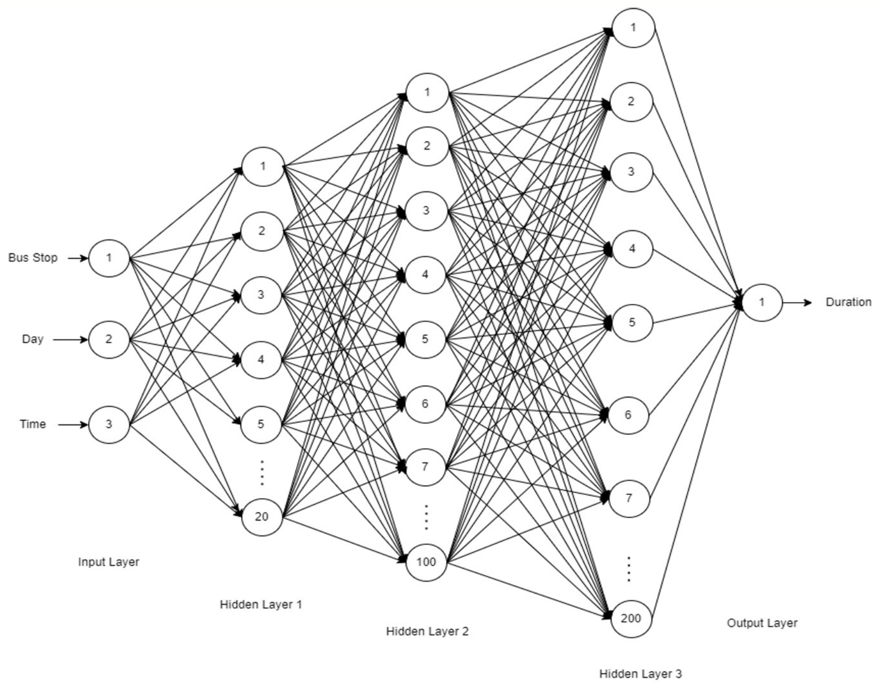


Bus stop	Duration	Hour	Mins	in
01-02	352	8	9	5
02-03	128	8	14	6
03-04	26	8	17	6
05-06	36	8	17	6
06-07	95	8	18	6
07-08	96	8	19	6
08-09	78	8	21	7

- Dataset cleaned and pre-processed to filter out missing and erroneous data
- Data entries are mapped to the nearest bus stop to approximate speed and compute journey duration
- MLP and MLP Regressor used to build a base model for predicting journey duration

DATASETS, MLP AND MLP REGRESSOR

- The main difference between the two models is the activation function used in the output layer.
- The MLP uses the rectified linear unit function (ReLU), which is defined as f(x) = max(0, x).
- The MLP Regressor uses a linear activation function, which is defined as f(x) = x.
- The size of each dataset after data cleaning and engineering:
    - Bus 1 dataset: 8323 rows
    - Bus 2 dataset: 3479 rows
    - Bus 3 dataset: 7599 rows
    - Bus 4 dataset: 7118 rows



RESULTS AND ANALYSIS

- MLP model outperformed MLP regressor model according to MAE, MSE, and RMSE values
- Prediction error is lower for MLP model than MLP regressor model
- These results show that MLP model is more accurate and reliable for small datasets with limited data availability, which is common in real-world applications.

PERFORMANCE OF MODELS TRAINED USING MLP

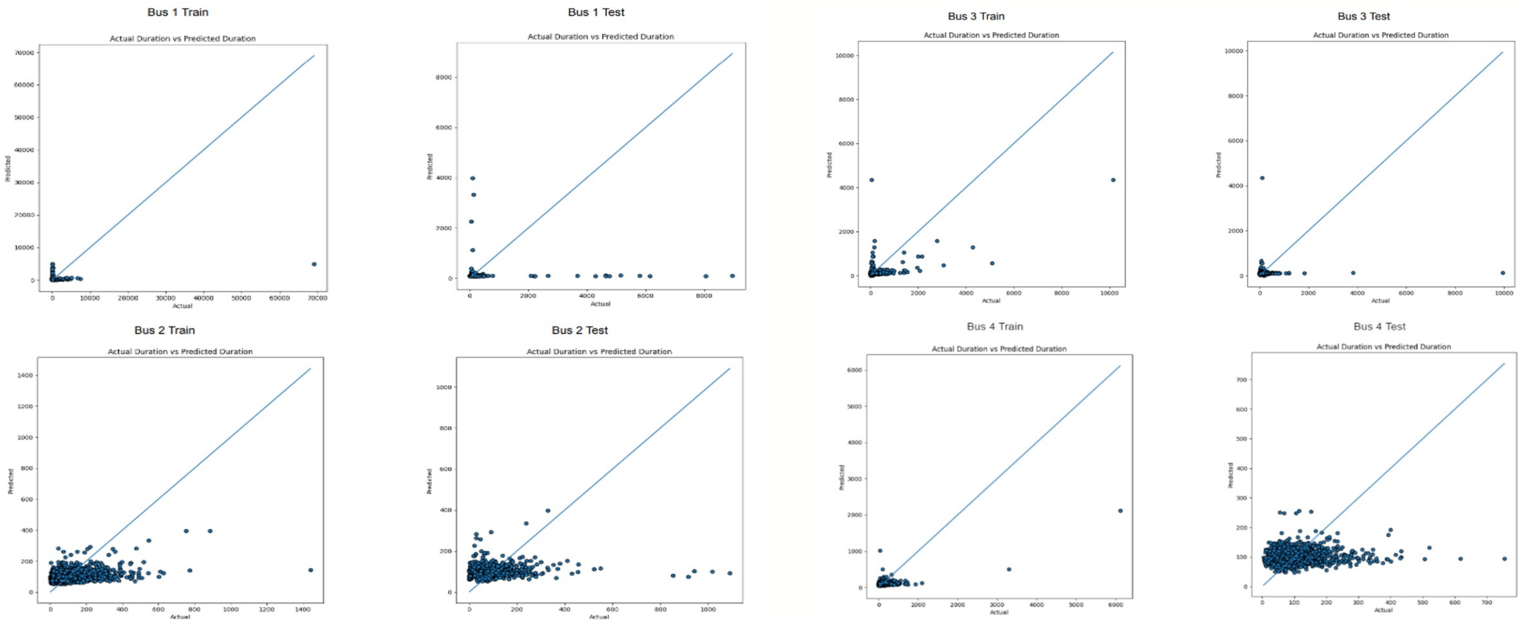
		R2	MAE	MSE	RMSE
Bus 1	Train	0.18	0.65	0.92	0.96
	Test	-0.05	0.84	1.90	1.38
Bus 2	Train	0.09	1.07	129.71	11.39
	Test	0.24	1.20	30.38	5.51
Bus 3	Train	0.11	0.79	6.50	2.55
	Test	-0.01	0.98	16.82	4.10
Bus 4	Train	0.36	0.70	1.78	1.33
	Test	-0.25	0.73	1.28	1.13

PERFORMANCE OF MODELS TRAINED USING MLP REGRESSOR

		R2	MAE	MSE	RMSE
Bus 1	Train	0.02	57.19	7822.39	88.44
	Test	0.01	55.37	6847.69	82.75
Bus 2	Train	0.56	66.66	36754.47	191.71
	Test	0.01	104.66	2887192.50	1699.17
Bus 3	Train	0.28	63.00	39837.04	199.59
	Test	-0.47	60.25	14607.86	120.86
Bus 4	Train	0.36	50.05	8653.77	93.03
	Test	0.03	51.00	5343.78	73.10

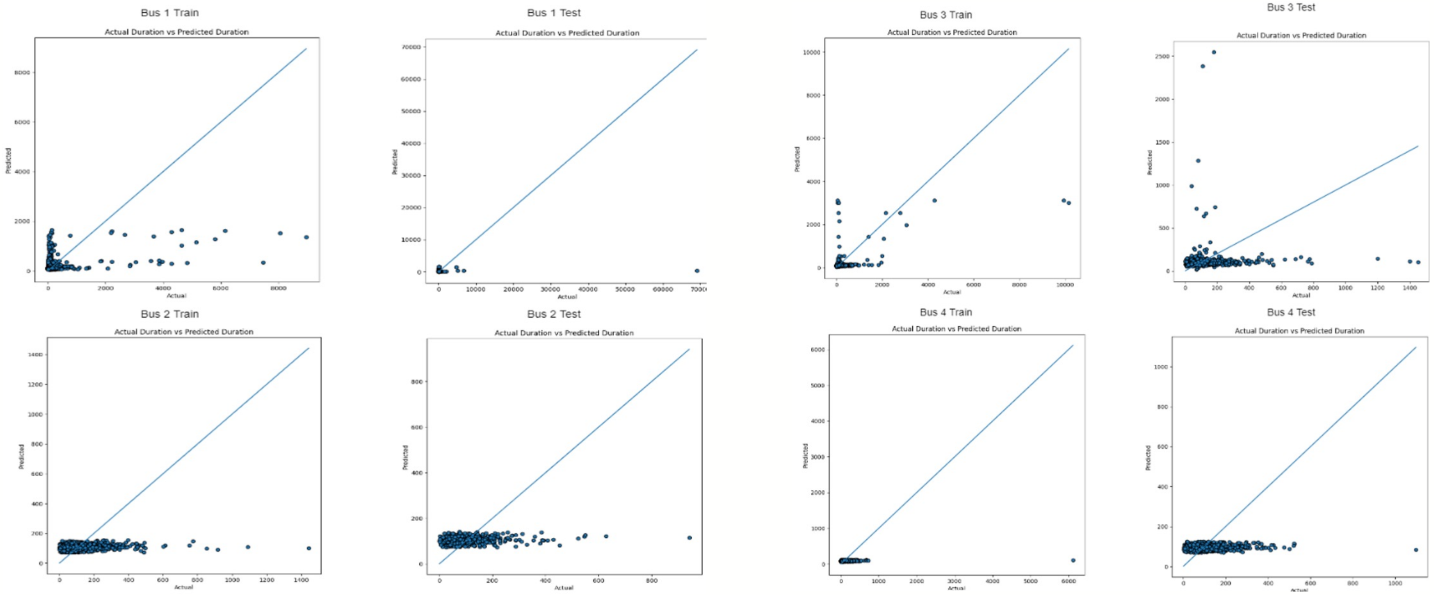
RESULTS AND ANALYSIS
MLP

- MLP model showed bias towards underestimating trip duration, indicating a need for improved pattern recognition
- Outliers observed in plots with journey durations ≥ 4000 seconds, likely due to bus breakdowns or road closures causing delays



RESULTS AND ANALYSIS
MLP REGRESSOR

- MLP Regressor showed high variability and inconsistency in predicting the same values for larger datasets
- Overall, MLP model is better suited for this application and can be further improved with better data and model tuning.



FUTURE WORK & CONCLUSIONS

- Extend study with larger and more diverse datasets that consider factors like weather and traffic conditions.
- Improve MLP Regressor model with different activation functions, network architectures, and regularisation techniques.
- Explore other machine learning models that can handle non-linear relationships.
- Deploy IoT-based fleet tracking system to collect more reliable data.
- Collaborate with other bus operators to obtain more datasets.
- Using machine learning for bus arrival time prediction has great potential, leading to further research that will boost prediction accuracy and enhance commuters' travel experiences.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ASEAN IVO
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