Improve The Accuracy of Identification of Truck Types by Using Recurrent Neural Network (RNN) under Different Levels of Noise

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Master Thesis Defense

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2/28/2020 RNK 312

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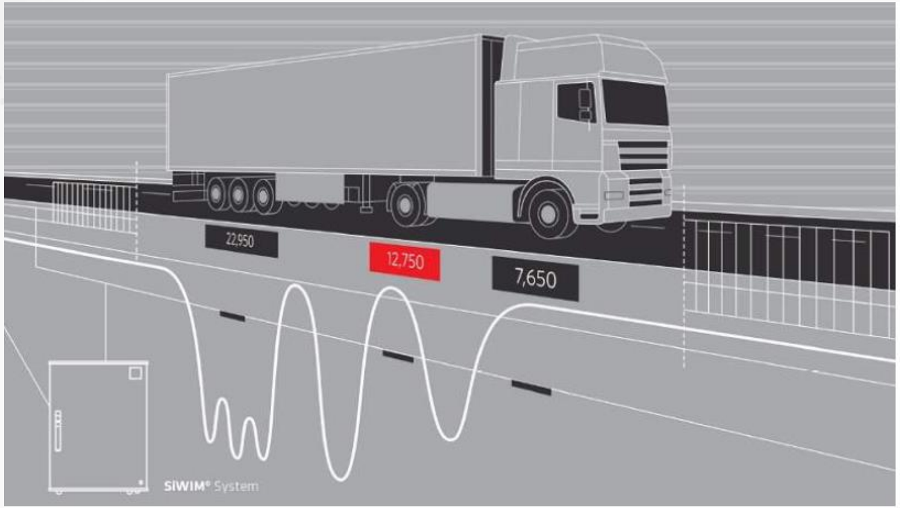
Problem Statement and Literature Review

Weigh-in-Motion (WIM) Problem



Weigh-in-Motion (WIM)

WIM problem is to determine the properties of the passing truck from bridge strain responses without causing the truck to stop completely. It can be divided into 3 parts:

※ Process of identification
※ Truck type classification
※ Obtain Axle loading, axle spacing, and speed of Truck

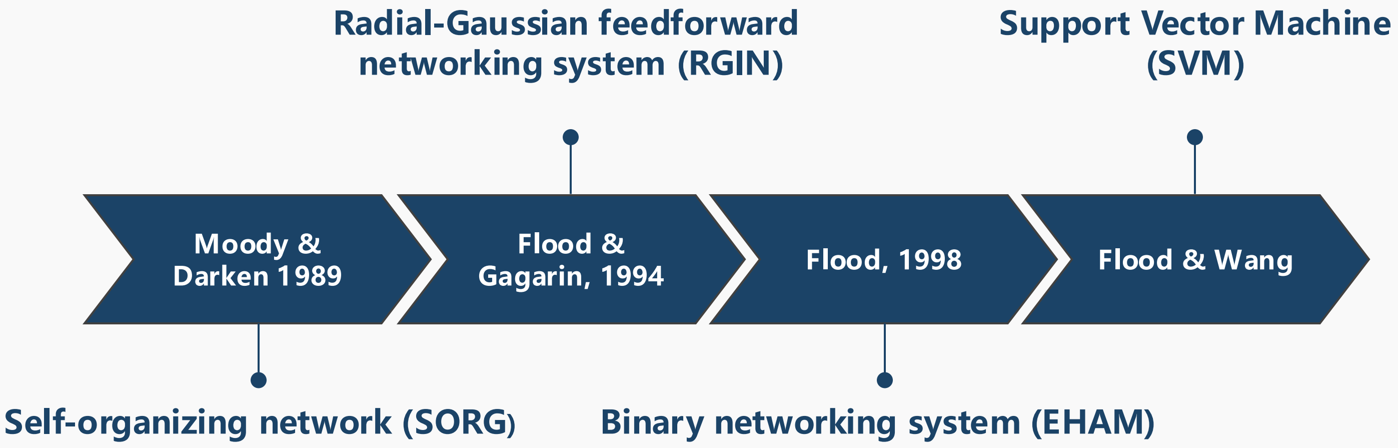
01 Efficient

significantly improve the efficiency of road transportation and avoid potential traffic accidents.

02 Economical

Construction costs on weighting stations and highway auxiliary roads can be avoided.

Literature Review: Developments of Weigh-in-Motion (WIM) With Artificial Neural Network



Truck Attribute

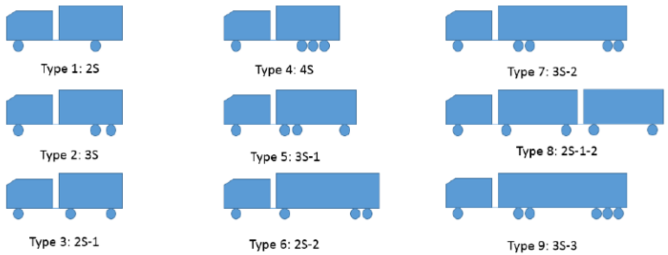


Figure 3-2. Nine truck types used in this research adopted from Gagarin and Flood's result (Gargarin & Flood, 1994)

Number of patterns for one truck: 2500

Total number of patterns : 2500 * 9 = 22500

- **Axle load varies**
- **Axle spacing varies**

Truck Type	Axle Loads (KN)						Axle Spacings (m)				
	1	2	3	4	5	6	1 and 2	2 and 3	3 and 4	4 and 5	5 and 6
1	13.3-53.4	8.8-80.1					2.74-6.10				
2	13.3-53.4	8.8-80.1	8.8-80.1				2.74-6.10	1.22			
3	13.3-53.4	8.8-80.1	8.8-80.1				2.74-4.98	5.49-11.6			
4	13.3-53.4	8.8-80.1	8.8-80.1	8.8-80.1			2.74-5.49	1.22	1.22		
5	13.3-62.3	8.8-71.2	8.8-71.2	8.8-80.1			2.74-6.10	1.22	6.10-11.6		
6	13.3-53.4	8.8-80.1	8.8-80.1	8.8-80.1			2.74-5.49	6.10-11.6	1.22		
7	13.3-53.4	8.8-71.2	8.8-71.2	8.8-80.1	8.8-80.1		2.74-6.10	1.22	6.10-11.6	1.22	
8	13.3-53.4	8.8-71.2	8.8-71.2	8.8-80.1	8.8-80.1	8.8-80.1	2.74-6.10	1.22	6.10-11.6	1.22	1.22
9	13.3-53.4	8.8-80.1	8.8-80.1	8.8-80.1	8.8-80.1		2.74-5.49	5.49	3.05	5.49	

Figure 3-3Axle load range and spacing range of nine truck types adopted from Gagarin and Flood's result (Gargarin & Flood, 1994)

Artificial Neural Network (ANN)

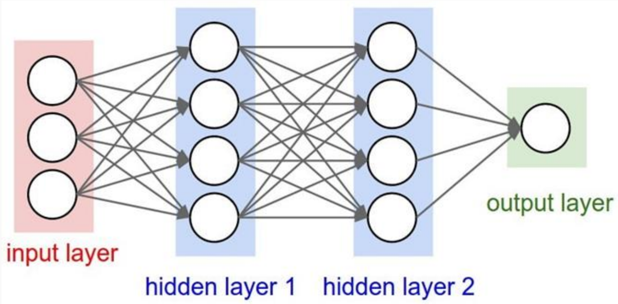
Massively Parallel Processing

Fault Tolerance

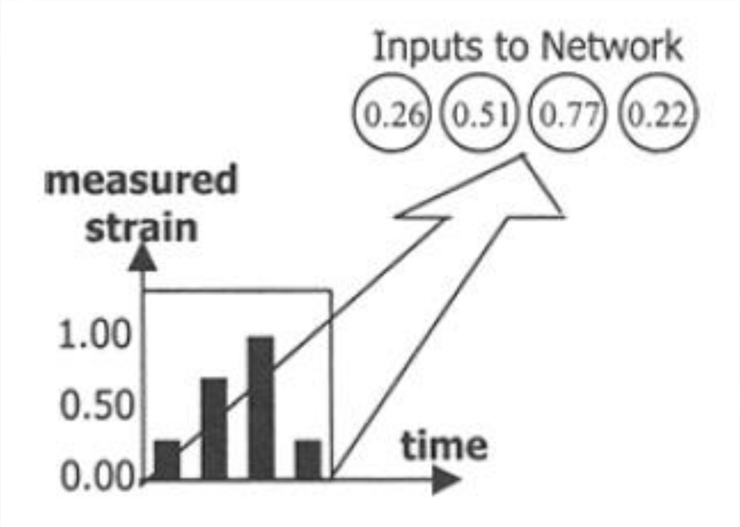
Self-learning, Self-organizing

Distributed Storage

Adaptive



Conventional Artificial Neural Network

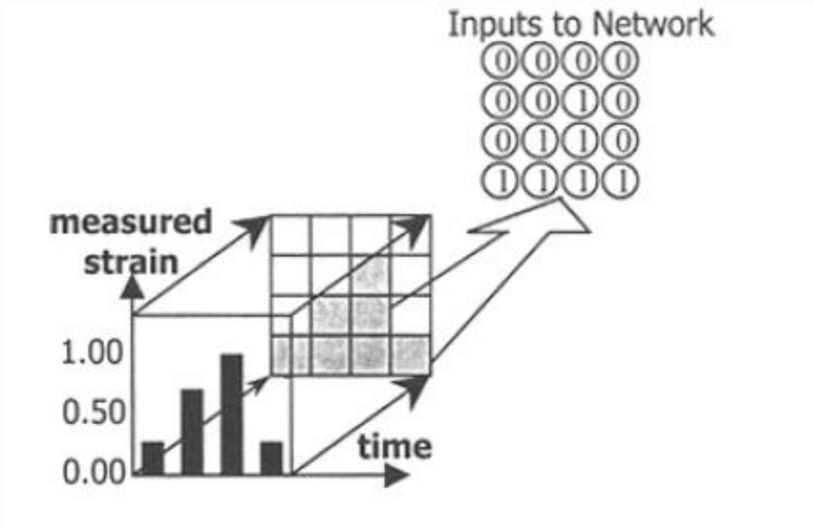


Self-organizing network (SORG)

Input: Vector of real-values

Output: Binary values.

Type 1:1 All the other type: 0

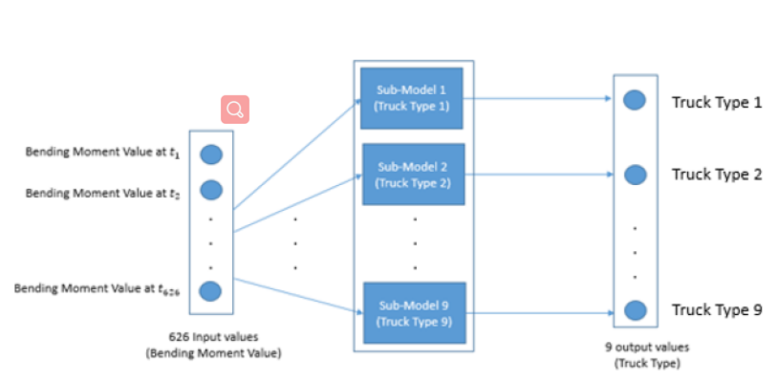


Binary networking system (EHAM)

Input: matrix of binary values.

Output: Sams as SORG

Support Vector Machine (SVM)

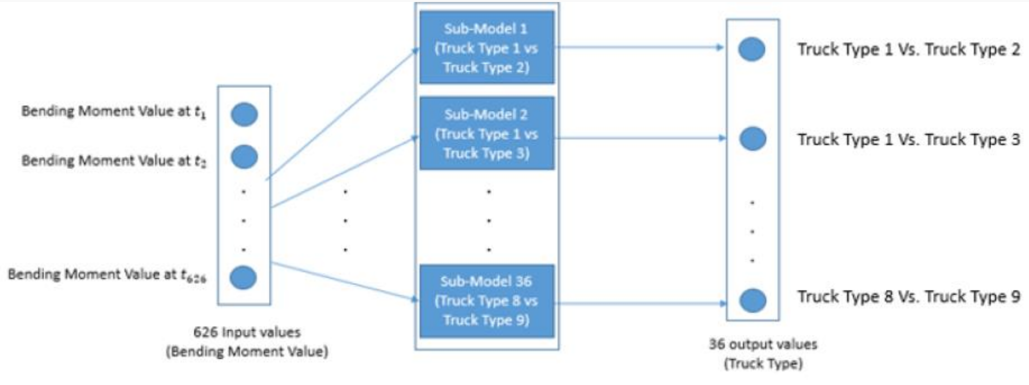


SVM one-vs-all

Input: Time-series data

Classification: Nine sub-model

Output: Binary values.



SVM one-vs-one

Input: Time-series data

Classification: 36 Nine sub-Model

Output: Binary values

Literature Review: Deep Learning (Deep Neural Network)

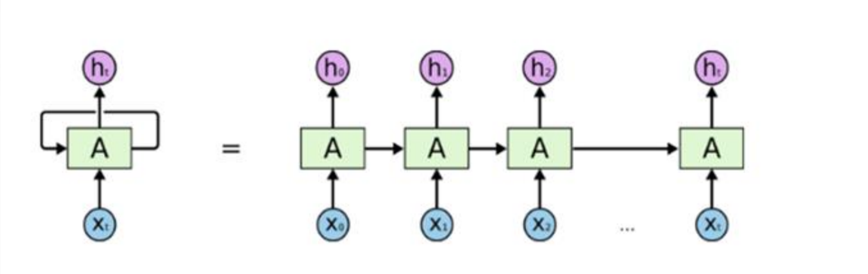


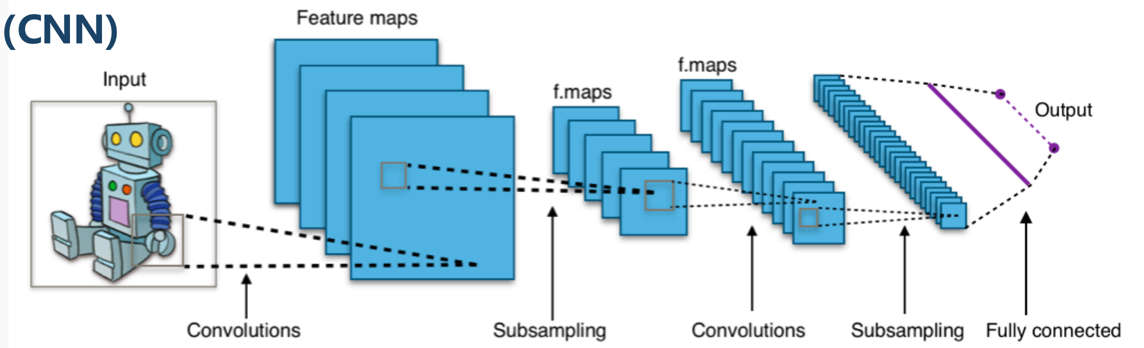
Figure 4-1. An unrolled RNN

Recurrent Neural Network (RNN)

- Time series data
- Stimulate dependency
- Memory function

Convolutional neural network (CNN)

- Grid-like data
- Static analysis
- Public feature extraction



Room for Improvement

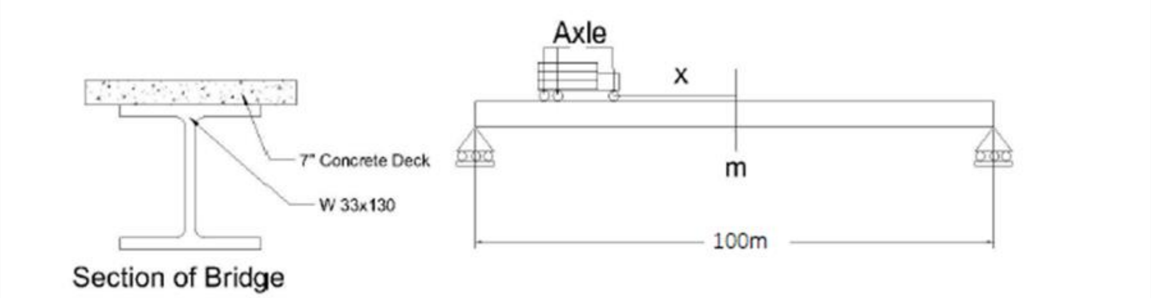
1. **Accuracy**
2. **Anti-noise ability**
3. **Extensibility**

02

PART

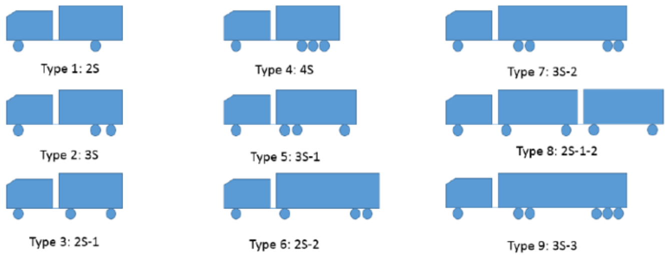
Data Simulation and Model Development

Bridge Model



Bridge Length	Velocity of Truck	Sample frequency	Number of patterns for each truck
100 m	10 m/s	50 HZ	2500

Truck Attribute



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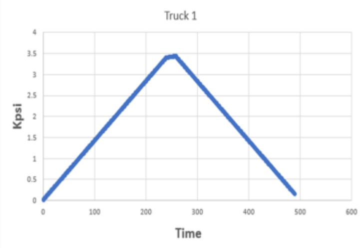
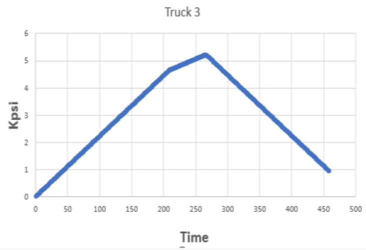
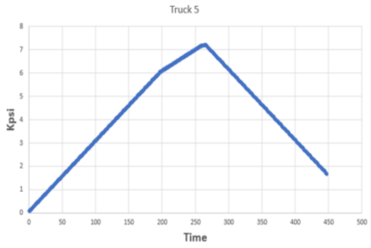
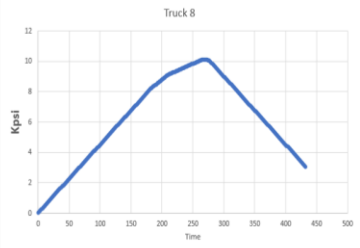
Partial Data Plot



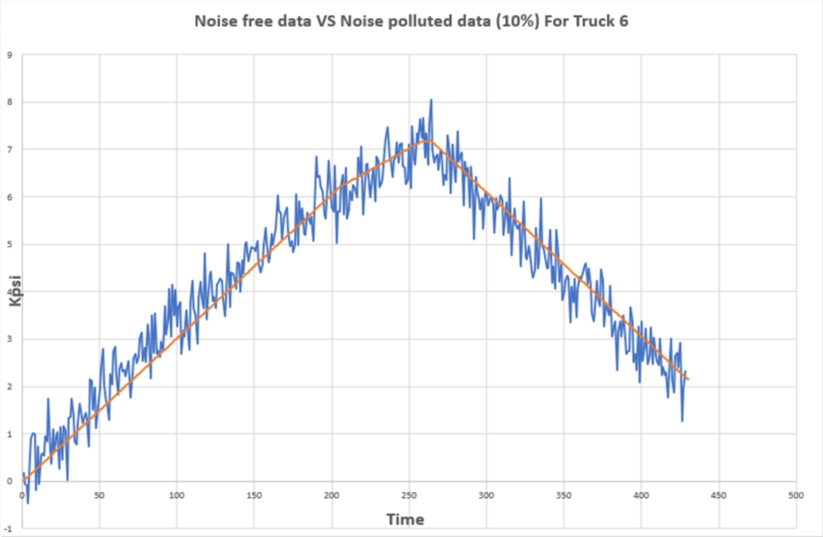






Truck 1 | **Truck 3** | **Truck 5** | **Truck 8**

Noise Free VS Noise Level 10%



White Gaussian noise

$$\sigma_{np} = \sigma_{nf} + RMS(\sigma_{nf}) * N_i * N_{rand} \quad (3.4)$$

Where σ_{np}= Noise polluted Stress response of the Bridge, σ_{nf} = Noise free Stress response of the Bridge, RMS = Root mean Square Value, N_i= Level of Noise, N_{rand}= Random noise vector with zero mean and one standard Deviation

the response recording system cannot record the strain response accurately. So we use White Gaussian Noise to simulate the deficiency of the measurement system.

Recurrent Neural Network (RNN)

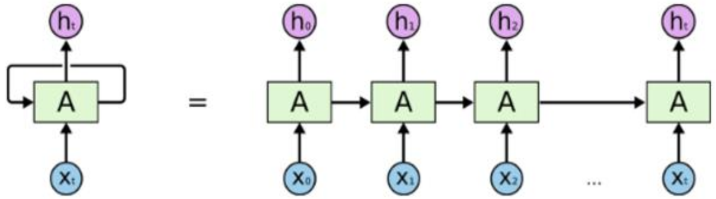


Figure 4-1. An unrolled RNN

Learning over a long-time range

Suitable for time-series data

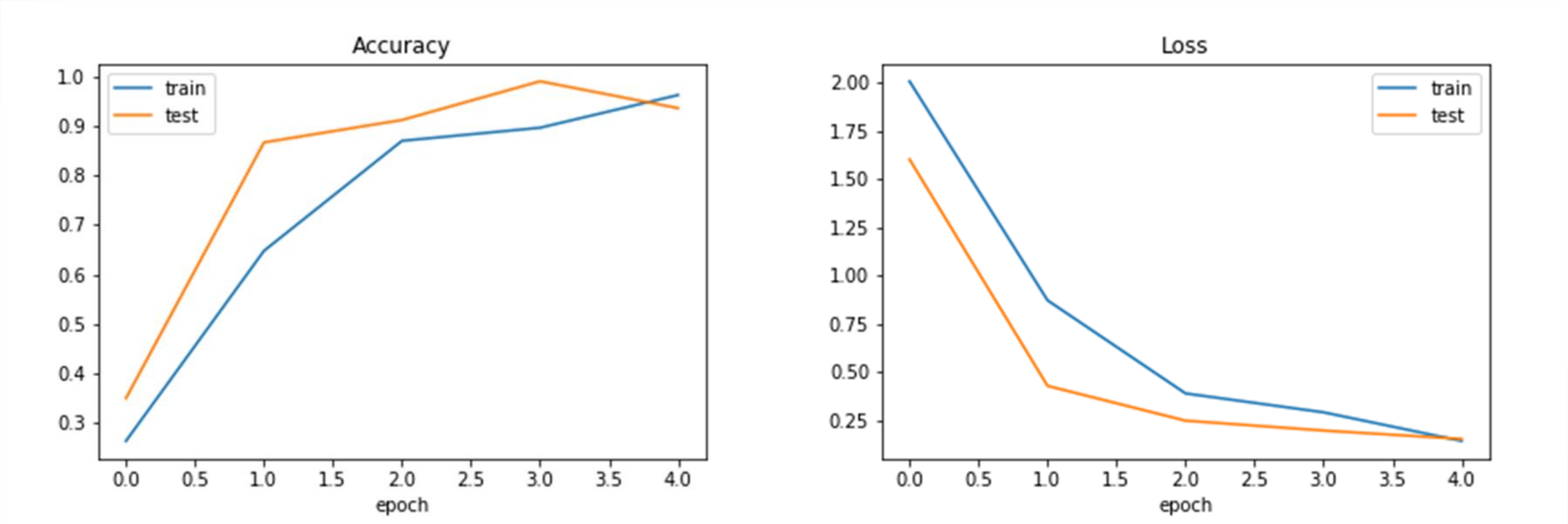
Programming Language	Software Library	Architecture	Normalized Exponential Function	Categorical Variables Form	Metrics	Data Separation	Data Normalization
Python	TensorFlow	Long short-term memory (LSTM)	Softmax	One-hot Encoding	Accuracy	45%: Training 5%: Validation 50%: Testing	Input: Time-series data. Output: [001000000]

03

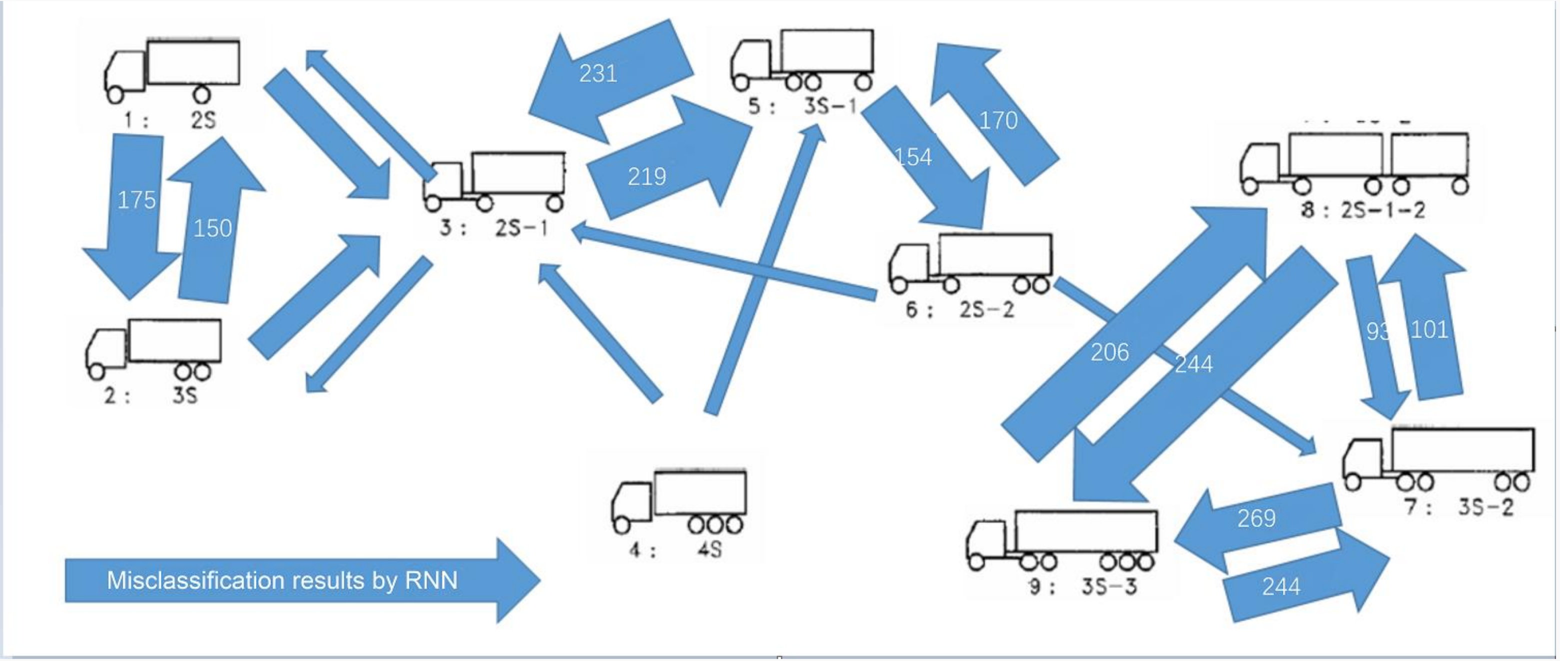
PART

Experiment Results and Analysis

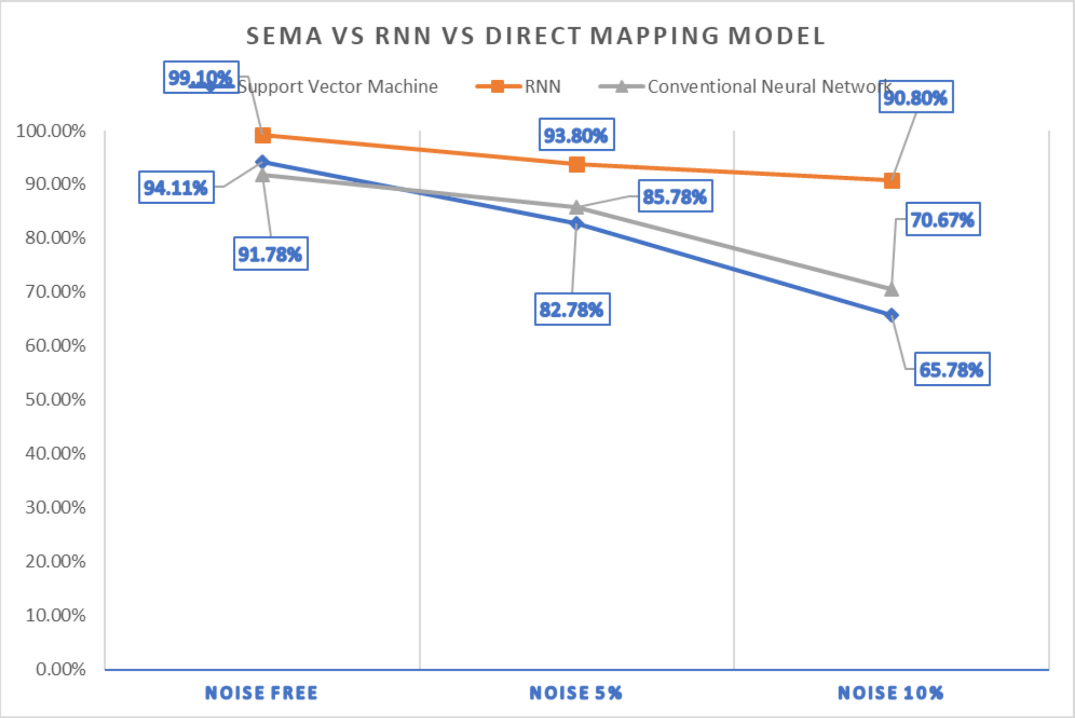
Accuracy and Loss Plot For 5% Level Noise from TensorFlow



Misclassification Results by RNN



Experiment Results and Analysis



Better Accuracy

Better Anti-Noise Ability

04

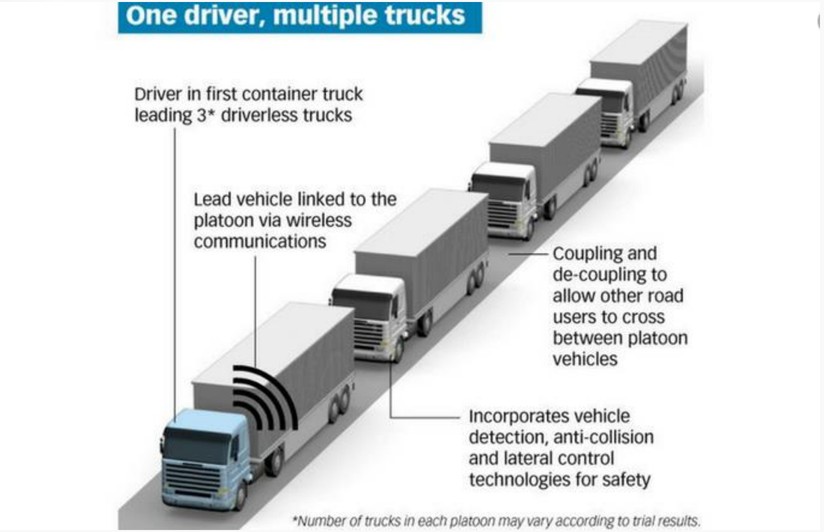
PART

Conclusion and Recommendations

Unsolved Problem and Future Work

1. Extensibility
2. Combine with other Machine learning Models
3. Get real data from relevant agencies. (If possible)
4. Combined with the trend of modern modes of transportation. e.g. : Truck Platooning

Truck Platooning



Truck Platooning

Truck platooning is the linking of two or more trucks in convoy, using connectivity technology and automated driving support systems. These vehicles automatically maintain a set, close distance between each other when they are connected for certain parts of a journey, for instance on motorways.

Truck Platooning is a very promising mode of transportation. In future work, we can also add this type of truck to the classification.

THANKS!