STOCK PRICE PREDICTION BY USING LONG SHORT-TERM MEMORY MODEL WITH MULTIPLE LOOK BACK PERIODS

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서울과학기술대학교 데이터사이언스학과 석사과정

Yaowamal Luetrakulset
(yaowamal.lue@gmail.com)

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1. INTRODUCTION

1. Background

- The stock market has long been a favorite among investors.
- To increase their profits, many investors would like to be able to anticipate stock prices, but this is challenging given the uncertain movement of stock prices.

2. Objectives

- Proposed a developed closing price prediction model by using three stocks from the Thai SET50 index (CPALL, AOT, LH).
- Comparing the look-back periods in LSTM (Long Short-Term Memory).
- Comparing CNN (Convolution Neural Networks) and LSTM (Long Short-Term Memory).
- Comparing the training period with two periods of historical stock data (2001 – 2018 and 2011 - 2018).
- Based on the type of historical stock data (stable and volatile type), we find a better number of window sizes for a model.

2. RELATED WORKS

1. Stock Price Prediction With Long Short-Term Memory Recurrent Neural Network (Jeenanunta et al., 2018)

- This research investigates the prediction of daily stock prices with a Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM) and the results show that LSTM gives the best performance with CPALL, SCB, and KTB with less than 2% error.

2. Stock Closing Price Prediction Using Machine Learning (Werawithayaset et al., 2019)

- This research uses the Multi-Layer Perceptron model, Support Vector Machine model, and Partial Least Square Classifier to predict the stock's closing price.
- Partial Least Square is the best algorithm of the three algorithms to predict the stock closing price.

3. Research on Stock Price Prediction Method Based on Convolutional Neural Network (Lounnapha et al., 2019)

- This research proposes a stock price prediction model based on a convolution neural network.
- The model based on CNN can effectively identify the changing trend of stock price and predict it which can provide a valuable reference for a stock price forecast.

3. METHODS

1. LSTM (Long Short-Term Memory)

- A type of recurrent neural network capable of learning order dependence in sequence prediction problems, such as time series, speech, and text.
- LSTM has a chain structure that contains four neural networks and different memory blocks called cells.

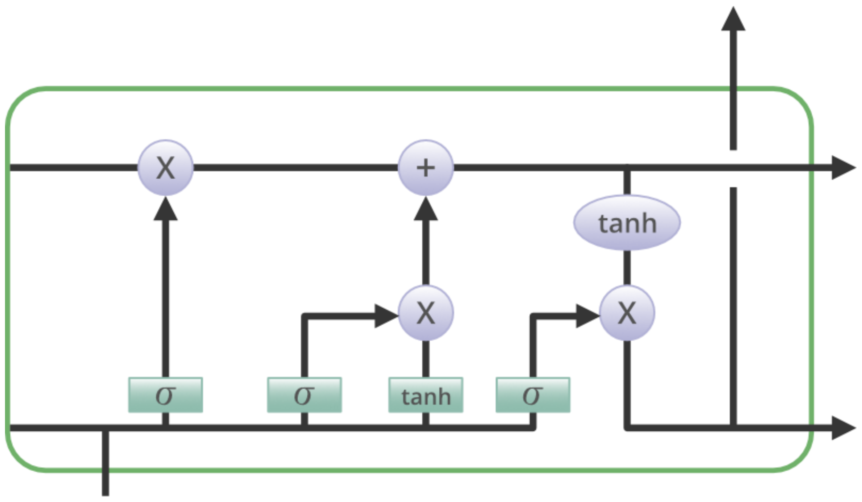


Fig 1. Structure Of LSTM [1]

2. Look-back

- A parameter to define the number of previous times to use as an input variable to predict the next period. [2]
- As known as the window size.

4. EXPERIMENTS

4.1. Data

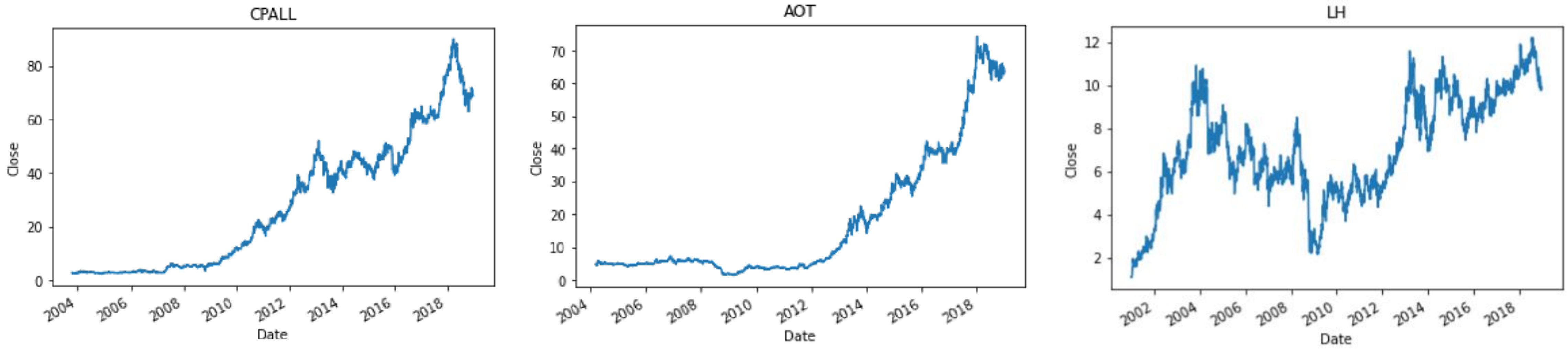
- **Three Thai SET50 index**
  1. CPALL (CP ALL PUBLIC COMPANY LIMITED)
     - Operates the convenience store business under the 7-Eleven trademark and franchises to other retailers in the territory of Thailand.
  2. AOT (AIRPORTS OF THAILAND PUBLIC COMPANY LIMITED)
     - The operator of airport business in Thailand.
  3. LH (LAND AND HOUSES PUBLIC COMPANY LIMITED):
     - The development of quality residential projects in the category of detached houses, townhouses, and residential condominiums for sale to target customers.

- **Collecting 2 date range data from the yfinance library**
  - 2001-01-01 to 2018-12-31
    - Training : Testing = 80 : 20
    - (2001 – 2015) : (2016 - 2018)
  - 2011-01-01 to 2018-12-31
    - Training : Testing = 80 : 20
    - (2011 - 2016) : (2017 - 2018)

4. EXPERIMENTS

4.1. Data

- **Type of historical stock data (Classified by visual graph)**
  - CPALL, AOT = Stable stock
  - LH = Volatile stock



4. EXPERIMENTS

4.2. Model

Prior Literature (Jeenanunta et al. 2019)

- CNN (Thesis)
  - Window size = 3
  - Epochs = 10, 20, 30, 100, 200, 300
  - Optimizer: adam, sgd, rmsprop

This Study

- CNN (modified version of Jeenanunta et al. 2019)
  - Window size = 5,7
  - Epochs = 10, 20, 30, 100, 200, 300
  - Optimizer: adam, sgd, rmsprop
- CNN (New)
  - Window size = 3,5,7
  - Epochs = 10, 20, 30, 100, 200, 300
  - Add LeakyReLU (to generalize to unseen data)
  - Optimizer: adam, sgd, rmsprop
- LSTM
  - Epochs = 1,10,20,30
  - Look back = 30, 60
  - Stacked multiple LSTM layers
  - Optimizer: adam, sgd, rmsprop

4. EXPERIMENTS

4.3.1. Result 1 - Comparing the look-back periods in LSTM (Long Short-Term Memory).

For short-term historical stock data (2011 - 2018)

- For stable stocks

  - Adam optimizer is suitable for 30 look back.

  - 30 look-back will get higher performance than 60 look-back.

Stock	Look back	Epochs	Adam		Sgd		RMSprop	
			RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
CPALL	30	1	0.094	1.57	1.147	2.527	1.818	2.689
		10	0.147	0.863	1.455	2.806	2.008	2.738
		20	1.068	1.637	1.382	2.555	1.296	1.972
		30	11.86	15.391	1.071	3.149	7.708	9.923
CPALL	60	1	2.475	3.454	2.844	3.937	4.338	5.808
		10	1.599	2.178	1.472	2.699	1.683	2.337
		20	1.619	2.173	0.23	2.213	0.377	0.953
		30	1.679	2.247	0.79	2.14	1.623	2.17
AOT	30	1	2.079	3.568	4.761	7.494	0.992	2.043
		10	3.294	5.155	3.245	5.183	1.089	2.031
		20	0.889	1.612	2.423	3.999	9.077	14.275
		30	24.803	38.589	4.397	6.913	18.55	28.754
AOT	60	1	1.324	2.407	4.589	7.226	7.573	12.204
		10	1.417	2.299	3.455	5.441	3.018	4.74
		20	1.695	2.738	3.773	5.884	3.89	6.027
		30	2.817	4.363	3.793	5.93	6.416	9.983

Stable data

- For a volatile stock

  - 30 look-back will get higher performance than 60 look-back.

  - In both cases with 30 look-back and 60 look back, it is suitable when the optimizer is Adam and epoch is one.

Stock	Look back	Epochs	Adam		Sgd		RMSprop	
			RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
LH	30	1	0.003	1.614	0.014	2.183	0.487	4.516
		10	0.622	5.786	0.153	2.127	0.123	1.435
		20	0.125	1.428	0.08	1.765	0.058	1.094
		30	0.072	1.147	0.177	2.548	0.194	1.923
LH	60	1	0.005	1.245	0.184	2.448	0.312	2.905
		10	0.038	1.065	0.15	2.196	0.039	1.037
		20	0.101	1.294	0.126	1.883	0.144	1.618
		30	0.123	1.433	0.004	1.497	0.157	1.697

Volatile data

4. EXPERIMENTS

4.3.1. Result 1 - Comparing the look-back periods in LSTM (Long Short-Term Memory).

For Long-term historical stock data (2001 - 2018)

- For stable stocks

  - 30 look-back got higher performance than 60 look-back.

- For a volatile stock

  - 60 look-back got higher performance than 30 look-back.

  (In the previous slide, 30 look-back was better with the short-term training dataset)

Stock	Look back	Epochs	Adam		Sgd		RMSprop	
			RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
CPALL	30	1	0.187	2.346	2.837	4.676	9.075	13.879
		10	1.109	1.808	2.753	4.431	0.14	3.911
		20	2.244	3.324	3.668	5.618	9.552	14.089
		30	15.84	22.419	5.004	7.757	10.74	15.35
CPALL	60	1	2.07	3.259	2.178	3.77	1.044	2.95
		10	1.625	2.483	2.011	3.768	0.261	1.951
		20	2.362	3.504	1.888	3.377	2.08	3.093
		30	2.413	3.723	3.249	5.113	2.368	3.481
AOT	30	1	6.804	12.472	2.139	4.016	0.463	2.69
		10	3.763	6.328	1.305	2.951	6.043	10.572
		20	5.334	9.291	1.829	3.602	12.884	22.856
		30	19.28	33.974	5.99	10.325	17.146	29.887
AOT	60	1	2.7	4.916	4.635	7.988	5.037	9.805
		10	0.744	2.248	4.029	6.942	3.017	5.16
		20	4.259	7.196	3.168	5.558	4.12	6.74
		30	6.012	10.643	3.472	6.081	4.718	7.691

Stable data

Stock	Look back	Epochs	Adam		Sgd		RMSprop	
			RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
LH	30	1	0.229	2.636	0.465	4.853	0.227	2.538
		10	0.259	2.683	0.053	1.94	0.324	3.315
		20	0.089	1.469	0.075	1.884	0.585	6.124
		30	0.714	7.18	0.351	3.975	0.227	3.28
LH	60	1	0.266	2.77	0.23	3.072	0.218	2.338
		10	0.205	2.205	0.04	1.917	0.036	1.177
		20	0.125	1.586	0.13	2.078	0.151	1.797
		30	0.067	1.297	0.18	2.828	0.195	2.206

Volatile data

4. EXPERIMENTS

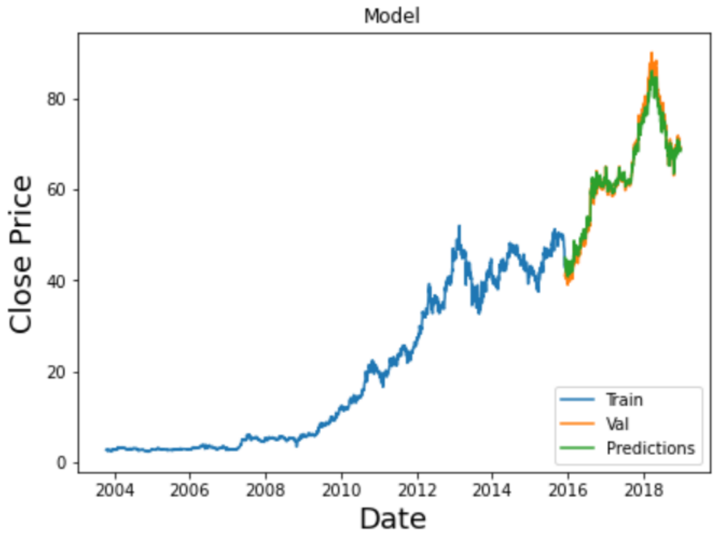
4.3.2. Result 2 - Comparing CNN (Convolution Neural Networks) and LSTM (Long Short-Term Memory).

- Based on the experiments of three models, LSTM shows the best performance.
- For the CNN(Thesis) models, because of less informative historical data in the early stage, the performance is poor.

CPALL (2001 - 2018) – Volatile data

<u>CNN (Thesis)</u>
Optimizer: Adam   Feature: 3
Epochs: 100
RMSE: 13.041   MAPE: 19.453

<u>CNN (New)</u>
Optimizer: RMSprop   Feature: 3
Epochs: 300
RMSE: 0.28   MAPE: 2.223



<u>LSTM</u>
Optimizer: RMSprop   Epochs: 10
RMSE: 0.14   MAPE: 3.911
Look-back: 30

4. EXPERIMENTS

4.3.2. Result 2 - Comparing CNN (Convolution Neural Networks) and LSTM (Long Short-Term Memory).

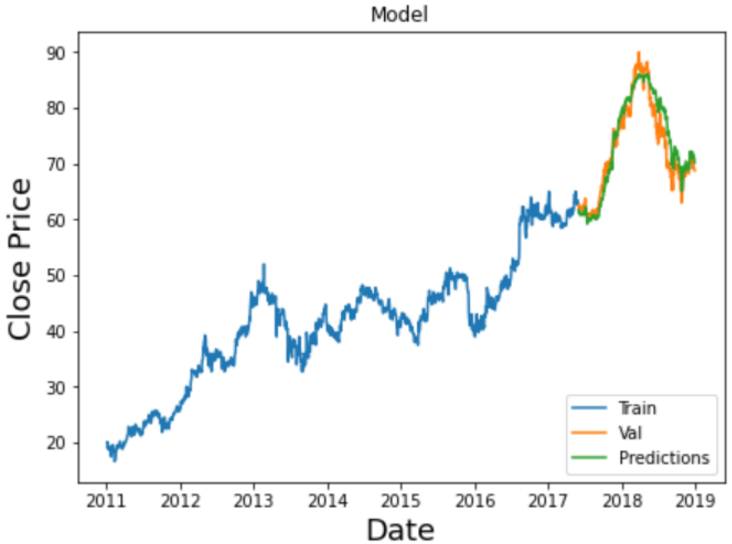
- By shortening the historical stock data range, LSTM shows the best performance.
- For the CNN(Thesis) models, the performance is better than in CPALL (Long-term data).

CPALL (2011 - 2018) – Volatile data

<u>CNN (Thesis)</u>
Optimizer: RMSprop   Feature: 3
Epochs: 20
RMSE: 1.782   MAPE: 6.029

<u>CNN (New)</u>
Optimizer: ADAM   Feature: 3
Epochs: 300
RMSE: 0.8   MAPE: 2.898

<u>LSTM</u>
Optimizer: Adam   Epochs: 1
RMSE: 0.094   MAPE: 1.157
Look-back: 30



4. EXPERIMENTS

4.3.2. Result 2 - Comparing CNN (Convolution Neural Networks) and LSTM (Long Short-Term Memory).

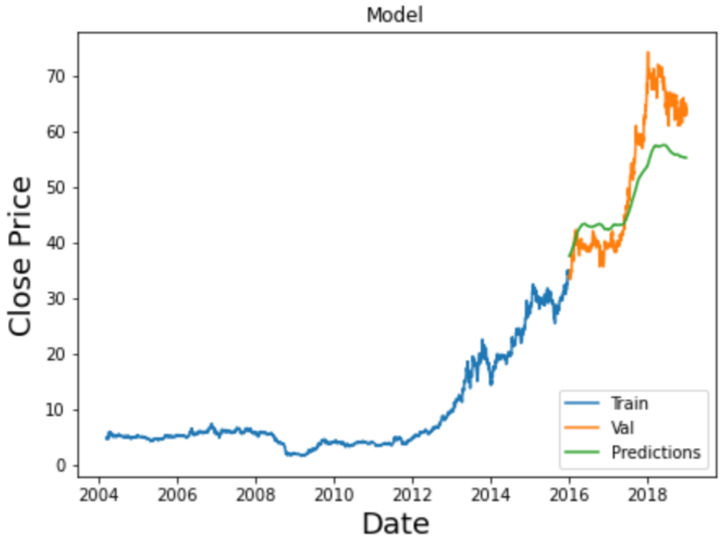
- LSTM and CNN(New) show a high performance. CNN(New) is the best performance.
- For the CNN(Thesis) models, the performance is required to improve.

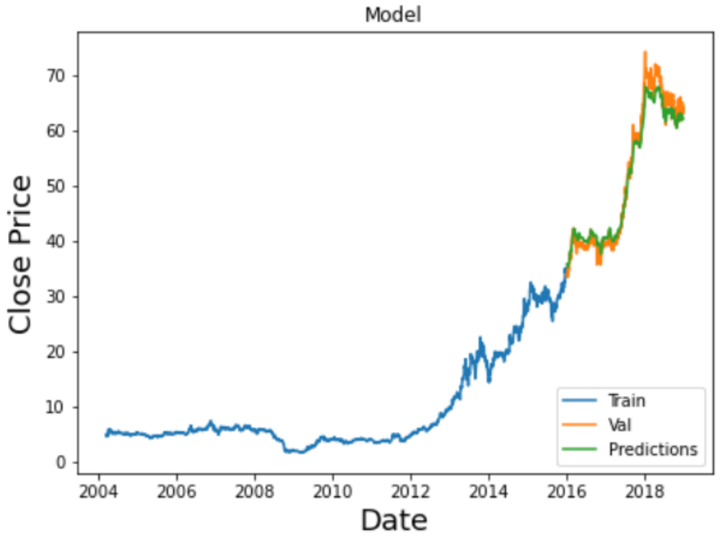
AOT (2001 - 2018) – Volatile data

CNN (Thesis)	
Optimizer: Adam	Feature: 3
Epochs: 20	
RMSE: 8.35	MAPE: 15.302

CNN (New)	
Optimizer: ADAM	Feature: 3
Epochs: 300	
RMSE: 0.065	MAPE: 9.206

LSTM	
Optimizer: RMSprop	Epochs: 1
RMSE: 0.463	MAPE: 2.69
Look-back: 30	





4. EXPERIMENTS

4.3.2. Result 2 - Comparing CNN (Convolution Neural Networks) and LSTM (Long Short-Term Memory).

- LSTM shows the best performance.
- For the CNN(Thesis) models, even shortening the historical stock data, the performance hardly increased.

AOT (2011 - 2018) – Volatile data

CNN (Thesis)
Optimizer: Adam Feature: 3
Epochs: 20
RMSE: 9.013 MAPE: 13.94

CNN (New)
Optimizer: Adam Feature: 3
Epochs: 100
RMSE: 4.81 MAPE: 7.593

LSTM
Optimizer: Adam Epochs: 20
RMSE: 0.889 MAPE: 1.612
Look-back: 30

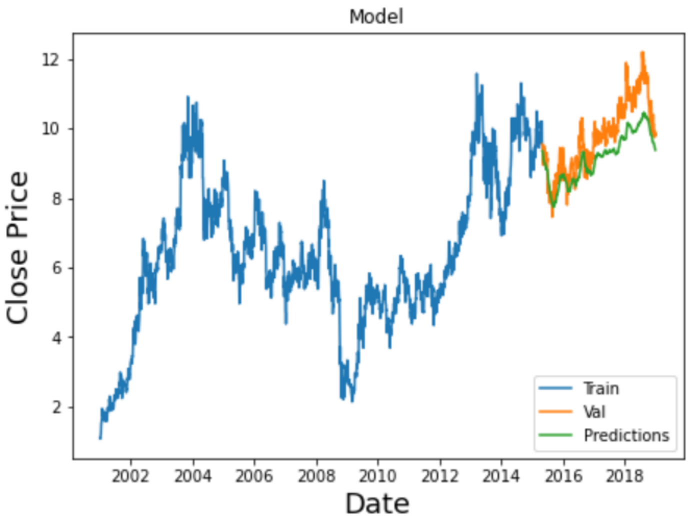
4. EXPERIMENTS

4.3.2. Result 2 - Comparing CNN (Convolution Neural Networks) and LSTM (Long Short-Term Memory).

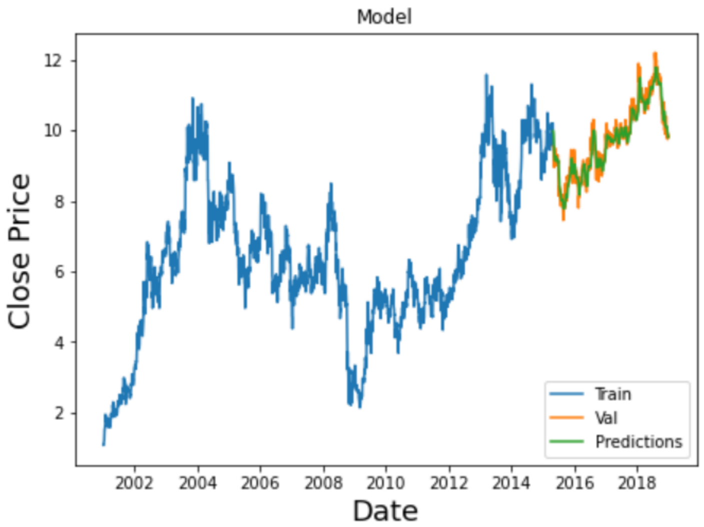
- LSTM and CNN show a high performance. CNN(New) is the best performance.
- Stable historical data works well in both CNN and LSTM.

LH (2001 - 2018) – Stable data

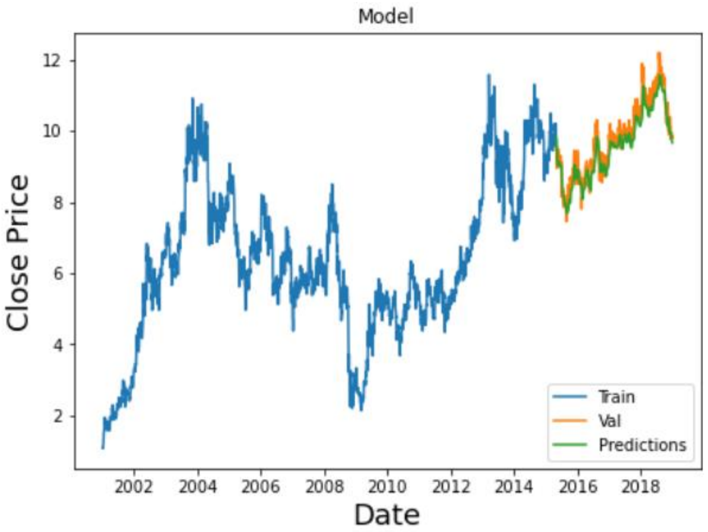
CNN (Thesis)
Optimizer: RMSprop   Feature: 3
Epochs: 10
RMSE: 0.154   MAPE: 4.04



CNN (New)
Optimizer: Adam   Feature: 5
Epochs: 30
RMSE: 0.003   MAPE: 2.13



LSTM
Optimizer: RMSprop   Epochs: 10
RMSE: 0.036   MAPE: 1.177
Look-back: 60



4. EXPERIMENTS

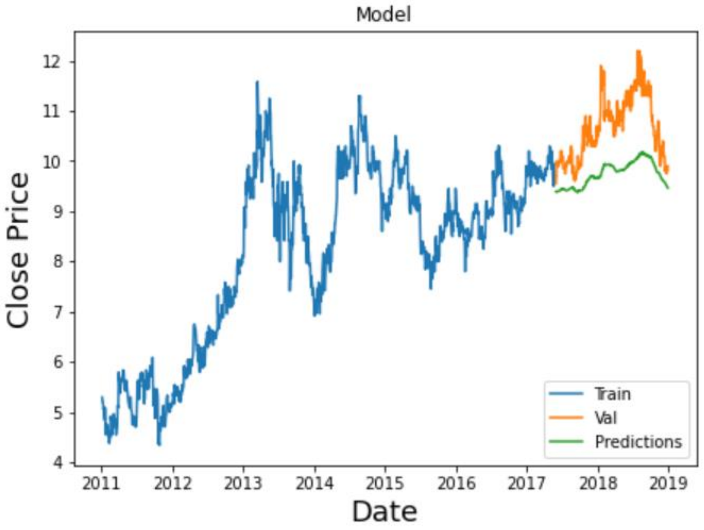
4.3.2. Result 2 - Comparing CNN (Convolution Neural Networks) and LSTM (Long Short-Term Memory).

- LSTM shows the best performance and very precisely.
- CNN models also show a high performance.

LH (2011 - 2018) – Stable data

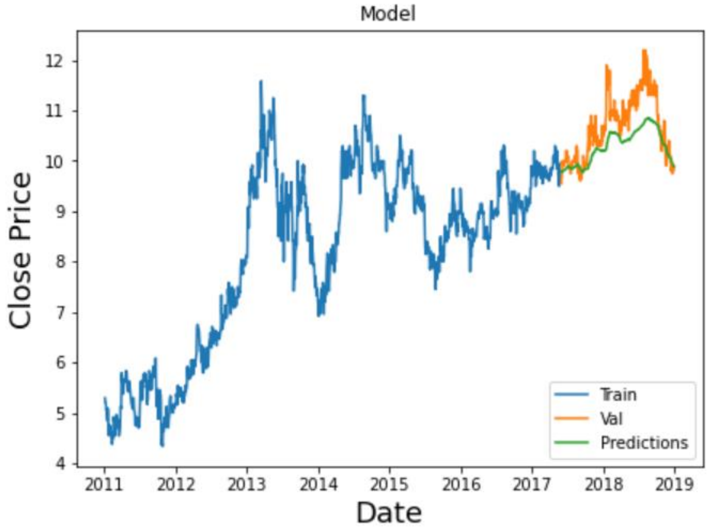
CNN (Thesis)

Optimizer: Adam Feature: 3
Epochs: 20
RMSE: 0.674 MAPE: 6.152



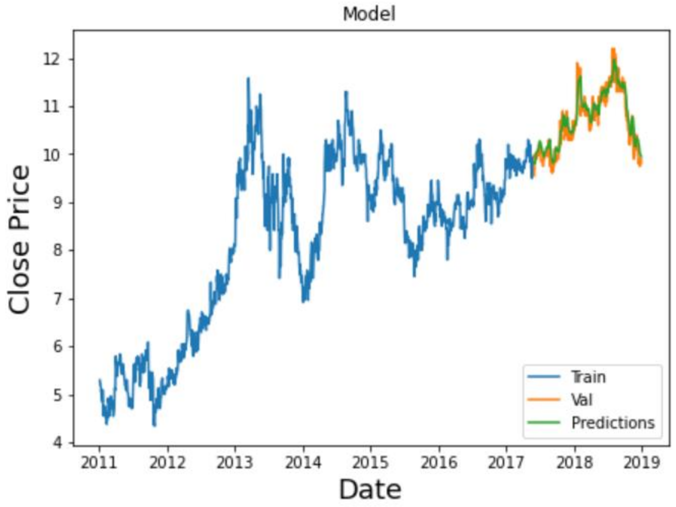
CNN (New)

Optimizer: ADAM Feature: 3
Epochs: 100
RMSE: 0.182 MAPE: 2.029



LSTM

Optimizer: Adam Epochs: 1
RMSE: 0.003 MAPE: 1.614
Look-back: 30



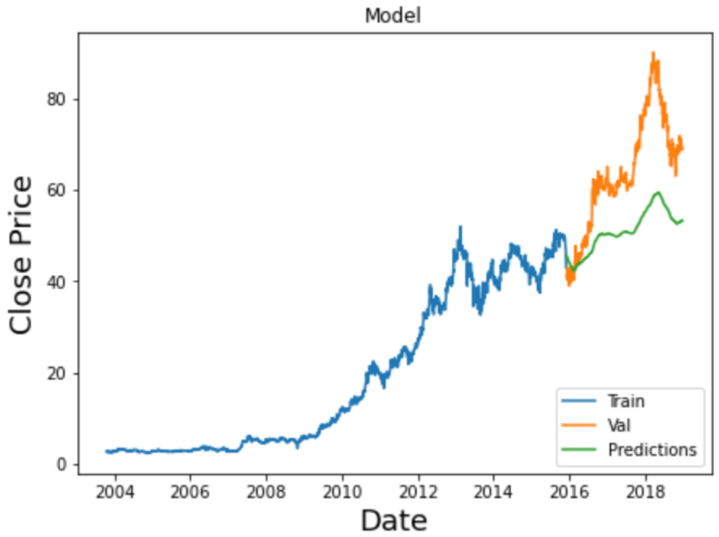
4. EXPERIMENTS

4.3.3. Result 3 - Comparing the training period with two periods of historical stock data (2001 – 2018 and 2011 - 2018)

- From the performance result, the 2011 – 2018 periods of historical stock data have higher performance than the 2001 – 2018 periods of historical stock data.
- The unpredictable data in the first range in historical stock data is a key factor that affects to the overall performance.

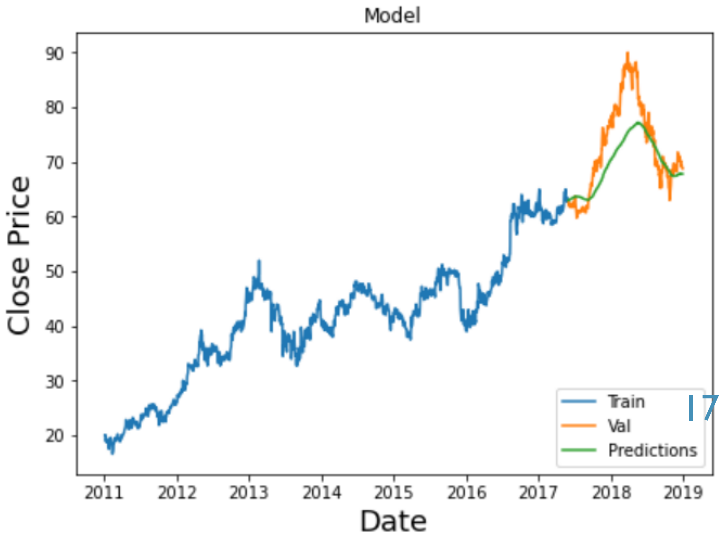
CPALL (2001 - 2018)
Long-term data

CNN (Thesis)
Optimizer: Adam Feature: 3
Epochs: 100
RMSE: 13.041 MAPE: 19.453



CPALL (2011 - 2018)
Short-term data

CNN (Thesis)
Optimizer: RMSprop Feature: 3
Epochs: 20
RMSE: 1.782 MAPE: 6.029



4. EXPERIMENTS

4.3.4. Result 4 - Based on the type of historical stock data (stable and volatile type), we find a better number of window sizes for a model.

- Removing some parts of the unpredictable historical data could increase the performance.
- Window size = 5 is suitable for volatile data.
- Window size = 3 is suitable for stable data in a long period (AOT).
- Window size = 7 is suitable for stable data with a relatively short period (CPALL).

CNN (THESIS)

SHORT-TERM (2011 - 2018)

No	Stock	Epochs	Adam		Sgd		RMSprop	
			RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1	CPALL	10	19.052	25.395	18.92	25.134	18.41	24.45
		20	15.404	20.419	21.92	29.263	1.782	6.029
		30	4.758	6.517	23.953	32.083	1.838	5.583
		100	10.515	13.865	28.826	38.85	17.122	22.779
		200	18.07	24.032	27.512	37.079	18.419	24.443
		300	19.643	26.111	27.829	37.59	19.118	25.295
2	AOT	10	24.331	38.493	23.302	36.437	20.738	32.456
		20	9.013	13.94	29.545	46.463	19.676	30.776
		30	18.925	29.726	31.521	49.668	16.727	26.114
		100	17.716	27.798	33.016	52.275	14.668	22.962
		200	24.81	38.81	35.678	56.68	14.463	22.709
		300	26.375	41.293	33.397	52.917	14.379	22.387
3	LH	10	1.278	11.765	2.077	19.184	1.818	16.815
		20	0.674	6.152	2.3	21.271	1.143	10.518
		30	1.004	9.252	2.108	19.471	1.025	9.405
		100	1.296	12	2.17	20.073	1.708	15.808
		200	1.77	16.391	1.993	18.428	1.121	10.328
		300	1.853	17.16	2.254	20.884	1.926	17.818

Window size = 3

No	Stock	Epochs	Adam		Sgd		RMSprop	
			RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1	CPALL	10	18.58	24.758	21.172	28.216	18.967	25.269
		20	1.328	4.813	24.178	32.372	10.492	13.741
		30	4.456	6.207	24.508	32.847	12.736	16.799
		100	10.998	14.508	27.502	37.024	15.188	20.155
		200	18.353	24.398	29.246	39.491	18.336	24.343
		300	19.133	25.456	26.779	36.106	19.728	26.173
2	AOT	10	19.496	30.449	25.546	40.02	24.174	37.862
		20	14.276	22.266	30.237	47.55	20.567	32.132
		30	17.364	27.285	26.921	42.299	21.537	33.737
		100	16.492	25.81	37.572	59.561	13.354	20.767
		200	26.692	41.78	33.358	52.978	14.138	22.185
		300	25.381	39.708	33.233	52.748	12.879	20.072
3	LH	10	0.6	5.618	2.395	22.162	1.427	13.139
		20	0.527	4.854	2.115	19.54	1.086	9.977
		30	0.352	3.389	2.148	19.851	0.833	7.602
		100	0.264	2.49	2.311	21.39	1.353	12.489
		200	0.249	2.379	1.978	18.282	1.402	12.954
		300	0.113	1.664	1.798	16.618	1.37	12.655

Window size = 5

No	Stock	Epochs	Adam		Sgd		RMSprop	
			RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1	CPALL	10	18.831	25.069	20.682	27.548	16.377	21.703
		20	0.119	5.045	22.298	29.778	17.253	22.927
		30	6.477	8.521	23.693	31.716	5.862	7.945
		100	13.091	17.362	29.133	39.297	15.696	20.862
		200	16.415	21.799	27.848	37.558	19.839	26.366
		300	19.428	25.839	25.355	34.167	19.489	25.84
2	AOT	10	18.465	28.816	26.692	41.843	24.957	39.141
		20	16.526	25.96	29.959	47.117	20.575	32.187
		30	12.017	18.807	27.894	43.856	17.148	26.784
		100	19.288	30.178	35.091	55.574	23.322	36.478
		200	25.234	39.496	30.223	47.655	27.284	42.7
		300	27.132	42.482	30.756	48.701	26.583	41.576
3	LH	10	0.844	7.726	2.177	20.12	0.696	6.354
		20	1.11	10.221	2.229	20.608	1.496	13.787
		30	0.812	7.463	2.259	20.892	2.106	19.495
		100	1.659	15.392	1.978	18.27	[illegible]	18.363
		200	1.812	16.783	2.148	19.873	1.82	16.816
		300	1.649	15.258	2.126	19.679	1.746	16.13

Window size = 7

4. EXPERIMENTS

4.3.4. Result 4 - Based on the type of historical stock data (stable and volatile type), we find a better number of window sizes for a model.

- A stock with volatile historical data will get a good prediction performance result with the CNN model.
- Stable data run up to with epoch = 100 with increase the performance.
- Stable data in long-term historical data using the window size = 7 has the highest performance among other window sizes.

CNN (THESIS)
LONG-TERM (2001 - 2018)

No	Stock	Epochs	Adam		Sgd		RMSprop	
			RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1	CPALL	10	17.908	26.535	19.718	28.947	18.483	27.289
		20	17.045	25.142	27.353	40.388	17.688	26.252
		30	13.376	20.064	29.941	44.67	19.494	28.487
		100	13.041	19.453	33.929	51.762	23.415	34.007
		200	18.846	27.417	25.574	37.802	25.263	36.765
		300	23.84	34.679	21.32	32.389	20.436	29.769
2	AOT	10	26.451	46.669	20.155	34.996	18.082	30.622
		20	8.35	15.302	26.005	47.006	19.156	33.027
		30	17.482	30.169	31.264	57.736	19.565	34.119
		100	18.358	31.744	37.716	71.217	21.576	37.569
		200	19.842	34.777	31.717	59.662	26.478	46.93
		300	23.996	42.575	24.876	45.247	20.179	35.485
3	LH	10	0.669	6.903	2.961	29.641	0.154	4.04
		20	1.051	10.502	3.08	30.866	2.024	20.368
		30	1.09	10.885	2.973	29.751	1.073	10.616
		100	2.546	25.568	3.032	30.454	2.201	22.02
		200	2.836	28.388	2.814	28.319	2.504	25.067
		300	2.469	24.66	2.546	25.682	1.901	19.023

Window size = 3

No	Stock	Epochs	Adam		Sgd		RMSprop	
			RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1	CPALL	10	19.199	28.227	20.107	29.502	16.367	24.643
		20	19.477	28.497	26.326	38.805	19.365	28.443
		30	14.43	21.595	28.404	42.275	16.518	24.711
		100	11.157	16.66	36.892	56.513	22.076	32.113
		200	22.29	32.376	25.987	38.449	23.946	34.859
		300	32.522	47.457	20.559	30.1	21.189	30.855
2	AOT	10	31.286	56.219	22.085	38.824	18.401	31.958
		20	6.04	13.705	25.226	45.477	19.514	33.637
		30	15.721	26.856	29.921	55.158	20.235	35.472
		100	18.082	31.719	36.641	69.19	21.276	37.176
		200	22.994	40.416	25.877	47.034	26.049	46.185
		300	26.21	46.769	25.784	47.088	22.345	39.462
3	LH	10	0.578	6.1	3.132	31.384	0.307	4.611
		20	1.033	10.331	2.849	28.504	1.787	17.9
		30	0.882	8.813	3.101	31.098	1.011	9.978
		100	2.215	22.245	2.928	29.385	2.556	25.694
		200	2.918	29.244	2.465	24.787	2.724	27.284
		300	2.686	26.839	2.38	24.012	2.753	27.61

Window size = 5

No	Stock	Epochs	Adam		Sgd		RMSprop	
			RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1	CPALL	10	18.446	27.238	24.713	36.063	19.332	28.346
		20	17.543	25.803	24.743	36.243	20.598	30.044
		30	14.493	21.696	34.119	51.341	16.516	24.632
		100	8.552	12.908	31.642	48.047	20.264	29.634
		200	16.575	24.238	23.162	33.932	21.865	31.721
		300	15.008	21.751	22.223	32.35	22.039	32.1
2	AOT	10	21.269	36.883	20.545	35.856	23.709	41.368
		20	4.834	13.429	24.852	44.735	20.495	35.579
		30	13.119	22.188	25.764	46.65	20.449	35.644
		100	17.971	31.652	37.387	70.998	23.225	40.723
		200	15.366	26.439	29.75	55.853	27.339	48.572
		300	21.811	38.436	23.045	41.124	23.72	42.213
3	LH	10	0.481	5.292	2.71	27.052	2.443	24.656
		20	1.068	10.687	2.833	28.325	1.566	15.647
		30	1.565	15.765	3.057	30.633	1.126	11.102
		100	2.756	27.712	2.985	29.971	1.306	17.99
		200	2.96	29.674	2.495	25.122	2.082	20.749
		300	2.82	28.178	2.73	27.632	2.145	21.384

Window size = 7

4. EXPERIMENTS

4.3.4. Result 4 - Based on the type of historical stock data (stable and volatile type), we find a better number of window sizes for a model.

- Running epochs >= 100 will increase the performance.
- Window size = 3 provides the best performance in the case of volatile stock.
- Window size = 5 and window size = 7 work best with optimizer = Adam.

CNN (NEW)
SHORT-TERM (2011 - 2018)

No	Stock	Epochs	Adam		Sgd		RMSprop	
			RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1	CPALL	10	16.48	24.941	23.387	34.032	20.896	30.466
		20	17.817	26.303	30.267	45.153	18.761	27.823
		30	16.672	24.519	34.581	52.171	19.787	28.979
		100	4.933	9.573	18.246	26.811	8.673	12.971
		200	13.577	21.347	16.017	23.802	11.463	16.84
		300	11.406	18.563	16.441	24.34	0.528	3.72
2	AOT	10	17.733	31.087	21.001	36.765	21.208	37.526
		20	18.081	31.443	25.273	45.678	18.114	31.431
		30	16.126	27.336	38.601	72.665	22.087	39.815
		100	16.869	28.749	37.648	71.725	19.022	33.094
		200	17.39	29.904	19.496	34.517	16.787	31.1
		300	16.865	28.883	13.239	22.663	19.275	34.439
3	LH	10	0.65	6.825	2.836	28.343	0.469	5.887
		20	0.352	4.039	2.832	28.319	1.427	14.102
		30	0.139	2.345	2.759	27.571	0.173	4.352
		100	0.272	2.78	1.545	15.284	0.112	6.607
		200	0.188	2.119	0.425	5.643	0.582	5.728
		300	0.046	1.579	0.605	7.06	0.067	3.218

Window size = 3

No	Stock	Epochs	Adam		Sgd		RMSprop	
			RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1	CPALL	10	19.199	25.51	23.091	30.875	20.124	26.807
		20	8.834	11.423	22.741	30.419	19.707	26.197
		30	7.768	10.015	26.683	35.838	6.517	8.875
		100	6.504	8.382	27.673	37.3	7.709	9.947
		200	5.221	6.821	24.827	33.431	9.481	12.361
		300	4.87	6.307	20.301	27.216	9.299	12.165
2	AOT	10	23.492	36.947	25.604	40.116	25.096	39.375
		20	21.518	33.684	27.762	43.639	22.955	35.878
		30	21.709	33.95	33.918	53.537	22.802	35.647
		100	13.839	21.812	37.083	58.862	20.954	32.749
		200	7.951	13.419	16.248	25.434	19.476	30.449
		300	8.872	14.644	15.882	24.87	16.374	25.57
3	LH	10	0.921	8.432	2.254	20.847	1.022	9.326
		20	0.627	5.751	2.321	21.47	1.037	9.473
		30	0.518	4.735	1.76	16.222	0.971	8.874
		100	0.3	2.8	1.545	14.216	0.286	3.266
		200	0.227	2.198	1.135	10.392	0.396	3.694
		300	0.247	2.353	0.693	6.34	0.537	4.919

Window size = 5

No	Stock	Epochs	Adam		Sgd		RMSprop	
			RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1	CPALL	10	18.601	24.719	21.227	28.299	22.443	29.961
		20	9.099	11.719	23.205	31.048	22.732	30.406
		30	6.835	9.006	23.999	32.15	20.167	26.897
		100	6.572	8.426	27.727	37.358	16.917	22.464
		200	2.68	3.63	24.076	32.412	11.815	15.43
		300	2.554	3.35	18.673	24.965	8.243	10.981
2	AOT	10	24.027	37.773	27.874	43.741	24.77	38.797
		20	22.082	34.522	31.441	49.524	23.391	36.552
		30	20.424	31.933	32.364	51.034	24.197	37.98
		100	12.087	19.222	34.803	55.188	20.626	32.272
		200	9.45	15.824	20.667	32.441	17.068	26.677
		300	8.788	14.863	19.083	29.858	14.546	22.876
3	LH	10	0.732	6.671	2.296	21.231	1.16	10.615
		20	0.544	5.056	2.006	18.519	0.734	6.682
		30	0.356	3.352	2.089	19.299	1.681	15.518
		100	0.156	1.808	1.534	14.115	0.878	8.077
		200	0.149	1.751	0.895	8.163	0.308	3.48
		300	0.126	1.659	0.717	6.552	0.726	6.661

Window size = 7

4. EXPERIMENTS

4.3.4. Result 4 - Based on the type of historical stock data (stable and volatile type), we find a better number of window sizes for a model.

- Adding Leaky ReLU increases overall performance.
- Window size = 3 provides the best performance among the other window sizes.
- Running epochs >= 100 will increase the performance.
- Size of feature = 5 is suitable with optimizer = Adam.

CNN (NEW)

LONG-TERM (2001 - 2018)

No	Stock	Epochs	Adam		Sgd		RMSprop	
			RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1	CPALL	10	20.594	30.049	25.634	37.545	17.935	26.803
		20	17.89	26.363	26.361	38.93	19.677	28.887
		30	18.137	26.825	36.79	55.716	18.704	27.586
		100	5.101	10.329	23.017	34.802	0.525	2.824
		200	13.193	21.75	11.237	17.178	5.082	8.467
		300	14.658	23.048	14.536	21.734	0.028	2.223
2	AOT	10	17.562	30.189	24.425	43.591	24.032	43.601
		20	18.19	31.529	35.849	66.832	23.587	42.524
		30	19.379	34.001	36.198	67.861	22.683	40.476
		100	19.633	34.076	42.44	80.965	23.787	42.092
		200	4.025	10.106	36.928	70.163	24.8	43.498
		300	0.065	9.206	15.703	27.59	22.261	39.902
3	LH	10	0.163	3.594	2.887	28.872	0.208	5.601
		20	0.159	2.71	2.77	27.684	0.002	4.756
		30	0.094	2.228	2.39	23.816	0.812	8.061
		100	0.166	1.98	1.662	16.474	0.444	4.585
		200	0.225	2.393	1.018	10.24	0.457	4.583
		300	0.007	1.607	0.453	5.8	0.419	4.205

Window size = 3

No	Stock	Epochs	Adam		Sgd		RMSprop	
			RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1	CPALL	10	14.436	21.846	27.428	40.411	19.046	28.109
		20	17.379	25.752	32.845	49.222	18.894	27.961
		30	18.053	26.638	32.453	48.847	18.617	27.555
		100	1.464	4.739	10.628	16.082	12.605	18.341
		200	11.489	18.811	16.27	24.149	3.091	5.888
		300	13.893	22.114	14.633	21.854	6.068	8.763
2	AOT	10	19.847	35.289	20.022	34.854	24.959	45.542
		20	17.077	29.403	29.627	54.526	22.571	40.602
		30	17.497	30.407	35.536	66.596	17.793	30.811
		100	17.31	29.727	39.716	75.717	22.36	39.121
		200	4.525	11.249	18.686	33.624	22.767	40.214
		300	6.821	13.769	15.629	27.057	21.919	39.322
3	LH	10	0.165	3.497	2.939	29.408	1.465	14.577
		20	0.135	2.716	2.872	28.72	1.013	10.029
		30	0.003	2.13	2.731	27.292	0.044	4.339
		100	0.035	1.718	1.734	17.194	0.1258	3.563
		200	0.196	2.164	0.548	6.28	0.126	2.383
		300	0.166	2	0.444	5.634	0.514	5.115

Window size = 5

No	Stock	Epochs	Adam		Sgd		RMSprop	
			RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
1	CPALL	10	16.48	24.941	23.387	34.032	20.896	30.466
		20	17.817	26.303	30.267	45.153	18.761	27.823
		30	16.672	24.519	34.581	52.171	19.787	28.979
		100	4.933	9.573	18.246	26.811	8.673	12.971
		200	13.577	21.347	16.017	23.802	11.463	16.84
		300	11.406	18.563	16.441	24.34	0.528	3.72
2	AOT	10	17.733	31.087	21.001	36.765	21.208	37.526
		20	18.081	31.443	25.273	45.678	18.114	31.431
		30	16.126	27.336	38.601	72.665	22.087	39.815
		100	16.869	28.749	37.648	71.725	19.022	33.094
		200	17.39	29.904	19.496	34.517	16.787	31.1
		300	16.865	28.883	13.239	22.663	19.275	34.439
3	LH	10	0.65	6.825	2.836	28.343	0.469	5.887
		20	0.352	4.039	2.832	28.319	1.427	14.102
		30	0.139	2.345	2.759	27.571	0.173	4.352
		100	0.272	2.78	1.545	15.284	[illegible]	6.607
		200	0.188	2.119	0.425	5.643	0.582	5.728
		300	0.046	1.579	0.605	7.06	0.067	3.218

Window size = 7

4. EXPERIMENTS

4.4. Real Scenario

LH stock (2011 - 2018)

- LSTM with optimizer = Adam, epochs = 1, look-back = 30
- Predicting close price from 2017.06 – 2018.12
- Condition:
    - If (predicted close price = down & close price = down) or (predicted close price = up & close price = up), the result is “Win”
    - Else the result = “Lose”
- Total result:
    - Win = 247
    - Lose = 142

Date	Predictions	Close	Predictions	Close	Result
2017-06-01	9.499625206	9.7	Up	Down	Lose
2017-06-02	9.503931046	9.8	Down	Up	Lose
2017-06-05	9.524619102	10	Down	Up	Lose
2017-06-06	9.5742836	9.95	Down	Down	Win
2017-06-07	9.624779701	9.95	Down	Down	Win
2017-06-08	9.669380188	9.9	Down	Down	Win
2017-06-09	9.699233055	9.9	Down	Down	Win
2017-06-12	9.718154907	9.95	Down	Up	Lose
2017-06-13	9.735147476	9.9	Down	Down	Win
2017-06-14	9.742582321	9.9	Down	Down	Win
2017-06-15	9.744511604	10	Down	Up	Lose
2017-06-16	9.755395889	9.95	Down	Down	Win
2017-06-19	9.762619019	10	Down	Up	Lose
2017-06-20	9.773324966	10	Down	Down	Win
2017-06-21	9.784021378	10	Down	Down	Win
2017-06-22	9.793281555	10	Down	Down	Win
2017-06-23	9.800598145	10.2	Down	Up	Lose
2017-06-26	9.830036163	10.2	Down	Down	Win
2017-06-27	9.865350723	10.2	Down	Down	Win
2017-06-28	9.898913383	10.2	Down	Down	Win
2017-06-29	9.927202225	10.2	Down	Down	Win
2017-06-30	9.949166298	10	Down	Down	Win

5. CONCLUSION

- We proposed a developed closing price prediction model by using three stocks from the Thai SET50 index (CPALL, AOT, LH).
- For comparing the look-back periods in LSTM, 30 look-back got higher performance in the case of volatile historical data and 60 look-back got higher performance in the case of stable historical data.
- In general, the results showed that LSTM outperformed CNN with high performance.
- In some cases, CNN outperforms the LSTM.
- For comparing the training period with two periods of historical stock data, the unpredictable data in historical stock data is a key factor that affects the overall performance.
- A number of window sizes are suitable for each specific model depending on the historical trend type.
- The LSTM can adapt to real-world stock price prediction.

THANK YOU

REFERENCES

[1] aakarshachug. (2023, May 31). Deep Learning - Introduction to Long Short-Term Memory. Retrieved from https://www.geeksforgeeks.org/deep-learning-introduction-to-long-short-term-memory/

[2] algoritma. Time Series Prediction With LSTM. Retrieved from https://algoritmaonline.com/time-series-prediction-with-lstm/

[3] Jeenanunta, C., Chaysiri, R., & Thong, L. (2018, May). Stock price prediction with long short-term memory recurrent neural network. In 2018 International Conference on Embedded Systems and Intelligent Technology & International Conference on Information and Communication Technology for Embedded Systems (ICESIT-ICICTES) (pp. 1-7). IEEE.

[4] Werawithayaset, P., & Tritilanunt, S. (2019, November). Stock closing price prediction using machine learning. In 2019 17th International Conference on ICT and Knowledge Engineering (ICT&KE) (pp. 1-8). IEEE.

[5] Sayavong, L., Wu, Z., & Chalita, S. (2019, September). Research on stock price prediction method based on convolutional neural network. In 2019 international conference on virtual reality and intelligent systems (ICVRIS) (pp. 173-176). IEEE.