# Sentiment Analysis with Facebook Data

Team Members 170275K - M.G.V.D. Jayawickrama 170676P - G.R.A. Weeraprameshwara Supervisors Dr. Nisansa de Silva (Internal) Mr. Yudhanjaya Wijeratne (External)

- 1. Problem
- 2. Motivation
- 3. Objectives
- 4. Related Work
- 5. Methodology
- 6. Results
- 7. Conclusion
- 8. Future Work
- 9. Appendix

# Outline

# 1. Problem



# Sentiment Analysis for Sinhala Colloquial Text?

# Reader's Perspective Instead of the Writer's Perspective

Product reviews in E-commerce sites, movie review analysis, political analysis use the writer's perspective

# Predicts the Facebook Reactions, not the Real Sentiment

Different people associate different sentiments with the same Facebook reaction

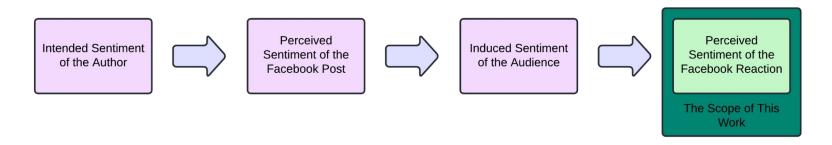


Figure: Scope of the work

# 2. Motivation



- Tests the usability of Facebook data [1] as a convenient means for sentiment analysis
- The first attempt to create a sentiment analysis model through the reader's perspective for Sinhala
- Enables Facebook users to estimate the reception of their posts prior to posting
- Contributes towards eradicating the research poverty of the Sinhala language
- Provides the means and methods to continue research in NLP on Sinhala language

# 3. Objectives



- 1. Develop a tool to detect sentiments in colloquial Sinhala text
- 2. Develop a tool to predict the Facebook user reactions to Sinhala text.
- 3. Compare with current tools to determine the best option.
- 4. Test the effectiveness of Facebook data for Sinhala language based sentiment analysis.
- 5. Introduce a methodology to develop accurate Sinhala NLP tools.
- 6. Provide the means and methods to continue research in NLP on Sinhala language.

	Learning the Basics	Developing baseline models	Compare other models	Embedding	Creating the new model
01				L	Н
02				L	Н
03			Н		L
04		Н	Н		
05	M	M		M	Н
06	M	M		Н	Н

# **4.** Related Work



### Sentiment analysis

- A study on negativity of parliament speeches by Rudkowsky et al. [2]
- o Identifies real-world events using Population Sentiment Orientation of social media data by L Che [3]
- A survey of sentiment analysis in social media by L. Yue et al. [4] to give an overview about current state

### Facebook data related sentiment analysis research

- Understanding facebook reactions to scholarly articles by Freeman et al. [5]
- Facebook sentiment: Reactions and emojis by Y.Tian et al.[6] with a
  diverse dataset and different model for each reaction

<sup>[2]</sup> E. Rudkowsky, M. Haselmayer, M. Wastian et al., "More than bags of words: Sentiment analysis with word embeddings," Communication Methods and Measures, vol. 12, no. 2-3, pp. 140–157, 2018

<sup>[3]</sup> L. Che, "Sentiment-based spatial-temporal event detection in social media data."

<sup>[4]</sup> L. Yue, W. Chen, X. Li, W. Zuo, and M. Yin, "A survey of sentiment analysis in social media," Knowledge and Information Systems, vol. 60, no. 2, pp. 617–663, 2019.

<sup>[5]</sup> C. Freeman, M. K. Roy, M. Fattoruso, and H. Alhoori, "Shared feelings: Understanding facebook reactions to scholarly articles," in JCDL. IEEE, 2019, pp.301–304

<sup>[6]</sup> Y. Tian, T. Galery, G. Dulcinati, E. Molimpakis, and C. Sun, "Facebook sentiment: Reactions and emojis," in Proceedings of the Fifth International Workshop on Natural Language Processing for Social Media. Valencia, Spain: Association for Computational Linguistics, Apr. 2017, pp. 11–16. [Online]. Available: https://www.aclweb.org/anthology/W17-1102

### Sinhala NLP research

- Survey on publicly available sinhala natural language processing tools and research by N. de Silva [7] to identify the advancements in Sinhala NLP
- Sentiment lexicon construction using sentiwordnet 3.0 by N.
   Medagoda et al. [8] which is the first Sinhala sentiment related research
- Sinhala language corpora and stopwords from a decade of sri lankan facebook by Wijeratne and N. de Silva [9] which is considered as one of the largest Sinhala datasets

### State of the art sentiment analysis models

- The model collection discussed by Senevirathne et al. [10] on sentiment analysis for sinhala language using deep learning techniques and the news comment dataset consists of 15000 data items
  - Conventional deep learning models such as GRU [11], LSTM [12]
  - Deep learning models with CNN layers [13]
  - Stacked BiLSTM models [14]
  - HAHNN [15]
  - Capsule networks [16]

<sup>[10]</sup> L. Senevirathne, P. Demotte, B. Karunanayake, U. Munasinghe, and S. Ranathunga, "Sentiment analysis for sinhala language using deep learning techniques," 2020.

<sup>[11]</sup> J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, "Empirical evaluation of gated recurrent neural networks on sequence modeling," arXiv preprint arXiv:1412.3555, 2014.

<sup>[12]</sup> S. Hochreiter and J. Schmidhuber, "Long short-term memory," Neural computation, vol. 9, no. 8, pp. 1735–1780, 1997.

<sup>[13]</sup> X. Wang, W. Jiang, and Z. Luo, "Combination of convolutional and recurrent neural network for sentiment analysis of short texts," in Proceedings of COLING 2016, the 26th international conference on computational linguistics: Technical papers, pp. 2428–2437, 2016.

<sup>[14]</sup> J. Zhou, Y. Lu, H.-N. Dai, H. Wang, and H. Xiao, "Sentiment analysis of chinese microblog based on stacked bidirectional lstm," IEEE Access, vol. 7,pp. 38856-38866, 2019.

<sup>[15]</sup> J. Abreu, L. Fred, D. Mac^edo, and C. Zanchettin, "Hierarchical attentional hybrid neural networks for document classification," in International Conference on Artificial Neural Networks. Springer, 2019, pp.396-402.

<sup>[16]</sup> W. Zhao, J. Ye, M. Yang, Z. Lei, S. Zhang, and Z. Zhao, "Investigating capsule networks with dynamic routing for text classification," 2018.

### Word embeddings

- FastText embeddings developed by P. Bojanowski et al. [17] and A. Joulin et al [18].
- Word2Vec embeddings developed by T. Mikolov et al. [19]
- Glove (Global Vectors) embeddings developed by J. Pennington et al.
   [20]

### Sentence embeddings

- Seq2Seq model introduced by I. Sutskeve [21]
- The modified version of the Seq2Seq model by K. Cho et al. [22] with the RNN units

<sup>[17]</sup> P. Bojanowski, E. Grave, A. Joulin, and T. Mikolov, "Enriching word vectors with subword information," Transactions of the Association for Computational Linguistics, vol. 5, pp. 135–146, 2017.

<sup>[18]</sup> A. Joulin, E. Grave, P. Bojanowski, and T. Mikolov, "Bag of tricks for efficient text classification," arXiv preprint arXiv:1607.01759, 2016.

<sup>[19]</sup> T. Mikolov, K. Chen, G. Corrado, and J. Dean, "Efficient estimation of word representations in vector space," arXiv preprint arXiv:1301.3781, 2013.

<sup>[20]</sup> J. Pennington, R. Socher, and C. D. Manning, "Glove: Global vectors for word representation," in Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP), pp. 1532–1543, 2014.

<sup>[21]</sup> I. Sutskever, O. Vinyals, and Q. V. Le, "Sequence to sequence learning with neural networks," in Advances in neural information processing systems, pp. 3104–3112, 2014. [22] K. Cho, B. Van Merri enboer, C. Gulcehre, D. Bahdanau, F. Bougares, H. Schwenk, and Y. Bengio, "Learning phrase representations using rnn encoder-decoder for statistical machine translation," arXiv preprint arXiv:1406.1078, 2014.

### Hyperbolic embeddings

- The work done by Q. Lu et al. [23] to understand the applications of hyperbolic embeddings by applying the concept in the medical field to improve state-of-the-art models
- Poincar'e embeddings introduced by M. Nickel et al. [24] for learning hierarchical representations in hyperbolic space
- Skip gram word embeddings in hyperbolic space introduced by M. Leimeister et al. [25]
- Reinforcing the methods introduced by M. Nickel by the work of B.
   Dhingra et al. [26] on embedding text on hyperbolic space

### Improving the state-of-the-art models

- The introduction of capsule networks by Hinton et al.[27] and Sabour et al. [28]
- Capsule-B model; previous state-of-the-art-model developed by W.
   Zhao et al. [14]
- Attention technique introduced by A. Vaswani et al. [29] to provide more attention to the syntax of data
- CNN architecture introduced by X. Wang et al. [30]

[27] Geoffrey E Hinton, Alex Krizhevsky, and Sida D Wang. 2011. Transforming auto-encoders. In International conference on artificial neural networks, pages 44–51. Springer.

[28] Sara Sabour, Nicholas Frosst, and Geoffrey E Hinton. 2017. Dynamic routing between capsules. Advances in neural information processing systems, 30.

[14] W. Zhao, J. Ye, M. Yang, Z. Lei, S. Zhang, and Z. Zhao, "Investigating capsule networks with dynamic routing for text classification," 2018.

[29] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, "Attention is all you need," in Advances in neural information processing systems, pp. 5998–6008, 2017.

[30] X. Wang, W. Jiang, and Z. Luo, "Combination of convolutional and recurrent neural network for sentiment analysis of short texts," in Proceedings of COLING 2016, the 26th international conference on computational linguistics: Technical papers, pp. 2428–2437, 2016.

# 5. Methodology



# Walkthrough

Conducting a Study on Existing Sentiment Analysis Models



Cleaning and Preparing the Dataset



Developing Baseline Machine Learning Models



Developing a Novel Sentiment Analysis Model



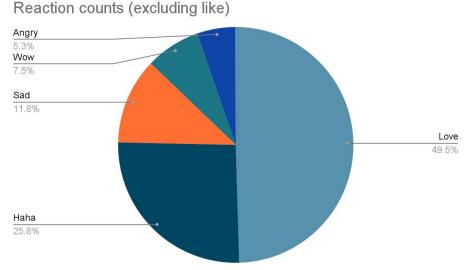
Creating
Two-Tiered
Embedding
Structures

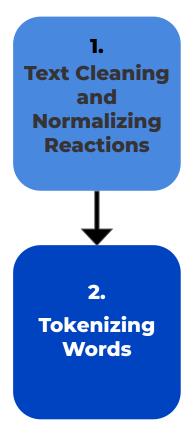


Testing the Current State-of-the-Art Models for Sentiment Analysis

### **Dataset**

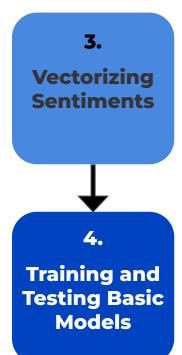
- Developed by Mr. Yudhanjaya Wijerathne and Dr. Nisansa de Silva [1]
- Contains 1.8 million Facebook posts spanning over a decade from different sources.
- Over 540 million user reactions
- 526,732 data rows after preprocessing steps





- Removing text in other languages, numbers, and other text that contains no sentimental value
- Scaling the reaction counts of each row so that their sum is 1
- Removes the bias towards posts with higher reaction counts

- Dividing each message into word tokens and removing stopwords [1]
- Stopwords do not contain a significant sentimental value



- Assigning the normalised reaction vector of a post to each of its word tokens
- For words included in multiple posts, the mean value of vectors assigned to them is taken

- Core Reaction Set Model [31]
- All Reaction Set Model [31]
- Star Rating Model [31-32]

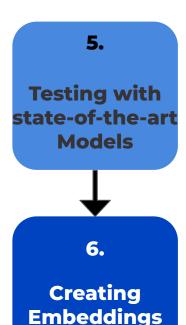
<sup>[31]</sup> V. Jayawickrama, G. Weeraprameshwara, N. de Silva, and Y. Wijeratne, "Seeking sinhala sentiment: Predicting facebook reactions of sinhala posts," arXiv preprint arXiv:2112.00468, 2021

### **Baseline models**

- Core Reaction Set model
  - Love, Haha, Wow, Sad, Angry
- All Reaction Set model
  - -Like, Love, Thankful, Haha, Wow, Sad, Angry
- Star Rating model
  - -Love, Wow as positive reactions
  - -Sad, Angry as negative reactions



Figure: Facebook reactions for each model



- Testing the performance of state-of-the-art models for sentiment analysis in predicting sentiments of Facebook data
- Identifying the suitability of the Facebook dataset [1]

- Creating word embeddings using FastText [17-18], Word2Vec [19], Glove [20], and Poincaré [24]
- Using word embeddings to develop sentence embeddings

[1] Y. Wijeratne and N. de Silva, "Sinhala language corpora and stop words from a decade of sri lankan facebook," arXiv preprint arXiv:2007.07884, 2020.

<sup>[17]</sup> P. Bojanowski, E. Grave, A. Joulin, and T. Mikolov, "Enriching word vectors with subword information," Transactions of the Association for Computational Linguistics, vol. 5, pp. 135–146, 2017.

<sup>[18]</sup> A. Joulin, E. Grave, P. Bojanowski, and T. Mikolov, "Bag of tricks for efficient text classification," arXiv preprint arXiv:1607.01759, 2016.

<sup>[19]</sup> T. Mikolov, K. Chen, G. Corrado, and J. Dean, "Efficient estimation of word representations in vector space," arXiv preprint arXiv:1301.3781, 2013.

<sup>[20]</sup> J. Pennington, R. Socher, and C. D. Manning, "Glove: Global vectors for word representation," in Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP), pp. 1532–1543, 2014.

<sup>[24]</sup> M. Nickel and D. Kiela, "Poincar'e embeddings for learning hierarchical representations," Advances in neural information processing systems, vol. 30,pp. 6338–6347, 2017.

## **Models Tested**

- Core Reaction Set model [31], All Reaction set model [32], Star Rating Model [31-32]
- Baseline models; GRU [11], LSTM [12], BiLSTM [33]
- Baseline models with CNN layer [13]
- stacked 2 and 3 layer LSTM and BiLSTM models [14]
- HAHNN [15]
- Capsule-A, Capsule-B [16]

[31] V. Jayawickrama, G. Weeraprameshwara, N. de Silva, and Y. Wijeratne, Seeking sinhala sentiment: Predicting facebook reactions of sinhala posts, "arXiv preprint arXiv:2112.00468, 2021.

[32] S. De Silva, H. Indrajee, S. Premarathna et al., "Sensing the sentiments of the crowd: Looking into subjects," in 2nd International Workshop on Multi-modal Crowd Sensing, 2014.

- [11] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, "Empirical evaluation of gated recurrent neural networks on sequence modeling," arXiv preprint arXiv:1412.3555, 2014.
- [12] S. Hochreiter and J. Schmidhuber, "Long short-term memory," Neural computation, vol. 9, no. 8, pp. 1735-1780, 1997.
- [33] M. Schuster and K. K. Paliwal, "Bidirectional recurrent neural networks," IEEE transactions on Signal Processing, vol. 45, no. 11, pp. 2673-2681, 1997.
- [13] X. Wang, W. Jiang, and Z. Luo, "Combination of convolutional and recurrent neural network for sentiment analysis of short texts," in Proceedings of COLING 2016, the 26th international conference on computational linguistics: Technical papers, pp. 2428–2437, 2016.
- [14] J. Zhou, Y. Lu, H.-N. Dai, H. Wang, and H. Xiao, "Sentiment analysis of chinese microblog based on stacked bidirectional lstm," IEEE Access, vol. 7,pp. 38856-38866, 2019.
- [15] J. Abreu, L. Fred, D. Mac^edo, and C. Zanchettin, "Hierarchical attentional hybrid neural networks for document classification," in International Conference on Artificial Neural Networks. Springer, 2019, pp.396-402.
- [16] W. Zhao, J. Ye, M. Yang, Z. Lei, S. Zhang, and Z. Zhao, "Investigating capsule networks with dynamic routing for text classification," 2018.

### Developing word embeddings for Facebook posts:

- FastText [17-18]
- o Glove [19]
- Word2Vec [20]
- Poincar'e [24]

### Developing sentence embeddings for Facebook posts:

- MaxPooling
- MinPooling
- AveragePooling
- Seq2Seq model [34]
  - with GRU [11] or LSTM [33] units
  - with or without an attention layer [29]

<sup>[17]</sup> P. Bojanowski, E. Grave, A. Joulin, and T. Mikolov, "Enriching word vectors with subword information," Transactions of the Association for Computational Linguistics, vol. 5, pp. 135–146, 2017.

<sup>[18]</sup> A. Joulin, E. Grave, P. Bojanowski, and T. Mikolov, "Bag of tricks for efficient text classification," arXiv preprint arXiv:1607.01759, 2016.

<sup>[19]</sup> T. Mikolov, K. Chen, G. Corrado, and J. Dean, "Efficient estimation of word representations in vector space," arXiv preprint arXiv:1301.3781, 2013.

<sup>[20]</sup> J. Pennington, R. Socher, and C. D. Manning, "Glove: Global vectors for word representation," in Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP), pp. 1532–1543, 2014.

<sup>[24]</sup> M. Nickel and D. Kiela, "Poincar'e embeddings for learning hierarchical representations," Advances in neural information processing systems, vol. 30,pp. 6338-6347, 2017.

<sup>[13]</sup> I. Sutskever, O. Vinyals, and Q. V. Le, "Sequence to sequence learning with neural networks," in Advances in neural information processing systems, pp. 3104–3112, 2014.

<sup>[11]</sup> J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, "Empirical evaluation of gated recurrent neural networks on sequence modeling," arXiv preprint arXiv:1412.3555, 2014.

<sup>[33]</sup> M. Schuster and K. K. Paliwal, "Bidirectional recurrent neural networks," IEEE transactions on Signal Processing, vol. 45, no. 11, pp. 2673-2681, 1997.

<sup>[29]</sup> A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, "Attention is all you need," in Advances inneural information processing systems, pp. 5998–6008, 2017

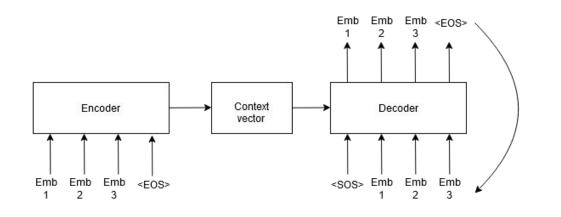
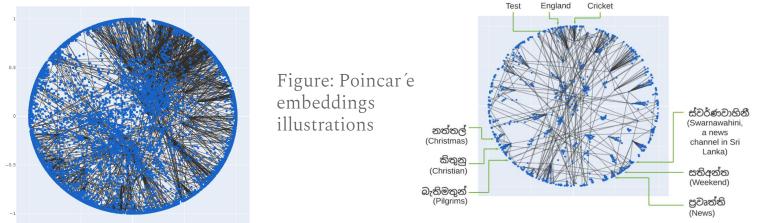
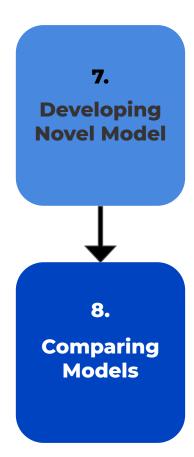


Figure: Two tier embeddings with Seq2seq model

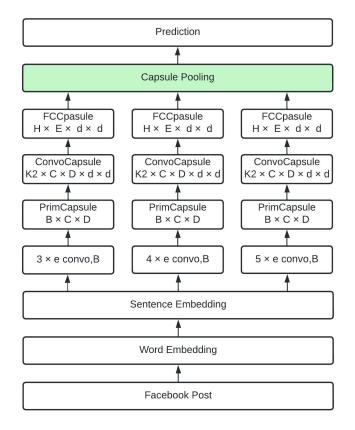




- Developing a novel model for sentiment analysis in colloquial Sinhala
- Combining Capsule-B and Bi-LSTM models

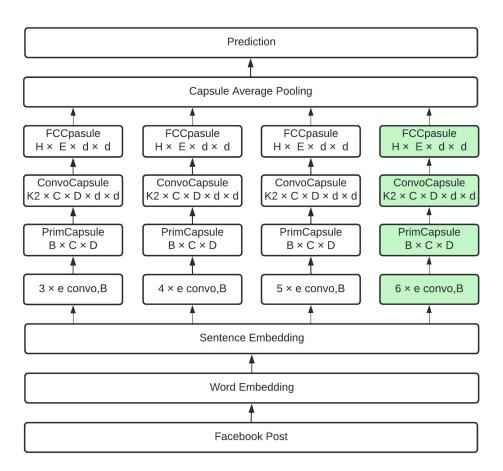
- Comparing the performance of models tested
- Deciding on the best model for sentiment analysis of Sinhala Facebook posts [1]

### Modifications for the Capsule-B [16] network with Bi-LSTM [33] layer

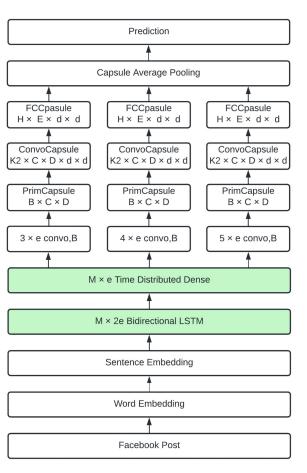


4 changes will be done to the architecture of the Capsule-B model

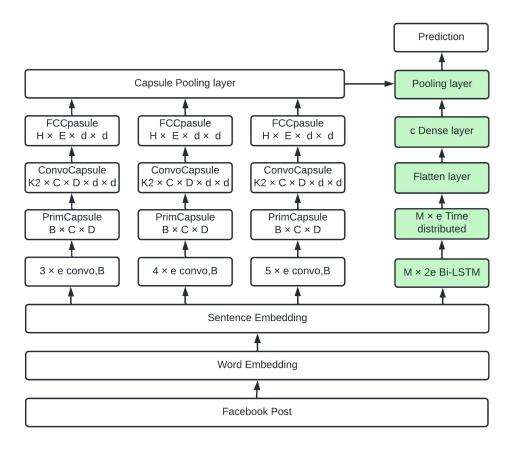
1. Changes in the capsule Average Pooling: The pooling layer will be changed to max or min pooling. 2. Addition of parallel paths to the Capsule-B model: The number of pipelines in the model will be increased.



3. Serial insertion of a Bi-LSTM model: The output of the Bi-LSTM model will be fed to the Capsule-B model.



4. Parallel insertion of a Bi-LSTM model: Bi-LSTM model will be inserted into the workflow of the Capsule-B model.



# 6. Results



# **6.1.** Baseline Model Results

(70)		Core Reaction [31]	All Reaction [31]	Star Rating [31-32]
	Like	-	96.26	-
	Love	51.64	17.69	-
	Wow	22.18	8.18	-
	Haha	30.60	10.68	-
95%	Sad	16.13	6.38	-
9370	Angry	13.18	4.95	-
	Thankful	-	0.00	-
	Positive	-	-	70.68
	Negative	-	-	42.07
	Star Rating	-	-	29.21

**Maximum F1 Score Achieved (%)** 

**Train** 

(%)

Reaction

2.00468, 2021 **35** [32] S. De Silva, H. Indrajee, S. Premarathna et al., "Sensing the sentiments of the crowd: Looking into subjects," in 2nd International Workshop on Multi-modal Crowd Sensing, 2014.

# Significance of the Outcome

### • A set of baseline models

- Tests the effectiveness of the Facebook dataset as a means for sentiment analysis
- Identifies Facebook reactions with a reasonable contribution towards sentiment
- Introduces a set of equations to quantify sentiments included in Facebook posts

Objective	Impact	Completeness
Develop a tool to detect sentiments in colloquial Sinhala text		
Develop a tool to predict the Facebook user reactions to Sinhala text.		
Compare with current tools to determine the best option.		
Test the effectiveness of Facebook data for Sinhala language based sentiment analysis.	Н	<b>✓</b>
Introduce a methodology to develop accurate Sinhala NLP tools.	M	<b>✓</b>
Provide the means and methods to continue research in NLP on Sinhala language.	M	<b>✓</b>

# **6.2.** Deep Learning Model Results

Model	F1 Score (%)		
	News comments [10]	Facebook dataset [1]	
Core Reaction [31]	-	49.80	
Star Rating Model [31-32]	-	33.77	
GRU [11]	54.83	81.33	
LSTM [12]	54.50	81.24	
BiLSTM [33]	57.71	82.58	
CNN [13]+ GRU [11]	54.19	81.37	
CNN [13] + BiLSTM [33]	58.53	81.00	

subjects," in 2nd International Workshop on Multi-modal Crowd Sensing, 2014.

<sup>[1]</sup> Y. Wijeratne and N. de Silva, "Sinhala language corpora and stopwords from a decade of sri lankan facebook," arXiv preprint arXiv:2007.07884, 2020.

<sup>[10]</sup> L. Senevirathne, P. Demotte, B. Karunanayake, U. Munasinghe, and S. Ranathunga, "Sentiment analysis for sinhala language using deep learning techniques," 2020.

<sup>[31]</sup> V. Jayawickrama, G. Weeraprameshwara, N. de Silva, and Y. Wijeratne, Seeking sinhala sentiment: Predicting facebook reactions of sinhala posts, arXiv preprint arXiv:2112.00468, 2021.

<sup>[32]</sup> S. De Silva, H. Indrajee, S. Premarathna et al., "Sensing the sentiments of the crowd: Looking into

<sup>[11]</sup> J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, "Empirical evaluation of gated recurrent neural networks on sequence modeling," arXiv preprint arXiv:1412.3555, 2014.

<sup>[12]</sup> S. Hochreiter and J. Schmidhuber, "Long short-term memory," Neural computation, vol. 9, no. 8, pp. 1735-1780, 1997.

<sup>[33]</sup> M. Schuster and K. K. Paliwal, "Bidirectional recurrent neural networks," IEEE transactions on Signal Processing, vol. 45, no. 11, pp. 2673-2681, 1997.

<sup>[13]</sup> X. Wang, W. Jiang, and Z. Luo, "Combination of convolutional and recurrent neural network for sentiment analysis of short texts," in Proceedings of COLING 2016, the 26th international conference on computational linguistics: Technical papers, pp. 2428–2437, 2016.

Model	F1 Score (%)			
	News comments [10]	Facebook dataset [1]		
Stacked LSTM 2 [14]	53.17	81.58		
Stacked LSTM 3 [14]	53.67	81.24		
Stacked BiLSTM 2 [14]	57.78	82.56		
Stacked BiLSTM 3 [14]	59.42	84.58		
HAHNN [15]	59.25	77.39		
Capsule A [16]	53.55	79.67		
Capsule B [16]	59.11	82.04		

<sup>[1]</sup> Y. Wijeratne and N. de Silva, "Sinhala language corpora and stopwords from a decade of sri lankan facebook," arXiv preprint arXiv:2007.07884, 2020.

<sup>[10]</sup> L. Senevirathne, P. Demotte, B. Karunanayake, U. Munasinghe, and S. Ranathunga, "Sentiment analysis for sinhala language using deep learning techniques," 2020.

<sup>[14]</sup> J. Zhou, Y. Lu, H.-N. Dai, H. Wang, and H. Xiao, "Sentiment analysis of chinese microblog based on stacked bidirectional lstm," IEEE Access, vol. 7,pp. 38856-38866, 2019. [15] J. Abreu, L. Fred, D. Mac^edo, and C. Zanchettin, "Hierarchical attentional hybrid neural networks for document classification," in International Conference on

<sup>[15]</sup> J. Abreu, L. Fred, D. Mac edo, and C. Zanchettin, Hierarchical attentional hybrid neural networks for document classification, in International Conference of Artificial Neural Networks. Springer, 2019, pp.396–402.

<sup>[16]</sup> W. Zhao, J. Ye, M. Yang, Z. Lei, S. Zhang, and Z. Zhao, "Investigating capsule networks with dynamic routing for text classification," 2018.

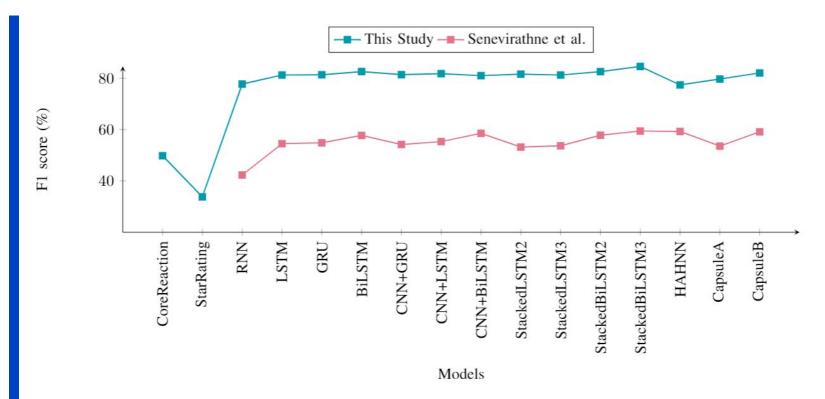


Figure: F1 score comparison of each model

### Significance of the Outcome

#### • Larger comparison of NLP tools

- Tests the Facebook dataset with deep learning models
- o Identifies the current state-of-the-art model: Stacked 3 Layer BiLSTM model
- Provides insight on suitable models for future developments
- Compares the baseline models against existing state-of-the-art deep learning models

Objective	Impact	Completeness
Develop a tool to detect sentiments in colloquial Sinhala text		
Develop a tool to predict the Facebook user reactions to Sinhala text.		
Compare with current tools to determine the best option.	Н	<b>✓</b>
Test the effectiveness of Facebook data for Sinhala language based sentiment analysis.	Н	<b>✓</b>
Introduce a methodology to develop accurate Sinhala NLP tools.		
Provide the means and methods to continue research in NLP on Sinhala language.		

# 6.3. Embedding Results

Word Embedding	dding Sentence Embedding F1 Score	
	Avg Pooling	87.01
	Seq2seq [34] GRU [11]	85.75
Word2Vec [20]	Seq2seq [34] GRU [11] + Attention [29]	87.29
	Seq2seq [34] LSTM [12]	86.01
	Seq2seq [34] LSTM + Attention [29]	86.53
	Max Pooling	86.22
	Seq2seq [34] GRU [11]	85.16
Glove [19]	Seq2seq [34] GRU + Attention [29]	85.12
	Seq2seq [34] LSTM [12]	85.16
	Seq2seq [34] LSTM + Attention [29]	85.12

<sup>45</sup> [29] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, "Attention is all you need," in Advances inneural information processing systems, pp.

Word Embedding	Sentence Embedding	F1 Score
	Avg Pooling	87.93
	Seq2seq [34] GRU [11]	86.23
fastText [17-18]	Seq2seq [34] GRU + Attention [29]	88.04
	Seq2seq [34] LSTM [12]	86.60
	Seq2seq [34] LSTM [12] + Attention [29]	87.72
	Max Pooling	85.77
	Seq2seq [34] GRU[11]	86.13
Hyperbolic [24]	Seq2seq [34] GRU [11] + Attention [29]	86.54
	Seq2seq [34] LSTM [12]	85.81
	Seq2seq [34] LSTM [12] + Attention [29]	86.30

### Significance of the Outcome

#### • Embeddings for Sinhala language

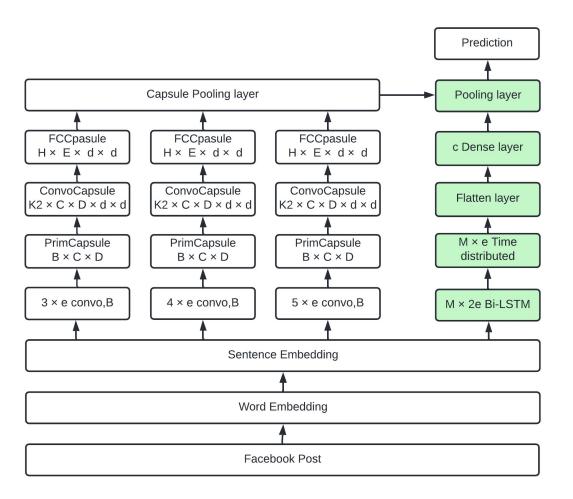
- Uses a significantly large dataset
- Tests a more granular structure with word and sentence embeddings
- Considers multiple combinations of existing tools
- Introduces hyperbolic embeddings for sentiment data in Sinhala for the first time

Objective	Impact	Completeness
Develop a tool to detect sentiments in colloquial Sinhala text	L	<b>✓</b>
Develop a tool to predict the Facebook user reactions to Sinhala text.	L	<b>✓</b>
Compare with current tools to determine the best option.		
Test the effectiveness of Facebook data for Sinhala language based sentiment analysis.		
Introduce a methodology to develop accurate Sinhala NLP tools.	M	<b>✓</b>
Provide the means and methods to continue research in NLP on Sinhala language.	Н	<b>✓</b>

#### **6.4.** Novel Model Results

Model	Performance Score			
	Accuracy	Precisión	Recall	F1 score
Original Capsule-B [16]	80.46	79.16	80.46	79.80
Capsule B max pooling	80.36	79.08	80.36	79.71
Capsule B min pooling	80.46	79.19	80.46	79.82
Capsule-B [16] additional parallel pipelines	80.12	78.74	80.12	79.42
Capsule-B [16] + serial BiLSTM [33] unit	74.36	55.34	74.39	63.47
Capsule-B [16] + parallel BiLSTM [33] unit	80.42	79.72	80.49	80.10

<sup>[16]</sup> W. Zhao, J. Ye, M. Yang, Z. Lei, S. Zhang, and Z. Zhao, "Investigating capsule networks with dynamic routing for text classification," 2018. [33] M. Schuster and K. K. Paliwal, "Bidirectional recurrent neural networks," IEEE transactions on Signal Processing, vol. 45, no. 11, pp. 2673–2681, 1997.



## Significance of the Outcome

#### • A novel sentiment analysis tool

- Introduces multiple architectural changes to Capsule-B model
- Tests parallel insertion of a RNN unit to the Capsule-B model, which is a novel approach
- Introduces a new state-of-the-art model for sentiment analysis in Sinhala which surpasses the previous models in performance

Objective	Impact	Completeness
Develop a tool to detect sentiments in colloquial Sinhala text	Н	✓
Develop a tool to predict the Facebook user reactions to Sinhala text.	Н	<b>✓</b>
Compare with current tools to determine the best option.	L	<b>✓</b>
Test the effectiveness of Facebook data for Sinhala language based sentiment analysis.		
Introduce a methodology to develop accurate Sinhala NLP tools.	Н	<b>✓</b>
Provide the means and methods to continue research in NLP on Sinhala language.	Н	<b>✓</b>

## 7. Conclusions



- Like and Thankful reactions hinder the process of identifying Facebook reactions effectively
- BiLSTM and Capsule-B models works well with the Facebook dataset
- Glove embeddings require a pretrained model for sinhala to perform better and hyperbolic embedding requires a parser customized for Sinhala language
- The architectural change on Capsule-B network by adding a parallel BiLSTM model outperforms the original Capsule-B model

#### 8. Future Work



- A parser that is efficient for Sinhala language
- The use of transformer models with attention layer
- Testing the embeddings with different deep learning models
- The testing of the novel models with external datasets
- The mapping between real emotions and the Facebook user reactions

# 9. Appendix



#### **Project Outcomes**

- A set of baseline models
- A larger comparison of models for NLP
- A new set of embeddings for Sinhala language
- A novel model for sentiment analysis
- A set of research papers focusing on each step to describe the methodology and provide guidelines to follow the research

Research Paper	Conference	Status	Description
Seeking Sinhala Sentiment Predicting Facebook Reactions of Sinhala Posts [31]	ICTer 2021	Published	Creating baseline models and testing the capability of Facebook data using the newly developed models
Sentiment Analysis Deep Learning Models: A Comparative Study on a Decade of Sinhala Language Facebook Data [35]	AIEE 2022	Published	Testing the models discussed in the work of Senevirathne with the Facebook dataset
Sinhala Sentence Embedding: A Two-Tiered Structure for Low-Resource Languages	PACLIC 2022	Under Review	Developing embeddings for Facebook posts using multiple techniques
Star Rating Model: An In-Depth View of a Sinhala Sentiment Analysis Model	MerCon 2022	Under Review	Exploring the star rating model
Sinhala Sentiment Analysis with a novel model	COLING 2022	Submission on May 17th	Developing the state-of-the-art sentiment analysis model
[31] V. Jayawickrama, G. Weeraprameshwara, N. de Silva, and Y. Wijer-atne, "Seeking sinhala sentiment: Predicting facebook reactions of sinhalaposts," arXiv preprint arXiv:2112.0046, 2021. [35] G. Weeraprameshwara, V. Jayawickrama, N. de Silva, and Y. Wijeratne, "Sentiment analysis with deep learning models: A comparative study on a decade of sinhala language facebook data," arXiv preprint arXiv:2201.03941, 2022.			

#### References

- [1] Y. Wijeratne and N. de Silva, "Sinhala language corpora and stopwords from a decade of sri lankan facebook," arXiv preprint arXiv:2007.07884, 2020.
- [2] E. Rudkowsky, M. Haselmayer, M. Wastian et al., "More than bags of words: Sentiment analysis with word embeddings," Communication Methods and Measures, vol. 12, no. 2-3, pp. 140–157, 2018
- [3] L. Che, "Sentiment-based spatial-temporal event detection in social media data."
- [4] L. Yue, W. Chen, X. Li, W. Zuo, and M. Yin, "A survey of sentiment analysis in social media," Knowledge and Information Systems, vol. 60, no. 2, pp. 617–663, 2019.
- [5] C. Freeman, M. K. Roy, M. Fattoruso, and H. Alhoori, "Shared feelings: Understanding facebook reactions to scholarly articles," in JCDL. IEEE, 2019, pp.301–304
- [6] Y. Tian, T. Galery, G. Dulcinati, E. Molimpakis, and C. Sun, "Facebook sentiment: Reactions and emojis," in Proceedings of the Fifth International Workshop on Natural Language Processing for Social Media. Valencia, Spain: Association for Computational Linguistics, Apr. 2017, pp. 11–16. [Online]. Available:
- https://www.aclweb.org/anthology/W17-1102
- [7] N. de Silva, "Survey on publicly available sinhala natural language processing tools and research," arXiv preprint arXiv:1906.02358, 2019.

- [8] N. Medagoda, S. Shanmuganathan, and J. Whalley, "Sentiment lexicon construction using sentiwordnet 3.0," in ICNC. IEEE, 2015, pp. 802–807.
- [9] Y. Wijeratne and N. de Silva, "Sinhala language corpora and stopwords from a decade of sri lankan facebook," arXiv preprint arXiv:2007.07884, 2020
- [10] L. Senevirathne, P. Demotte, B. Karunanayake, U. Munasinghe, and S. Ranathunga, "Sentiment analysis for sinhala language using deep learning techniques," 2020.
- [11] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, "Empirical evaluation of gated recurrent neural networks on sequence modeling," arXiv preprint arXiv:1412.3555, 2014.
- [12] S. Hochreiter and J. Schmidhuber, "Long short-term memory," Neural computation, vol. 9, no. 8, pp. 1735–1780, 1997.
- [13] X. Wang, W. Jiang, and Z. Luo, "Combination of convolutional and recurrent neural network for sentiment analysis of short texts," in Proceedings of COLING 2016, the 26th international conference on computational linguistics: Technical papers, pp. 2428–2437, 2016.
- [14] J. Zhou, Y. Lu, H.-N. Dai, H. Wang, and H. Xiao, "Sentiment analysis of chinese microblog based on stacked bidirectional lstm," IEEE Access, vol. 7,pp. 38856–38866, 2019.

- [15] J. Abreu, L. Fred, D. Mac^edo, and C. Zanchettin, "Hierarchical attentional hybrid neural networks for document classification," in International Conference on Artificial Neural Networks. Springer, 2019, pp.396–402.
- [16] W. Zhao, J. Ye, M. Yang, Z. Lei, S. Zhang, and Z. Zhao, "Investigating capsule networks with dynamic routing for text classification," 2018.
- [17] P. Bojanowski, E. Grave, A. Joulin, and T. Mikolov, "Enriching word vectors with subword information," Transactions of the Association for Computational Linguistics, vol. 5, pp. 135–146, 2017.
- [18] A. Joulin, E. Grave, P. Bojanowski, and T. Mikolov, "Bag of tricks for efficient text classification," arXiv preprint arXiv:1607.01759, 2016.
- [19] T. Mikolov, K. Chen, G. Corrado, and J. Dean, "Efficient estimation of word representations in vector space," arXiv preprint arXiv:1301.3781, 2013.
- [20] J. Pennington, R. Socher, and C. D. Manning, "Glove: Global vectors for word representation," in Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP), pp. 1532–1543, 2014.
- [21] I. Sutskever, O. Vinyals, and Q. V. Le, "Sequence to sequence learning with neural networks," in Advances in neural information processing systems, pp. 3104–3112, 2014.
- [22] K. Cho, B. Van Merri enboer, C. Gulcehre, D. Bahdanau, F. Bougares, H. Schwenk, and Y. Bengio, "Learning phrase representations using rnn encoder-decoder for statistical machine translation," arXiv preprint arXiv:1406.1078, 2014.

- [23] Q. Lu, N. de Silva, S. Kafle, J. Cao, D. Dou, T. H. Nguyen, P. Sen, B. Hailpern, B. Reinwald, and Y. Li, "Learning electronic health records through hyperbolic embedding of medical ontologies," in Proceedings of the 10th ACM International Conference on Bioinformatics, Computational Bi-ology and Health Informatics, pp. 338–346, 2019
- [24] M. Nickel and D. Kiela, "Poincar 'e embeddings for learning hierarchical representations," Advances in neural information processing systems, vol. 30,pp. 6338–6347, 2017.
- [25] M. Leimeister and B. J. Wilson, "Skip-gram word embeddings in hyperbolic space," arXiv preprint arXiv:1809.01498, 2018.
- [26] B. Dhingra, C. J. Shallue, M. Norouzi, A. M. Dai, and G. E. Dahl, "Embedding text in hyperbolic spaces," arXiv preprint arXiv:1806.04313, 2018.
- [27] Geoffrey E Hinton, Alex Krizhevsky, and Sida D Wang. 2011. Transforming auto-encoders. In International
- conference on artificial neural networks, pages 44-51. Springer.
- [28] Sara Sabour, Nicholas Frosst, and Geoffrey E Hinton. 2017. Dynamic routing between capsules. Advances in
- neural information processing systems, 30.
- [29] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, "Attention is all you need," in Advances in neural information processing systems, pp. 5998–6008, 2017.

- [30] X. Wang, W. Jiang, and Z. Luo, "Combination of convolutional and recurrent neural network for sentiment analysis of short texts," in Proceedings of COLING 2016, the 26th international conference on computational linguistics: Technical papers, pp. 2428–2437, 2016.
- [31] V. Jayawickrama, G. Weeraprameshwara, N. de Silva, and Y. Wijeratne, "Seeking sinhala sentiment: Predicting facebook reactions of sinhala posts," arXiv preprint arXiv:2112.00468, 2021
- [32] S. De Silva, H. Indrajee, S. Premarathna et al., "Sensing the sentiments of the crowd: Looking into subjects," in 2nd International Workshop on Multi-modal Crowd Sensing, 2014.
- [33] M. Schuster and K. K. Paliwal, "Bidirectional recurrent neural networks," IEEE transactions on Signal Processing, vol. 45, no. 11, pp. 2673–2681, 1997.
- [34] I. Sutskever, O. Vinyals, and Q. V. Le, "Sequence to sequence learning with neural networks," in Advances in neural information processing systems,pp. 3104–3112, 2014.
- [35] G. Weeraprameshwara, V. Jayawickrama, N. de Silva, and Y. Wijeratne, "Sentiment analysis with deep learning models: A comparative study on a decade of sinhala language facebook data," arXiv preprint arXiv:2201.03941, 2022.

