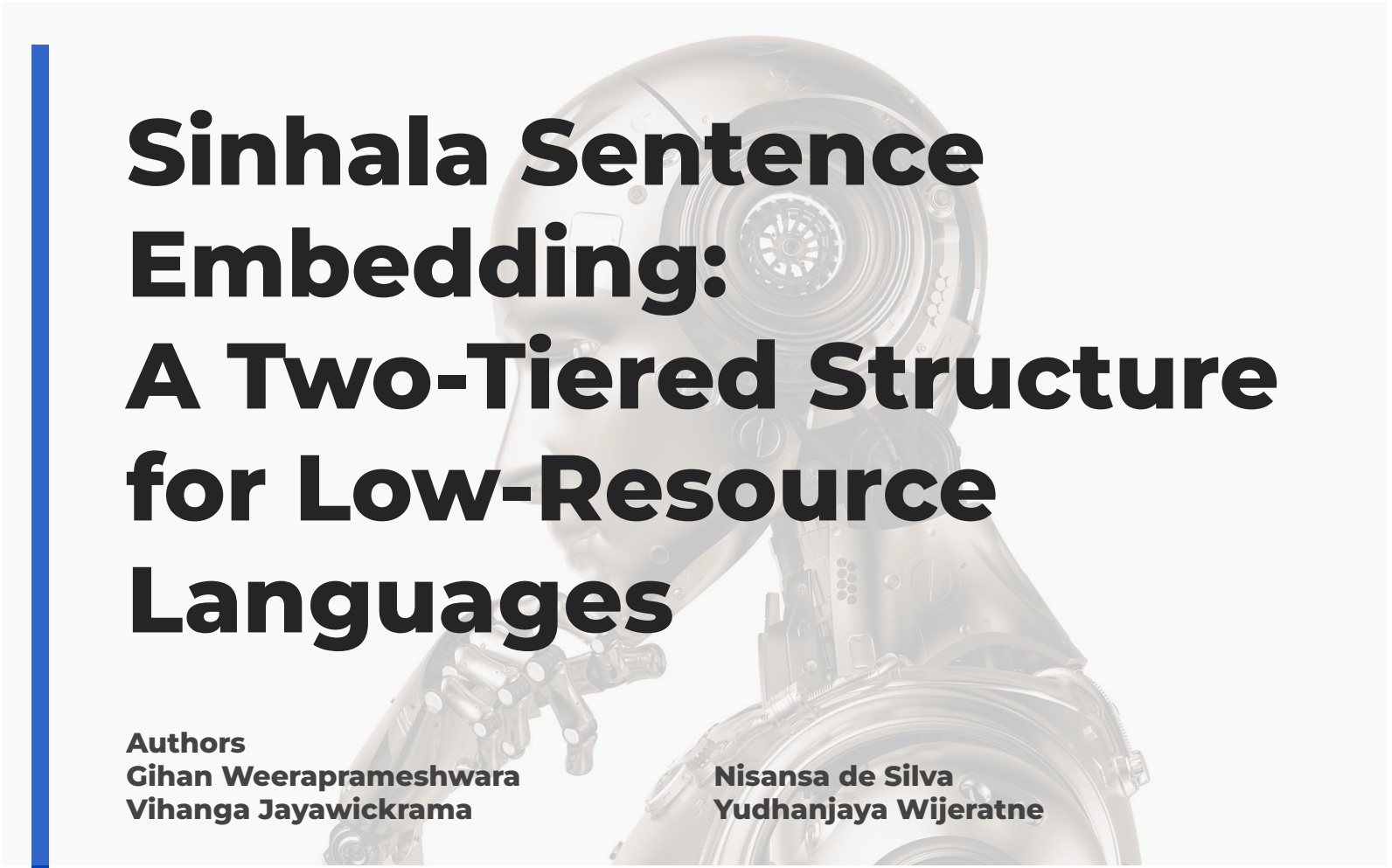
Sinhala Sentence Embedding: A Two-Tiered Structure for Low-Resource Languages



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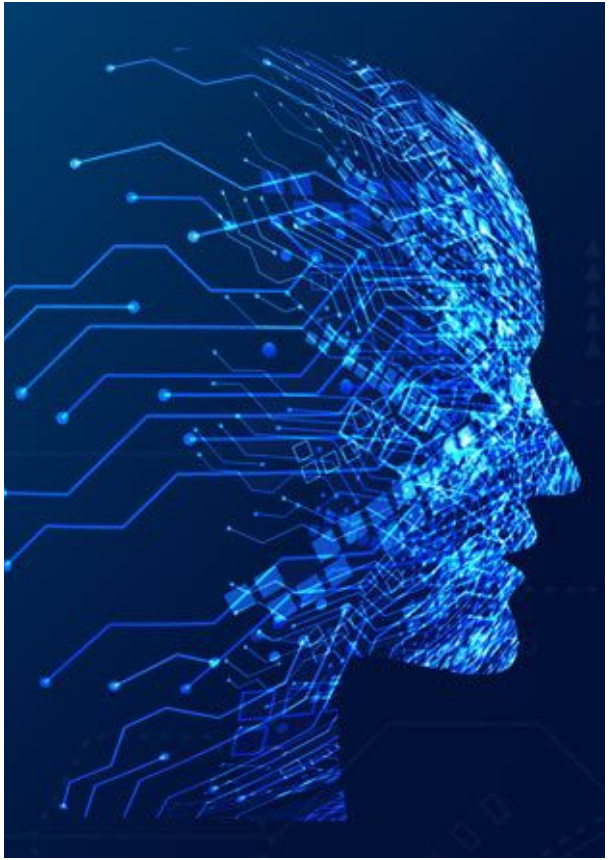
Outline

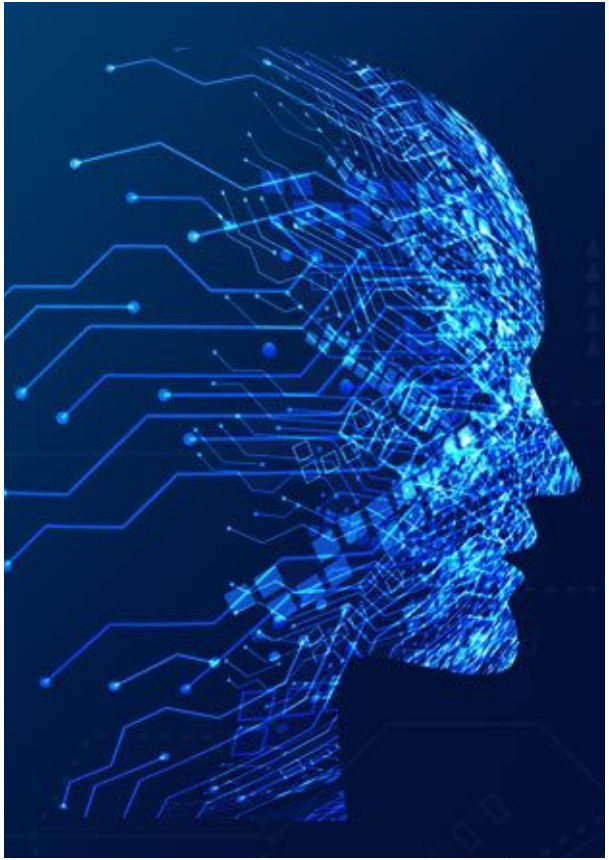
1. Problem
2. Solution
3. Related Work
4. Methodology
5. Results
6. Conclusion
7. Future Work

1. Problem



An efficient embedding structure for Sinhala ?

2. Solution



A two tiered embedding structure using word and sentence embeddings

Sinhala Colloquial Text

- Sinhala and English codemixed
- Any other language is excluded

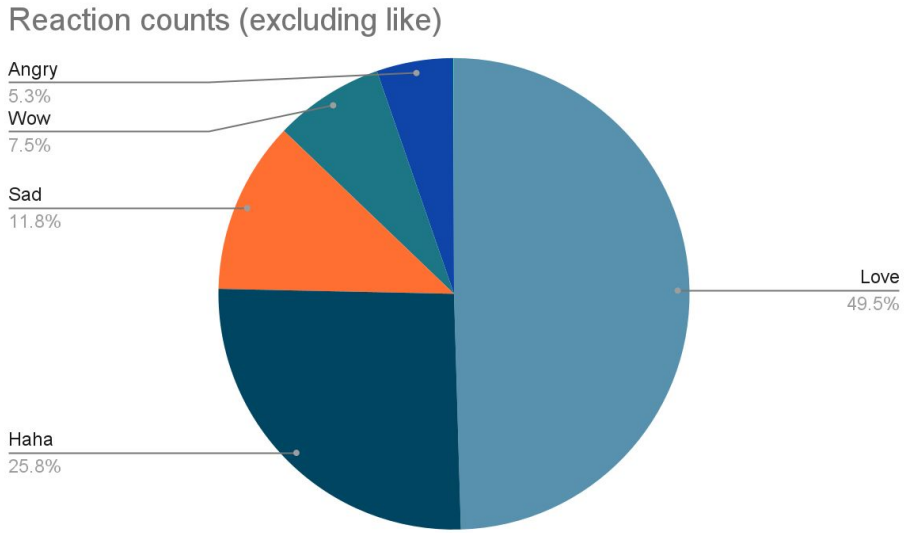
Using a Facebook dataset [1]

Using Facebook reactions as the annotations

[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.

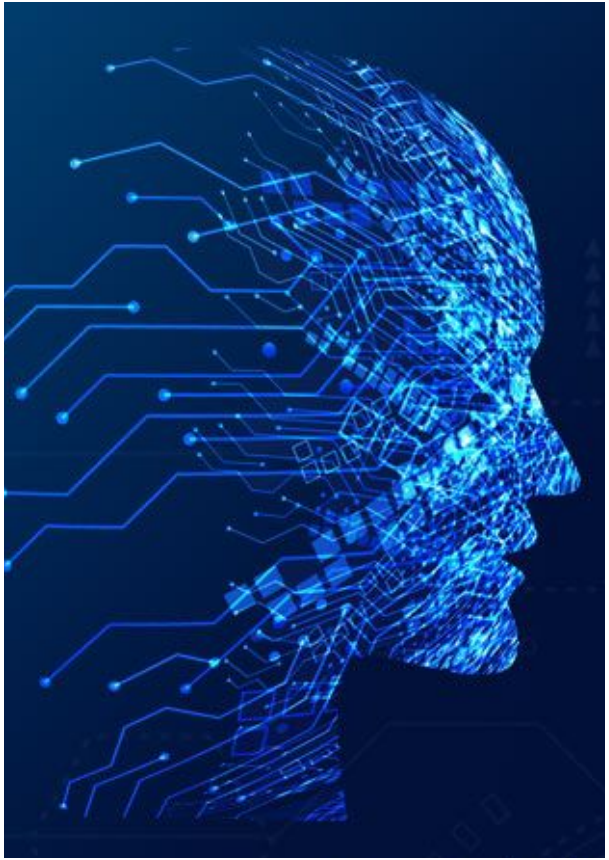
Dataset

- Developed by Yudhanjaya Wijerathne and 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



[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.

3. Related Work



- **Word embeddings**
  - FastText embeddings developed by P. Bojanowski et al. [2] and A. Joulin et al [3].
  - Word2Vec embeddings developed by T. Mikolov et al. [4]
  - Glove (Global Vectors) embeddings developed by J. Pennington et al. [5]

- **Sentence embeddings**
  - Seq2Seq model introduced by I. Sutskeve [6]
  - The modified version of the Seq2Seq model by K. Cho et al. [7] with the RNN units

[2] 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.
[3] A. Joulin, E. Grave, P. Bojanowski, and T. Mikolov, "Bag of tricks for efficient text classification,"arXiv preprint arXiv:1607.01759, 2016.
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- **Hyperbolic embeddings**
  - The work done by Q. Lu et al. [8] 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. [9] for learning hierarchical representations in hyperbolic space
  - Skip gram word embeddings in hyperbolic space introduced by M. Leimeister et al. [10]
  - Reinforcing the methods introduced by M. Nickel by the work of B. Dhingra et al. [11] on embedding text on hyperbolic space

[8] 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,” inProceedings of the10th ACM International Conference on Bioinformatics, Computational Bi-ology and Health Informatics, pp. 338–346, 2019
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[10] M. Leimeister and B. J. Wilson, “Skip-gram word embeddings in hyperbolic space,”arXiv preprint arXiv:1809.01498, 2018.
[11] 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.

- **Sinhala NLP research**
  - Survey on publicly available sinhala natural language processing tools and research by N. de Silva [12] to identify the advancements in Sinhala NLP
  - The model collection discussed by Senevirathne et al. [13] on sentiment analysis for sinhala language using deep learning techniques and the news comment dataset consists of 15000 data items
  - The research work of Jayawickrama et al.[14] to understand the Facebook dataset[1] and the sentiment mapping of Facebook reactions
  - The annotation method and the deep learning model used in this paper is taken from the work of G. Weeraprameshwara et al [15]

[12] N. de Silva, "Survey on publicly available sinhala natural language processing tools and research,"arXiv preprint arXiv:1906.02358, 2019.
[13] L. Senevirathne, P. Demotte, B. Karunanayake, U. Munasinghe, andS. Ranathunga, "Sentiment analysis for sinhala language using deep learning techniques," 2020.
[14] Vihanga Jayawickrama, Gihan Weeraprameshwara, Nisansa de Silva, and Yudhanjaya Wijeratne. 2021. Seeking sinhala sentiment: Predicting facebook reactions of sinhala posts. In 2021 21st International Conference on Advances in ICT for Emerging Regions (ICter), pages 177–182. IEEE.
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Reaction Mapping

- Positive reactions
  - Love, Wow
- Negative reactions
  - Sad, Angry
- Neglected reactions
  - Like, Thankful, Haha, Care

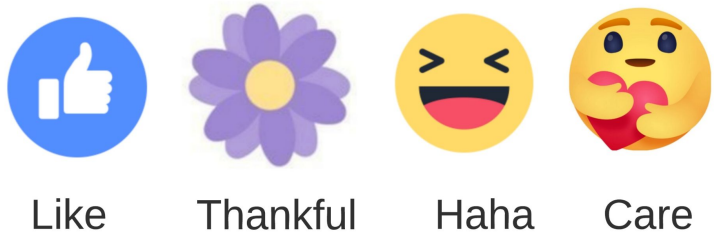
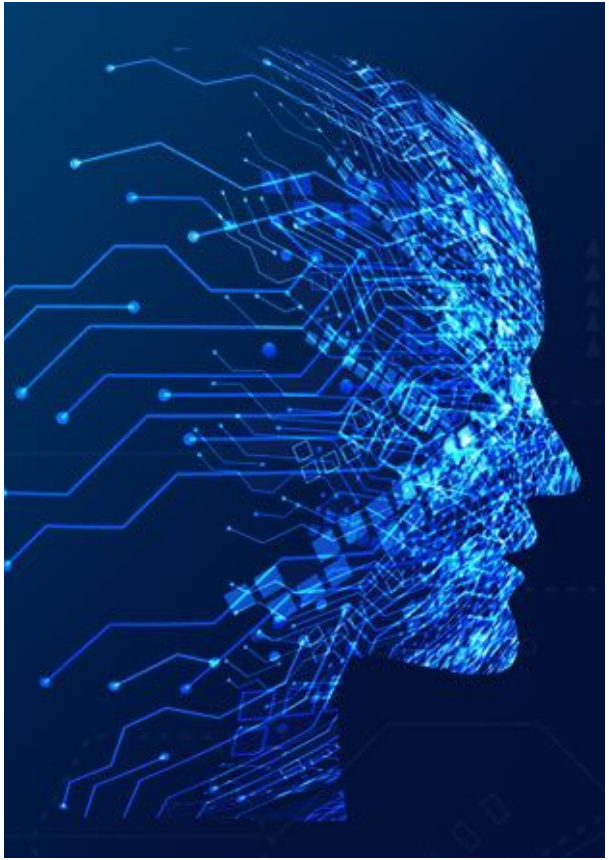
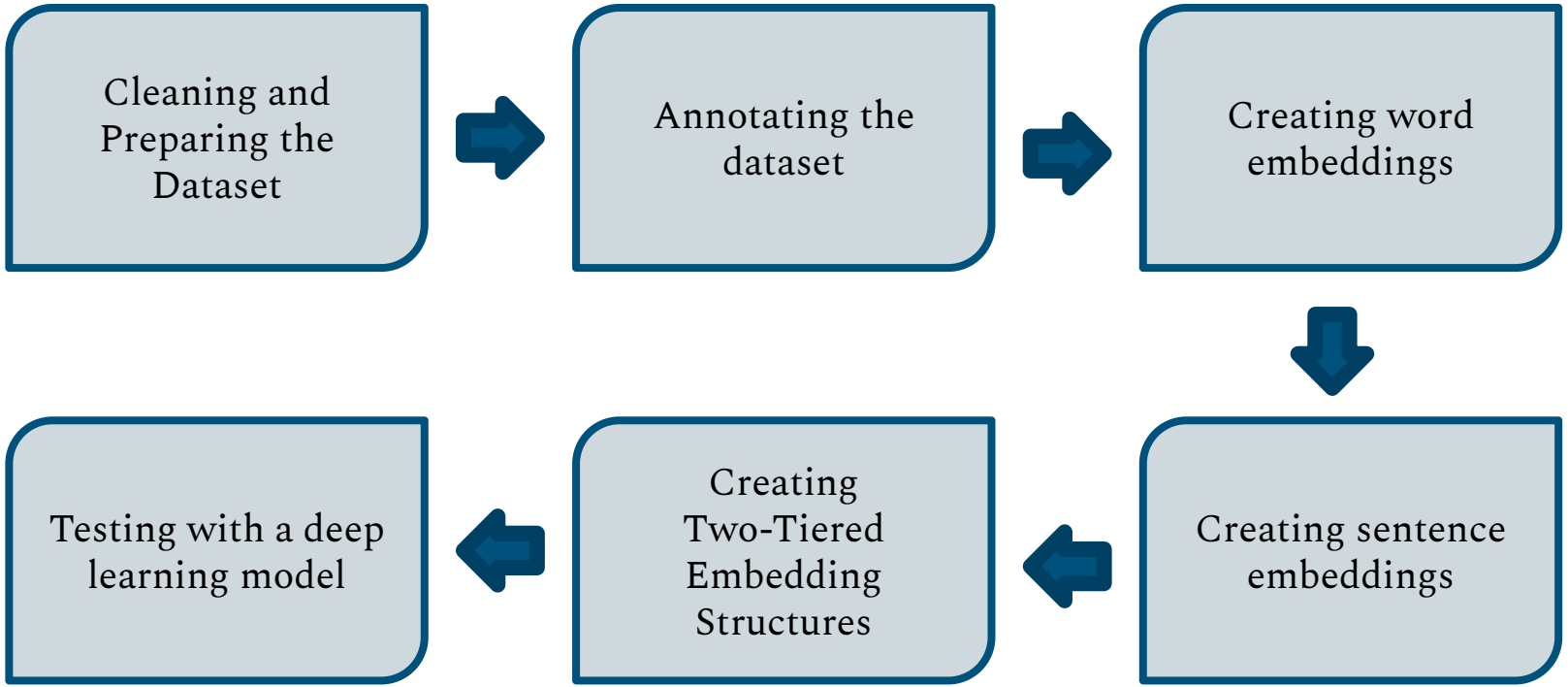


Figure: Reaction Annotation

4. Methodology



Walkthrough



Developing word embeddings for Facebook posts:

- FastText [16-17]
- Glove [18]
- Word2Vec [19]
- Poincar´e [20]

[16] 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.
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Developing sentence embeddings for Facebook posts:

- MaxPooling
- MinPooling
- AveragePooling
- Seq2Seq model [21]
  - with GRU [22] or LSTM [23] units
  - with or without an attention layer [24]

[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] 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.
[23] M. Schuster and K. K. Paliwal, “Bidirectional recurrent neural networks,”IEEE transactions on Signal Processing, vol. 45, no. 11, pp. 2673–2681, 1997.
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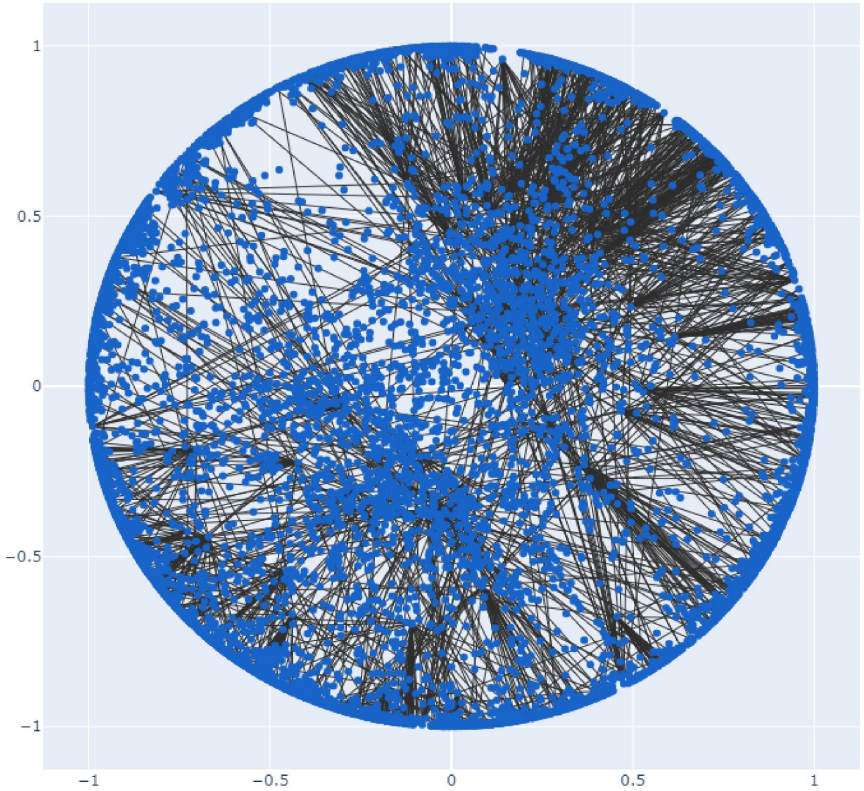


Figure: Poincar´e embeddings illustrations

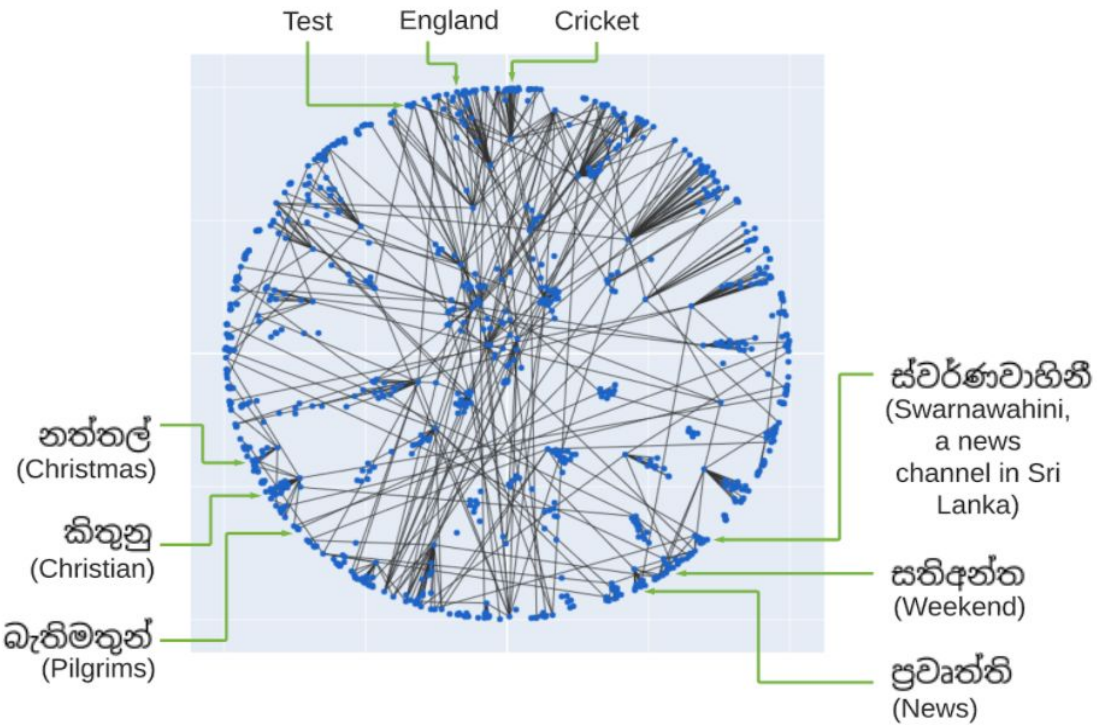


Figure: Poincar´e embeddings illustrations

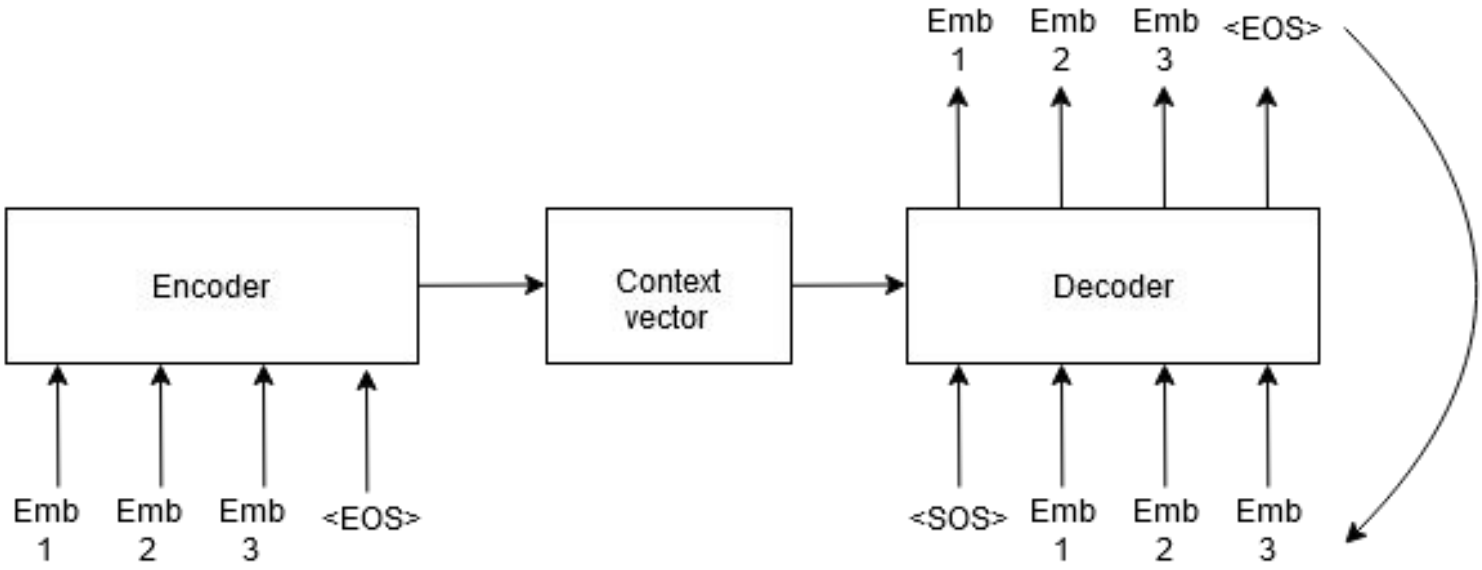
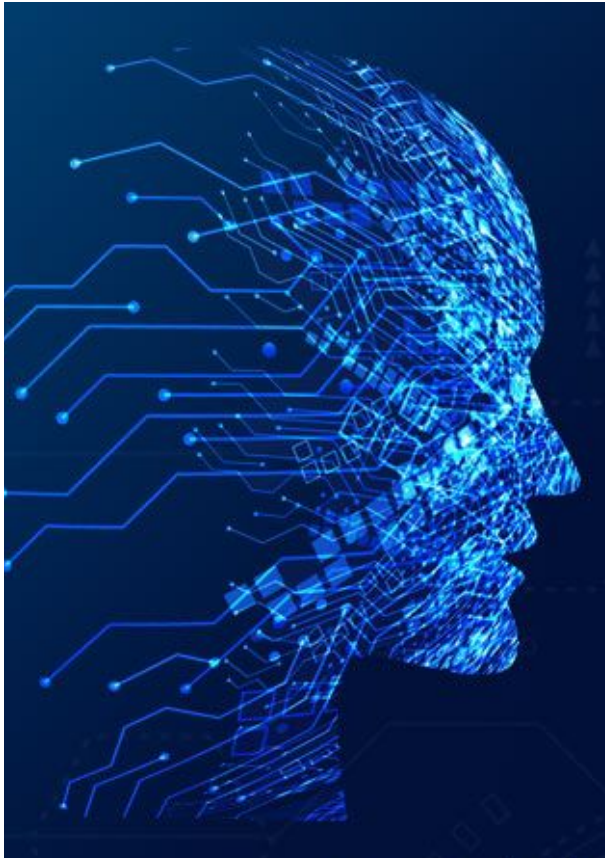


Figure: Two tier embeddings with Seq2seq model

5. Results



Word Embedding	F1 Score
fastText (Sinhala News comments) [13]	81.37
fastText [16-17]	**83.76**
Glove [18]	82.28
Word2Vec [19]	83.56
Hyperbolic [20]	82.84

[13] L. Senevirathne, P. Demotte, B. Karunanayake, U. Munasinghe, andS. Ranathunga, "Sentiment analysis for sinhala language using deep learning techniques," 2020.
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Word Embedding	Sentence Embedding	F1 Score
Word2Vec	Avg Pooling	87.01
	Seq2seq [21] GRU [22]	85.75
	Seq2seq [21] GRU [22] + Attention [24]	**87.29**
	Seq2seq [21] LSTM [23]	86.01
	Seq2seq [21] LSTM [23] + Attention [24]	86.53
Glove	Max Pooling	**86.22**
	Seq2seq [21] GRU [22]	85.16
	Seq2seq [21] GRU [22] + Attention [24]	85.12
	Seq2seq [21] LSTM [23]	85.16
	Seq2seq [21] LSTM [23] + Attention [24]	85.12

[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] 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.
[23] M. Schuster and K. K. Paliwal, "Bidirectional recurrent neural networks,"IEEE transactions on Signal Processing, vol. 45, no. 11, pp. 2673–2681, 1997.
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Word Embedding	Sentence Embedding	F1 Score
fastText	Avg Pooling	87.93
	Seq2seq [21] GRU [22]	86.23
	Seq2seq [21] GRU [22] + Attention [24]	**88.04**
	Seq2seq [21] LSTM [23]	86.60
	Seq2seq [21] LSTM [23] + Attention [24]	87.72
Hyperbolic	Max Pooling	85.77
	Seq2seq [21] GRU [22]	86.13
	Seq2seq [21] GRU [22] + Attention [24]	**86.54**
	Seq2seq [21] LSTM [23]	85.81
	Seq2seq [21] LSTM [23] + Attention [24]	86.30

[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] 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.
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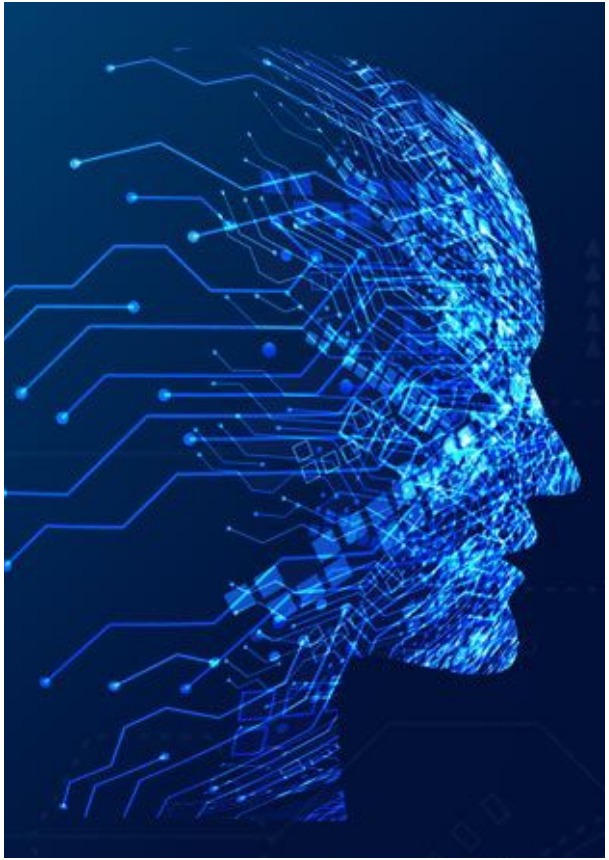
Significance of the Outcome

- **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

6. Conclusions



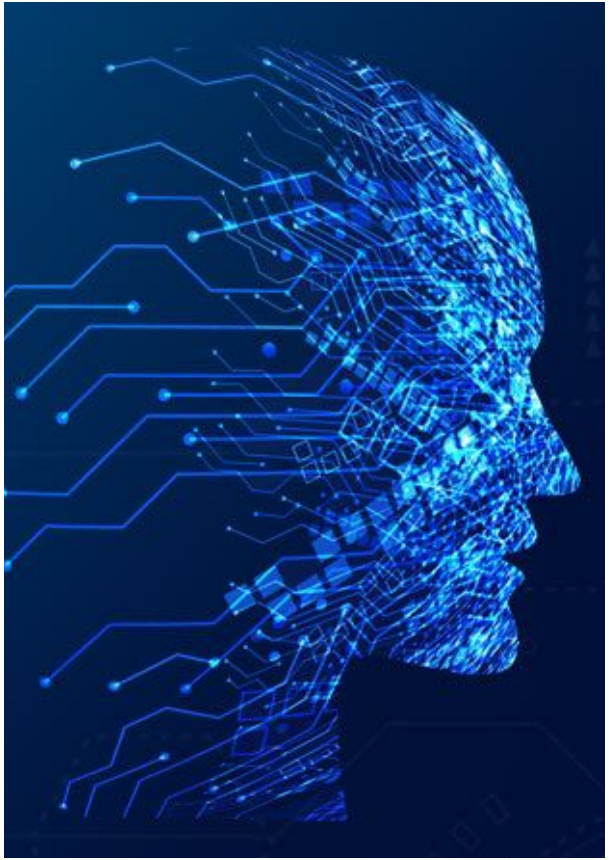
- **Introducing a two tier architecture is more efficient than relying on simple word embedding architecture**

- **fastText word embedding combined with sentencer embedding structure of Seq2seq model with GRU and attention layers can be identified as the best performing model**

- **Hyperbolic embedding does not surpass fastText and Word2Vec embeddings due to not having a proper parser**

- **Glove embeddings lacks the performance due to not having a proper pre-trained Glove model for Sinhala language**

7. Future Work



- **A parser that is customized for Sinhala language which can help for hyperbolic embedding**
- **Developing a well trained Glove model for Sinhala language**
- **Pure Sinhala embeddings instead of Sinhala-English codemixed embedding**
- **Testing the embeddings with different deep learning models an the use of transformer models**
- **Testing the embeddings with external databases**

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

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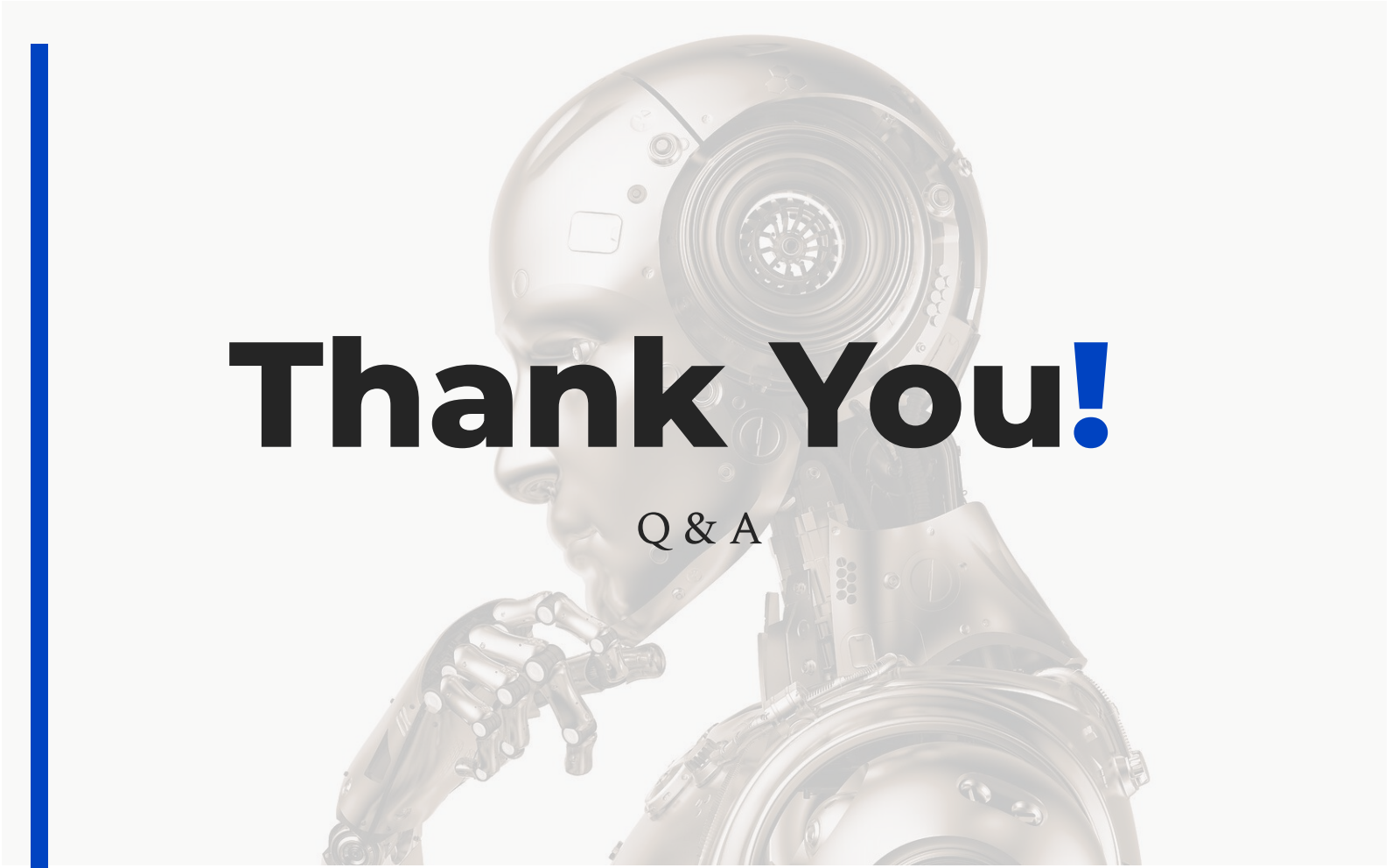

Thank You!

Q & A