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BMIRTE: Design of a Bioinspired Model for Improving Readability of Translated Sentences via Ensemble Operations

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Abstract: Sentence readability is determined via multiple metrics that include, Flesch Reading Ease, Fog Scale, Flesch-Kincaid Grade Levels, Smog Index, Coleman-Liau Index, Automated Readability Index, Dale-Chall Readability Score, Linear Write Formula, and their consensus. But individual use of these models results in uncertain sentence structures, which limits their usability levels. Moreover, scanning through every combination of these techniques to generate fused readability models is impractical and highly complex under real-time scenarios. To overcome these limitations, this text proposes design of a novel Bioinspired Model for Improving Readability of Translated Sentences via Ensemble Operations. The proposed model initially collects a set of translated texts, and applies stochastic ensemble readability testing via Genetic Algorithm (GA) based process. Due to use of stochastic modelling, the proposed optimizer is capable of identifying corpus specific readability evaluation techniques, that can be used to improve overall readability of multiple sentence types. To perform this task, a readability-based fitness function was evaluated, which assisted in identification of optimum ensemble operations. The model also tracks iterative performance levels of different ensemble combinations, which assists in incrementally improving real-time readability performance for different corpus types.The proposed model was evaluated on multiple translated corpuses, and it was observed that the proposed model outperformed various state-of-the-art methods in terms of readability accuracy, precision, recall, computational delay and memory requirement metrics. Due to which, it was observed to be capable of deployment for a wide variety of real-time post-processing scenarios for translated-texts.

Keywords: *Readability, Bioinspired, Corpus, Accuracy, Precision, Recall, Delay, Ensemble, Operations*

1. Introduction

Improving a sentence's readability is accomplished through the use of a specialized application for language processing called sentence readability improvement. This application requires the intelligent organization of translated words in order to achieve higher levels of translation efficiency. In order to accomplish this task, researchers have proposed a wide variety of models, and each of these models aims to optimize the readability scores of an ensemble by rearranging the words in the ensemble. Figure 1 depicts a model that is typical in that it uses a combination of multiple readability metrics [1]. The results of the readability metrics are manually processed by understanding the levels of different users. These findings are then put to use to continuously replace words using context-specific datasets, which subsequently makes it possible to continuously optimize readability. The translated texts are then subjected to additional analysis in search of areas for improvement. In the event that temporal improvements are spotted in peak patterns, the peak values of readability configurations will be used for performance optimizations. In the event that this is not the case, the process of shuffling will be repeated until peaks are observed in various readability indices.

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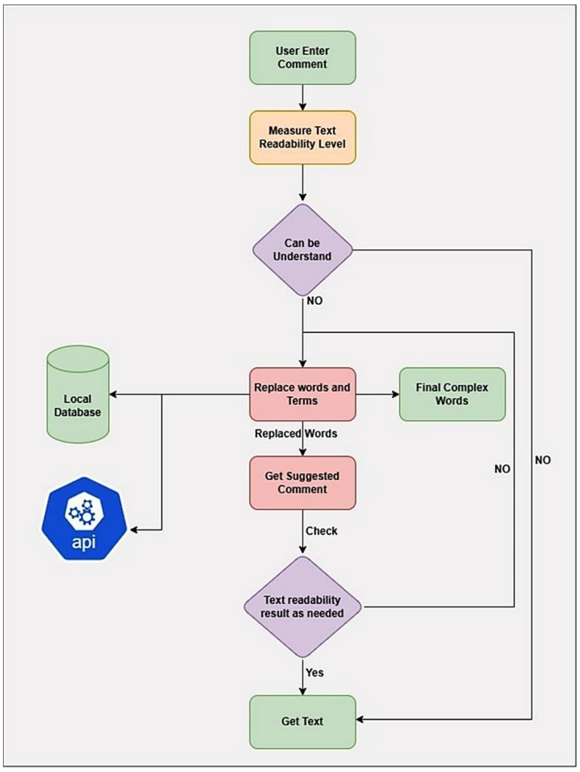

Fig 1. Design of a typical readability improvement model via continuous optimizations

Similar models are proposed by researchers, and each of them varies in terms of their internal performance characteristics. A discussion about such models [2, 3, 4] in terms of their context-specific nuances, functional advantages, application-specific limitations, and deployment-specific future scopes is discussed in the next section of this text. This discussion led to the observation that the individual use of these readability metrics results in uncertain sentence structures, which restricts their applicability. Additionally, it is impractical and extremely difficult to generate fused readability models by combing through every possible combination of these techniques in real-time scenarios. Section 3 suggests creating a novel Bioinspired Model for Improving Readability of Translated Sentences via Ensemble Operations to get around these drawbacks. The proposed model first compiles a set of translated texts and then uses a Genetic Algorithm (GA)-based process for stochastic ensemble readability testing. The proposed optimizer can identify corpus-specific readability evaluation techniques that can be used to enhance the overall readability of various sentence types thanks to the use of stochastic modeling. A readability-based fitness function was assessed to complete this task, which helped in identifying the best ensemble operations. The model keeps track of the levels of iterative performance of various ensemble combinations, which helps to gradually enhance real-time readability performance for various corpus types. Section 4 evaluated the proposed model by comparing its accuracy, precision, recall, delay, and storage metrics to those of other state-of-the-art methods. This text concludes with some performance-specific observations about the suggested model as well as suggestions for ways to further improve it for a variety of use cases.

2. Literature Review

A wide variety of text translation models are proposed by researchers, and each of them vary in terms of their internal characteristics. For instance, work in [5, 6] proposes use of text invariance, and Convolutional Neural Network with Bidirectional Long Short-Term Memory (CNN BiLSTM), which assists in extraction of multimodal feature sets for identification of high efficiency translations. But these models are not scalable, and thus cannot be used for larger datasets. To overcome this issue, work in [7] proposes use of Pre-Trained Word Embedding with Language Models that improves translation performance for large-scale use cases. Similar models are discussed in [8, 9, 10], wherein researchers have proposed use of Transformer-based Translator Model (TTM), simplified conversions, and machine learning, that assists in improving translation performance under different use cases. Extensions to these models are discussed in [11, 12, 13], wherein threshold-based translation, Term-Level Comparisons view (TLC), and transformer models to represent texts into multimodal feature sets. These sets are classified via an integration of convolutional networks with linear classifiers for optimum performance under real-time conversation dataset samples.

Models that use Connectionist Text Proposal Network (CTPN) [14], Cross-Modal Reranking [15], Text Simplification (TS) [16], Neural Transformers [17], Bidirectional Encoder Representations fromTransformers (BERT) [18], Non-Autoregressive Neural Machine Translation (NANMT) [19], and Deep Learning techniques [20], are also discussed by researchers. These models are not directly used for translations, but can be extended to this application via internal reconfigurations. Work in [21, 22, 23, 24] proposes use of Adaptive Adapters (AA), Generative Adversarial Network (GAN), Multi-Stage Information Interactions, and Sentence-Level

Agreement Architecture, which aim at integration of previously discussed methods and use them for translation use cases. Extensions to these models are discussed in [25, 26, 27, 28], which propose use of Convolutional Neural Network (CNN), Context-Aware Bidirectional Translation (CABT), Graph Convolution Network (GCN), and fused deep learning methods, that aim at enhancing performance of translation for large-scale data sample sets. Work in [29, 30, 31] also proposes use of Teacher-Free Knowledge Distillation, and regular expression analysis, which aims at improving translation performance under different use cases. But individual use of these models results in uncertain sentence structures, which limits their usability levels. Moreover, scanning through every combination of these techniques to generate fused readability models is impractical and highly complex under real-time scenarios. To overcome these limitations, next section of this text proposes design of a novel Bioinspired Model for Improving Readability of Translated Sentences via Ensemble Operations. The proposed model was also evaluated under different use cases.

3. Design of the proposed Bioinspired Model for Improving Readability of Translated Sentences via Ensemble Operations

The review of existing models reveals that individual use of these models leads to ambiguous sentence structures, which restricts their levels of usability. Additionally, it is impractical and extremely difficult to generate fused readability models by combing through every possible combination of these techniques in real-time scenarios.

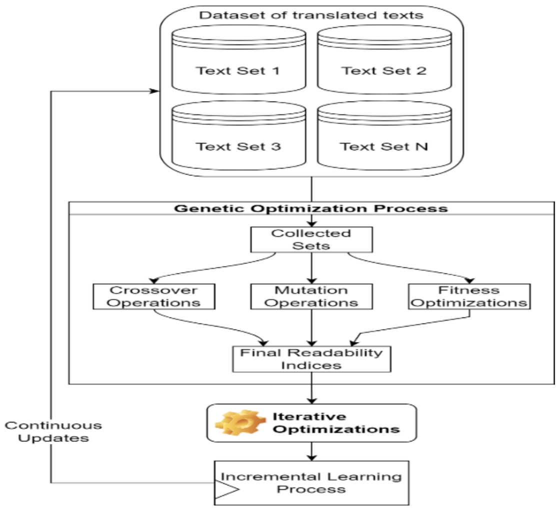

Fig 2. Overall flow of the proposed translation process

This section of the text suggests the design of a novel Bioinspired Model for Improving Readability of Translated Sentences via Ensemble Operations to get around these limitations. The proposed model first gathers a set of translated texts and then uses stochastic ensemble readability testing via a Genetic Algorithm (GA) based process, as shown in the model's flow diagram in figure 2. The proposed optimizer can identify corpus-specific readability evaluation techniques that can be used to enhance the overall readability of various sentence types thanks to the use of stochastic modelling. A readability-based fitness function was assessed to complete this task, which helped in identifying the best ensemble operations. The model keeps track of the levels of iterative performance of various ensemble combinations, which helps to gradually enhance real-time readability performance for various corpus types.

The model initially collects large datasets that contain different translated texts. These texts are individually processed by a Genetic Algorithm, which works via the following process,

- To initiate the optimization process, setup following Genetic Algorithm parameters,
  - Genetic Algorithm iterations needed during optimization (N_i)
  - Total solutions which will be optimized during these iterations (N_s)
  - Rate at which the model will learn from itself (L_r)
  - Total number of words present in the translated sentence (Nw)
- Find the fitness score for the translated sentence via equation 1,

$$f_{ref} = FL(S) + FG(S) + SM(S) + CL(S) + AR(S) + GF(S) \dots (1)$$

Where, FL represents Flesch Reading Scale which is evaluated via equation 2, FG represents Flesch Kincaid Grade levelswhich is evaluated via equation 3, SM represents SMOG readability levelwhich is evaluated via equation 4, CL represents Coleman-Liau indexwhich is evaluated via equation 5, AR represents automated readability indexwhich is evaluated via equation 6, GF represents Gunning Fog index which is evaluated via equation 7 for given input sentence sets.

$$FL(S) = 206.835 - 1.015 * \left(\frac{NW}{NS}\right) - 84.6\left(\frac{NSyl}{NW}\right) \dots (2)$$

$$FG(S) = 0.39 * \left(\frac{NW}{NS}\right) + 11.8 * \left(\frac{NSyl}{NW}\right) \dots (3)$$

$$SM(S) = 1.043 * \sqrt{NPW * \frac{30}{NS}} + 3.1291 \ldots (4)$$

$$CL(S) = 0.0588 * L(100) - 0.296 * S(100) - 15.8 \ldots (5)$$

$$AR(S) = 4.71 * \left(\frac{NC}{NW}\right) + 0.5 * \left(\frac{NW}{NS}\right) - 21.43 \ldots (6)$$

$$GF(S) = 0.4 * \left[\frac{NW}{NS} + 100 * \frac{NCW}{NW}\right] \ldots (7)$$

Where, $NW, NS, NSyl, NPW, NC$ & NCW represents number of words in the input sentence, number of sentences, number of syllables in the sentence, number of polysyllabic words, number of characters, and number of complex words, while $L(100)$& $S(100)$ represents average number of characters per 100 words, and average number of sentences per 100 words.

- Initially, generate N_s different solutions as per the following process,
  - Stochastically shuffle words in the sentence and evaluate new fitness of the solution via equation 1, as per the conditions in the equation 8,

$$f_{new} > f_{ref} \ldots (8)$$

  - If the condition is not valid, then regenerate new shuffled solutions.
- Generate N_s such solutions, and then estimate fitness threshold via equation 9,

$$f_{th} = \sum_{i=1}^{N_s} f_{new_i} * \frac{L_r}{N_s} \ldots (9)$$

- Mark all solutions with $f_{new} > f_{th}$ as 'Crossover', while mark others as 'Mutate' solutions
- Scan all solutions for N_i iterations, and regenerate all 'Mutate' solutions

At the end of all iterations, select solution with maximum fitness levels. This will ensure that readability score of the processed sentences is higher than the original translated sentence sets. The converted text is post-processed via incremental learning, which assists in continuous improvement in translation accuracy levels. This is done via the following process,

- From the converted text, perform reverse translation into the original language and compare with original text to evaluate learning score (LS) via equation 10,

$$LS = f(Original) - f(RT) \ldots (10)$$

Where, $f(Original)$& $f(RT)$ represents fitness scores of the original and reverse translated texts.

- If this score is positive, then re-evaluate the GA process, and obtain new translation solutions
- Else, use the solution and update it into the corpus

The process of updating will assist in continuously improving quality of the corpus, which will allow the model to achieve better results for future translations. Due to which, the accuracy of translation is improved under real-time use cases. Efficiency of this model was evaluated under multiple translation corpuses, and can be observed from the next section of this text.

4. Result analysis and comparison

The proposed model uses a combination of multiple readability score optimizations via Genetic Algorithm and uses an incremental learning model for continuous optimizations during text translations. To validate performance of this model, the following datasets were used,

- Phenomenon-wise Dataset for Machine Translation Robustness on User-Generated Contents or PheMT, which can be downloaded from https://github.com/cl-tohoku/PheMT
- A Large-Scale Multilingual Speech-To-Text Translation Corpus or CoVoST, which is available at https://github.com/facebookresearch/covost

Both sets had a total of 20k entries, which weresplit in a ratio of 75:25 such that 75% of the entries could be used for training the model, and remaining 25% of the entries could be used for testing &validating the model under a variety of different scenarios. Some of the examples of the proposed translations are mentioned as follows,

- *Input Sentence*: Hurry up and liberalize the import of cheese
  - *Modified Sentence*: Liberalize the import of cheese, hurry up!
- *Input Sentence*: Your dinner is so early you're going to get hungry
  - *Modified Sentence*: You're going to get hungry as your dinner is so early

The accuracy (A), precision (P), and recall (R) values for both datasets were used to assess the performance of the proposed model which are evaluated via equations 11, 12 and 13 as follows,

$$A = \frac{N_c}{N_t} \ldots (11)$$

$$P = \frac{N_c + N_{ci}}{N_t} \ldots (12)$$

$$R = \frac{N_{ci} + N_{cc}}{N_t} \ldots (13)$$

Where, N_c represents number of correctly translated words, while N_t represents total words that are to be translated, while N_{ci}&N_{cc} represents total words that are correctly translated but in incorrect position &

correct position respectively in the given text.The results were compared with those obtained from the CNN Bi LSTM [6], TTM [8], and TLC [12] models. This performance for translation may be assessed in terms of accuracy w.r.t. Number of Test Sentences (NTS) by looking at table 1, which compares results for PheMT evaluation input sets.

NTS	A (%) CNN Bi LSTM [6]	A (%) TTM [8]	A (%) TLC [12]	A (%) BMI RTE
1667	84.17	90.23	88.18	95.36
3333	84.36	91.07	88.44	95.83
5000	84.56	91.87	88.70	96.28
6667	84.75	92.67	88.95	96.73
8333	84.95	93.51	89.21	97.20
10000	85.14	94.35	89.46	97.66

Table 1. Results of accuracy for PheMTclassifications

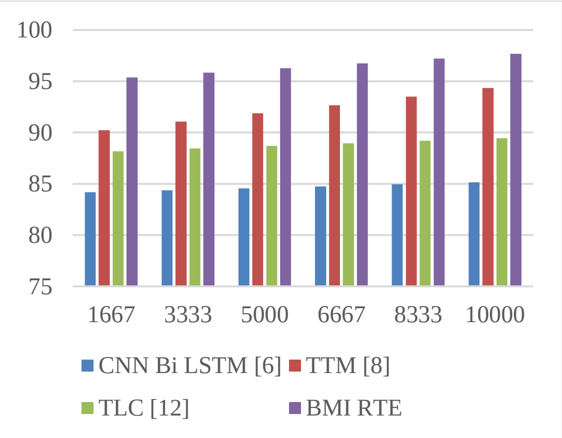

Fig 3. Results of accuracy for PheMT classifications

Based on this evaluation on different sentence sets and figure 3, it can be observed that the proposed model showcases 10.5% better accuracy than CNN Bi LSTM [6], 3.2% higher accuracy than TTM [8], and 8.3% higher accuracy than TLC [12] in terms of average performance levels. This is due to integration of multiple readability metrics and their optimization via Genetic Algorithm, which assisted in improving overall performance under different use cases. Similarly, precision for the PheMT dataset can be observed from table 2 as follows,

NTS	P (%) CNN Bi LSTM [6]	P (%) TTM [8]	P (%) TLC [12]	P (%) BMI RTE
1667	83.18	83.07	78.27	88.79
3333	83.65	85.33	80.75	90.68
5000	84.08	87.72	83.23	92.61
6667	84.49	90.18	85.69	94.54
8333	84.82	92.26	87.59	96.11
10000	85.10	93.94	88.93	97.30

Table 2. Results of precision for PheMTclassifications

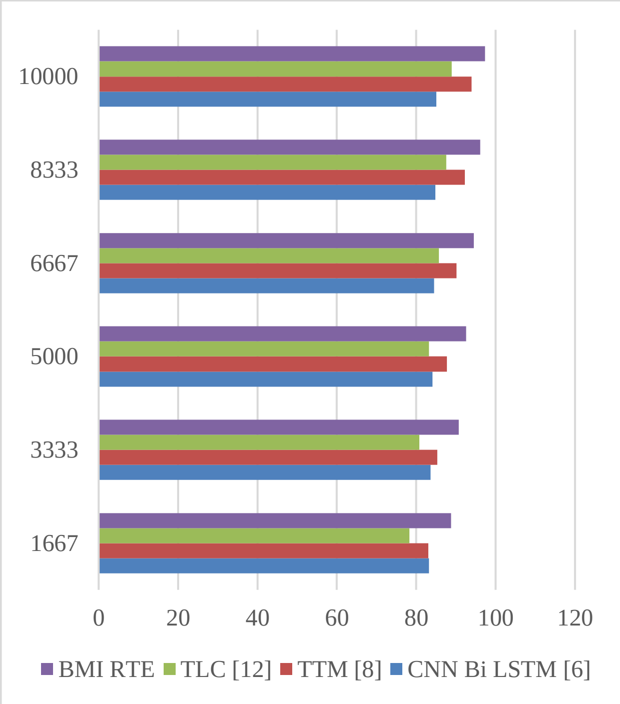

Fig 4. Results of precision for PheMT classifications

Based on this analysis of various sentence sets and Figure 4, it can be seen that the proposed model exhibits average performance levels that are 12.4% more precise than CNN Bi LSTM [6], 3.5% more precise than TTM [8], and 8.5% more precise than TLC [12]. This is because multiple readability metrics were integrated with incremental learning, and their optimization using genetic algorithms helped to improve overall performance for various use cases. Similar to this, table 3's recall data for the PheMT dataset can be seen as follows,

NTS	R (%) CNN Bi LSTM [6]	R (%) TTM [8]	R (%) TLC [12]	R (%) BMI RTE
1667	88.16	91.24	77.90	93.39
3333	87.51	91.68	80.50	94.27
5000	86.85	92.24	83.07	95.17
6667	86.15	92.88	85.59	96.08
8333	85.66	93.60	87.54	96.87
10000	85.39	94.38	88.91	97.56

Table 3. Results of recall for PheMTclassifications

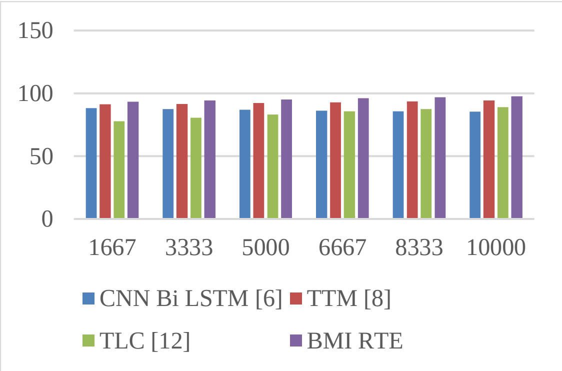

Fig 5. Results of recall for PheMT classifications

According to this analysis of the various sentence sets and Figure 5, the proposed model exhibits average performance levels that are 9.5% higher recall than CNN Bi LSTM [6], 2.4% higher recall than TTM [8], and 7.5% higher recall than TLC [12]. This is because multiple readability metrics have been integrated with incremental learning and continuous optimizations, and their optimization through genetic algorithms has helped to improve overall performance under various use cases. Similar to that, table 4 shows the accuracy for the CoVoST dataset as follows,

NTS	A (%) CNN Bi LSTM [6]	A (%) TTM [8]	A (%) TLC [12]	A (%) BMI RTE
1667	84.20	89.70	88.31	95.22
3333	84.38	91.19	88.55	95.91
5000	84.57	92.33	88.78	96.47
6667	84.76	93.17	89.00	96.93
8333	84.95	93.86	89.23	97.33
10000	85.15	94.50	89.47	97.72

Table 4. Results of accuracy for CoVoSTclassifications

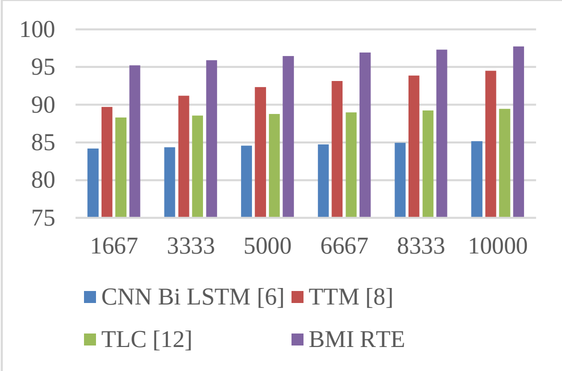

Fig 6. Results of accuracy for CoVoST classifications

Based on this analysis of various sentence sets and Figure 6, it can be seen that the proposed model exhibits accuracy levels that are on average 10.4% higher than CNN Bi LSTM [6], 3.2% higher than TTM [8], and 7.4% higher than TLC [12]. This is because different readability metrics are combined by a genetic algorithm, which helps to improve performance across a range of use cases. Similar to that, table 5 shows the precision for the CoVoST dataset as follows,

NTS	P (%) CNN Bi LSTM [6]	P (%) TTM [8]	P (%) TLC [12]	P (%) BMI RTE
1667	80.33	85.31	84.70	90.92
3333	81.38	87.07	85.74	92.31
5000	82.44	88.95	86.77	93.75
6667	83.49	90.91	87.80	95.21
8333	84.32	92.62	88.63	96.43
10000	84.93	94.05	89.27	97.41

Table 5. Results of precision for CoVoSTclassifications

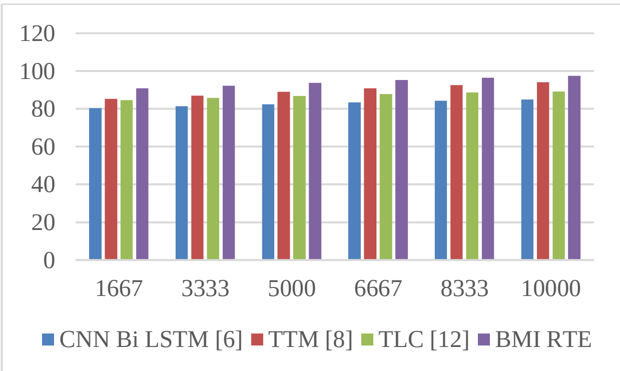

Fig 7. Results of precision for CoVoST classifications

According to this analysis of various sentence sets and Figure 7, it can be seen that the proposed model exhibits average performance levels that are 9.4% more precise than CNN Bi LSTM [6], 2.8% more precise than TTM [8], and 6.5% more precise than TLC [12]. This is because different readability metrics are combined by a genetic algorithm, which helps to improve performance across a range of use cases. Similar to that, table 6 shows the recall for the CoVoST dataset as follows:

NTS	R (%) CNN Bi LSTM [6]	R (%) TTM [8]	R (%) TLC [12]	R (%) BMI RTE
1667	87.53	86.49	84.50	93.89
3333	86.98	87.99	85.55	94.61
5000	86.43	89.61	86.62	95.39
6667	85.88	91.30	87.70	96.19
8333	85.51	92.82	88.58	96.92
10000	85.33	94.11	89.25	97.57

Table 6. Results of recall for CoVoSTclassifications

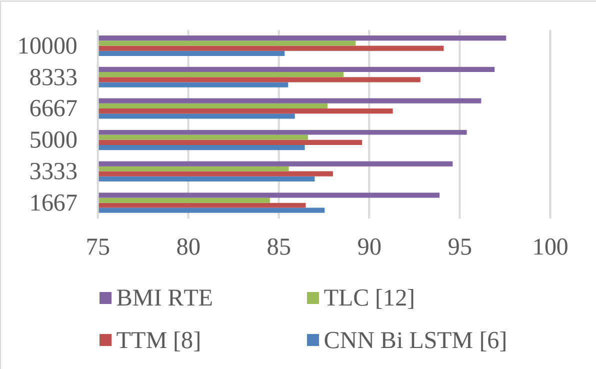

Fig 8. Results of recall for CoVoST classifications

Based on this analysis of the various sentence sets and Figure 8, it can be seen that, on average, the proposed model performs 12.3% better in recall than CNN Bi LSTM [6], 3.4% better than TTM [8], and 8.3% better than TLC [12]. This is because different readability metrics are combined by a genetic algorithm with incremental learning, which helps to improve overall performance for various use cases. These improvements enable the proposed model to enhance translation performance for various scenarios, making it suitable for real-time translation deployments.

5. Conclusion& Future Scope

The proposed model uses a combination of multiple readability indices with Genetic Algorithm and incremental learning in order to estimate correctly translated sentence sets. The model also uses reverse translations in order to continuously validate its performance and improve it via constant database updates. These operations result in the proposed model having average performance levels that are 10.5% higher than CNN Bi LSTM [6], 3.2% higher than TTM [8], and 8.3% higher than TLC [12] in terms of accuracy. This is a result of the combination of various readability metrics and the genetic algorithm's optimization of those metrics, which helped to enhance overall performance for various use cases. While the proposed model also achieves, in terms of average performance levels, 12.4% better precision than CNN Bi LSTM [6], 3.5% higher precision than TTM [8], and 8.5% higher precision than TLC [12]. This is because multiple readability metrics were integrated with incremental learning, and their optimization using genetic algorithms helped to improve overall performance for various use cases. In terms of consistency, the proposed model displays average performance levels that are 9.5% higher recall than CNN Bi LSTM [6], 2.4% higher recall than TTM [8], and 7.5% higher recall than TLC [12]. This is because multiple readability metrics have been integrated with incremental learning and continuous optimizations, and their optimization through genetic algorithms has helped to improve overall performance under various use cases. When compared to other sets, it was found that the proposed model exhibits accuracy levels that are on average 10.4% higher than CNN Bi LSTM [6], 3.2% higher than TTM [8], and 7.4% higher than TLC [12]. This is because different readability metrics are combined by a genetic algorithm, which helps to improve performance across a range of use cases. In terms of average performance levels, it also shows precision improvements of 9.4% over CNN Bi LSTM [6], 2.8% over TTM [8], and 6.5% over TLC [12]. This is because different readability metrics are combined by a genetic algorithm, which helps to improve performance across a range of use cases. While, in terms of average performance levels, the model achieves 12.3% better recall than CNN Bi LSTM [6], 3.4% higher recall than TTM [8], and 8.3% higher recall than TLC [12]. This is because different readability metrics are combined by a genetic algorithm with incremental learning, which helps to improve overall performance for various use cases. These improvements enable the proposed model to enhance translation performance for various scenarios, making it suitable for real-time translation deployments. In future, performance of the model must be validated on larger sets, and can be improved via integration of deep learning transformers, which allow the model to achieve better performance under different scenarios. Moreover, the model's performance can also be enhanced via deployment of hybrid bioinspired computing models, which assists in continuous parametric tuning for real-time deployments.

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