2023 IEEE 3rd Mysore Sub Section International Conference (MysuruCon)

Text Post-processing on Optical Character Recognition output using Natural Language Processing Methods

1st Thangam
Department of Computer Science and Engineering
Amrita School of Computing,
Amrita Vishwa Vidyapeetham,
Bengaluru, India
s_thangam@blr.amrita.edu

2nd Kumaran U
Department of Computer Science and Engineering
Amrita School of Computing,
Amrita Vishwa Vidyapeetham,
Bengaluru, India
u_kumaran@blr.amrita.edu

3rd Dipshikha Biswas
Department of Computer Science and Engineering
Amrita School of Computing,
Amrita Vishwa Vidyapeetham,
Bengaluru, India
dipshikha.biswas461@gmail.com

4th Sneha B
Department of Computer Science and Engineering
Amrita School of Computing,
Amrita Vishwa Vidyapeetham,
Bengaluru, India
snehabalaji74@gmail.com

5th Suneel Nadipalli
Department of Computer Science and Engineering
Amrita School of Computing,
Amrita Vishwa Vidyapeetham,
Bengaluru, India
nsuneel89@gmail.com

6th Saleem Raja
University of Technology and Applied Sciences,
Shinas Sultanate of oman
saleem.abdulsamad@shct.edu.om

2023 IEEE 3rd Mysore Sub Section International Conference (MysuruCon) | 979-8-3503-4035-8/23/$31.00 ©2023 IEEE | DOI: 10.1109/MysuruCon59703.2023.10396964

***Abstract*— The technique of turning images of printed or written text from scanned documents, images of documents, or simple photos into machine-encoded text is known as optical character recognition (OCR). OCR has proven to be very useful in terms of digitizing documents and making them easier to analyze. Despite the advancement in the technology since it was introduced, there are still areas OCR falls short. If either the written text is illegible, or the OCR software isn't powerful enough, it results in inaccurate translations. This research work aims at addressing this shortcoming by performing post-processing on OCR outputs primarily using Transformers such as BERT in a two-step pipeline to correct these mistakes and improve the quality of the document.**

***Keywords*— OCR, document processing, Transformers, BERT**

I. Introduction

Systems for optical character recognition (OCR) turn a scanned document or a picture into text encoded in characters. This technique divides a document image into character pictures in the linear reading order using image-analysis heuristics. An automatic classifier is then used to determine which character code most closely corresponds to each character image. These systems are still not flawless, though. The OCR algorithm occasionally wrongly identifies letters and incorrectly detects text that is scanned, resulting in misspellings as well as grammatical faults in the output text. As a result, there are frequent mistakes in the scanned texts. It seems sensible to look at how possible it is to automatically rectify such OCR results in this situation.

The majority of errors in the written text are spelling-related. As a result, spell checkers are widely used and a crucial component of many apps, such as messaging services, productivity and collaboration tools, and search engines. However, many effective spelling checkers are created by businesses and trained on vast amounts of confidential user data. Many publicly accessible off-the-shelf correctors, however, do not utilize the context of the misspelled word, as demonstrated by Enchant, GNU Aspell, and JamSpell.

In the context of spelling mistakes, there are different types and categories of errors. Cognitive errors refer to using pairs of homophones (words that sound the same but have different meaning and are spelt differently) in the wrong place. This refers to pairs such as peace-piece, pair-pear and bear-bare. The second type of error would be real-world errors, which is when an extra letter is added to or a letter is omitted from a word and the resulting word still exists in the dictionary. This most commonly occurs in the context of texting or hurried typing. Examples are tree-three, beat-beet, etc. In contrast to that, are non-word errors are when the resulting word isn't an English word. Finally, are short form or slang words. These refer to words born out of popular use on the internet, mostly among social media platforms. For example, "r" for "are", "kewl" for "cool", "str8" for "straight", etc. The work focuses on the first three types of errors.

Automated systems that can identify writing mistakes made by learners are useful tools for assessing and learning second languages. Error correction has received the majority of attention in recent years, with error detection performance being measured as a byproduct of the correction output. This is based on the idea that systems can come up with a fix for every fault they find, but accurate systems for fixing errors might not be the best for finding them in the first place.

Even without language modelling, LSTM models based on OCR offer greater performance in mistake correction. With better accuracy than previous language models and the added benefit of being language-independent, LSTM models hold great potential for application in language-independent OCR. Bidirectional Encoder Representations from Transformers (BERT), which is suggested in this paper, improves fine-tuning-based approaches. A "masked language model" (MLM) pre-training goal is how BERT gets over the unidirectionality restriction outlined before. The purpose of BERT's MLM (masked language model) is to, after randomly masking part of the tokens from the input, estimate the original vocabulary id of a masked word only based on its context. Unlike the left-to-right language model pre-training, the MLM goal allows the representation to incorporate the left and the right context, therefore a pre-trained a deep bidirectional Transformer is being used.

II. Related Work

The field of spelling error identification and correction has been extensively studied, leading to the development of various approaches and techniques. This section presents a review of related works in the domain of spelling error detection and correction.

In the work titled "NeuSpell: A Neural Spelling Correction Toolkit" [1], Jayanthi et al. introduce NeuSpell, an open-source spelling correction toolkit that employs neural models for spelling error detection and correction. The authors use a bi-LSTM network for error detection and BERT MLM for correction. This work emphasizes the importance of contextual representations in improving correction rates and introduces ten distinct models for evaluation.

"Semi-Character Recurrent Neural Network for Robust Word Recognition" by Sakaguchi et al. [2] explores the use of Semi-Character RNNs for non-contextual error correction. The authors propose a word recognition model based on a semi-character level RNN, highlighting its robust performance compared to existing character-based spell-checkers. However, this approach lacks context consideration, similar to NeuSpell.

Rei and Yannakoudakis present a study focused on error detection in learner writing in "Compositional Sequence Labeling Models for Error Detection in Learner Writing" [3]. They investigate various neural network architectures, including CNN, RNN, and LSTM, for error detection. The authors propose a bidirectional LSTM-based framework that outperforms competitors in identifying errors in learner writing. However, this work solely concentrates on detection and neglects correction.

Addressing language-specific challenges, "UTTAM: An Efficient Spelling Correction System for Hindi Language" [4] by Jain et al. introduces an end-to-end system for Hindi spelling correction. This system employs the Viterbi method and considers complex character sets and word inflections unique to Hindi. However, it faces limitations with out-of-vocabulary words and stop words. "Spelling Error Correction with Soft-Masked BERT" by Zhang et al. [5] combines Bi-GRU detection with soft-masked BERT correction, achieving promising results on a Chinese dataset. While leveraging BERT's language representation, this approach struggles with certain error types due to the limitations of BERT's pre-training methodology.

The utilization of Statistical Machine Learning (SMT) for OCR error correction is explored by Afli et al. in "Using SMT for OCR Error Correction of Historical Texts" [6]. This work addresses a wide range of OCR errors through translation models, achieving significant improvements. However, similar to other studies, it lacks the consideration of contextual information. Several works have significantly contributed to the development of spelling error correction techniques. "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding" [7] introduces BERT, a powerful pre-trained language model that has been instrumental in various NLP tasks. Similarly, "Attention Is All You Need" [8] proposes the Transformer architecture, which revolutionized NLP by emphasizing attention mechanisms over convolutions and repetitions.

Biswas et al. [9] propose a Natural Question Generation method utilizing Transformers and Reinforcement Learning. Their approach leverages machine learning techniques for generating contextually relevant questions. The paper by Sneha et al.[10] introduces a Speech Recognition system employing Weighted Finite-State Transducers. It focuses on improving accuracy and efficiency in speech recognition technology. Veena et al.[11] present a learning method for coreference resolution using semantic role labeling features. Their approach aims to enhance the resolution of references in natural language processing.

Venugopalan [13] and Gupta propose an enhanced guided LDA model augmented with BERT for aspect term extraction in sentiment analysis, focusing on improved topic identification. Mohan [14] and Kumar provide a comprehensive survey on Topic Modeling in Text Summarization, discussing various techniques and their applications in summarizing textual data.

Madi and Al-Khalifa [15] propose an Error Detection system for Arabic Text using Neural Sequence Labeling, focusing on improving accuracy in error detection in Arabic text. Huang, Xu, and Yu [16] introduce Bidirectional LSTM-CRF Models for Sequence Tagging, emphasizing the significance of bidirectional models in sequence labeling tasks. Ma and Hovy [17] present an End-to-end Sequence Labeling approach via Bi-directional LSTM-CNNs-CRF, highlighting the efficiency of their proposed model in sequence labeling tasks. Deng, Cheng, and Wang [18] propose a Self-attention-based BiGRU and capsule network for named entity recognition, focusing on enhancing the identification of named entities in text. Liu, Jin, Yang, Lv, Wang, and Chen [19] present an Attention-based BiGRU-CNN for Chinese question classification, focusing on improving the accuracy of classifying Chinese questions using attention mechanisms.

These papers cover a range of topics in natural language processing, including neural models like NeuSpell and semi-character RNNs to language-specific systems like UTTAM and broader approaches like BERT and the Transformer architecture, question generation, speech recognition, coreference resolution, attendance tracking, sentiment analysis, text summarization, error detection, sequence tagging, named entity recognition, and question classification. They highlight the application of various machine learning techniques, such as Transformers, LSTM, CNNs, and BERT, to improve different aspects of language processing tasks. While each approach contributes valuable insights, there remains a need to further explore context-aware correction techniques to enhance spelling error detection and correction accuracy.

Utilizing BiLSTM for error detection and BERT's Masked Language Model (MLM) for error correction in sentences in the methodology uses two of the most advanced tools in natural language processing. This work builds upon prior research by integrating the robust error detection capability of BiLSTM with the contextual understanding and language modeling capacity of BERT. By combining these techniques, the system can efficiently identify and rectify various types of errors, such as grammatical, syntactical, and semantic, within text. This integration enables a more comprehensive and accurate approach to enhancing the overall quality and fluency of text, reflecting a substantial step forward in the field of automated language refinement.

III. Theoretical Overview

A. *Bi-LSTM (Bidirectional Long Short-Term Memory)*

Bidirectional Long Short-Term Memory (BiLSTM) networks are a type of recurrent neural network (RNN) architecture used in spelling correction applications within natural language processing (NLP). BiLSTM networks are designed to capture contextual information from both past and future words in a sequence, making them effective for tasks like spelling error detection and correction. By processing input sequences in two directions, BiLSTM can model dependencies between words and their surrounding context, allowing it to identify and correct spelling errors based on the broader linguistic context.

B. *BiGRU (Bidirectional Gated Recurrent Unit)*

Bidirectional Gated Recurrent Unit (BiGRU) networks are another variant of recurrent neural networks employed in spelling correction tasks in NLP. Similar to BiLSTM, BiGRU networks can capture contextual information from both directions in a sequence. GRU units within BiGRU enable efficient modeling of sequential dependencies and are particularly useful for tasks involving long-range dependencies and context, such as detecting and correcting spelling errors by considering the surrounding linguistic context.

C. *BiRNN (Bidirectional Recurrent Neural Network)*

Bidirectional Recurrent Neural Networks (BiRNN) represent a broader category of architectures that encompass both BiLSTM and BiGRU networks. In the context of spelling correction within NLP, BiRNNs are employed to process input sequences bidirectionally, allowing them to capture contextual information from both past and future words. By utilizing the bidirectional nature of BiRNNs, spelling errors can be identified and corrected by considering the contextual cues provided by adjacent words, enhancing the accuracy of the spelling correction process.

D. *BERT MLM (Bidirectional Encoder Representations from Transformers Masked Language Modeling)*

Bidirectional Encoder Representations from Transformers (BERT) with Masked Language Modeling (MLM) is a state-of-the-art pre-trained language model widely utilized in spelling correction applications within natural language processing (NLP). BERT MLM is designed to understand the contextual relationships between words by predicting missing words in a sentence.

In the context of spelling correction, BERT MLM can identify and correct spelling errors by leveraging its comprehensive understanding of language patterns and contexts. By masking out certain words and predicting their correct forms, BERT MLM can effectively capture subtle linguistic nuances and contextually relevant corrections for accurate spelling error detection and correction.

E. *GloVe (*Global Vectors for Word Representation

Global Vectors for Word Representation (GloVe) is a widely used word embedding technique in natural language processing (NLP) that maps words into continuous vector spaces based on their co-occurrence statistics in large text corpora. While not a direct solution for spelling correction, GloVe embeddings play a crucial role in providing contextual information for spelling-related tasks. By capturing semantic relationships between words, GloVe embeddings enable spelling correction algorithms to understand word similarities, thereby aiding in identifying potential misspellings and suggesting appropriate corrections. These embeddings contribute to the enhancement of spelling correction accuracy by leveraging the semantic context of words within a sentence or text passage.

IV. Proposed Working principle and workflow

The work serves as a comparative study between 3 models for the task of detection, namely BiLSTM, BiGRU and BiRNN. Each of these models has their own architecture and was designed specifically for the task of error detection as a variation of text classification, one of the strong suites for each of these models.

Figure 1 presents a basic overview on the pipeline used to detect and correct OCR based errors in a sentence. This represents the three main phases involved in this process, that is – Dataset Building and Error Induction, Error Detection and finally Error Correction. The dataset used for this research work consists of the questions present in the benchmark SQuAD dataset and OCR -like error is induced into it. Using BiLSTM, BiGRU and BiRNN, a comparative study of detecting spelling errors is performed. BERT Masked Language Model is used to correct the detected misspelt word based on the context of the sentence. The final outputs are coherent sentences that have minimal misspelt errors.

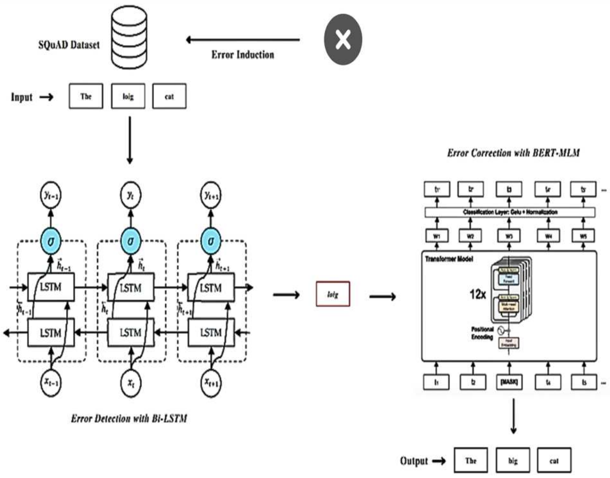

Fig. 1 General Workflow

A. *Dataset Building*

The SQuAD dataset contains data collected in a question-answer pair format, but for the said application in this particular project, only the questions present in the dataset are needed. Thus, a custom version of the SQuAD dataset is created containing only the questions. Further into the project, the main objective is to deal with the correction of Optical Character Recognition errors, thus given a percentage, the same amount of error is induced into the question. The errors induced are of letters that can be mistook as split or joined to give rise to other letter. Examples are "nn" – "m", "w" – "vv", "cl" – "d", etc.

B. Dataset Noise Induction

For the given dataset, noise is induced into the questions that were extracted. For the noise induction function, a percentage is first given and this represents the overall number of words where the error will be induced. The given number of words are selected at random from the entire corpus. These words are stored and error is induced into them. The error that is induced, is in the form of OCR. For example, if the word is 'clean', then the OCR error induction will make it 'dean' as clean and dean look interchangeable with illegible handwriting. Such type of joining of words or separation of words are common OCR errors.

C. Detection

The final dataset that has both noisy sentences as well as their corresponding clean sentences. Now, this problem is treated as supervised learning one, where each error is manually annotated. The error in each sentence is detected parallelly with the help of three neural network architectures:

- Bidirectional Long Short-Term Memory: The model is built using Keras' Sequential model classes and strings together each of the separate layers in a sequential and ordered manner. The first layer is an embedding layer to represent the words as a vector and in this case, these vectors are GLOVE 100-d vectors, which explain the output dimension of 100. Next is a Dropout layer with shutdown probability of 20%. This layer helps prevent over fitting by randomly shutting down neurons each epoch to push for uniform learning. The next 2 layers are both bidirectional layers to help with data flow in both directions. The model then has another dropout layer of 25% and finally a dense connected network to output probability for 2 classes: correct or incorrect.
- Bidirectional Gated Recurrent Unit: This is similar to the BiLSTM model except it differs in that it uses a BiDirectional class wrapper around the standard GRU class object. Just as with BiLSTM, the Softmax activation function is used in the final dense layer and the total number of parameters comes out to be close to 2 million.
- Bidirectional Recurrent Neural Network: Relying on the Sequential class once again, the model consists of an embedding layer, a dropout layer, two bidirectional layers wrapped around simple RNN layers, another Dropout layer and finally the fully connected dense layer with 2 nodes as the classification output.

These three architectures are analyzed in a comparative study manner and results are obtained accordingly.

D. Correction

The masked language model of BERT, can be helpful in correcting the detected misspelt word. This works in the following manner:

- The error that was detected by the Bidirectional Architecture is given a '[MASK]' token
- The sentence with the original words and the masked token is sent to BERT
- BERT uses its encoder-decoder architecture along with attention mechanism to decode the masked token
- It lists out five words in decreasing order of probability and the word with the highest probability is chosen
- This word replaces the [MASK] token in the sentence and thus, the corrected sentence is obtained as the output

V. RESULTS

A. Detection Network

For the purpose of this research work, a custom dataset was used, that comprised of all the questions present in the SQuAD dataset was used. All the models employed for this work, have been tried and tested on 13,016 sentences in the Google Colab environment.

The detection network consisted of the usage of three models, namely, BiLSTM, BiGRU and BiRNN studied in a comparative analysis manner. The word embedding of each sentence in the dataset is passed to each of these three models and that yields the sentence with a [MASK] token for all the incorrect words. The accuracies of each of these models are detailed in Table 1.

TABLE I. DETECTION MODEL RESULTS COMPARISON

Model	**Accuracy**
Bi-LSTM	98%
Bi-GRU	85.2%
Bi-RNN	85.1%

The models were made to run for around ten epochs while also including early stopping so as to prevent overfitting. Table 1 enumerates the 3 different models used for the detection part of the spelling task. As observed, BiLSTM outperformed the others by a huge margin of around 13%. This can be attributed to the bi-directional flow, the solved vanishing gradient problem and the hidden gates that learn to optimally control data flow. BiGRU, on the other hand, works well with smaller datasets and tends to oversimplify the relations and leading to lower accuracy. And finally, BiRNN suffers from vanishing gradient problem resulting in its slightly lower accuracy.

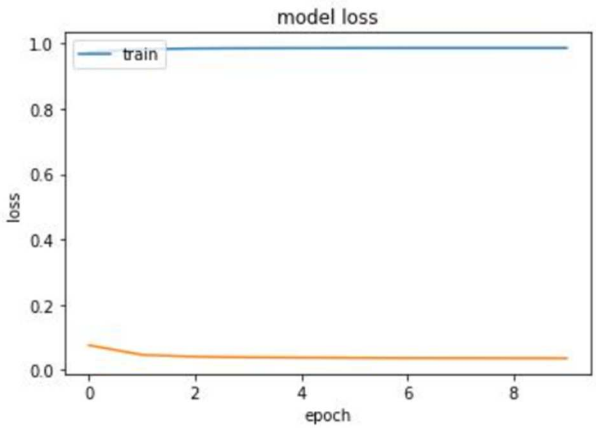

Fig. 2 Bi-LSTM Model loss v/s epoch

Figure 2 shows the changes in loss and accuracy for the best working model – BiLSTM. It can be observed that this model has a good accuracy and loss from the very beginning of training and continues to maintain the same throughout the rest of the epochs as well. It can thus be inferred that BiLSTM is a model that is well suited to the task of OCR spelling error detection.

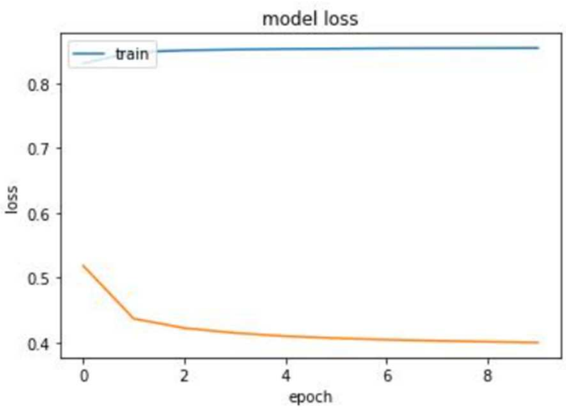

Fig. 3 Bi-GRU Model loss v/s epoch

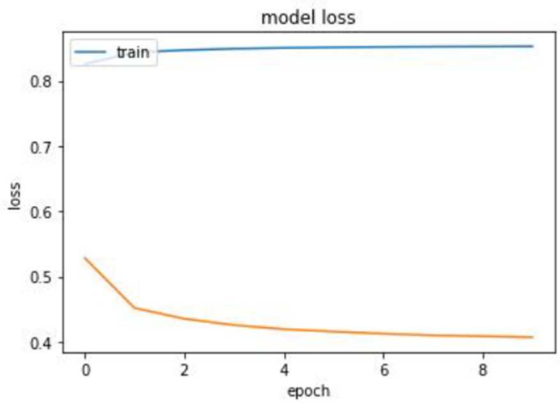

Fig. 4 Bi-RNN Model loss v/s epoch

Figure 3 and Figure 4 show the working of BiGRU and BiRNN respectively on the dataset. While the accuracies may be steady, it takes a few epochs to bring the loss down to a minimum.

B. Correction Network

The accuracy of BERT is 99.94%, the attention-based encoder-decoder mechanism helps focus on the context of a word in a given sentence and this improves the robustness and accuracy of the model. The model accepts a vector embedded sentence consisting of the MASK token in place of the misspelt word and predicts possible candidates to replace the token and selects the one with the highest score. This was done by fine-tuning a pretrained BERT model and has yielded a very high accuracy.

VI. CONCLUSION

Spelling error detection and correction, a crucial task within natural language processing, involves identifying and rectifying erroneous spellings in text. Its significance spans across applications such as text editing, text-to-speech synthesis, and machine translation, wherein accurate spelling profoundly impacts readability and precision. However, this task grapples with the intricate nature of human language. The presence of colloquialisms, abbreviations, and diverse linguistic expressions complicates the error identification process for spelling correction systems. Striking a balance is essential to minimize false positives, as undue corrections of correctly spelled words may disrupt the reader's comprehension.

In this project, an Optical Character Recognition (OCR) spelling error detection and correction system has been developed. It proficiently addresses spelling errors arising from the amalgamation of handwritten characters, often misinterpreted by OCR processes. The system first detects such errors and subsequently executes a rectification protocol, yielding accurately corrected words as output. Tailored variations of the Bi-LSTM, Bi-GRU, and Bi-RNN models are deployed for effective error detection. Meanwhile, the error correction stage leverages the potent BERT-MLM model to rectify identified mistakes.

Among the models, the custom-configured Bi-LSTM model showcases superior performance, boasting an impressive accuracy metric of 98%. Following suit, the Bi-GRU and Bi-RNN models yield respective accuracies of 85.2% and 85.1%. Additionally, the incorporation of BERT's attention-based encoder-decoder mechanism significantly elevates accuracy and robustness, making it an optimal choice for the error correction network. Notably, the BERT model attains an exceptional 99.94% accuracy rate when addressing OCR-induced spelling errors. This project seamlessly integrates advanced neural network architectures with BERT's context-focused correction prowess, culminating in a system for accurate and contextually-aware spelling error detection and correction.

VII. FUTURE SCOPE

The evolution of spelling error detection and correction through natural language processing (NLP) holds promising future directions. Research and development could focus on advancing machine learning algorithms, refining their accuracy and efficiency for intricate natural language text. The integration of Conditional Random Fields (CRFs), commonly used in sequence labeling tasks, might contribute to enhancing these algorithms.

The prospect of context incorporation is noteworthy. Future systems could leverage contextual cues from sentences or documents to enhance accuracy. Analyzing neighboring words to identify the correct spelling exemplifies this context-aware approach. Additionally, synergizing spelling correction with other NLP tasks like language translation, text classification, and information extraction could amplify system performance by mitigating the impact of spelling errors on outputs.

Extending the scope to new languages stands as a valuable avenue. Tailoring or creating spelling error detection and correction systems for diverse languages could broaden their applicability and effectiveness. Streamlining user interaction is another facet of progress, with potential integration into user-friendly interfaces like word processor spell checkers, simplifying error identification and rectification.

In sum, the field of NLP-driven spelling error detection and correction holds substantial untapped potential. Future advancements have the capacity to revolutionize various applications by fine-tuning machine learning, harnessing context, expanding linguistic inclusivity, and enhancing user interfaces. As these strides unfold, the impact on an array of domains is likely to be substantial.

REFERENCES

[1] Sai Muralidhar Jayanthi, Danish Pruthi, Graham Neubig, 'NeuSpell: A Neural Spelling Correction Toolkit', 2020, EMNLP.

[2] Keisuke Sakaguchi, Kevin Duh, Matt Post, Benjamin Van Durme, 'Robsut Wrod Reocginiton via Semi-Character Recurrent Neural Network', 2017, Association for the Advancement of Artificial Intelligence.

[3] Marek Rei, Helen Yannakoudakis, 'Compositional Sequence Labeling Models for Error Detection in Learner Writing', 2016, Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics, pages 1181–1191

[4] Amrita Jain, Minni Jain, Goonjan Jain, Devendra K.Tayal, "UTTAM": An Efficient Spelling Correction System for Hindi Language Based on Supervised Learning, 2018, ACM Transactions on Asian and Low-Resource Language Information ProcessingVolume 18 Issue 1 March 2019 Article No.: 8pp 1–26

[5] Zhang, Shaohua, Haoran Huang, Jicong Liu and Hang Li. "Spelling Error Correction with Soft-Masked BERT." ACL (2020), Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics

[6] Haithem Afli, Zhengwei Qiu, Andy Way, Páraic Sheridan "Using SMT for OCR Error Correction of Historical Texts", ACL (2016), Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC'16)

[7] Jacob Devlin, Ming-Wei Chang, Kenton Lee, Kristina Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding", ACL (2019), Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)

[8] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, "Attention Is All You Need" , ACL (2017), 31st Conference on Neural Information Processing Systems (NIPS 2017), Long Beach, CA, USA.

[9] D. Biswas, S. Nadipalli, B. Sneha, D. Gupta and A. J, "Natural Question Generation using Transformers and Reinforcement Learning," 2022 OITS International Conference on Information Technology (OCIT), Bhubaneswar, India, 2022, pp. 283-288, doi: 10.1109/OCIT56763.2022.00061.

[10] D. Biswas, S. Nadipalli, B. Sneha and M. Supriya, "Speech Recognition using Weighted Finite-State Transducers," 2022 IEEE 7th International conference for Convergence in Technology (I2CT), Mumbai, India, 2022, pp. 1-5, doi: 10.1109/I2CT54291.2022.9824703.

[11] G. Veena, D. Gupta, A. N. Daniel and S. Roshny, "A learning method for coreference resolution using semantic role labeling features," 2017 International Conference on Advances in Computing, Communications and Informatics (ICACCI), Udupi, India, 2017, pp. 67-72, doi: 10.1109/ICACCI.2017.8125818.

[12] D. Biswas, S. Jayan, S. Nadipalli, S. B and S. R, "Attendance Tracking with Face Recognition Through Hidden Markov Models," 2022 International Conference on Electronics and Renewable Systems (ICEARS), Tuticorin, India, 2022, pp. 1640-1645, doi: 10.1109/ICEARS53579.2022.9751888.

[13] Venugopalan, M., & Gupta, D. (2022). An enhanced guided LDA model augmented with BERT based semantic strength for aspect term extraction in sentiment analysis. Knowledge-Based Systems, 246, 108668. https://doi.org/10.1016/j.knosys.2022.108668

[14] Mohan, G.B., Kumar, R.P. (2022). A Comprehensive Survey on Topic Modeling in Text Summarization. In: Sharma, D.K., Peng, SL., Sharma, R., Zaitsev, D.A. (eds) Micro-Electronics and Telecommunication Engineering . ICMETE 2021. Lecture Notes in Networks and Systems, vol 373. Springer, Singapore. https://doi.org/10.1007/978-981-16-8721-1_22

[15] Madi N, Al-Khalifa H. Error Detection for Arabic Text Using Neural Sequence Labeling. 2020, Applied Sciences.

[16] Zhiheng Huang, Wei Xu , Kai Yu, "Bidirectional LSTM-CRF Models for Sequence Tagging." 2016, Baidu Research

[17] Xuezhe Ma, Eduard Hovy , "End-to-end Sequence Labeling via Bi-directional LSTM-CNNs-CRF." 2016, Language Technologies Institute Carnegie Mellon University

[18] Jianfeng Deng, Lianglun Cheng, Zhuowei Wang, "Self-attention-based BiGRU and capsule network for named entity recognition." 2019, ArXiv abs/2002.00735 (2020): n. pag.

[19] Liu, Jin & Yang, Yihe & Lv, Shiqi & Wang, Jin & Chen, Hui. , 'Attention-based BiGRU-CNN for Chinese question classification. Journal of Ambient Intelligence and Humanized Computing.', 2019, Journal of Ambient Intelligence and Humanized Computing

[20] Li, Yunghui & Harfiya, Latifa Nabila & Purwandari, Kartika & Lin, Yue-Der, 'Real-Time Cuffless Continuous Blood Pressure Estimation Using Deep Learning Model' , 2020, Sensors (Basel)

[21] Shi, Lukui & Du, Kang & Zhang, Chaozong & Ma, Hongqi & Yan, Wenjie, 'Lung Sound Recognition Algorithm Based on VGGish-BiGRU', 2019, IEEE Access (Volume: 7)

[22] Devlin, Jacob, et al. "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." arXiv, 2018, Google AI Language

[23] Dahiya, Pawan & Rani, Sheetal, 'A Review of Recognition Technique Used Automatic License Plate Recognition System' 2015, International Journal of Computer Applications

[24] Ceshine Lee, 'Understanding Bidirectional RNN in PyTorch' 2017, https://towardsdatascience.com/understanding-bidirectional-rnn-in-pytorch-5bd25a5dd66