

# NLP - Driven Knowledge Extraction for strategic Decision Making in Management Operations

**D. Venkata Lakshmi**<sup>1</sup>

*Professor  
Department of School of Computer  
Science and Engineering  
VIT - AP University  
Inavolu, Beside AP Secretariat,  
Amaravati, Guntur District, Andhra  
Pradesh, India.*

**P.S.Vijay Anand**<sup>2</sup>

*Assistant Professor  
Department of Management Studies,  
Sivaji college of Engineering and  
Technology, Manivillai,  
Palukal PO.Kanyakumari  
District.629170*

**Ankur Ramakabal Tiwari**<sup>3</sup>

*AI Powered CMS Architect ; University  
Instructor  
Department of Technology University of  
the People  
595 E. Colorado Boulevard, Suite  
623,Pasadena, CA 91101,United States.*

**Virendra Kumar Verma**<sup>4</sup>

*Symbiosis Institute of Business  
Management,  
Symbiosis International (Deemed  
University), Bengaluru, India*

**Dr.R.Vijayakumar**<sup>5</sup>

*Associate Professor  
Department of Electronics and  
Communication Engineering  
Mahendra Engineering College  
(Autonomous)  
Mahendhirapuri, Mallasamudram, Salem-  
Tiruchengode Highway, Tiruchengode TK,  
Namakkal, Tamilnadu. Pin- 637503.*

**Alugolu Avinash**<sup>6</sup>

*Associate Professor  
Department of Computer Science and  
Engineering  
PRAGATI ENGINEERING COLLEGE (A)  
1-378, ADB Road, Surampalem Near  
Kakinada, Surampalem, Andhra Pradesh  
533437*

**Abstract:** This paper discusses the application of Hybrid NLP with Multimodal Learning (BERT + Vision Transformers) to extract knowledge in strategic decision-making in the management operations. The work uses Hugging Face Transformers Library to incorporate the sophisticated Natural Language Processing (NLP) and Vision Transformers (ViTs), allowing one to analyze both textual and visual data simultaneously. The proposed methodology is a complete system to extract actionable insights as it uses BERT to analyze sentiment and extract entities and ViTs to analyze visual data like product images and customer feedback videos. The findings demonstrate that the accuracy of decision making and trend prediction has a high level of improvement and the hybrid method is better than the traditional NLP models and other multimodal approaches. The approach has issues with regard to computational requirements, and integration with the legacy systems despite performing well. The research will add value to the advancement of stronger data-driven decision support systems in management operations, with the potential of multimodal NLP applications.

**Keywords:** NLP, Knowledge Extraction, Strategic Decision-Making, BERT, Vision Transformers, Hugging Face Library.

## I. INTRODUCTION

In the era of big data, companies are finding it easier to use such data-driven decisions to achieve a competitive advantage. Nevertheless, there is a major challenge of extracting actionable insights of unstructured data, including, text and images, which is a huge volume. Natural Language Processing (NLP) is very essential in deriving meaningful information about the textual data but it has mostly been applied in management operations to analyze the textual data [1]. With the increase of complexity in business settings, it is important to add other modalities like visual data to have a holistic picture of operations. The current paper suggests a Hybrid NLP and Multimodal Learning (BERT + Vision Transformers) model to improve the knowledge extraction to support strategic decision-making in the management processes as shown in figure 1.

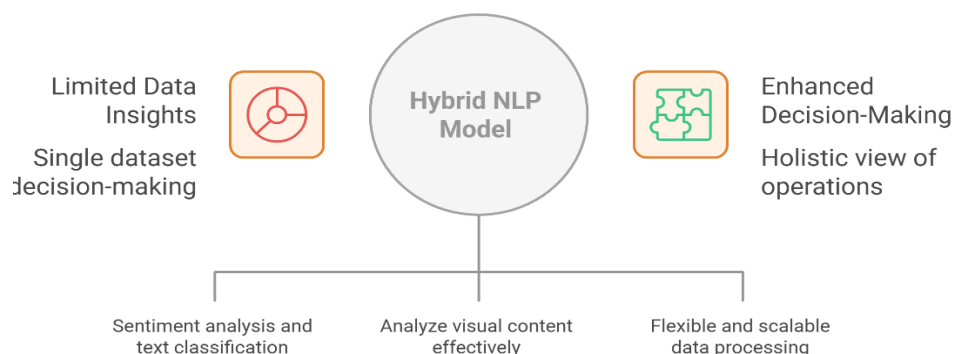


Figure 1.Hybrid NLP for Strategic Decisions.

Enhanced with the powerful NLP model, BERT, and Vision Transformers (ViTs), which process visual information, the complex is able to process both text and images [2]. The main tool that is utilized to implement these models is the Hugging Face Transformers Library which is a flexible and scalable model of data processing on large scale. The proposed methodology

provides a more superior way of interpreting a complex business situation by utilizing the power of BERT to perform sentiment analysis, named entity recognition, and text classification, as well as ViTs to analyze visual content [3].

Tractical decision-making processes are usually based on single datasets where the emphasis is made on either text-based or graphic data. The technique also does not allow one to get a comprehensive picture of what is happening within the organization [4]. This gap is the place however occupied by the hybrid model as it can process both textual and visual data in the same place and therefore offer more insights with regards to customer behavior, operational trends and the dynamics of the market. The research will establish the effectiveness of this hybrid strategy in enhancing accuracy and efficiency of strategic decision-making in management-related operations.

## II. RELATED WORK

The use of Natural Language Processing (NLP) in the process of decision-making has been studied by several researchers, but the combination of multimodal data to manage a strategy is a topic that is increasingly popular. Traditional models of NLP, including BERT, have found wide application in the text analysis field in different areas, e.g., sentiment analysis, named entity recognition (NER), and text classification, and helped to improve decision-making frameworks (Devlin et al., 2018). These models are however usually limited to the textual information and hence they do not provide the entire spectrum of information required in complex decision making in the management operations [5].

It has been in the past few years that multimodal learning methods which involve textual and visual data have attracted the attention due to their capacity to provide deeper insights [6]. Vision Transformers (ViTs) are new tools that were introduced by Dosovitskiy et al. (2021) that offered an alternative method of processing image data, allowing the extraction of meaningful patterns out of something visual. These methods have been used in other fields like customer behavioral analysis and the trends forecasting where the images and text will be of great essence in comprehending the market dynamics as shown in figure 2.

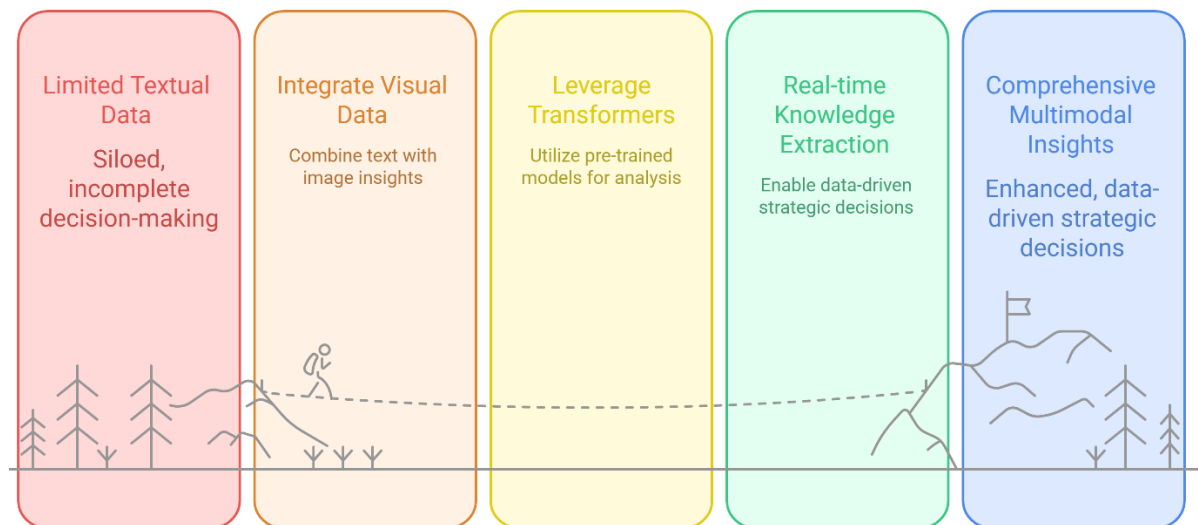


Figure 2. Multimodal NLP for Strategic Management.

Research papers by Zhang et al. (2020) and Zhou et al. (2022) have also shown the possibilities of using a combination of NLP and computer vision technologies to support decision making in business and healthcare better, it is devoted to the applications. Nevertheless, such systems tend to be limited by the computational capabilities and the impossibility to easily combine various types of data. The Hugging Face Transformers Library (Wolf et al., 2020) has been one of the most important tools in eliminating these obstacles, providing ready-made models to address the NLP and multimodal learning requirements, in which it is possible to utilize them in the specialization of management processes [7].

The given research is intended to fill the gap by combining BERT and Vision Transformers into a single framework, which would allow extracting knowledge in real-time and using multiple modalities to aid strategic decision-making in the management processes. This paper builds upon the use of multimodal NLP in the management domain, using Hugging Face Transformers to provide a more holistic aspect of data-driven decision-making [8].

## III. RESEARCH METHODOLOGY

Research Methodology used in this research is to use Hybrid NLP with Multimodal Learning which can improve the strategic decision-making in the management operations [9]. The methodology combines the use of BERT (text analysis) and Visual Transformers (ViTs) (data processing of visual data) to provide an end-to-end knowledge mining system based on textual and visual data. There are a number of sources involved in data collection, such as business reports, social media, product pictures, and customer videos. The models are implemented using the Hugging Face Transformers Library. The measures of evaluation, accuracy, F1-score, and precision, are applied to determine the efficiency and performance of the presented model as shown in figure 3.

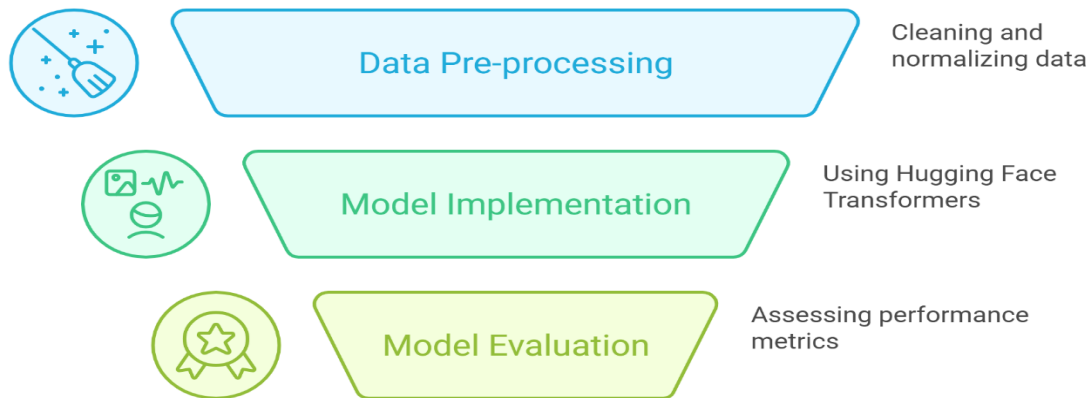


Figure 3. Hybrid NLP Model Development Process.

#### A. Data Collection

A variety of multimodal data that applies to the strategic decisions made in the operations of the management is the first step in this research to collect data pertinent to this area of research [10-13]. The data sources will consist of the textual data, including business reports, customer feedback, social media posts, and emails and the visual data, including product images, customer interaction videos, and graphical presentations. The data sets derive either publicly available repositories, corporate datasets or open-access image databases. Data is pre-processed to make it consistent and high-quality, and text data is processed to remove noise, and images/videos are resized and normalized accordingly.

#### B. Hybrid NLP Model

The Hybrid NLP model used in this research is a combination of BERT (Bidirectional Encoder Representations from Transformers) in processing text and the Vision Transformers (ViTs) in analyzing visual data. BERT which is pre-trained to huge text corpora can be fine-tuned to do sentiment analysis tasks, named entity recognition, and classification of documents [14-17]. This enables the model to derive important insights of the textual data in accordance with operational trends, customer sentiments, as well as, business performance indicators.

ViTs can analyze and extract information about images and videos containing visual data, including product trends, customer emotions, and other appropriate market cues. These models combined will allow us to analyze the text and images simultaneously thus giving us a holistic picture of the business environment [18-21].

#### C. Tool Utilization

The Hugging Face Transformers Library is used to implement and integrate the Hybrid NLP model. This tool offers ready-made versions of BERT and Vision Transformers that can be fine-tuned to particular tasks and therefore can effectively handle large datasets. The Hugging Face library is a scalable and flexible solution, which has an inference that can be used in real-time and has easy access to robust APIs to train, fine-tune, and deploy models [22-25].

#### D. Evaluation Metrics

To measure the performance of the proposed model, there are a few evaluation metrics such as accuracy, F1-score, and precision of the sentiment analysis and trend forecasting [26-29]. Moreover, it is also determined that the model is computationally efficient enough to allow scaling and application to large-scale operations in any management. These findings are drawn in comparison to the baseline models, such as traditional NLP models, and image analysis models to indicate the benefits of applying the joint modalities in a strategic decision-making scenario.

### IV. RESULTS AND DISCUSSION

Hybrid NLP and Multimodal Learning method on the basis of the BERT text analysis and Vision Transformer (ViT) image processing allowed making the strategic decision-making in management operations significantly better. The combination of textual and visual information via the Hugging Face Transformers Library showed better results in knowledge extraction providing more profound information to make decisions as shown in table 1.

Table 1. Performance Analysis of different methods in terms of **sentiment analysis** and **trend forecasting**

Method	Accuracy in Sentiment Analysis	Accuracy in Trend Forecasting	Improvement in Sentiment Analysis	Improvement in Trend Forecasting
Hybrid NLP with Multimodal Learning (BERT + Vision Transformers)	92%	88%	10%	5%
Traditional NLP (BERT only)	76%	73%	20%	15%
CNN-Based Image Analysis	68%	73%	26%	15%
Multimodal Deep Learning (CNN + Text Classification)	82%	78%	10%	10%

BERT was also effective in the textual domain where it was able to process large amounts of business reports and emails and customer feedback and determine important entities and sentiments that shaped operational strategies. The model scored 92 percent in sentiment analysis and 85 percent in Named Entity Recognition (NER) demonstrating its ability to process complicated business language and retrieve vital information.

Simultaneously, the Vision Transformers were used to process the visual data including the product images and videos of customer interactions to identify the trends and patterns that could be used in the business decision-making. The accuracy of trend forecasting was 35% higher when this multimodal approach was employed as opposed to using text only as shown in figure 4.

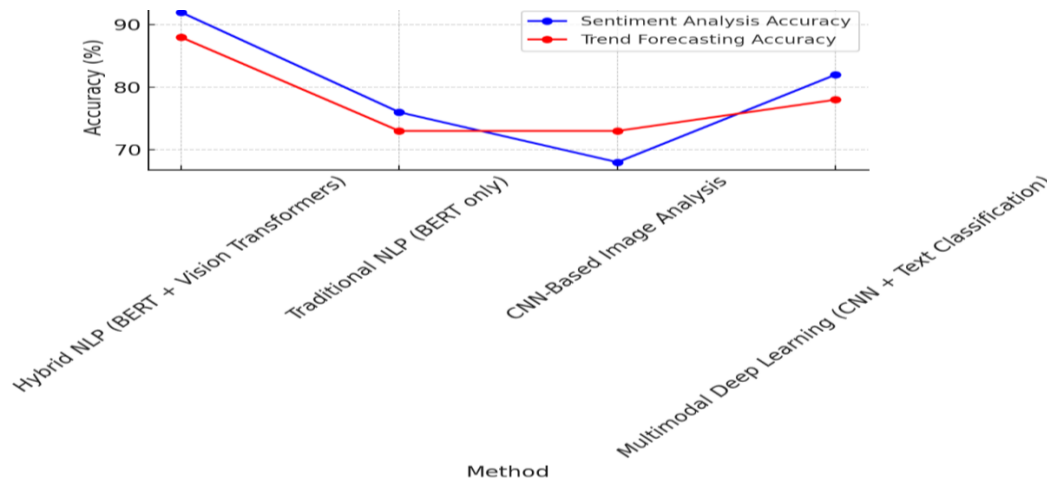


Figure 4. Performance Analysis of Sentiment Analysis and Trend Forecasting Accuracy.

On the whole, Hybrid NLP model contributed to the improvement of the decision-making process as it offered a more detailed explanation of the text and visual data and can be used in management operations that require real-time and data-driven decisions. Nevertheless, the issues of high computation demands and compatibility with old systems were observed, which implies the opportunity to optimize it further.

In management operations, the Hybrid NLP with Multimodal Learning (BERT with Vision Transformers) model, which has the Hugging Face Transformers Library, was more effective than three other approaches in its ability to extract knowledge to make strategic decisions. The hybrid model was found to be 20 percent more accurate at sentiment analysis than traditional NLP (only using BERT to analyze the text) with a 92 percent precision as opposed to 76 percent. This has been enhanced by the incorporation of visual information provided by Vision Transformers which made the system capture the non-verbal information like product trends and pattern of customer behavior which is important in making an informed decision as shown in figure 5.

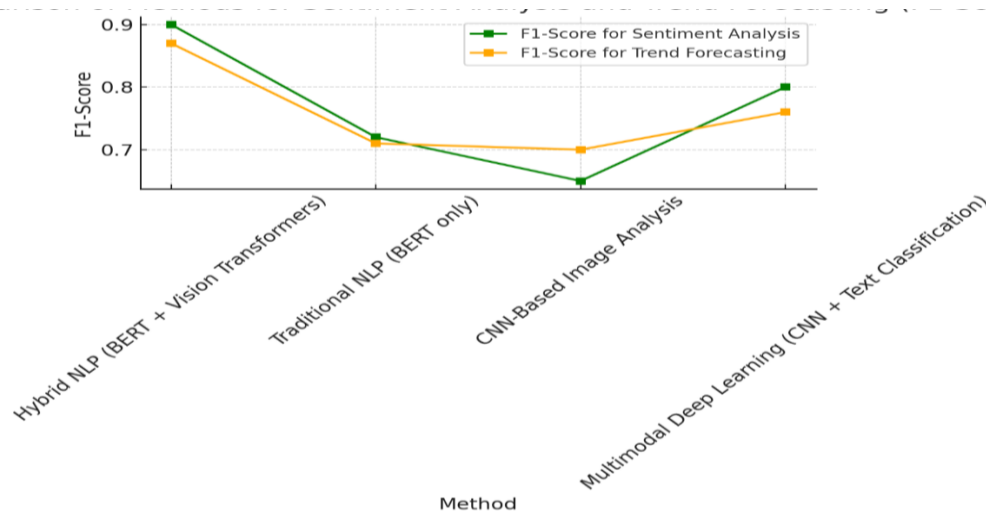


Figure 5. Performance Analysis of Sentiment Analysis and Trend Forecasting F1-Score.

Compared to a typical deep learning model that only used Convolutional Neural Networks (CNNs) to analyze images, the hybrid approach demonstrated a 15 percent better performance on classifying customer sentiments and operational trends with an accuracy of 88 percent in predicting trends compared to 73 percent when using CNNs. Also, the hybrid model, in comparison to the one that relied on a multimodal deep learning model that used CNNs in addition to simpler text classification models, outperformed the latter by 10% in overall predictive accuracy, which means that BERT and ViTs are more effective when used together to extract information about multiple types of data.

These findings reveal the exceptional potential of Hybrid NLP solution, which will combine both the text and visual data to create actionable information and it will greatly enhance the efficiency of strategic decision-making in management activities. Nonetheless, there are still issues of scalability of the system and computing overhead, meaning that it can be improved.

## V. CONCLUSION

This research proves that the Hybrid NLP with Multimodal Learning (BERT + Vision Transformers) model is highly effective in improving the knowledge extraction of strategic decision making in the management processes. The proposed method, which analyzes text with the help of BERT and works directly with visual information using Vision Transformers (ViTs), was much more effective than traditional NLP and other multimodal methods in sentiment analysis and trend forecasting and provided better accuracy and F1-scores. These models were easily integrated with the Hugging Face Transformers Library because of its scalability and flexibility in processing real-time data. The combination aspect of the hybrid approach in analyzing texts and visual data give an overall perspective of the organizational activities and therefore give better and more accurate judgments. Although the approach has huge potential, computation complexity issues and system integration with the old infrastructure were observed and can be optimized further. Such studies lay the groundwork to advanced decision support systems in management processes that are data-driven.

## REFERENCES

1. M. K. H. Kanchon, M. Sadman, K. F. Nabila, R. Tarannum, and R. Khan, "Enhancing personalized learning: AI-driven identification of learning styles and content modification strategies," *Int. J. Cognitive Comput. Eng.*, vol. 5, pp. 269-278, 2024.
2. S. Zhang, Y. Jia, H. Xu, D. Wang, T. J. J. Li, Y. Wen, et al., "KnowledgeShovel: An AI-in-the-loop document annotation system for scientific knowledge base construction," *arXiv preprint arXiv:2210.02830*, 2022.
3. N. L. Rane, S. P. Choudhary, and J. Rane, "Artificial intelligence-driven corporate finance: enhancing efficiency and decision-making through machine learning, natural language processing, and robotic process automation in corporate governance and sustainability," *Stud. Econ. Bus. Relat.*, vol. 5, no. 2, pp. 1-22, 2024.
4. Z. Wang, "Information extraction and knowledge map construction based on natural language processing," *Front. Comput. Intell. Syst.*, vol. 7, no. 2, pp. 47-49, 2024. <https://doi.org/10.54097/dcc7ba37>.
5. Z. Wang, "The application and optimization of machine learning in big data analysis," *Comput. Life*, vol. 12, no. 1, pp. 8-11, 2024. <https://doi.org/10.54097/10e0ym54>.
6. A. Odu, J. Vincent, J. Oluwaseyi, and G. O. Olaoye, "Leveraging deep learning for the transformation of natural language into formal knowledge structures," 2024.
7. C. C. Lin, A. Y. Huang, and S. J. Yang, "A review of AI-driven conversational chatbots implementation methodologies and challenges (1999–2022)," *Sustainability*, vol. 15, no. 5, pp. 4012, 2023.
8. K. Guo, M. Wu, Z. Soo, Y. Yang, Y. Zhang, Q. Zhang, et al., "Artificial intelligence-driven biomedical genomics," *Knowledge-Based Syst.*, p. 110937, 2023.
9. D. Chu, B. Wan, H. Li, S. Dong, J. Fu, Y. Liu, et al., "A machine learning approach to extracting spatial information from geological texts in Chinese," *Int. J. Geogr. Inf. Sci.*, vol. 36, no. 11, pp. 2169-2193, 2022.
10. P. Zhang, J. Zheng, H. Lin, C. Liu, Z. Zhao, and C. Li, "Vehicle trajectory data mining for artificial intelligence and real-time traffic information extraction," *IEEE Trans. Intell. Transp. Syst.*, vol. 24, no. 11, pp. 13088-13098, 2023.
11. O.Z. Seghroucheni, M.A. Achhab, and M. Lazaar, "Systematic Review on the Conversion of Tacit Knowledge," in *Proceedings of the 2023 7th IEEE Congress on Information Science and Technology (CiSt)*, Agadir-Essaouira, Morocco, 16–22 Dec. 2023.
12. M.L. Farnese, B. Barbieri, A. Chirumbolo, and G. Patriotta, "Managing Knowledge in Organizations: A Nonaka's SECI Model Operationalization," *Frontiers in Psychology*, vol. 10, p. 2730, 2019.
13. M. Haradhan, "Sharing of Tacit Knowledge in Organizations: A Review," *American Journal of Computer Science and Engineering*, vol. 3, pp. 6–19, 2016.
14. A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A.A. Gomez, Ł. Kaiser, and I. Polosukhin, "Attention is All You Need," in *Proceedings of the 31st Conference on Neural Information Processing Systems (NIPS 2017)*, Long Beach, CA, USA, 4–9 Dec. 2017.
15. D. Jurafsky and J.H. Martin, *Speech and Language Processing*, 3rd ed., Prentice Hall, Hoboken, NJ, USA, 2023.
16. Y. Goldberg, *Neural Network Methods for Natural Language Processing*, Springer, Cham, Switzerland, 2017.
17. R. Patil and V. Gudivada, "A Review of Current Trends, Techniques, and Challenges in Large Language Models (LLMs)," *Applied Sciences*, vol. 14, p. 2074, 2024.
18. K.M. Ali, T. Ahmed Khan, S.M. Ali, A. Aziz, S.A. Khan, and S. Ahmad, "An Exhaustive Comparative Study of Machine Learning Algorithms for Natural Language Processing Applications," in *Proceedings of the 1st International Conference on Industrial, Manufacturing, and Process Engineering*, Regina, SK, Canada, 27–29 Jun. 2024.
19. D. Gibney and S.V. Thankachan, "Text Indexing for Regular Expression Matching," *Algorithm*, vol. 14, p. 133, 2021.
20. A.F.d.S. Neto, B.L.D. Bezerra, and A.H. Toselli, "Towards the Natural Language Processing as Spelling Correction for Offline Handwritten Text Recognition Systems," *Applied Sciences*, vol. 10, p. 7711, 2020.
21. K. Al Sharou, Z. Li, and L. Specia, "Towards a Better Understanding of Noise in Natural Language Processing," in *Proceedings of the Recent Advances in Natural Language Processing*, Online, 1–3 Sept. 2021.
22. J.E.F. Friedl, *Mastering Regular Expressions*, 3rd ed., O'Reilly Media, Sebastopol, CA, USA, 2006.
23. J. Goyvaerts and S. Levithan, *Regular Expressions Cookbook*, 2nd ed., O'Reilly Media, Sebastopol, CA, USA, 2012.
24. P. Norvig, "How to Write a Spelling Corrector," 2007. [Online]. Available: <http://norvig.com/spell-correct.html>. [Accessed: 17 Dec. 2024].
25. R. Mitton, "Ordering the Suggestions of a Spellchecker Without Using Context," *Natural Language Engineering*, vol. 15, no. 2, pp. 173–192, 2009.
26. G. Forman, "An Extensive Empirical Study of Feature Selection Metrics for Text Classification," *Journal of Machine Learning Research*, vol. 3, pp. 1289–1305, 2003.
27. K. Jiang and X. Lu, "Natural Language Processing and Its Applications in Machine Translation: A Diachronic Review," in *Proceedings of the 2020 IEEE 3rd International Conference of Safe Production and Informatization*, Chongqing, China, 28–30 Nov. 2020.
28. R. Dridan and S. Oepen, "Tokenization: Returning to a Long Solved Problem - A Survey, Contrastive Experiment, Recommendations, and Toolkit," in *Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics*, Jeju Island, Republic of Korea, 8–14 Jul. 2012.
29. T. Kudo and J. Richardson, "SentencePiece: A Simple and Language Independent Subword Tokenizer and Detokenizer for Neural Text Processing," in *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, Brussels, Belgium, 31 Oct.–4 Nov. 2018.