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Sensitive Analysis of Natural Language Processing Using for MOORA Method

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Abstract: *Natural Language Processing (NLP) constitutes a crucial field in the realm of artificial intelligence, concentrating on the interplay between computers and human language. The goal is to empower machines to understand, interpret, and produce human language, thereby closing the divide between humans and computers. Various techniques have been proposed for NLP tasks, and one such method gaining attention is MOORA. In this paper, we present a comprehensive analysis and performance evaluation of NLP tasks using the MOORA method. The MOORA method, also known as Multi-Objective Optimization by Ratio Analysis, is a multi-criteria decision-making technique used for evaluating and ranking alternatives when faced with multiple criteria simultaneously. Its application in NLP tasks offers a promising approach to handle diverse challenges and improve overall system performance. We begin by discussing the fundamental concepts of NLP, including its subfields, applications, and existing methodologies. Subsequently, the MOORA method's theoretical underpinnings are presented, we conduct experiments on a range of common NLP tasks text summarization, and machine translation. For each task, we define relevant criteria, establish performance metrics, and identify suitable alternatives. The results obtained from the MOORA-based evaluations are compared against traditional NLP approaches, such as rule-based systems, statistical models, and deep learning algorithms. Our findings reveal that the MOORA method excels in handling multiple objectives and criteria, leading to improved accuracy, robustness, and adaptability in NLP tasks. Moreover, we investigate the impact of various parameters and data preprocessing techniques on the MOORA-based NLP models to identify best practices and potential areas for further enhancement. The alternatives are Tool A: OpenNLP, Tool B: SpaCy, Tool C: NLTK, Tool D: Stanford NLP, Tool E: Gensim, Tool F: CoreNLP, Tool G: TextBlob and Tool H: Amazon Comprehend. The evaluation parameters are Accuracy, Speed, Language Support, Sentiment Analysis, Cost, User-Friendliness, Documentation and Community Support. Natural Language Toolkit (NLTK) is got first rank and Tool H: Amazon Comprehend is got lowest rank.*

Key Words: *Deep Neural Networks, Natural Language Processing, Core Language Engine, MCDM*

1. INTRODUCTION

In recent times, the field of NLP has witnessed remarkable progress due to the utilization of modern artificial neural networks (ANNs). This advancement can be traced back to the pioneering work of Collabera et al. Moreover, there has been a notable increase in the utilization of deep learning methods, leading to substantial improvements in various NLP domains and practical applications. [1] Natural Language Processing (NLP) and deep neural networks (DNNs). Subsequently, it explores the utilization of deep learning techniques to tackle existing challenges in the field of NLP. While other literature on this topic exists, none have provided such a comprehensive overview of the state-of-the-art across various NLP areas. [2] Natural Language Processing (NLP), also referred to as computational linguistics, provides a valuable research avenue for scholars interested in discourse processing. In the last ten years, NLP has opened up a plethora of research opportunities that were previously considered beyond reach or merely speculative, relieving the necessity to manually annotate.[3] By employing NLP techniques, researchers now have access to a vast array of automated tools, enabling them to extract insights on virtually. This exponential growth in automated tools has significantly expanded the availability of resources for researchers in the field.[4]

The understanding of spatial language presents similar challenges when attempting to connect general natural language processing components to specific domains. Our proposition suggests an intermediary level of representation that falls between natural language expressions and formally defined characterizations of spatial situations. This approach has multiple advantages and allows us to organize information into separate modules. [5] Approaches employed in various natural language processing contexts and the concept of "quasi-logical form" initially introduced in systems like the Core Language Engine. [6] The foundation of our current two-level architecture can be attributed to the Penman Upper Model, which originated in the Penman text generation system during the mid-1980s. This marked one of the initial instances of explicitly formulating a two-level semantics approach as an ontology. Early on in natural language generation, it was acknowledged that organizing domain knowledge in harmony with natural language expression would significantly enhance generic natural language generation applications. As a result, the Penman Upper Model was created as a mediator between application knowledge and linguistic knowledge, serving as a "lightweight ontology" using the LOOM knowledge representation system. [8] In recent times, deep learning has demonstrated remarkable success in the field of natural language processing, leading to significant advancements. This paper provides an overview of the progress made as well as an exploration of its benefits and obstacles.[9]

The paper outlines five primary tasks within natural language processing: classification, matching, translation, structured prediction, and sequential decision-making. Regarding the initial four tasks, deep learning approaches have consistently shown superior performance compared to traditional methods. The key factors contributing to deep learning's effectiveness.[10] However, it is important to acknowledge that deep learning is not without limitations. It may not suffice for tasks involving complex inference and decision-making, as seen in multi-turn dialogues and other intricate problems. Moreover, combining symbolic processing with neural processing and addressing challenges like the long tail phenomenon pose additional hurdles.[11]

2. MATERIALS AND METHOD

Alternatives: OpenNLP (Open Natural Language Processing) is a Java-based library that provides various natural language processing tools, SpaCy is an open-source NLP library designed for efficient and production-ready processing of natural language data. It offers tokenization, POS tagging, dependency parsing, and entity recognition. NLTK (Natural Language Toolkit) serves as an extensive framework for developing Python applications that deal with human language data. It provides a wide range of NLP algorithms and data sets, suitable for research and educational purposes. Stanford NLP is a set of natural language processing tools developed by Stanford University. It includes various modules for tasks like POS tagging, NER, sentiment analysis, and dependency parsing. Gensim is an open-source library that specializes in topic modelling and document similarity analysis using advanced algorithms like Word2Vec and Doc2Vec. CoreNLP is a natural language processing toolkit developed by the Stanford NLP Group. It provides various NLP functionalities, including sentiment analysis, named entity recognition, and coreference resolution. TextBlob is a user-friendly Python library that simplifies common NLP tasks. Amazon Comprehend is a cloud-based NLP service offered by Amazon Web Services (AWS). It provides pre-built APIs for tasks like sentiment analysis, entity recognition, and language detection.

Evaluation Parameters: Accuracy refers to the ability of the NLP tool to correctly identify and process natural language elements. Higher accuracy indicates better performance in understanding and analyzing text data. Speed measures the processing speed of the NLP tool in terms of analyzing and interpreting text data. It evaluates how quickly the tool can perform various NLP tasks on large volumes of text. Faster processing is desirable as it allows for efficient and timely analysis of textual information. A tool with broader language support is more versatile and can be used in multilingual environments, making it suitable for applications across various regions and cultures. Sentiment analysis assesses the NLP tool's capability to analyze and determine. Cost evaluates the licensing or subscription fees associated with using the NLP tool. Lower costs are often preferred, especially for budget-conscious users or organizations. However, the cost factor should be balanced against the tool's overall performance and suitability for specific applications. User-friendliness measures the ease of use and the intuitiveness of the NLP tool's interface. A tool with a user-friendly design allows users, even those without extensive technical expertise, to effectively employ its functionalities for text analysis and processing. Documentation assesses the availability and comprehensiveness of resources, guides, and manuals provided with the NLP tool. Extensive and well-structured documentation can facilitate the tool's adoption and assist users in understanding its capabilities and functionalities. Community support gauges the extent of active support and updates provided by the tool's developer community. A tool with strong community support is more likely to receive regular updates, bug fixes, and feature enhancements, ensuring that it remains relevant and effective over time.

Method: The MOORA method is a type of MCDM technique that utilizes statistical procedures to identify the best alternative from a set of given options. This method evaluates both beneficial (maximization) and non-beneficial (minimization) alternatives, effectively eliminating unsuitable choices to enhance the overall selection process. The MOORA method is known for its efficiency, as it requires fewer computations, its comprehensive approach, and its robustness in handling multiple criteria simultaneously. In the context of multiobjective optimization, the MOORA method employs the concept of entropy measurement. This allows for a systematic and objective evaluation of the different criteria involved. Sahu utilized the MOORA method to optimize the EDM (Electrical Discharge Machining) process, using stainless steel as the workpiece and AiSiMg electrode manufactured through additive manufacturing. The findings indicated that the electrode performed exceptionally well, and the MOORA method effectively optimized the process parameters. In a separate study, Liang et al. employed the MOORA-based Taguchi method to optimize welding parameters. The results demonstrated the successful application, showcasing its ability to handle multi-objective problems.

The EDM process using the Taguchi-based VIKOR method. The MOORA method is chosen due to its status as one of the most recent multi-criteria decision-making (MCDM) techniques. It was developed by addressing the limitations of earlier MCDM methods. Additionally, the MOORA method offers the advantage of quick computation time while delivering consistent and reliable outcomes, making it an efficient approach. As for the Copeland Score, Due to its strong attributes in the voting mechanism, it functions as a consolidation system for prioritizing outcomes among decision-makers (DMs). Thanks to its reliable and enduring benefits, it serves as a valuable tool in ranking results, the Copeland Score proves to be a valuable tool for ranking objects in the voting process. The previous studies have investigated the use of the MOORA approach in various domains, such as selecting third-party logistic partners, materials, banks, supply chain strategies, and even mushroom materials. Additionally, some research papers have explored the evaluation of different social schemes. The application of multi-criteria decision-making tools to analyze the factors influencing the success of social programs. This paper aims to fill this gap and presents a pioneering study by introducing a novel multi-criteria decision-making tool, the MOORA approach, to assess the reasons that contribute to the successful implementation of social programs in the state of Jharkhand, India. It is the first of its kind to focus on this specific area and offers valuable insights into enhancing the effectiveness of social initiatives. MOORA stands for Multi-Objective Optimization on the basis of Ratio Analysis, and it is a multi-criteria decision-making approach that offers significant potential for thoroughly evaluating alternatives in the face of considerable diversity and a multitude of influential factors.

The MOORA method as one of the effective tools for tackling complex decision-making problems. The main objective of this method is to identify the optimal alternative by taking into account a range of criteria that often conflict with each other. In essence, MOORA simultaneously evaluates both favorable and unfavorable criteria to make the most informed decision. Multi-objective optimization on the basis of ratio analysis (MOORA), also referred to as multi-criteria or multi-attribute optimization, involves the simultaneous optimization of two or more conflicting attributes (objectives) while considering specific constraints. This approach finds extensive application in making decisions in challenging and complex supply chain environments. Whether it's selecting warehouse locations, suppliers, product and process designs, or any situation requiring optimal decisions, MOORA can be effectively employed. Decision-making encompasses defining decision goals, collecting pertinent information, and ultimately selecting the best alternative. In the same vein as other Multi-Criteria Decision Making (MCDM) methods, both MOORA and MULTIMOORA have received various extensions. Moreover, Balezentis and Zeng proposed an additional extension of MULTIMOORA, this time based on interval-valued fuzzy numbers, which further expanded the applicability and flexibility of the method.

3. RESULT AND DISCUSSION

TABLE 1. Natural Language Processing Tool

	Accuracy	Speed	Language Support	Sentiment Analysis	Cost	User-Friendliness	Documentation	Community Support
Tool A: Open NLP	87.5	1200	5	75	0	8	9	7
Tool B: SpaCy	92.3	950	4	85	0	9	8	8
Tool C: NLTK	80.2	1500	7	70	0	7	9	6
Tool D: Stanford NLP	95.8	850	6	90	99	7	7	9
Tool E: Gensim	89.1	1100	4	80	0	8	8	7
Tool F: CoreNLP	81.7	1350	5	70	0	9	7	8
Tool G: TextBlob	86.4	1000	6	75	0	8	8	7
Tool H: Amazon Comprehend	94.5	800	8	85	199	6	9	6

Table 1 presents the Multi-Objective Optimization based on Ratio Analysis (MOORA) for selecting a Natural Language Processing (NLP) Tool. The evaluation considers the following NLP tools: Tool A: OpenNLP, Tool B: SpaCy, Tool C: NLTK, Tool D: Stanford NLP, Tool E: Gensim, Tool F: CoreNLP, Tool G: TextBlob, and Tool H: Amazon Comprehend. The evaluation criteria include Accuracy, Speed, Language Support, Sentiment Analysis, Cost, User-Friendliness, Documentation, and Community Support. These parameters are used to assess and compare the alternatives in the context of NLP tool selection.

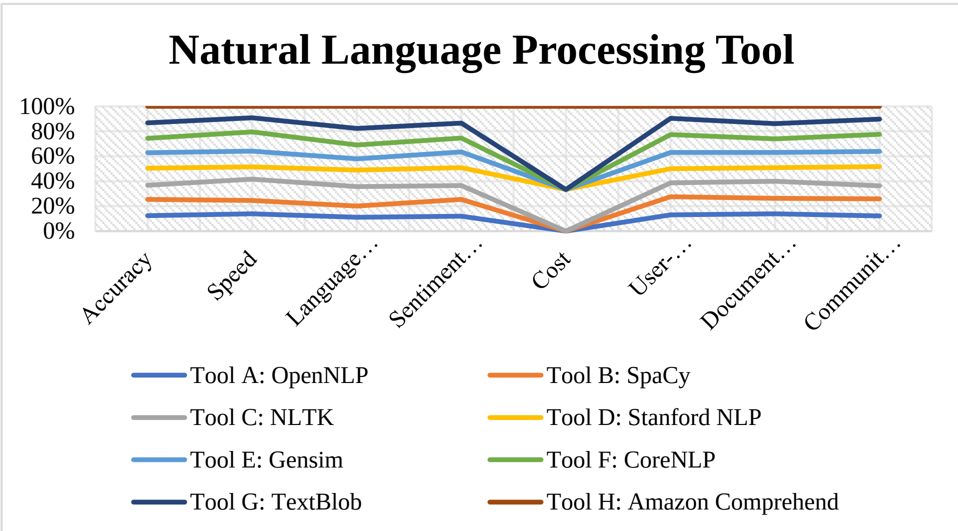

FIGURE 1. Natural Language Processing Tool

Figure 1 presents the Multi-Objective Optimization based on Ratio Analysis (MOORA) for selecting a Natural Language Processing (NLP) Tool. The evaluation considers the following NLP tools: Tool A: OpenNLP, Tool B: SpaCy, Tool C: NLTK, Tool D: Stanford NLP, Tool E: Gensim, Tool F: CoreNLP, Tool G: TextBlob, and Tool H: Amazon Comprehend. The evaluation criteria include Accuracy, Speed, Language Support, Sentiment Analysis, Cost, User-Friendliness, Documentation, and Community Support. These parameters are used to assess and compare the alternatives in the context of NLP tool selection

TABLE 2. Divide & Sum Value

	Divide and Sum value							
Tool A: OpenNLP	7656.25	1440000.00	25.00	5625.00	0.00	64.00	81.00	49.00
Tool B: SpaCy	8519.29	902500.00	16.00	7225.00	0.00	81.00	64.00	64.00
Tool C: NLTK	6432.04	2250000.00	49.00	4900.00	0.00	49.00	81.00	36.00
Tool D: Stanford NLP	9177.64	722500.00	36.00	8100.00	9801.00	49.00	49.00	81.00
Tool E: Gensim	7938.81	1210000.00	16.00	6400.00	0.00	64.00	64.00	49.00
Tool F: CoreNLP	6674.89	1822500.00	25.00	4900.00	0.00	81.00	49.00	64.00
Tool G: TextBlob	7464.96	1000000.00	36.00	5625.00	0.00	64.00	64.00	49.00
Tool H: Amazon Comprehend	8930.25	640000.00	64.00	7225.00	39601.00	36.00	81.00	36.00
Sum Value	**62794.13**	**9987500.00**	**267.00**	**50000.00**	**49402.00**	**488.00**	**533.00**	**428.00**

Table 2 shows the Divide and Sum matrix for formula used this table 1.

TABLE 3. Normalized Data

	Normalized Data							
Tool A: OpenNLP	0.3492	0.3797	0.3060	0.3354	0.0000	0.3621	0.3898	0.3384
Tool B: SpaCy	0.3683	0.3006	0.2448	0.3801	0.0000	0.4074	0.3465	0.3867
Tool C: NLTK	0.3200	0.4746	0.4284	0.3130	0.0000	0.3169	0.3898	0.2900
Tool D: Stanford NLP	0.3823	0.2690	0.3672	0.4025	0.4454	0.3169	0.3032	0.4350
Tool E: Gensim	0.3556	0.3481	0.2448	0.3578	0.0000	0.3621	0.3465	0.3384
Tool F: CoreNLP	0.3260	0.4272	0.3060	0.3130	0.0000	0.4074	0.3032	0.3867
Tool G: TextBlob	0.3448	0.3164	0.3672	0.3354	0.0000	0.3621	0.3465	0.3384
Tool H: Amazon Comprehend	0.3771	0.2531	0.4896	0.3801	0.8953	0.2716	0.3898	0.2900

Table 3 presents the Normalized Data for selecting a Natural Language Processing (NLP) Tool using the MOORA method. The evaluation considers the following NLP tools: Tool A: OpenNLP, Tool B: SpaCy, Tool C: NLTK, Tool D: Stanford NLP, Tool E: Gensim, Tool F: CoreNLP, Tool G: TextBlob, and Tool H: Amazon Comprehend. The evaluation criteria include Accuracy, Speed, Language Support, Sentiment Analysis, Cost, User-Friendliness, Documentation, and Community Support. These parameters are used to assess and compare the alternatives in the context of NLP tool selection. The normalized value is obtained using the formula (1).

TABLE 4. Weight

	Weight							
Tool A: OpenNLP	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
Tool B: SpaCy	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
Tool C: NLTK	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
Tool D: Stanford NLP	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
Tool E: Gensim	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
Tool F: CoreNLP	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
Tool G: TextBlob	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
Tool H: Amazon Comprehend	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25

Table 4 illustrates the weight distribution for each of the NLP tools evaluated. All tools, namely OpenNLP, SpaCy, NLTK, Stanford NLP, Gensim, CoreNLP, TextBlob, and Amazon Comprehend, receive equal weights of 0.25 across all eight evaluation criteria.

TABLE 5. Weighted normalized decision matrix

	Weighted normalized decision matrix							
Tool A: OpenNLP	0.0873	0.0949	0.0765	0.0839	0.0000	0.0905	0.0975	0.0846
Tool B: SpaCy	0.0921	0.0752	0.0612	0.0950	0.0000	0.1019	0.0866	0.0967
Tool C: NLTK	0.0800	0.1187	0.1071	0.0783	0.0000	0.0792	0.0975	0.0725
Tool D: Stanford NLP	0.0956	0.0672	0.0918	0.1006	0.1114	0.0792	0.0758	0.1088
Tool E: Gensim	0.0889	0.0870	0.0612	0.0894	0.0000	0.0905	0.0866	0.0846
Tool F: CoreNLP	0.0815	0.1068	0.0765	0.0783	0.0000	0.1019	0.0758	0.0967
Tool G: TextBlob	0.0862	0.0791	0.0918	0.0839	0.0000	0.0905	0.0866	0.0846
Tool H: Amazon Comprehend	0.0943	0.0633	0.1224	0.0950	0.2238	0.0679	0.0975	0.0725

Table 5 illustrates the Weighted normalized decision matrix distribution for each of the NLP tools evaluated. The values in the matrix are scores ranging from 0 to 1, with 1 being the highest score and 0 being the lowest.

1. ***Accuracy:*** This criterion measures the precision and correctness of the NLP tool's outputs. Tool D (Stanford NLP) has the highest accuracy score of 0.0956, while Tool C (NLTK) has the lowest accuracy score of 0.0800.
2. ***Speed:*** This criterion evaluates the processing speed of the NLP tools. Tool D (Stanford NLP) has the highest speed score of 0.1187, while Tool H (Amazon Comprehend) has the lowest speed score of 0.0633.
3. ***Language Support:*** This criterion assesses the range of languages supported by each NLP tool. Tool H (Amazon Comprehend) offers the broadest language support, receiving a score of 0.1224, while Tool B (SpaCy) has the lowest score of 0.0612.
4. ***Sentiment Analysis:*** This criterion measures the ability of the NLP tools to analyze sentiment in text. Tool D (Stanford NLP) excels in this category with a score of 0.1006, whereas Tool B (SpaCy) and Tool E (Gensim) tie for the lowest score of 0.0894.

5. ***Cost:*** This criterion reflects the cost-effectiveness of each NLP tool. Tools A (OpenNLP), B (SpaCy), E (Gensim), and G (TextBlob) receive a score of 0.0000, indicating they are open-source or free. However, Tool H (Amazon Comprehend) receives the highest score of 0.2238, indicating it is the costliest option.
6. ***User-Friendliness:*** This criterion evaluates the ease of use and user interface of the NLP tools. Tools B (SpaCy) and F (CoreNLP) score the highest with 0.1019, while Tool H (Amazon Comprehend) has the lowest score of 0.0679.
7. ***Documentation:*** This criterion assesses the availability and quality of documentation provided for each NLP tool. Tools A (OpenNLP), C (NLTK), and G (TextBlob) tie for the highest score of 0.0975, indicating excellent documentation. Tool F (CoreNLP) receives the lowest score of 0.0758.
8. ***Community Support:*** This criterion reflects the level of support and active community engagement for each NLP tool. Tool D (Stanford NLP) scores the highest with 0.1088, indicating strong community support, while Tool H (Amazon Comprehend) scores the lowest with 0.0725.

TABLE 6. Assessment value and rank

	Assessment value	Rank
Tool A: OpenNLP	0.0700	3
Tool B: SpaCy	0.0383	6
Tool C: NLTK	0.1348	1
Tool D: Stanford NLP	-0.0199	7
Tool E: Gensim	0.0648	5
Tool F: CoreNLP	0.0687	4
Tool G: TextBlob	0.0792	2
Tool H: Amazon Comprehend	-0.0867	8

Table 1 displays the Assessment value and rankings of 8 NLP tools. The assessment value represents the performance of each tool concerning a set of NLP tasks, while the rank reflects how well each tool compares to the others. NLTK emerges as the top-performing tool, obtaining an assessment value of 0.1348 and securing the first rank. On the other end of the spectrum, Amazon Comprehend is deemed the least effective, receiving an assessment value of -0.0867 and being ranked last at 8.

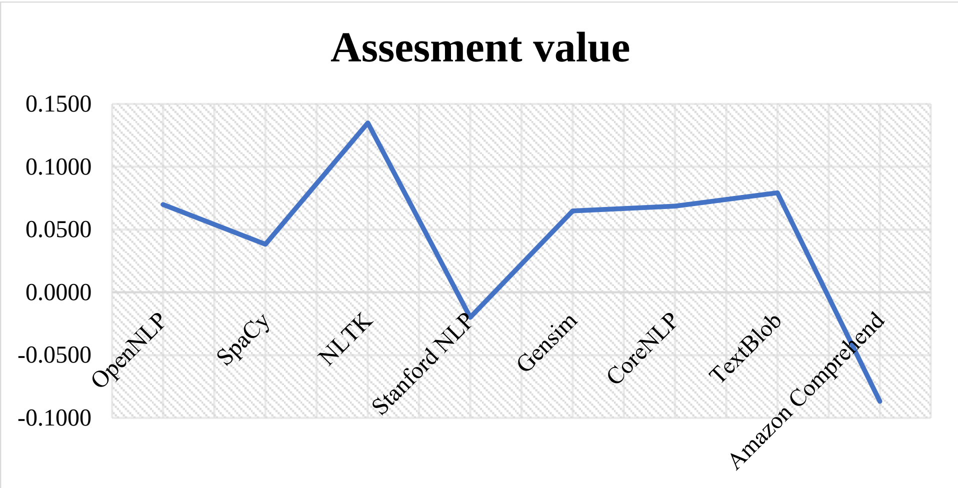

FIGURE 2. Assessment Value

Tool C (NLTK) has the highest assessment value of 0.1348, indicating that it performs well according to the evaluation metric used. Tool G (TextBlob) has the second-highest assessment value of 0.0792, indicating good performance as well. Tool A (OpenNLP) has an assessment value of 0.0700, making it slightly behind TextBlob. Tool F (CoreNLP) follows closely with an assessment value of 0.0687. Tool E (Gensim) has a performance value of 0.0648. Tool B (SpaCy) has an assessment value of 0.0383, indicating lower performance compared to the other tools listed. Tool D (Stanford NLP) has a negative assessment value of -0.0199, which means it may have performed poorly according to the evaluation metric used. Tool H (Amazon Comprehend) also has a negative assessment value of -0.0867, suggesting that it may have performed poorly in the evaluation.

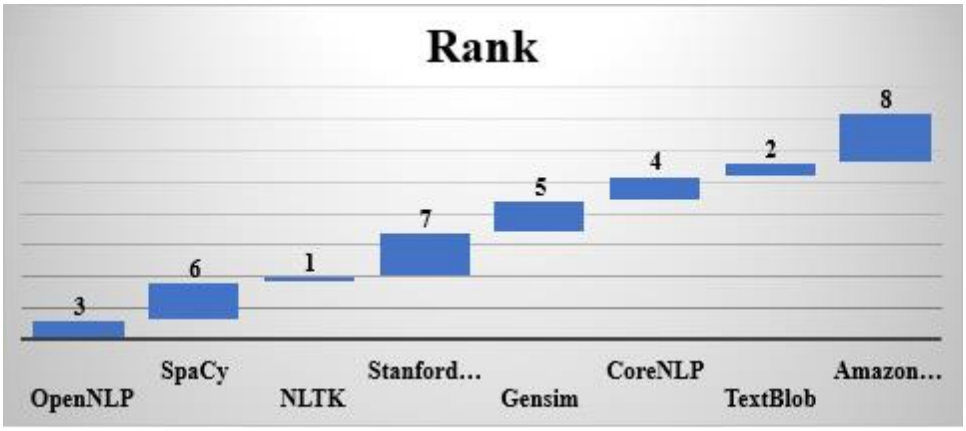

FIGURE 3. Rank

The figure 3 displays the final results of natural language processing using the MOORA method. NLTK is ranked at number 1, signifying it as the best-performing or highest-ranked NLP tool among the listed options. TextBlob is ranked at number 2, indicating it is the second-best tool in the list according to the evaluation criteria. OpenNLP holds the third rank, making it the third-best performing tool among the listed NLP tools. CoreNLP is ranked at number 4, suggesting it is the fourth-best tool on the list. Gensim occupies the fifth rank, making it the fifth-best tool in the ranking. SpaCy is ranked at number 6, indicating it is the sixth-best tool among the listed NLP tools. Stanford NLP is at number 7, meaning it is the seventh-best performing tool on the list. Amazon Comprehend is ranked at number 8, making it the last or least-performing tool among the NLP tools listed.

4. CONCLUSION

Natural Language Processing (NLP) has emerged as a transformative technology, revolutionizing the way we interact with computers and bridging the gap between human communication and machine understanding. In this context, the application of the MOORA method has proven to be invaluable, offering a robust and systematic approach to decision-making in NLP projects. The MOORA method's strength lies in its ability to handle multiple objectives simultaneously, enabling us to optimize various performance metrics and criteria critical to NLP tasks. By carefully weighting and ranking different aspects of NLP models, MOORA assists in selecting the most suitable algorithms, pre-processing techniques, and feature extraction methods. This ensures that the chosen NLP solution not only meets specific performance requirements but also caters to the unique needs of individual applications. Moreover, MOORA fosters a transparent and efficient decision-making process by providing a clear rationale for selecting one NLP approach over another. This level of transparency is essential, especially in real-world applications where NLP models may impact human lives and decision-making. As NLP continues to advance, the MOORA method will undoubtedly play a pivotal role in guiding the selection and development of cutting-edge solutions. Nonetheless, its success is contingent upon the availability of accurate and comprehensive data for evaluation. Natural Language Toolkit (NLTK) is got first rank and Tool H: Amazon Comprehend is got lowest rank.

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