A Review of Natural Language Processing Techniques in Word Processing Applications

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Abstract—**The paper underscores the use of Natural Language Processing (NLP) in modern word processors and its application for improving engagement among users through context-based suggestions, grammar correction, and sentiment analysis. This study brings to the fore the part that NLP algorithms play in mechanizing writing by providing feedback in real-time and intel- ligent text suggestions that increase writing speed and efficiency. The paper will further show that NLP can create an intuitive writing experience by enabling users to unleash their creativity in expressing effective thoughts. A comparative analysis of existing NLP-integrated word processors points out the main strengths and improvements suggested. It cumulatively reaffirms that NLP is changing the superstructure of word processors, whereby the digital space for writing is oiled to meet mixed requirements of assorted forms of users. Natural Language Processing (NLP) has gained significant prominence in recent years, contributing to a wide range of applications including machine translation, email spam detection, information extraction, summarization, and more. This paper outlines the four phases of NLP, discussing its various levels and components, particularly Natural Language Generation (NLG). It also traces the history and evolution of NLP and presents current trends, challenges, and applications. In addition, the paper provides an overview of datasets, models, and evaluation metrics used in NLP research and development.**

Keywords: Natural Language Processing, Natural Language Generation, NLP Evaluation Metrics, Word Processing

I. INTRODUCTION

Language is construed as a representative code and rules through which information, thinking, and ideas of a person are communicated. Natural language is the primary form of communication among humans, encompassing an extensive set of words, expressions, and structures enabling the com- munication of more complex ideas and feelings. Nevertheless, natural language presents limitations in human-machine com- munication. Traditionally, computers powered on machine- dependent languages that were non intuitive and not very friendly to most users. This limitation inspired the birth of Natural Language Processing (NLP) within the realm of tasks falling in between computer science, linguistics, and artificial intelligence. In this regard, NLP has established a growing crossroad between human communication and ma- chine understanding, allowing computers to digest natural language through mechanisms somewhat in parallel to how people understand it [1]. Put simply, it is meant to unite the man-machine language simply and naturally. Usefulness and ease of use are essential for any application, viz., chatbots, virtual assistants, and automated translation services, where the principle of use and accuracy of communication cannot be overlooked. Developments in NLP are generally split into two basic subdivisions: Natural Language Understanding and Natural Language Generation. NLU deals with interpreting the semantics of text by various tasks, such as sentiment analysis, named entity recognizing as well as part-of-speech tagging. Elsewhere, NLG takes a structured form of data and transforms it into text understandable to humans, such as rewriting a database entry into an accessible summary. Another example is to make automatic replies in a conversation setting [3]. The science of linguistic study, Language, is at the center of the monumental development of NLP technology. Initial linguistic concepts such as Phonology, Morphology, Syntax, Semantics, and Pragmatics have all played a significant role in conceiving how an NLP system is designed. No other breakthrough thinker on linguistics has contributed hugely to syntax, and hence, it arrived at computational approaches to the processing of languages. His theories based on generative grammar served as the basis for many of the earlier computational models of syntax and assisted researchers in formulating formal methods for parsing sentences [2]. Before proceeding to the next stage, building a solid knowledge base will be somewhat pertinent in outlining a direction for practical experimentation on many goals. This will involve a survey of the lexical, grammatical, and semantic techniques of NLP, following their development and discussing issues facing researchers. Then, it discusses the interactive role of linguistics in developing contemporary NLP techniques, the key achievements and challenges as set out in the text, as well as the new vistas the field could probably explore in the research other than those touched upon here

II. LITERATURE REVIEW

In Natural Language Processing (NLP), the user experience of word processors is greatly enhanced. NLP acts as a new tool to be used in improving text editing, grammatical corrections, sentiment analysis, and real-time suggestions by letting computers understand, process, and generate a human language. The introduction of advanced NLP models as word processors evolve encourages smarter and more intuitive user interactions. This review explores the development process in NLP, the role in word processors, and what still remains to be solved as an important challenge [1].

Statistical NLP models, including those described in [4], created text analysis technologies on probabilistic grounds, therefore making error perception and prediction more accurate in word processing systems. This allowed word processors to accomplish such text analysis tasks as text classification and sentiment analysis. These accomplishments laid the foundation for the history of language generation.

NLP for word processing deals basically with the proposed enhancement in the interaction of the user with the textual data, that is, text correction, lexical semantics, word prediction, and document summarization. One of the basic problems confronting the actual application of NLP in the domain of word processing has to do with, as described by [14], how to achieve a proper application of knowledge about Natural Language Understanding, a complex task concerning the parsing and analysis of both the syntactic and semantic aspects related to specifying the meaning of text. For Natural

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Language Generation, a mode to accomplish text outputs per data that are structured in a manner to ameliorate text prediction and automated content generation should successfully apply in a manner as stipulated, all with view [3].

[3] Emphasize the importance of natural language generation (NLG) systems, which became crucial in developing predictive text and auto-completion features. These systems provided an understanding of how structured text generation can improve word processing tools, supporting user-centric features like context-aware text suggestions.

Another focus area in word processing in NLP includes POS tagging and named entity recognition, a technique that helps to ascertain grammatical constructs and to extract meaning from entities themselves [4]. POS tagging identifies the roles of words in a sentence (e.g., verb, noun), while NER recognizes proper nouns or entities such as locations, dates, and names. As a result of the rapid adoption of NLP tools in word editing tools, there has been an influx of new features such as grammar correction, spelling correction, and thereafter editor spelling for example, in Microsoft Word and Google Docs. These algorithms usually use models like hidden Markov models (HMMs) or conditional random fields (CRFs) for error detection and correction . While lately these methods have yielded excellent readability of text, many issues revolve around understanding more complex grammatical rules like subject-verb agreement in any long sentence. Moreover, word prediction and autocomplete features are widely used in modern word processors, enhancing writing speed and accuracy. These systems use n-gram models and recurrent neural networks (RNNs) to predict the next word or phrase based on the user's input, thus assisting with document composition [5].

More advanced systems, like the ones found in Google's Smart Compose, use context-aware models such as transformers
[6] to make intelligent, real-time suggestions for completing sentences, even anticipating the next logical steps in the writing process. The introduction of word embeddings, notably those as Word2Vec or FastText [5], has transformed NLP for word processes to enable machines to comprehend semantic relationships among words. This contribution significantly enhanced the development of text similarity measures, autocorrect features, and more appropriate synonym suggestions.

[6] introduced transformer models with self-attention mechanisms, which revolutionized NLP. The transformer architecture enhanced NLP capabilities in word processing by improving the model's ability to retain long-range dependencies, which are critical for context-aware autocorrect and predictive text applications.

Summarization is another NLP application relevant to word processing, as outlined [7]. By automatically condensing large text volumes, summarization tools assist users in generating concise versions of documents, which is particularly beneficial in professional and academic writing.

Modern approaches using transformer-based models like BERT and GPT have achieved significant developments in this domain; their outputs comprise more contextually relevant and coherent summaries [8][9].

The principle of few-shot learning, as introduced [10], allows for the quick adaptation of models to new tasks with a very small amount of training data. This approach becomes particularly useful in a self-adapting personal word processing system further, enabling learning user-specific preferences on conditions such as tone and style with minimal user input.

[20] Considerations for personalized NLP. An exploration of how language generation systems can be personalized for particular users. This is of particular importance for text generation, which could be used to provide personalized writing suggestions that could match the user's style and result in better user satisfaction for word processing.

NLP integration into word processing must invariably enhance the user experience, but many problems remain. Such problems include ambiguity in natural language. Words that can take multiple meanings or sentences that have complex structures can confuse the NLP models, resulting in errors in interpretation and generation [14]. For instance, homonyms, such as ”lead” (the metal) and ”lead” (to guide), require contextual understanding which is not always easy for NLP systems to resolve.

Another major problem is dealing with different styles of writing. Different users write in different ways, using slang, colloquialism, or domain-specific terminology that NLP models might easily miss. Such variability may affect the performance of grammar correction and predictions, with creative writing or professional writing different from structured forms suffering particularly.

The latest trend in NLP for word processing involves a move towards pretrained models such as BERT [8] and GPT [9]. These models have set new standards in many NLP tasks. Trained on huge datasets, they can be adjusted to suit specific uses like predicting text, fixing errors, and summarizing content. This approach boosts accuracy and cuts down the need to engineer features for each task

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III. NLP IN WORD PROCESSORS: KEY TOPICS

A. Techniques and Algorithms in NLP for Word Processing

Natural Language Processing is the process of understand- ing, generation, and manipulation of text using various tech- niques and algorithms. The whole purpose of this is to improve the user experience through more intuitive interactions such as real-time suggestions, grammar correction, and content generation.

1) Text Correction and Grammatical Error Detection: Algorithms for text correction aim to spot and fix spelling and grammar mistakes in documents. Old-school methods, like rule-based systems, depend on set grammar rules and a word list to fix errors. But newer ways bring in machine learning. For example many people use conditional random fields (CRFs) and hidden Markov models (HMMs) to correct spelling and check grammar [14]. Also, today's word proces- sors such as Microsoft Word and Google Docs, use neural networks sequence-to-sequence models [9], to handle trickier grammar issues like making subjects and verbs agree and getting sentence structure right.

2) 1.2 Word Prediction and Autocomplete: Word prediction is an important feature in word processors that improves writ- ing efficiency by suggesting words or completing sentences as you type. Traditionally, n-gram models were used for this purpose, predicting the next word based on the preceding words [5]. However, recent advancements in natural language processing have led to the development of transformer models like BERT [8] and GPT [5]. These models outperform n-gram models by effectively capturing long-range dependencies and understanding context. They offer more accurate predictions by learning from vast amounts of text data and adapting to individual writing styles.

B. Applications of NLP in Word Processing

NLP has been effectively incorporated into word processing applications, boosting user productivity, improving writing quality, and aiding in document management. The following applications have experienced notable growth in recent years:

Real-Time Grammar and Spell Checkers: Real-time grammar and spell-checking tools are now standard features in word processors, employing sophisticated NLP algorithms to offer corrections while users type. Applications like Gram- marly, along with the integrated checkers in Google Docs and Microsoft Word, provide recommendations for spelling, grammar, punctuation, and even writing style. These tools generally utilize a mix of rule-based approaches and machine learning models, especially deep learning techniques, to detect and rectify intricate grammatical errors (Graham, 2019).

1) Automated Text Summarization: Automated summariza- tion plays a vital role in natural language processing (NLP) within word processing. By examining extensive text passages, NLP systems can create brief summaries that highlight the key concepts. In the past, summarization techniques were primar- ily extractive, focusing on picking out significant sentences from the original text. However, recent developments have moved towards abstractive summarization, where the model constructs entirely new sentences, often utilizing transformer- based models such as BERT and T5 [13]. This approach yields more coherent and human-like summaries, enhancing the user's capacity to quickly absorb large volumes of information.

C. Recent Advances in NLP for Word Processing

This means that developing algorithms and models drives the improvement of faultless accuracy, efficiency, and user sat- isfaction when it comes to the processing of natural language. Outlining key innovations that have changed the field in recent times.

1) Transformers and Pretrained Models: Transformers, stimulate by self-consideration mechanisms, have remodeled NLP by picking up complex circumstantial relationships in passage. Unlike RNNs, they process complete sequences together, enabling important progresses in models like BERT and GPT. Pretrained on endless datasets, these models provide common-purpose prose likenesses that can be adjusted for distinguishing tasks, lowering data and computational needs while transfering newfangled efficiency

2) Transformer Models: The emergence of transformer models such as BERT [8] and GPT-3[10] has greatly improved word processing tasks, including contextual grammar correction, text prediction, and content generation. These models enhance the understanding of context, leading to more precise suggestions and real-time feedback.

3) Multilingual Support: Models like mBERT and XLM-R [24] have broadened the scope of NLP applications to include multilingual word processing, enabling smooth text translation, multilingual content creation, and cross-lingual information extraction, thus enhancing accessibility for users around the world.

4) Contextual Grammar and Spell Checking: NLP- driven tools now provide more precise grammar and style recommendations by grasping the context in which words are utilized. These tools surpass basic spelling checks, correcting sentence structure and suggesting style enhancements, as demonstrated by systems like Grammarly [12].

5) Abstractive Text Summarization: Models like T5 [13] have improved text summarization abilities, producing concise and coherent summaries from extensive documents, which helps users save time when dealing with lengthy content.

D. Challenges and Limitations in NLP for Word Processing

While NLP has revolutionized word processing, several challenges still hinder its full potential. These challenges include handling language ambiguity, domain-specific language use, and computational demands.

1) Ambiguity in Language: Ambiguity in language is one of the biggest hurdles in natural language processing (NLP). Words can have various meanings based on their context, which can perplex even the most advanced NLP models. For example, homonyms such as ”lead” (the metal) and ”lead” (to guide) need to be interpreted based on the surrounding context [14]. In word processing applications, these ambiguities can result in incorrect suggestions or mistakes in grammar and spelling corrections.

2) Computational Demands: Deep learning models, especially large transformer-based ones, demand significant computational power and resources. Models like GPT-3 contain billions of parameters, making them challenging to implement in environments with limited resources [10]. Furthermore, training these models on extensive datasets can be both time-consuming and costly, which restricts their availability to smaller companies or individual developers.

3) Handling Diverse Writing Styles: Another issue is the need to accommodate a variety of writing styles. Word pro- cessors must support different types of text, from academic articles to creative writing, each requiring distinct stylistic and syntactical choices. NLP models often find it difficult to handle informal writing, slang, and specialized jargon, which complicates their ability to provide consistent and accurate suggestions across various writing scenarios

IV. NLP Models Text Processing Features in Word Processing

Natural Language Processing (NLP) models have greatly enhanced the text processing capabilities of modern word processors, especially through automation, generative text, context-aware auto-correction, and other advanced features. Here’s an overview of how specific NLP models contribute to these functionalities:

A. Automated Text Generation and Suggestions

Very recently, with the advent of models such as GPT-3 from OpenAI, word processors are able to produce coherent and relevant text with only slight input from the user. The linguistic generation of GPT-3 enables text suggestions that are not only contextually exhaustive but also stylistically agreeable, helping users to come up with ideas, finishing off sentences, or completing whole segments of content. In particular, this functionality has been enjoyed by content developers and students who can boost their productivity with the help of GPT-3-induced suggestions [10].

B. Contextual Spell Checking and Auto-Correction

Models like BERT, Bidirectional Encoder Representations from Transformers, used bidirectional context to improve accuracy in auto-correction software and spell-check functions in word processors. Unlike traditional spell that rely on simple dictionary lookups, BERT understands the context of surrounding words and will accordingly detect and suggest fixes that best fit the intended meaning. For example, it can differentiate between homophones (their vs. there) or catch subtle grammatical mistakes; hence, it would prove a more effective tool for users [8].

C. Context-Aware Writing Style Suggestions

Transformers like T5 (Text-to-Text Transfer Transformer) have extended the functionalities of word processors to provide style and tone adjustments based on user needs.T5’s text-to- text format allows it to be applied flexibly to paraphrasing, summarizing, or expanding sentences in formal, conversa- tional, technical, or any other style, depending on the need. This finds applications in various writing tasks-such as drafting professional emails, technical reports, or even social media updates [13].

D. Grammar Checking and Sentence Structuring

XLNet is an autoregressive pretraining generalization model that has enhanced sentence structuring and grammar-checking functions within word processors. XLNet harnesses power from both bidirectional contexts and the perks of autoregres- sive models, giving it much improved ability to perceive sen- tence grammar and offering more probable syntax and gram- mar suggestions. This is particularly useful in tasks requiring complex sentence structures, such that XLNet enhances real- time logical flow and clarity of sentences.

E. Real-Time Summarization and Key Point Extraction

Real-time summarization features utilizing transformer models like T5 let word processors extract long texts into short summaries. This process is of considerable help in note- taking and documentation, letting the user quickly produce summaries of lengthy texts, reports, or articles. NLP models extract moving points, allowing the user to take time and focus more on important material, thus becoming true helpers in raising productivity and enabling accessibility [13].

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F. Multilingual Translation and Language Detection

Other existing solutions are focused on detecting the lan- guage and doing real-time translation, allowing for word processing software to prove rather useful for non-native speakers. Linguists may now switch between languages or translate text within a document with ease, which improves user experience in multilingual environments. Multilingual BART has also been trained with many languages so as to ensure accurate translations and language support in context [15]. These combined NLP models have changed text editors into advanced AI-driven tools for users that offer accompanied automation, correction of typings, and writing assistance for various contexts and languages. Their incorporation has pro- vided a more confident, context-oriented, and user-comfortable writing environment to the word processor

V. Comparative Analysis and Discussion

In the domain of Natural Language Processing (NLP) appli- cations in word processing, a plethora of methods and models have been developed to tackle tasks such as text summa- rization, auto-completion, grammar correction, and contextual support. These advancements enhance writing productivity and user interaction by streamlining and enriching language- oriented features in word processors. In this context, we delve into the resemblances and distinctions between key NLP methodologies, evaluate their advantages and constraints, and explore ongoing trends and challenges within the discipline.

1. Text Summarization Text summarization tools integrated into word processors offer a valuable function by condensing lengthy documents or articles into informative summaries. Key models such as T5 (Text-to-Text Transfer Transformer) and BART (Bidirectional and Auto-Regressive Transformers) are commonly used for this purpose. These models leverage transformer architectures to generate summaries by framing the task as a sequence-to-sequence problem [13]. While T5 is known for its adaptability and ability to handle various tasks using a unified text-to-text approach, BART excels in crafting fluent summaries thanks to its dual encoding-decoding strategy. T5 demonstrates superior performance across a range of summarization tasks due to its multi-task learning capacity, whereas BART is renowned for producing syntactically and contextually coherent summaries [20]. Strengths: These mod- els have proven effective in summarizing extensive documents, making them valuable for academic writing, business reports, and content summarization. Weaknesses: Despite their advan- tages, both T5 and BART demand significant computational resources and vast amounts of data, potentially limiting their usability in resource-constrained settings. 2. Auto-Completion Word processors use auto-completion and, in a sense, it is similar to models like GPT-3 which are able to predict what the next word or sentence will be given a partial input. With its ability to churn out completions that are both coherent and sense-taking in their context, GPT-3 is also adept at real-time assisting a user with suggestions for sentences or phrases. Nevertheless, the model generates text in a left-to- right way through its consideration to the context window, as opposed to BERT-based models that will analyze both contexts before and after your tokens and encode it in a bidirectional manner [10]. Strengths: Due to its versatility, GPT produces relevant suggestions with very little input from the user; this improves productivity by providing phrasings that mirror natural language patterns. Weaknesses: GPT-3's sheer scale makes it computationally intensive, and it may occasionally generate repetitive or verbose completions, highlighting the need for refinement in word processor-specific applications. 3. Grammar and Contextual Spell Checking For instance, BERT and its variants like RoBERTa are popularly being used for grammar and spell check functions in several word processing tools. These models are great at catching grammatical errors, suggesting possible fixes for them, and providing context- aware edits to give better structure to the sentence. For robust and rapid contextual improvements without a mask token, we leverage RoBERTa [23], an hyper optimized version of BERT. This feature of understanding the left and right contexts of a word in sentences allows for BERT-based models to identify errors with precision where older, one-directional models may get confused. Strengths: These models' bidirectional nature allows for higher accuracy in detecting and correcting con- textual errors, making them valuable for technical writing and business communication where precision is essential. Weaknesses:However, one drawback with these models is that they can generate false positives in complicated language contexts like idioms or imaginative writing. On top of that, to achieve these results may require high computational resources to run those models which makes them less applicable for lightweight scenarios. 4. Contextual Writing Style Adaptation For the models such as T5 and GPT-3, style flexibility can be the extent to which the models will help to make the paraphrases, tone changes, and language transitions to be guided. T5, for example, can tune itself to the desired tone through task-specific prompts, which prove invaluable for professional writing and content moderation. It is a frequently used model in word processors for stylistic ideas as GPT-3 can create infinitely creative variations of user input. GPT-3 usually comes up with unexpected tone-incongruent sentences because it is not very tractable in style-specific applications though [10][13]. Strengths: The versatility of these models allows word processors to enhance writing for specific audi- ences or stylistic goals, whether formal, casual, or academic. Weaknesses: The models' variability and occasional lack of control in stylistic adaptations can lead to suggestions that may deviate from the intended tone, indicating a need for more adaptable, style-conscious algorithms

VI. Future Directions

Given the rapid advancements and identified gaps in NLP applications within word processing, several potential direc- tions for future research can help

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address current limitations and unlock new capabilities. As word processors increasingly rely on sophisticated NLP models, there is an opportunity to refine their efficiency, adaptability, and contextual under- standing. The following are some promising areas for research and open questions for the NLP and computational linguistics communities.

1) Personalized and Adaptive NLP Models: Current NLP models, however, do not yet possess the skills to accommo- date the individual writing preferences, tones, and vocabu- laries of diverse users. This provides room for models to personalize suggestions over time. Leveraging an individual user's interactions, NLP systems can bind the context-specific recommendations they provide, aligning themselves closer to what the user prefers, thus reducing correction fatigue [20]. Researchers have started to investigate models that learn user- specific language patterns based upon feedback on the fly to promote user engagement and productivity.

Key Question:

- How can personalized NLP models be developed to learn user preferences while ensuring data privacy (e.g., federated learning approaches)?

2) Resource-Efficient Models for Real-Time Applications: Many recent high-performing NLP frameworks, from LSTMs and CRFs to BERT and GPT-3, come with heavyweight computational demands, which poses constraints on their de- ployment on personal devices with diminished computational powers [6]. The research on model distillation and pruning is crucial to forming lightweight but efficient NLP solutions for real-time text processing, especially in mobile-type word processors. Techniques such as quantization, which apply a perspective to the complexity of a model to keep its perfor- mance intact, seem encouraging to make NLP models more resource-efficient for overall applications [17].

Key Question:

- How do we optimize NLP models for computational efficiency without compromising accuracy and response time?

3) Bias Mitigation and Inclusive Language Models: Given the domain of NLP, one needs to ensure that the use of NLP systems caters to inclusive and unbiased language. Often, biases in NLP models simply reflect the biases that are virulent in training data, leading to unintentional biases or exclusion in generated text [18]. Research into debiasing algorithms and ethical language modeling is crucial to creating word processors that accommodate the target populations without enduring harmful biases.

- What mechanisms are available to detect and mitigate biases within NLP systems so as to ensure that models can ethically adapt across these different social contexts and cultures?

A. Emerging Topics and Open Research Questions

Privacy-Conscious NLP: Federated learning allows a prag- matic approach to training natural language processing models while keeping training data within the user's devices while still contributing to the model improvement [19]. Future work could target refining federated learning techniques to provide a better balance between privacy and model adaptability. Low-Resource Language Processing: Low-Resource Language Processing: Creating NLP models for low-resource languages is important for inclusivity, making it possible for NLP-driven word processing to expand into more linguistic communities. Zero-shot learning, for example, is an approach that can operate without much labeled data, and new strategies like these can solve this problem. Human-AI Collaboration in Text Generation: NLP systems should allow for real-time collaborative interaction and learning from user interactions so that word processors can become more instinctive when learning how to write creatively or technically [20]. The proposed future directions will allow researchers to keep on refining NLP for word processors, creating models that become adaptive, fair, and accessible. Such inventions will make user experience better by granting powerful and inclusive language processing features to everyday writing tools

Conclusion

This review summarized the recent advances, impediments and prospects in NLP applications for word processing. Over the years, NLP has grown in leaps and bounds generational advancements transforming classic word processors to smart-knowledge-based inter-operable systems capable os giving contextual cues ,auto corrections ,summarization of content etc. This has resulted in digital writing environments that are more accessible, efficient and user-friendly to help guide users generate content of a higher quality and complexity.The field has been advanced by a number of significant contributions such as Transformer models (e.g, BERT and GPT) which dramatically increased the context sensitivity and linguistic sophistication of NLP systems [45]. In the same vein, growing employment of multitask learning and unsupervised training procedures have diminished reliance on hand-crafted task- specific features engineering enabling a single-spanning man- ner across many NLP tasks [22]. These advances are rein- forced by work on model efficiency through distillation and quantization, bringing NLP tools within reach of deployment in resource-limited contexts like mobile devices [17]. Several limitations remain reflective of some of the advances. Adaptive NLP in current models is limited and is frequently unable to personalize the responses based on individual and fine user preferences in real-time. These powerful NLP models still require high-end computing power, restraining them from being fit for real-time applications, and have internal biases introduced by the training data that affect the systems' inclu- sivity and ethicality [18]. The other aspect where explainability is turning out to be huge in influence relates to the user's desire to know the suggestions and corrections that are made by their word processors. For the future of the NLP technology into word processing, such challenges must receive attention. The research on personalized and privacy-conscious NLP could pave the development of adaptive models that learn upon users' preferences while protecting valuable data [20]. Furthermore, cross-linguistic capabilities and bias elimination from NLP models further create opportunities to build a more accessible and equitable word processor. Finally, explainable AI will play a significant role in developing user-friendly, transparent applications for NLP that create confidence and make the process of decision-making in digital writing tasks easier. In conclusion, while NLP has created riveting events in the affairs between word processing of old and future ones, changes in this fluid field shall remain in constant movement to offer lots of opportunities for growth. Researchers and practitioners shall continue to redress what is underwhelming, embarking NLP in word processing on the path towards more adaptive, efficient and ethical applications for digital writings to be revisited by a diverse consumer target of that exigent moment

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