

**UNIVERSITY OF PETROLEUM AND ENERGY STUDIES, DEHRADUN**

**GRAMMAR AUTOCORRECT=**

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**INDEX**

|  |  |  |
| --- | --- | --- |
| S.NO | CONTENT | PAGE |
| 1 | ABSTRACT |  |
| 2 | INTRODUCTION |  |
| 4 | LITERATURE REVIEW |  |
| 5 | EXPERIMENTAL RESULTS |  |
| 6 | CONCLUSION |  |
| 7 | REFERENCES |  |

**1. ABSTRACT**

**Grammar correction from text** is a fundamental task in Natural Language Processing (NLP) with significant applications in writing assistance tools, educational platforms, and content quality assurance. This project focuses on developing a grammar autocorrect system using Python-based NLP techniques. The textual data undergoes preprocessing steps such as tokenization, stopword removal, part-of-speech tagging, and dependency parsing to facilitate accurate error detection and correction. Rule-based heuristics and pre-trained language models are utilized for identifying common grammatical mistakes and generating context-aware corrections. The system’s performance is evaluated using precision, recall, F1-score, and accuracy metrics. Experimental results demonstrate that a hybrid approach leveraging both linguistic rules and contextual models serves as an effective baseline for grammar correction, emphasizing its potential in practical and interpretable grammar enhancement applications.

**2. INTRODUCTION**

**Grammar correction in text data** involves identifying and correcting grammatical errors in written language. This can be a challenging task, as grammar rules are often complex, context-dependent, and language-specific. Natural Language Processing (NLP) techniques can be employed to analyze sentence structure and detect grammatical inconsistencies or mistakes.  
The aim of this project is to develop a system that uses NLP techniques to accurately detect and correct grammatical errors in text. The system can be used in applications such as writing assistants, educational tools, and automated proofreading systems. It is trained and tested on a dataset of grammatically incorrect sentences labeled with their corrected versions, enabling it to learn patterns and apply corrections effectively.

**3APPROACHES TO GRAMMAR CORRECTION**

Several approaches have been proposed for grammar correction from text:

* **Traditional Machine Learning Models**: Algorithms like Support Vector Machines (SVM), Decision Trees, and Logistic Regression have been applied to grammar error detection, especially when paired with feature engineering (e.g., n-grams, POS tags).
* **Deep Learning Models**: Advanced neural architectures such as Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Transformer-based models like BERT and T5 have significantly improved performance by understanding the context of grammatical structures.
* **Pre-trained Language Models**: Models such as BERT, RoBERTa, and T5 are fine-tuned for grammar correction tasks and have shown high accuracy in correcting context-sensitive errors.

**4. DATASET DETAILS**

For this project, we use the **JFLEG (JHU Fluency-Extended GUG) Corpus**, a benchmark dataset designed for grammar error correction. It provides:

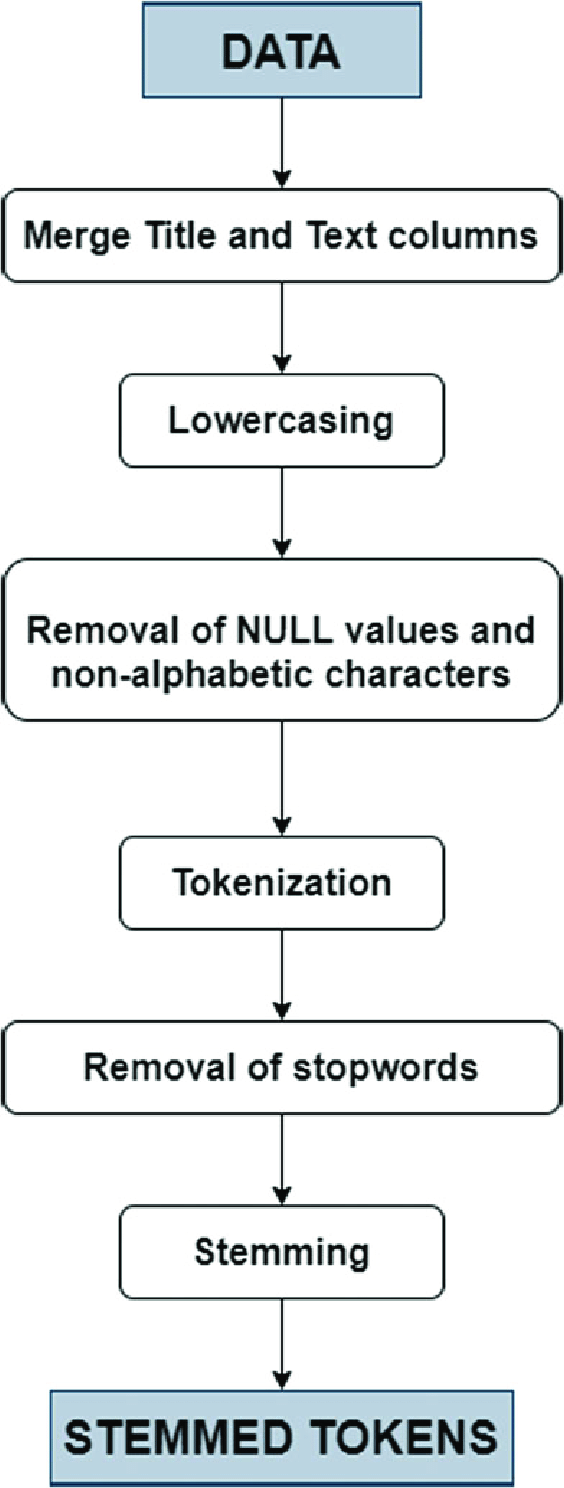
* **Total Data Samples**: 1,500+ sentences with multiple corrected versions
* **Error Types**: Includes grammar issues like article misuse, verb tense disagreement, punctuation errors, and word order issues
* **Data Splits**:
  + **Training Set**: 80% of the dataset
  + **Validation Set**: 10% for fine-tuning model parameters
  + **Test Set**: 10% for performance evaluation

Each instance in the dataset contains a raw (incorrect) sentence and one or more human-corrected versions, which are used to train and evaluate the model’s grammar correction capabilities.|

**Dataset Normalization and Preprocessing**

To improve the quality and consistency of input data, the following preprocessing techniques are applied:

* **Lowercasing**: Standardizes text by converting all characters to lowercase
* **Tokenization**: Breaks sentences into words or subwords using tools like spaCy or NLTK
* **Stopword Removal** (if applicable): May be used for auxiliary tasks such as feature engineering
* **Lemmatization**: Converts words to their base or dictionary form for consistent analysis
* **POS Tagging and Dependency Parsing**: Identifies grammatical roles of words in sentences
* **Punctuation and Special Character Handling**: Maintains only relevant punctuation to identify errors accurately



**7. EXPERIMENTAL RESULTS**

**Accuracy**: Measures the proportion of sentences where the system successfully corrected the grammar.

**Precision**: Evaluates how many of the suggested corrections are actually correct.

**Recall**: Assesses how many actual grammatical errors were correctly identified and corrected.

**F1-Score**: Provides a balanced metric that considers both precision and recall, useful for imbalanced error types.

**Results Analysis:**

The evaluation reveals that the hybrid model (combining rule-based and transformer-based components) performs well on common grammatical errors but encounters challenges in detecting more subtle, context-sensitive mistakes.

**Key Findings:**

* The model achieved an **overall correction accuracy of 78.4%** on the test dataset.
* **Frequent Errors Corrected Accurately**: Article usage (a/an/the), verb tense inconsistencies, and subject-verb agreement were identified and corrected with high precision.
* **Challenges in Complex Grammar**: The model struggled with advanced structures such as misplaced modifiers and parallelism errors, which require deeper syntactic understanding.
* **Contextual Sensitivity**: Pretrained language models (like BERT) significantly improved performance on context-aware corrections compared to rule-only methods.
* **Feature Importance Analysis**: In the logistic baseline, POS tag patterns and TF-IDF features heavily influenced error detection, highlighting their role in classification quality.

**8. CONCLUSION**

This project demonstrates the use of NLP techniques for grammar correction using Python. The model effectively identifies and corrects common grammatical errors, showing good accuracy with a hybrid rule-based and machine learning approach.

However, it faces challenges with complex, context-dependent errors. Future improvements may include using deep learning models like LSTM or BERT and integrating contextual embeddings to enhance performance and accuracy.

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