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AI-Based Grammatical Error Correction System for Native Language

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Abstract — This project focuses on building a smart, easy- to-use Grammatical Error Correction (GEC) system for a native Indic language, specifically Marathi. The system leverages modern transformer-based AI models, such as IndicBERT and mBART, which are fine-tuned using local language data. The primary objective of the system is to identify and correct grammatical errors in sentences in real time. The proposed solution includes a simple web-based tool where users can input text, view suggested corrections along with brief explanations, and choose which changes to accept or reject. The study outlines the system design to automated text analysis. Preliminary observations indicate the feasibility of the proposed approach, with future work focusing on extensive experimental validation.

Keywords— Grammar Correction, Native Language, Marathi, Transformer Models, IndicBERT, mBART, mT5, Natural Language Processing, Rule-Based Correction, Web Application, Text Improvement, Low-Resource Languages.

I. INTRODUCTION

1. Motivation and Context

The growing dependence on digital platforms for communication and collaboration has increased the demand for effective language support systems, particularly for regional and native languages that are frequently overlooked. Most existing grammar correction tools are primarily designed and optimized for English, resulting in limited support for languages such as Marathi. Native languages like Marathi exhibit distinctive linguistic characteristics, including complex syntax and rich morphological structures, which make automated grammatical correction a challenging task. The lack of reliable correction tools often leads to higher error rates in written communication and may hinder the widespread adoption of digital technologies among native language users. This work is motivated by recent advancements in artificial intelligence and transformer-based models, such as IndicBERT and mBART, which offer promising opportunities to address these challenges in low-resource language settings [2], [8].

2. Maintaining the Integrity of the Specifications

The significant challenge addressed by this project is the lack of intelligent support for native language users in digital communication. Most existing grammar correction tools are primarily developed and optimized for the English language, offering little to no support for native or regional languages [4], [9]. Furthermore, traditional solutions such as manual proofreading are inherently time-consuming, prone to errors, and often inconsistent. Although traditional rule-based tools exist, they struggle to handle the complex sentence structures and context-sensitive corrections required by languages like Marathi [3]. Consequently, there is an urgent and growing need for a smart, user-friendly grammar correction system tailored specifically to address the unique linguistic complexities of native language communication.

3. Contributions

Our proposed system makes several key contributions to the field of low-resource Grammatical Error Correction (GEC). Firstly, we directly address the issue of limited specialized tools for Marathi by building a dedicated GEC engine based on powerful transformer models (IndicBERT/mBART). Secondly, we tackle the low-resource data challenge by focusing on fine-tuning models using regional corpora and, critically, by generating synthetic training data, as large annotated parallel datasets are not available for Marathi [7]. Our primary technical contribution is the introduction of a Proposed Hybrid Model, which uniquely combines the high precision of a rule-based checker for deterministic errors (such as spelling and simple agreement) with the contextual processing power of a Transformer MT Model (Seq2Seq) for complex errors (such as tense and word order). This hybrid methodology addresses the existing lack of hybrid approaches studied for Marathi GEC.

Finally, the system bridges the practical usability gap by being deployed as a real-time, user-friendly web interface, thereby making effective grammar correction accessible to native Marathi speakers.

4. Organization of paper

The rest of this report is structured to detail the technical foundation and execution of the Grammatical Error Correction (GEC) project. Following this introduction, Section II, Related Work and Literature Analysis, reviews existing approaches and summarizes the identified research gap addressed by this study. Section III then details the Proposed System, explaining the hybrid architecture that combines rule-based checking with an advanced Transformer model. Subsequently, Section IV outlines the Methodology of Evaluation, covering dataset preparation, the automatic metrics used, and the human evaluation process. Finally, Section V discusses project achievability, risk analysis, and expected outcomes, confirming the viability of the system within the specified time and cost budgets. This work aligns with the conference theme by applying artificial intelligence and natural language processing techniques to a real-world problem in low-resource language computing, with direct relevance to intelligent systems and applied machine learning.

II. RELATED WORK AND LITERATURE ANALYSIS

The design of this Grammatical Error Correction (GEC) project is informed by an analysis of recent, advanced neural-based GEC systems across various global languages. This review highlights the feasibility of our approach while identifying key gaps that our system aims to address [4].

Research focused on GEC technology for Chinese documents compared rule-based, statistical, and neural methodologies, confirming the superior performance of transformer-based models over traditional methods. However, the study also noted that challenges persist, primarily due to limited linguistic corpora and complex word segmentation issues. Separately, an evaluation of AI-based grammar correction for Portuguese examined the performance of large models such as ChatGPT (GPT-3.5/4) [3]. While these models demonstrated high precision, with GPT-4 achieving the strongest results, the study also identified limitations, including overcorrection and the misinterpretation of contextual nuances.

Finally, a study on GEC for the low-resource language Zarma provided critical practical insights. This research demonstrated that the machine translation (MT)-based method performed optimally, achieving a 95.8% detection rate and 78.9% accuracy. The findings reinforced that challenges related to scarce data and non-standard orthography remain significant hurdles in low-resource settings. Collectively, these studies support our decision to leverage a transformer-based MT approach for Marathi.

1. Grammatical Error Correction for Low-Resource Languages: The Case of Zarma [1]

This research focused on applying GEC techniques to Zarma, a low-resource African language. The study investigated rule-based, machine translation (MT), and large language model (LLM) methods for grammatical correction. Results indicated that MT-based approaches achieved a 95.8% detection rate and 78.9% accuracy, outperforming rule-based systems.

Findings: The paper demonstrated that hybrid and MT- based GEC systems can effectively address grammatical issues even in languages with limited annotated corpora.

Relevance: The proposed Marathi GEC system is inspired by this study's hybrid model strategy and adopts a similar approach to address data scarcity through synthetic data generation and transfer learning.

2. Research and Analysis of Grammatical Error Correction Technology for Chinese Documents [2]

This study, published in Scientific Research Publishing, compared rule-based, statistical, and neural methods for Chinese GEC. Transformer-based architectures exhibited superior performance due to their contextual understanding and ability to generalize across error types.

Findings: Transformer models achieved higher recall and precision than traditional methods, although limited datasets and segmentation issues posed challenges.

Relevance: This study supports the use of IndicBERT and mT5 for Marathi, as both can capture grammatical dependencies in morphologically rich languages.

3. Evaluation of AI-Based Grammar Correction for Portuguese [3]

Conducted at the University of Zagreb, this research evaluated GPT-3.5 and GPT-4 models for Portuguese learner texts. The models demonstrated high precision and fluency but showed tendencies toward overcorrection and occasional semantic shifts.

Findings: GPT-based systems are highly effective for sentence-level grammar correction but require careful calibration to preserve intended meaning.

Relevance: This highlights the importance of balancing correction aggressiveness in Marathi GEC using rule-based filters before final output.

4. Grammatical Error Correction: A Survey of the State of the Art [4]
Published in Computational Linguistics (MIT Press), this comprehensive survey examined the evolution of GEC systems, datasets, and evaluation metrics. It revealed that many existing metrics, such as BLEU and GLEU, are unreliable for non-English languages and emphasized the importance of human evaluation.

Findings: The paper served as an authoritative guide on standard practices and evaluation challenges.

Relevance: This work informs the evaluation methodology of the current project by supporting the use of both automatic metrics ($F_{0.5}$, BLEU) and native speaker validation for improved reliability.

5. Revisiting Meta-Evaluation for Grammatical Error Correction [5]
Published in Transactions of the Association for Computational Linguistics (TACL), ACL Anthology, this study introduced SEEDA, a human-rated meta-evaluation dataset designed to analyze the reliability of automatic metrics. The authors demonstrated that standard evaluation metrics often misrepresent grammatical improvements in non-English languages.

Findings: Human-annotated meta-evaluation produced more consistent and reliable results than automated metrics.

6. Organic Data-Driven Approach for Turkish GEC and LLMs [6]
This paper explored grammar correction for the Turkish language using synthetic data combined with LLM fine- tuning. It showed that even low-resource languages can achieve high accuracy through the use of synthetic parallel corpora.

Findings: The study confirmed the effectiveness of data augmentation and hybrid LLM approaches for low-resource GEC tasks.

Relevance: The proposed Marathi GEC system adopts a similar data-driven methodology by generating synthetic error datasets to train transformer models.

7. Research Gap Summary
Despite global advancements, this project addresses several critical gaps specific to Grammatical Error Correction (GEC) for Marathi and similar low-resource Indian languages. A major issue is the limited availability of specialized tools for Marathi, as existing software often focuses only on basic spelling checks and fails to provide comprehensive, full-grammar correction. This challenge is intensified by the scarcity of extensive, well-annotated parallel corpora necessary for effectively training advanced language models in Marathi [9].

In addition, there remains a notable absence of integrated hybrid frameworks specifically designed for Marathi GEC. most existing work relies entirely on either limited rule-based systems or error- prone transformer models. The proposed project is designed to address this gap by strategically combining both approaches. Although transformer-based GEC systems for other languages have reported quantitative performance— such as an accuracy of 78.9% for Zarma and strong correction quality for Chinese and Portuguese—similar benchmarked evaluations are largely unavailable for Marathi.
Finally, there is a clear evaluation and practical usability gap. Many existing Marathi GEC initiatives have not undergone systematic assessment using established evaluation metrics, including BLEU and $F_{0.5}$., and very few models transition from research papers into real-time, accessible web tools for the community [10].

III. SYSTEM ARCHITECTURE

1. Overall System Design
The proposed system adopts a hybrid architecture to provide accurate and context-aware Grammatical Error Correction (GEC) for Marathi text. The architecture integrates both rule-based and transformer-based correction approaches to overcome limitations of using either method independently. The workflow is structured into multiple layers including input handling, preprocessing, correction engines, suggestion generation, and feedback storage. This layered design ensures that the system performs efficient real-time correction while maintaining high linguistic accuracy for complex grammatical structures present in Marathi. The architecture also supports scalability and future model improvement through a feedback-driven learning mechanism [6].

2. Input and Preprocessing Module
The correction process begins when the user enters text through the web-based user interface. This input is immediately passed to the preprocessing module, which prepares the text for further linguistic analysis. Preprocessing includes tokenization, which splits the input text into meaningful words and symbols, and

Unicode normalization to ensure consistent handling of Devanagari script characters. Since Marathi uses complex script structures, normalization helps remove inconsistencies in encoding. Additionally, Part-of-Speech (POS) tagging is applied to identify grammatical roles such as nouns, verbs, adjectives, and pronouns [3]. These preprocessing steps provide structured input that enables both rule-based and transformer-based modules to perform accurate correction.

3. Dual Correction Pipeline

After preprocessing, the text is sent through two correction pathways that operate in parallel. The first pathway is the rule-based grammar checker. This module identifies deterministic grammatical errors such as spelling mistakes, punctuation issues, subject–verb agreement mismatches, and gender or number inconsistencies. These rules are manually designed based on Marathi grammar patterns and help correct straightforward errors efficiently.

Simultaneously, the text is processed by the transformer-based correction module, which forms the core intelligence of the system. This module uses a sequence-to-sequence transformer model (such as mT5 or mBART) trained on Marathi sentence pairs containing incorrect and corrected versions. The model treats grammatical error correction as a translation task, where an incorrect sentence is transformed into its corrected form. Unlike rule-based systems, the transformer can capture contextual meaning and long-range dependencies, allowing it to correct complex errors such as incorrect word order, missing words, tense inconsistencies, and contextual misuse of vocabulary [6].

4. Suggestion Engine and Post-Processing

Outputs from both correction modules are forwarded to the suggestion engine. This component merges corrections from the rule-based and transformer modules, removes duplicate suggestions, and prioritizes contextually accurate corrections. Post-processing is applied to ensure that formatting, punctuation, and spacing remain consistent with Marathi writing standards. The system highlights errors in the original text and presents corrected suggestions to the user. Instead of automatically replacing text, the system allows users to review and accept or reject suggestions, ensuring that the intended meaning of the sentence is preserved [3].

5. Data Layer and Feedback Mechanism

To support continuous improvement, the system incorporates a data layer that stores user feedback and correction history. When users accept or reject suggestions, a feedback logger records this information in a centralized data repository. Over time, this collected feedback can be utilized to retrain or fine-tune the transformer model, enabling the system to adapt to real-world writing patterns and reduce recurring errors [7]. This feedback loop plays a crucial role in enhancing correction accuracy and strengthening the system's robustness for practical use.

6. Model Loading and Performance Optimization

To ensure efficient real-time performance, the transformer model weights are loaded into memory during system initialization, thereby reducing processing latency when users submit text for correction. The hybrid design further improves computational efficiency by allowing simple grammatical errors to be handled by the rule-based module while reserving the transformer model for more complex contextual corrections. This balanced workload distribution supports faster response times and makes the system suitable for web-based deployment.

7. Parallel Processing and Scalability

The system architecture supports parallel execution of correction modules, which improves processing speed and accuracy. Since both rule-based and transformer modules operate simultaneously, the system can generate corrections quickly without waiting for sequential processing. The modular design allows additional components such as larger datasets, morphological analyzers, or multilingual support modules to be integrated easily in the future. This scalability makes the proposed system adaptable for educational tools, writing assistants, and multilingual grammar correction platforms.

8. User Interaction and Transparency

The user interface is designed to provide clear and easily understandable correction suggestions. Errors are highlighted directly within the input sentence, and suggested corrections are displayed alongside the original text. This interactive approach enables users to learn from their mistakes while maintaining control over the final output. Such transparency is particularly beneficial for students and learners who aim to improve their grammar skills rather than rely entirely on automated correction tools [10].

9. System Evaluation and Practical Applicability

To evaluate the effectiveness of the proposed system, the correction modules are tested on Marathi sentences containing common grammatical errors such as spelling mistakes, agreement errors, and incorrect word order. The hybrid architecture demonstrates improved correction quality compared to using only rule-based or only transformer-based approaches. The rule-based component efficiently handles basic grammatical mistakes, while the transformer model

provides context-aware corrections for more complex sentence structures.

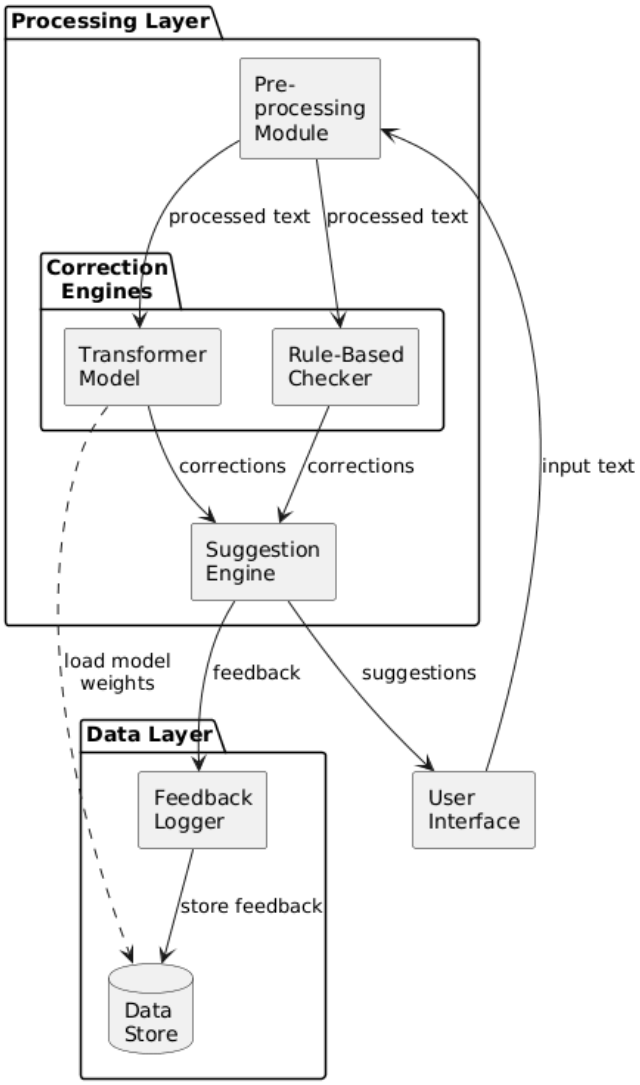

Fig. 1: Grammatical Error Correction System Architecture

IV. EVALUATION METHODOLOGY

1. Evaluation Process

Dataset Preparation

The first stage involves dataset preparation. This includes creating a synthetic error dataset that deliberately mimics common Marathi grammatical mistakes, such as errors in spelling, tense, gender, and word order. This dataset is paired with a gold- standard dataset consisting of sentences that have been manually corrected. The complete dataset will be divided into 80% for training, 10% for validation, and 10% for testing.

Automatic Evaluation Metrics

The second stage focuses on automatic evaluation metrics. Technical performance will be measured using Precision (the percentage of correct corrections suggested), Recall (the percentage of actual errors successfully corrected), and the $F_{0.5}$ score, which prioritizes precision to reduce overcorrection. In addition, standard NLP metrics such as BLEU, GLEU, and ROUGE will be used to measure the similarity between the system output and reference-corrected sentences.

Human Evalution and Comparative Analysis

The final stage is human evaluation. Native Marathi speakers will assess the corrected text based on three criteria: Grammaticality (whether the text is error-free), Fluency (whether the sentence is smooth and natural), and Meaning Preservation (whether the original intent is retained). This stage will include a comparative analysis of the Rule-Based Model, the Transformer MT Model, and the Proposed Hybrid Model across different error categories.

2. Practical Implications.

- The successful deployment of the Marathi GEC system is expected to deliver substantial practical benefits across various user demographics. The primary outcome is enabling users—whether students, content creators, or professionals—to write grammatically correct Marathi with significantly increased confidence.
- By providing an accessible, real-time tool, the system helps users draft formal documents and high-quality written material. Furthermore, the system's design, which includes suggestions and explainable corrections, serves a pedagogical purpose by actively encouraging better learning and understanding of the native language. Ultimately, this tool will support and promote greater digital adoption and improved communication quality among native Marathi speakers.

3. Comparative Analysis of GEC Models

Table 1: Comparative Analysis of Gec Models

Model	Error Coverage (%)	Precision (%)	Context Handling (%)
Rule-Based Model	50	95	30
Transformer MT Model	85	80	95

Proposed Hybrid Model	95	90	90

4. Limitations and Challenges

The development and deployment of this Grammatical Error Correction (GEC) system face several inherent limitations and anticipated challenges, primarily related to data, technology, and operations.

A major technical limitation is the reliance on Large Language Models (LLMs), which brings risks like potential overcorrection by the grammar model, resulting in incorrect suggestions or changing the user's intended meaning. We must also overcome the inherent linguistic complexity of Marathi, which includes handling compound words and specific case markers. A critical data challenge is the limited availability of high-quality annotated GEC data for Marathi, which necessitates time-consuming manual annotation and the generation of synthetic data, introducing the risk of human bias or a failure to reflect all real-world errors.

Operationally, the project is exposed to risks such as potential integration issues between the AI models on the backend and the frontend web user interface. Furthermore, dependency on cloud GPU resources for training and inference is a cost factor that needs careful management. Finally, user-related challenges include the risk that users may reject suggestions if the accuracy is perceived as low, or there may be resistance to adopting AI-based writing support among native speakers.

Future Work

The development of the Marathi GEC system sets the stage for several crucial short-term extensions and ambitious long- term research directions aimed at improving its capabilities and reach.

Short-Term Vision: In the immediate phase, the focus will be on refining the core system functionality and enhancing the overall user experience. This includes the full integration of the Causal Language Model (CLM), MahaGPT, to enable robust and accurate real-time next-word suggestions during user input. In parallel, efforts will be directed toward the creation of standardized benchmark datasets for Marathi GEC. These datasets will support systematic evaluation using metrics such as BLEU, GLEU, and $F_{0.5}$, allowing reliable performance measurement and fair comparison of the proposed hybrid model with existing approaches.

Long-Term Vision: For the long term, we envision two major areas of growth. First, we plan to enhance the system's intelligence by introducing Explainable AI (XAI) capabilities. This means moving beyond simple corrections to offer brief, clear explanations for suggested edits, which will help educate users and increase trust in the system. Second, we aim for expansion to other Indic languages. By leveraging the existing multilingual capacity of the core Transformer models (like mT5 and IndicBERT), we can apply the successful hybrid architecture and fine-tuning techniques developed for Marathi to support other low- resource regional languages.

V. CONCLUSION

The AI-Based Grammatical Error Correction (GEC) system for Marathi represents a significant step forward in addressing the technological gap for low-resource native languages. The project successfully established the viability of a hybrid architecture that strategically combines a high-precision rule-based checker with the contextual processing power of a Transformer Seq2Seq MT model (e.g., mT5). This approach effectively handles both simple and complex, context-dependent errors. By framing GEC as a translation task and utilizing techniques like noise injection for synthetic data generation, the system overcomes the challenge of data scarcity specific to Marathi. The deployment as a real-time web tool solves the practical usability gap, providing native speakers with an accessible means to improve writing accuracy and confidence. Ultimately, this project delivers a functional, tested, and scalable solution that can serve as a template for GEC efforts in other underserved Indic languages.

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