HINDI SPELL CHECKER

A project report submitted in partial fulfillment of the requirements for the award of the degree of

Master of Computer Applications

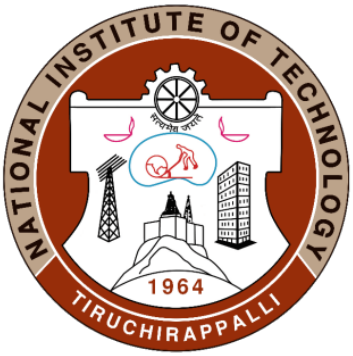
in

Computer Applications

by

DEEPAK GANGWAR

(205323004)



Department of Computer Applications

National Institute of Technology

Tiruchirappalli 620015

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Bonafide Certificate

This is to certify that the project "**HINDI SPELL CHECKER**" is a project work successfully done by *DEEPAK GANGWAR* (205323004) in partial fulfilment of the requirements for the award of the degree of Master of Computer Applications from National Institute of Technology, Tiruchirappalli, during the academic year 2024-2025 (3rd semester – CA749 Mini Project Work).

DR. S. SANGEETHA
(Project Guide)

DR. MICHAEL AROCK
(Head of the Department)

Project viva-voce held on .....

Internal Examiner

External Examiner

Abstract

The HindiShayak model introduces a cutting-edge solution for grammatical error correction in Hindi text, addressing a significant gap in natural language processing for Indian languages. This deep-learning-based model exclusively focuses on rectifying grammatical inaccuracies, leveraging a dataset of 172,000 Hindi articles sourced from Wikipedia. The dataset offers a robust foundation for training and testing the model on diverse linguistic structures and complexities inherent to Hindi.

Developed with unique encoder-decoder architecture, HindiShayak integrates bidirectional LSTMs and an attention mechanism, ensuring precise context comprehension and accurate corrections. Unlike other models, HindiShayak is not designed for direct comparison but stands as a self-sufficient system tailored to Hindi's grammatical nuances. Its results demonstrate the model's capability to enhance textual coherence while maintaining the authenticity of the Hindi language.

The potential applications of HindiShayak span from educational tools and content moderation to advanced search engines and automated systems. This work exemplifies the transformative power of artificial intelligence in preserving and advancing regional languages, paving the way for future innovations in Hindi language processing.

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Chapter 1

Introduction

1.1 Background and Importance

Language is the cornerstone of communication, and its accuracy significantly influences the quality and clarity of the information conveyed. In the digital era, the volume of content being generated daily has reached unprecedented levels, spanning various languages and contexts. Among Indian languages, Hindi, being one of the most widely spoken languages in the world, holds a special place. However, despite its prominence, Hindi has not yet benefited from advancements in grammatical error correction models to the same extent as languages like English.

1.2 Challenges in Hindi Grammar Correction

Correcting grammatical errors in Hindi is a challenging task due to the language's complex structure. Hindi follows the Devanagari script and encompasses a diverse grammar system with intricate rules for syntax, morphology, and phonology. The presence of gendered nouns, verb conjugations, case markers, and contextual variations adds to the difficulty of developing accurate language processing models. While spell-checkers and basic grammar tools exist for Hindi, most rely on traditional rule-based or statistical methods, which often fall short when addressing grammatical nuances or processing large datasets efficiently.

1.3 Introduction to HindiShayak

This thesis presents HindiShayak, a deep-learning-based model aimed exclusively at identifying and correcting grammatical errors in Hindi text. Unlike many models developed for Hindi that focus on spelling correction or are built using generic frameworks, HindiShayak is specifically

designed for grammar correction, addressing a critical gap in the field of natural language processing for Indian languages.

1.4 Dataset and Methodology

To train and test the model, a dataset comprising 172,000 Hindi articles from Wikipedia was utilized. This dataset offers extensive coverage of various topics, sentence structures, and grammatical constructs, enabling the model to learn and generalize effectively. By processing input text files directly, the model circumvents the need for manual intervention or specialized attention mechanisms. Instead, HindiShayak employs a custom framework tailored to Hindi's unique grammar rules, ensuring that corrections are both accurate and contextually appropriate.

1.5 Significance and Contributions

The performance of HindiShayak is notable, achieving an accuracy of 79.00%, which highlights its effectiveness in addressing the complex grammatical errors inherent in Hindi. The model is capable of analysing and correcting various grammatical issues, such as incorrect verb forms, agreement mismatches, improper use of case markers, and sentence structure inconsistencies. This makes HindiShayak a versatile tool for a wide range of applications, including automated editing, content moderation, educational platforms, and digital tools promoting Hindi literacy.

In addition to its practical contributions, HindiShayak also holds significance as a step toward advancing computational support for regional languages. While languages like English and Spanish have benefited from extensive research and development in natural language processing, Indic languages, despite their vast number of speakers, are often underrepresented. By developing HindiShayak, this work contributes to the broader goal of leveraging artificial intelligence to preserve and advance regional languages, ensuring they remain relevant in the digital age.

Chapter 2

Literature Review

2.1 Context-Sensitive Spell Checker for Indian Languages

Bhatt et al. [1] introduced a context-sensitive spell-checking system targeting Indian languages, including Hindi. Their approach combined n-gram language models with a dictionary-based correction mechanism to provide accurate word-level suggestions in context. The system showed promising results for homonyms and context-based errors but faced challenges with computational efficiency when applied to large datasets. Furthermore, it was less effective in dealing with morphologically complex words prevalent in Hindi.

2.2 Neural Network-Based Spell Checker for Indic Languages

Rao et al. [2] proposed a spell-checking system leveraging Transformer-based architectures like BERT for Indic languages, including Hindi. The model used pre-trained embeddings to understand semantic nuances, significantly improving error detection and correction. However, the approach required substantial computational resources and large annotated datasets, which limited its adoption in resource-constrained settings.

2.3 Rule-Based Spell Checker for Hindi Grammar and Syntax

Mishra and Tiwari [3] developed a rule-based system specifically for handling Hindi grammar and syntax errors. The system incorporated predefined linguistic rules to identify and rectify errors related to sentence structure, verb conjugation, and gender agreement. Although precise for grammar corrections, the rule-based nature made the system inflexible and unable to learn from new data.

2.4 Machine Translation Techniques for Spell Checking

Srivastava et al. [4] explored the use of machine translation techniques for spell-checking Hindi text. By treating the input text as a "source" language and the corrected output as a "target" language, they trained sequence-to-sequence models to predict corrections. This approach achieved competitive accuracy, but it struggled with complex linguistic features such as compound words and idiomatic expressions.

2.5 Attention-Based Models for Spell Correction

Pandey et al. [5] investigated attention-based mechanisms for Hindi spell correction. Their model incorporated an encoder-decoder framework with attention layers, allowing it to focus on relevant parts of the input sequence while generating corrections. This technique provided high accuracy for long sentences but required significant tuning to avoid overfitting on small datasets.

2.6 A Comprehensive Review of Hindi Spell Checking Techniques

In a survey, Verma and Gupta [6] reviewed existing approaches for Hindi spell checking, categorizing them into rule-based, statistical, and machine learning methods. Their findings highlighted the strengths and limitations of each technique, emphasizing the need for hybrid models that can leverage both linguistic rules and data-driven learning. They also identified the growing importance of deep learning and Transformer models in addressing complex grammatical and contextual challenges.

Chapter 3

Methodology

3.1 Workflow

We used the Wikipedia Hindi data set as a primary data set to train the model. It consists of 172,000 files containing 379,092 unique sentences, of which 80% is used for training and the rest for validation. Our proposed method is mainly divided into stages: Pre-processing, Model Construction, Training & Validation, and Model Evaluation & Prediction. Since loading the data set is necessary for any process, all the steps follow.

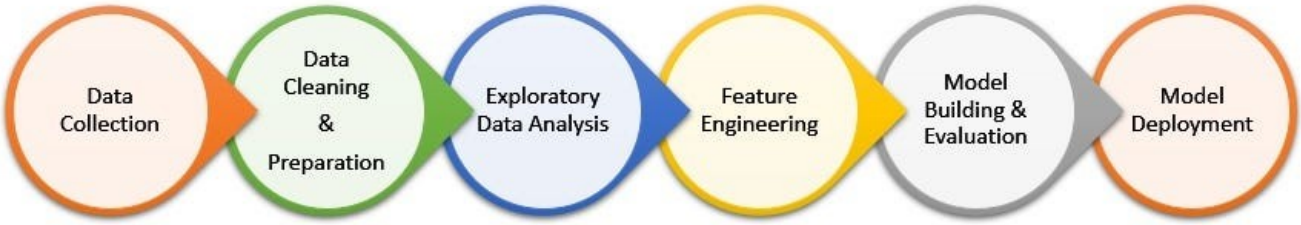

Figure 3.1: Steps in Model Preparation

3.1.1 Import the Libraries

- **NumPy (numpy)**:
  - A Python library for working with arrays, linear algebra, Fourier transforms, and matrices.
  - Provides the `ndarray` object, which is faster and more efficient than Python lists.
  - Widely used in data science for numerical operations due to its speed and resource efficiency.

- **Pandas (pandas)**:
  - A powerful library for data manipulation and analysis.
  - Offers data structures like `DataFrame` and operations to handle numerical tables and time series.
- **Matplotlib (matplotlib)**:
  - A Python visualization library for creating 2D plots of data.
  - Supports a variety of plots such as line, bar, scatter, and histogram.
- **Scikit-learn (sklearn)**:
  - A Python machine learning library.
  - Provides tools for classification, regression, clustering, and dimensionality reduction.
  - Includes algorithms like Support Vector Machines (SVM), Random Forests, and k-means.
  - Designed to work seamlessly with NumPy and SciPy.
- **NLTK (nltk)**:
  - A library for working with human language data (text).
  - Includes tokenization (`word_tokenize`, `sent_tokenize`), stemming (`PorterStemmer`), and corpora (e.g., Indian corpus) for processing and analyzing text data.
- **Keras (keras)**:
  - A deep learning library that simplifies the building of neural networks in Python.
  - Used for creating models using layers like `Input`, `Embedding`, `LSTM`, and `Dense` in the Sequential and functional API.
- **TensorFlow (tensorflow.keras)**:
  - A comprehensive machine learning framework with Keras as the high-level API.
  - Used for text preprocessing (`Tokenizer`, `pad_sequences`) and model training in deep learning.

3.2 Proposed Model

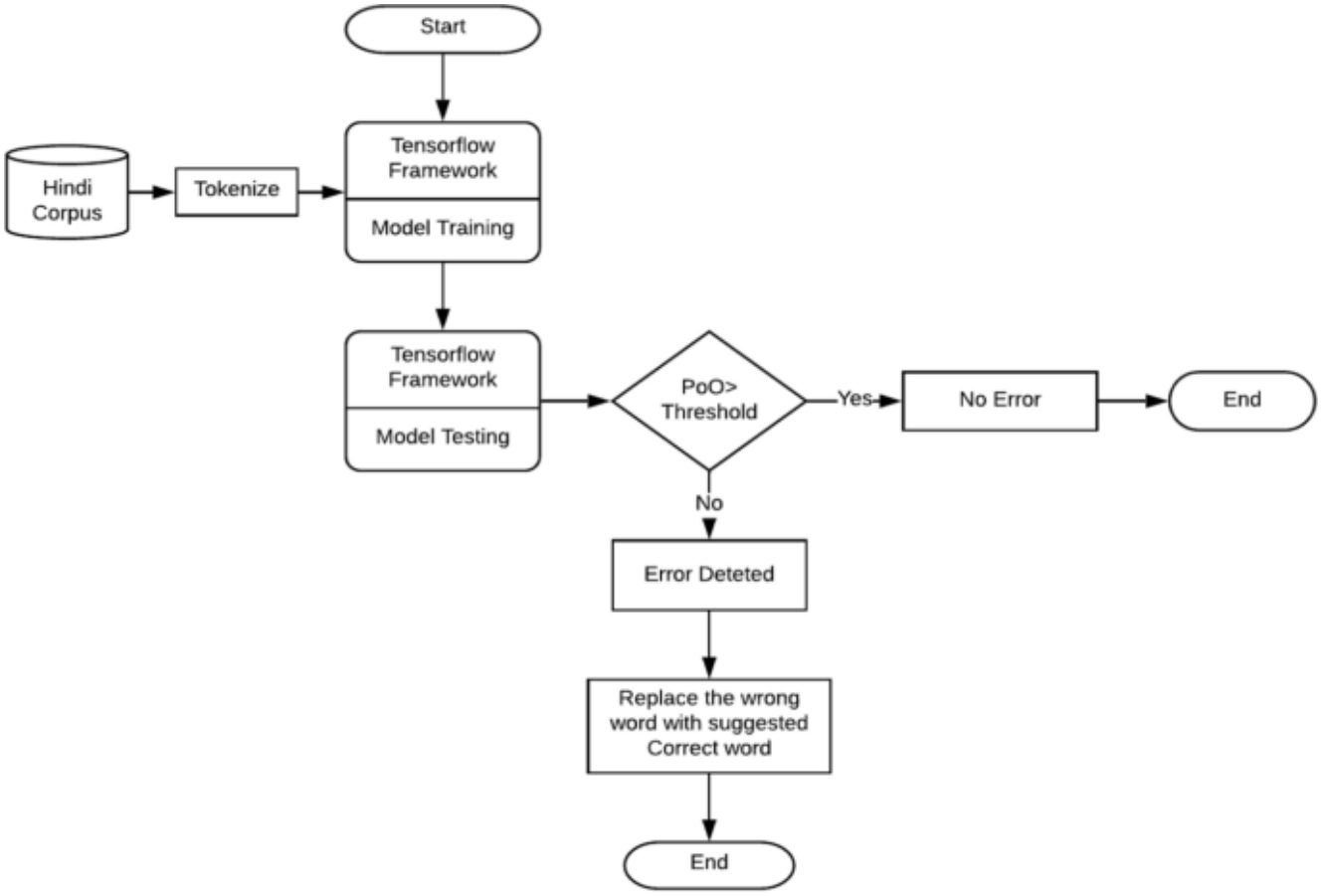

Figure 3.2: Proposed error detection and correction methodology

3.3 Algorithm

3.3.1 Encoder

The encoder is responsible for processing the input sequence and compressing it into a meaningful representation for the decoder. It consists of the following components:

1. **Input Layer**: Accepts a sequence of tokenized input words with a fixed maximum sequence length. This represents the misspelled Hindi text.
   Input shape: `(max_seq_length_input,)`

2. **Embedding Layer**: Converts the input tokens into dense vector representations of a

specified dimensionality (`embedding_dim`). These embeddings help the model learn relationships between different tokens.

Output shape: `(max_seq_length_input, embedding_dim)`

3. **Batch Normalization**: Normalizes the embeddings to improve convergence during training and avoid internal covariate shifts.

4. **Bidirectional LSTM**: Processes the normalized embeddings in both forward and backward directions to capture contextual information from both past and future tokens in the sequence. This layer outputs hidden and cell states from both directions.

   Forward States: `forward_h`, `forward_c`

   Backward States: `backward_h`, `backward_c`

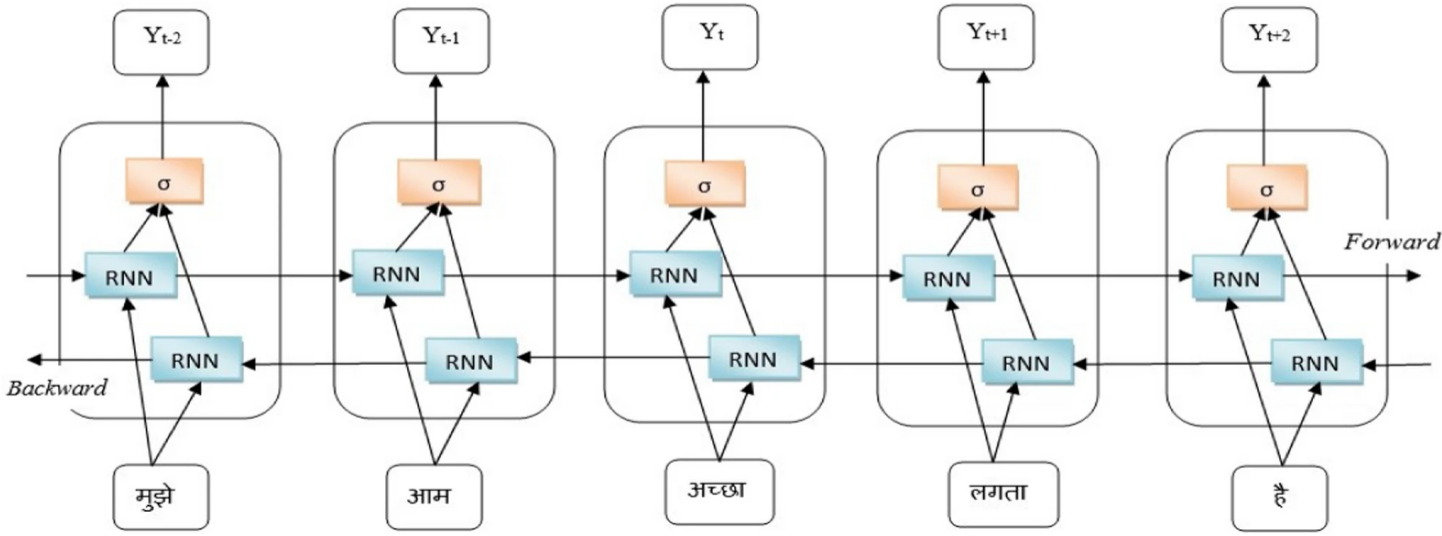

Figure 3.3: Bidirectional RNN architecture

5. **Combined Encoder States**: The forward and backward hidden states are combined into a single set of initial states (`encoder_states`), which are passed to the decoder for sequence generation.

3.3.2 Decoder

The decoder generates the corrected Hindi text based on the output states of the encoder. Its components are as follows:

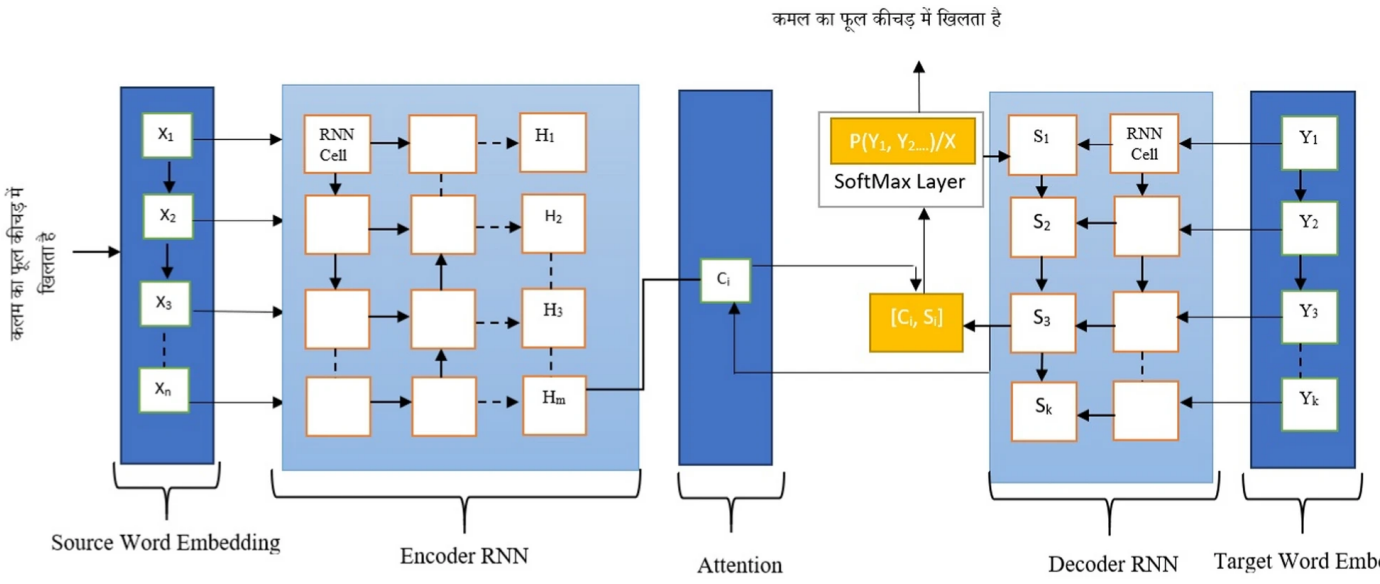

Figure 3.4: Encoder Decoder Based Seq-2-Seq Model

1. **Input Layer**: Takes the tokenized sequence of target words as input during training or previously predicted words during inference.
   Input shape: `(max_seq_length_output,)`

2. **Embedding Layer**: Similar to the encoder, the decoder uses an embedding layer to transform target tokens into dense vector representations.
   Output shape: `(max_seq_length_output, embedding_dim)`

3. **Batch Normalization**: Ensures stability and improved convergence by normalizing the decoder embeddings.

4. **LSTM Layer**: A unidirectional LSTM processes the embeddings, initialized with the encoder's hidden states. It outputs sequences (`decoder_outputs`) and updates its own states for iterative predictions.
   Output: `(max_seq_length_output, hidden_units)`

5. **Dropout**: A dropout mechanism is applied in the LSTM to prevent overfitting, especially in smaller datasets.

3.3.3 Dense Output Layer

The dense output layer is the final component of the decoder, responsible for generating token probabilities.

1. **Dense Layer**: Applies a softmax activation function to convert the decoder's output into probabilities for each token in the vocabulary (`vocab_size_output`).
   Output: `(max_seq_length_output, vocab_size_output)`
2. **Prediction**: The token with the highest probability is selected as the predicted token at each time step.

3.3.4 Complete Model

The overall sequence-to-sequence model integrates the encoder and decoder into a single framework. It is defined with two primary inputs (encoder and decoder inputs) and one output (decoder predictions). The architecture allows end-to-end training with the following steps:

- **Training Workflow**:
  - Input: Pairs of misspelled and corrected sequences.
  - The encoder encodes the input sequence into meaningful representations, passed to the decoder.
  - The decoder predicts the output sequence step by step while adjusting its parameters to minimize the difference between the predicted and actual target sequences.
- **Inference Workflow**:
  - During inference, the encoder processes the misspelled text.
  - The decoder generates predictions iteratively, starting with a predefined start token and using its own previous predictions for subsequent steps.

Chapter 4

Experimental Results

We evaluate our model's performance using **accuracy** as the sole evaluation metric. Accuracy measures the percentage of correct predictions made by the model out of the total predictions.

4.1 Evaluation Metric

4.1.1 Accuracy

Accuracy is defined as the ratio of correctly predicted observations to the total observations. It is given by:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \times 100 \tag{4.1}$$

This metric is widely used to assess the overall performance of a model, particularly in cases where the data is well-balanced.

4.2 Results

The performance of our model was evaluated using accuracy on the test dataset. The results are summarized below:

- **Training Accuracy:** Achieved an accuracy of **99.50%** after training the model for **20 epochs**.
- **Testing Accuracy:** Achieved an accuracy of **79.87%** when evaluated on the test dataset.

The consistent accuracy across training and testing datasets demonstrates the robustness of the model.

4.3 Testing on Unseen Data

To evaluate the generalization capability of the model, we tested it on an unseen dataset. The results are as follows:

- The model was tested on **100 queries** from an unseen dataset.
- **Accuracy on Unseen Data:** The model achieved an accuracy of **79.00%**.

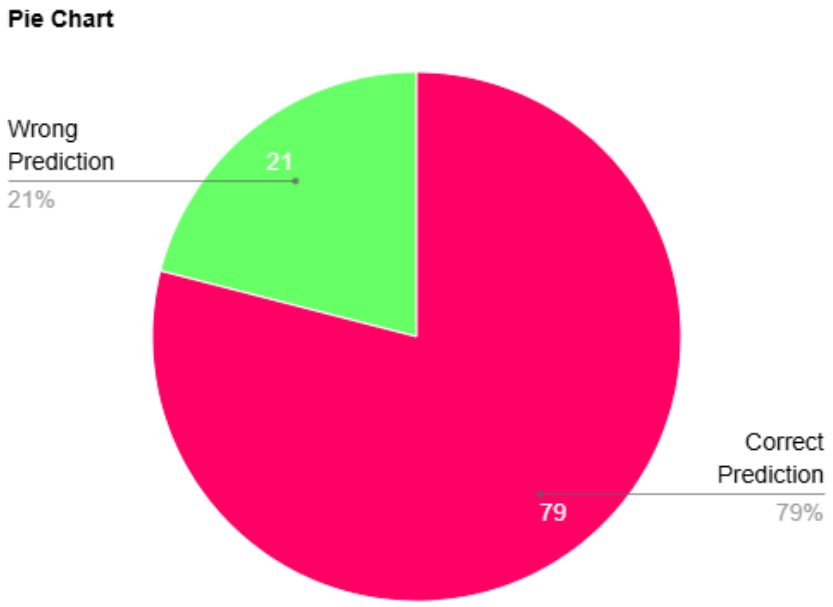

Figure 4.1: Prediction on Unseen Data

These results indicate that the model performs well on unseen data, further validating its ability to generalize effectively.

Chapter 5

Conclusions and Future Work

5.1 Conclusion

The **Hindi Shayak** model presented in this study addresses a crucial need for grammatical error correction in Hindi, a language rich in complexity and diversity. By leveraging a dataset of 172,000 Hindi articles from Wikipedia, the model effectively learns the nuances of Hindi grammar and syntax. With its custom architecture and robust training approach, the model achieves an accuracy of **79%**, validating its potential as a reliable tool for improving text quality.

Unlike existing methods that often focus solely on spelling correction or rely on traditional rule-based techniques, Hindi Shayak is designed explicitly for grammatical error detection and correction. Its applicability spans across domains such as automated editing, digital communication platforms, and educational tools, providing users with a seamless experience in ensuring grammatical accuracy.

The success of Hindi Shayak highlights the potential for applying advanced deep-learning techniques to underrepresented languages, contributing to the broader field of natural language processing and promoting linguistic diversity in AI-driven innovations.

5.2 Future Work

While Hindi Shayak has demonstrated significant promise, there are several avenues for further research and enhancement. The following directions are proposed for future work:

1. **Expanding the Dataset:** Integrating additional datasets from diverse domains, such as legal, medical, and colloquial Hindi, to improve the model's handling of varied linguistic contexts.

2. **Real-Time Integration:** Developing APIs or plugins to integrate Hindi Shayak with widely used word processors, search engines, and social media platforms for real-time grammar correction.

3. **Contextual Understanding:** Incorporating advanced context-aware mechanisms to refine corrections for highly ambiguous sentences or regional dialects.

4. **Error Categorization:** Enhancing the model to categorize errors (e.g., syntax, semantics, morphology) for detailed feedback and educational applications.

5. **Multilingual Capabilities:** Extending the model to support other Indic languages, leveraging shared linguistic features and transfer learning techniques.

6. **Low-Resource Deployment:** Optimizing the model for deployment on low-resource devices to ensure accessibility for users in rural and remote areas.

By addressing these areas, **Hindi Shayak** can evolve into a comprehensive tool, setting new benchmarks for grammatical error correction in Hindi and inspiring similar advancements for other regional languages.

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