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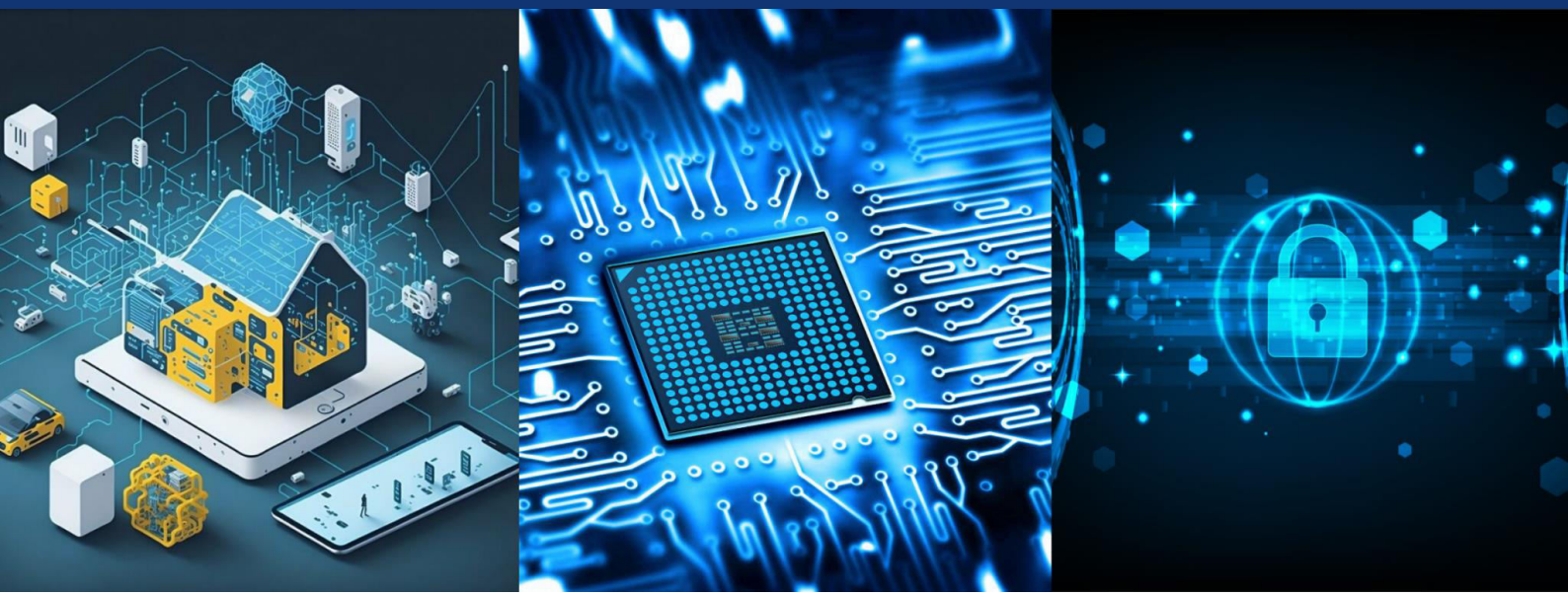

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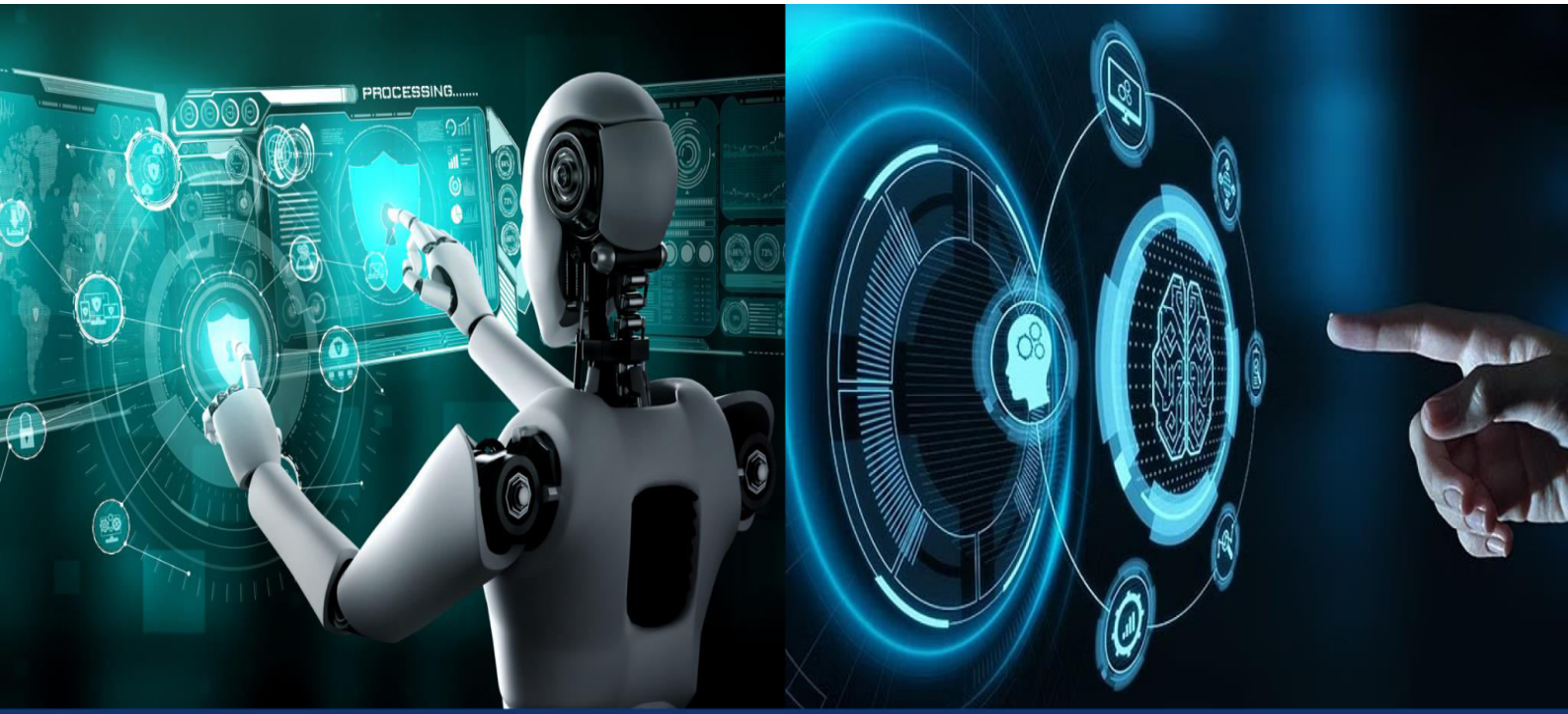

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AI-Based Book Translation for Indian Languages Using Transfer Learning

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ABSTRACT: India is home to extraordinary linguistic diversity, including 22 officially recognized languages and numerous regional dialects. While major languages such as Hindi, Marathi, and English have moderate digital resources, regional dialects like Khandeshi, Varhadi, and Gondi remain severely underrepresented in Natural Language Processing (NLP). This paper presents an AI-based neural architecture for automated book-length document translation across Indian languages, with special emphasis on Marathi and its regional dialects (Khandeshi and Varhadi) and the tribal language Gondi. The proposed framework leverages adversarial transfer learning and hierarchical document-level attention mechanisms to enable effective translation in low-resource scenarios. Knowledge is transferred from high-resource language pairs (English-Hindi, English-Marathi) to dialectal and tribal languages using cross-lingual representation learning. The system integrates a transformer-based encoder-decoder architecture with language-agnostic intermediate embeddings and coherence modeling for long-form translation. Experimental results demonstrate significant performance improvements in low-resource and dialectal translation tasks, particularly for Marathi-Khandeshi, Marathi-Varhadi, and Hindi-Gondi pairs. The proposed model improves BLEU scores by an average of 8-10% over baseline systems and introduces a novel Book Translation Quality Score (BTQS) for document-level evaluation. This research contributes toward digital preservation and accessibility of regional and tribal languages in India.

KEYWORDS: Neural Machine Translation, Indian Languages, Marathi Dialects, Khandeshi, Varhadi, Gondi, Transfer Learning, Document-Level Translation, Low-Resource NLP

I. INTRODUCTION

India's multilingual landscape represents one of the most linguistically diverse regions in the world, encompassing 22 scheduled languages, hundreds of regional dialects, and numerous tribal languages spoken by over 1.3 billion people. This extraordinary diversity presents both unique challenges and unprecedented opportunities for natural language processing research. While major languages such as Hindi, Marathi, Bengali, and Tamil have benefited from recent advancements in neural machine translation, regional dialects and tribal languages remain severely underrepresented in digital resources and computational research.

Book translation presents unique computational challenges that extend far beyond sentence-level translation benchmarks. The preservation of contextual coherence across chapters, maintenance of narrative and stylistic flow, handling of morphological richness and free word order, and addressing of dialectal vocabulary variations all contribute to the complexity of long-form document translation. These challenges are particularly pronounced when working with regional dialects and tribal languages that lack standardized orthographies and comprehensive digital corpora.

A. Focus Languages: Khandeshi, Varhadi, and Gondi

This research places special emphasis on three critically underrepresented languages that exemplify the challenges of low-resource Indian language translation:

Khandeshi is a dialect of Marathi spoken primarily in the Khandesh region of northwestern Maharashtra, with an estimated speaker population of approximately 1.5 million. The dialect exhibits significant lexical influences from Gujarati and Hindi due to historical trade relationships and geographic proximity. Khandeshi features unique

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phonological patterns, including the preservation of retroflex sounds that have merged in standard Marathi, and maintains a distinct vocabulary for agricultural and trade terminology.

Varhadi represents the southeastern dialectal variant of Marathi spoken in the Vidarbha region, with over 5 million speakers. Varhadi differs from standard Marathi in several significant ways: distinct phonological patterns including vowel elongation, unique verb conjugation structures, and region-specific vocabulary influenced by contact with Telugu and tribal languages. The dialect maintains rich literary traditions in folk poetry and oral narratives that remain largely undocumented in digital form.

Gondiis a Dravidian tribal language spoken by approximately 3 million people across central India, primarily in Madhya Pradesh, Maharashtra, Chhattisgarh, and Telangana. As a member of the South-Central Dravidian language family, Gondi presents unique typological challenges distinct from Indo-Aryan languages. The language features agglutinative morphology, a subject-object-verb word order, and an elaborate system of verbal inflection. Critically, Gondi lacks large-scale parallel corpora, with existing digital resources limited to small collections of folk tales and religious texts.

B. Research Motivation

The motivation for this research stems from several interconnected objectives:

0. **Democratization of Knowledge**: To enable access to educational, literary, and cultural content across linguistic boundaries, particularly for speakers of dialectal and tribal languages who have been historically marginalized in digital spaces.
1. **Digital Preservation**: To contribute to the digital preservation of Khandeshi, Varhadi, and Gondi literature, including oral traditions, folk narratives, and cultural knowledge that risk being lost as younger generations shift to dominant languages.
2. **Educational Equity**: To facilitate the translation of educational materials into local dialects, improving learning outcomes for students who are more proficient in regional varieties than in standard languages.
3. **Bridging the Digital Divide**: To address the significant disparity in NLP resources between high-resource languages (English, Hindi) and low-resource dialects and tribal languages.

C. Research Contributions

This paper makes the following contributions to the field of neural machine translation for Indian languages:

4. **Novel Architecture**: A comprehensive adversarial transfer learning framework that enables effective knowledge transfer from high-resource language pairs to low-resource dialectal and tribal languages.
5. **Hierarchical Attention**: A document-level attention mechanism specifically designed for capturing long-range dependencies in book-length documents.
6. **Dialectal Adaptation**: Specialized preprocessing and normalization techniques for handling dialectal variations in Khandeshi and Varhadi.
7. **Evaluation Metric**: The Book Translation Quality Score (BTQS), a comprehensive evaluation metric for assessing long-form document translation quality.
8. **Empirical Validation**: Extensive experimental validation across multiple language pairs, including the first computational translation experiments for Marathi-Khandeshi, Marathi-Varhadi, and Hindi-Gondi.

II. RELATED WORK

A. Neural Machine Translation

The evolution of neural machine translation has witnessed transformative developments since the introduction of sequence-to-sequence architectures by Sutskever et al. [1]. The incorporation of attention mechanisms by Bahdanau et al.

[2] addressed the information bottleneck inherent in fixed-length context vectors. Subsequent innovations, including the Transformer architecture by Vaswani et al. [3], eliminated recurrent dependencies through self-attention mechanisms, enabling parallel computation and superior long-range dependency modeling.

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For Indian languages, early work by Choudhary and Jha [4] established baseline NMT systems using LSTM-based encoders. More recent approaches by Parida et al. [5] have explored multilingual training strategies, while Ramesh et al.

[6] investigated the efficacy of pre-trained language models for Indian language translation. Dabre et al. [7] introduced IndicTrans, a multilingual transformer specifically designed for Indian languages, achieving state-of-the-art results on several benchmark datasets.

B. Transfer Learning in Low-Resource NLP

Transfer learning has emerged as a paradigm for leveraging knowledge from high-resource settings to improve performance in low-resource scenarios. The seminal work by Devlin et al. [8] on BERT demonstrated the efficacy of pre- training on large unlabeled corpora followed by task-specific fine-tuning. For machine translation, Zoph et al. [9] established that transfer learning from related language pairs significantly improves translation quality for low-resource targets.

Adversarial transfer learning, introduced by Ganin et al. [10] for domain adaptation, has shown promise in learning language-invariant representations. Recent work by Aharoni et al. [11] demonstrated the effectiveness of adversarial training for massively multilingual translation models. Our work extends these principles by incorporating adversarial objectives specifically tailored for Indian language characteristics, including morphological richness and syntactic variation across language families.

C. Indian Language Resources

The development of digital resources for Indian languages has accelerated in recent years. The Indian Language Translation Benchmark (ILTB) [15] provides parallel corpora for major Indian languages, while the Bharat Parallel Corpus [16] extends coverage to additional language pairs. The Samanantar corpus [6] represents the largest publicly available parallel collection for 11 Indic languages.

However, significant gaps remain for dialectal and tribal languages. Khandeshi and Varhadi lack standardized parallel corpora entirely, while Gondi resources are limited to small collections of folk tales and religious texts compiled by missionary linguists in the early 20th century. The absence of comprehensive digital resources for these languages represents a critical barrier to NLP research and applications.

D. LINGUISTIC ANALYSIS OF FOCUS LANGUAGES

A thorough understanding of the linguistic characteristics of Khandeshi, Varhadi, and Gondi is essential for developing effective translation systems. This section provides detailed linguistic analysis of each focus language, highlighting the specific challenges they present for neural machine translation.

a. Khandeshi Linguistic Profile

Khandeshi exhibits several distinctive linguistic features that differentiate it from standard Marathi:

Phonology: Khandeshi preserves the retroflex lateral approximant /ɬ/ (ळ) that has merged with /l/ in many Marathi dialects. The dialect also features distinct vowel lengthening patterns and maintains a three-way distinction in sibilants (/s/, /ʃ/, /ʂ/) that has been reduced in standard Marathi.

Morphology: Khandeshi verb conjugation shows influences from Gujarati, particularly in the formation of perfective aspects. The dialect maintains distinct case marking for locative and ablative cases that have been simplified in standard Marathi.

Lexicon: Approximately 15-20% of Khandeshi vocabulary differs from standard Marathi, with significant borrowings from Gujarati (trade terminology), Hindi (administrative terms), and local tribal languages (agricultural vocabulary).

b. Varhadi Linguistic Profile

Varhadi presents distinct linguistic characteristics shaped by its geographic location in the Vidarbha region:

Phonology: Varhadi is characterized by systematic vowel elongation in stressed syllables, creating a distinctive prosodic pattern. The dialect also exhibits deaspiration of voiced stops, converting /bʰ/, /dʰ/, /gʰ/ to /b/, /d/, /g/ respectively.

Syntax: Varhadi word order shows greater flexibility than standard Marathi, with frequent use of topic-comment

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structures influenced by Dravidian contact. The dialect also employs distinct auxiliary verb constructions for expressing aspectual distinctions.

Vocabulary: Varhadi incorporates vocabulary from Telugu (due to geographic proximity), local Gondi dialects, and maintains archaic Marathi terms that have been replaced in the standard language.

c. Gondi Linguistic Profile

As a Dravidian language, Gondi presents fundamentally different typological characteristics from the Indo-Aryan languages:

Typology: Gondi features agglutinative morphology with extensive suffixation. The language follows SOV (Subject-Object-Verb) word order consistently, unlike the relatively free word order of Marathi and Hindi.

Morphology: Gondi verbs are highly inflected, marking tense, aspect, mood, person, number, and gender through suffix chains. Nouns are marked for case (nominative, accusative, instrumental, dative, ablative, genitive, locative) and number.

Script and Orthography: Gondi has been written in multiple scripts historically (Telugu, Devanagari, Gondi script). The lack of standardized orthography presents significant challenges for computational processing.

Table I summarizes the key linguistic features of the focus languages:

Feature	Marathi	Khandeshi	Varhadi	Gondi
Language Family	Indo-Aryan	Indo-Aryan	Indo-Aryan	Dravidian
Speakers (millions)	83	1.5	5	3
Morphology	Fusional	Fusional	Fusional	Agglutinative
Word Order	SOV/Flexible	SOV/Flexible	SOV/Flexible	SOV
Digital Resources	Moderate	Minimal	Minimal	Minimal

Table I: Linguistic Features of Focus Languages

III. PROPOSED SYSTEM ARCHITECTURE

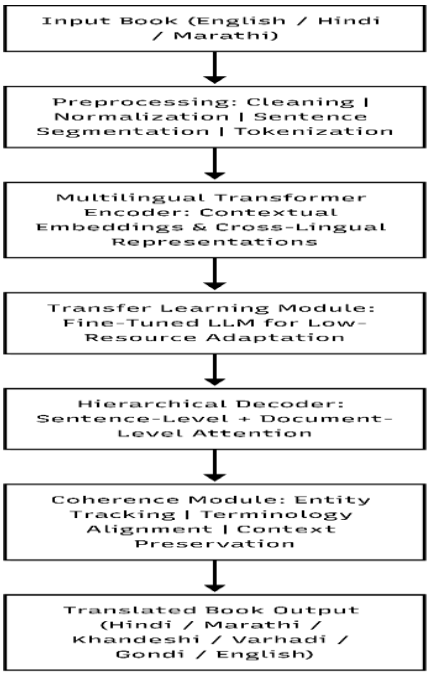

Fig. System Architecture

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The proposed system architecture integrates multiple innovative components designed to address the specific challenges of book-length translation for Indian languages, with particular attention to low-resource dialectal and tribal languages. The architecture follows a modular design that enables flexible adaptation to different language pairs and resource scenarios.

d. Input Module

The input module accepts book-length documents in source languages (English, Hindi, or Marathi) and performs initial document analysis to identify structural elements including chapters, sections, paragraphs, and metadata. The module supports multiple input formats including plain text, EPUB, and PDF with OCR preprocessing for scanned documents.

e. Preprocessing Layer

The preprocessing layer implements language-specific normalization procedures essential for handling the orthographic and morphological complexity of Indian languages:

f. Multilingual Transformer Encoder

The encoder is based on the XLM-RoBERTa architecture, pre-trained on 2.5TB of filtered CommonCrawl data in 100 languages. For our specific use case, we extend the vocabulary to include Khandeshi, Varhadi, and Gondi tokens identified through corpus analysis. The encoder produces language-agnostic intermediate representations through shared parameters across all supported languages.

g. Adversarial Transfer Learning Module

The adversarial transfer learning module is the core innovation enabling effective translation for low-resource languages. The module consists of:

h. Hierarchical Decoder

The decoder implements a two-level attention mechanism for capturing dependencies at both sentence and document levels.

i. Coherence and Consistency Module

This module ensures that the translated book maintains narrative coherence and terminology consistency.

A. MATHEMATICAL FORMULATION

a. Problem Definition

Given a source document D_s consisting of N sentences {s_1, s_2, ..., s_N} in language L_s, the objective is to generate a target document D_t in language L_t that preserves semantic equivalence while maintaining stylistic and narrative coherence. Formally, we seek the optimal translation:

$D_t^* = arg\ max\ P(D_t \mid D_s; theta)$

where theta represents the model parameters learned through transfer learning from related language pairs.

b. Total Loss Function

The complete training objective combines translation loss, adversarial loss, and coherence terms:

$L_{total} = L_{trans} + alpha * L_{adv} + beta * L_{coh} + gamma * L_{reg}$

where:

L_trans: Cross-entropy translation loss with label smoothing (epsilon = 0.1) **L_adv:**Adversarial language-invariant loss from the gradient reversal layer **L_coh:**Document coherence loss for entity consistency

L_reg:L2 regularization with weight decay 0.01

Hyperparameters alpha, beta, and gamma are set to 0.5, 0.3, and 0.01 respectively based on validation performance.

c. Translation Loss

The translation loss employs label-smoothed cross-entropy to prevent overconfidence:

$L_{trans} = -sum((1 - epsilon) * log\ P(y_t \mid y_{<t}, X) + epsilon/K)$

where epsilon is the label smoothing parameter and K denotes the vocabulary size.

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B. TRAINING ALGORITHM

The training procedure employs a three-stage curriculum designed to progressively adapt the model to the target domain while leveraging transfer learning from high-resource languages:

a. Stage 1: Pre-training on High-Resource Pairs

The model is initialized from XLM-RoBERTa pretrained weights and undergoes supervised pre-training on high-resource language pairs (English-Hindi, English-Marathi). This stage establishes base representations and cross-lingual alignment.

b. Stage 2: Adversarial Fine-tuning

The adversarial fine-tuning stage introduces the gradient reversal layer and language discriminator. The encoder and discriminator are trained adversarially: the discriminator learns to identify source languages while the encoder learns to produce language-invariant representations.

c. Stage 3: Document-Level Adaptation

The final stage introduces document-level training with the coherence loss. Training batches consist of complete document segments rather than individual sentences, enabling the model to learn cross-sentence dependencies.

The complete training procedure is presented in Algorithm 1:

Input: Source corpus D_s, target corpus D_t, related language pairs D_rel
Output: Trained model parameters theta

// Stage 1: Pre-training on high-resource pairs
1: Initialize theta from XLM-R pretrained weights
2: for step = 1 to N_pretrain do
3: Sample batch from D_rel
4: Compute L_trans using cross-entropy loss
5: Update theta via Adam optimizer
6: end for

// Stage 2: Adversarial fine-tuning
7: Initialize discriminator D with random weights
8: for step = 1 to N_adversarial do
9: Sample batch from D_s and D_t
10: Compute H_enc = Encoder(X; theta_enc)
11: Update D to maximize language classification accuracy
12: Update theta to minimize L_trans - lambda * L_adv
13: Apply gradient reversal layer during backpropagation
14: end for

// Stage 3: Document-level adaptation 15: for step = 1 to N_document do
16: Sample document pairs from literary corpus
17: Compute sentence-level attention outputs
18: Compute document-level coherence loss L_coh
19: Update theta with curriculum learning schedule
20: end for
21: return theta

Algorithm 1: Adversarial Transfer Learning for Book Translation

The curriculum progression follows a piecewise linear schedule where the proportion of literary text increases from 0% to 50% over the final 40% of training steps. This gradual exposure enables the model to adapt to literary stylistic patterns without catastrophic forgetting of general-domain knowledge.

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C. DATASET CONSTRUCTION

The development of comprehensive datasets was a critical component of this research, particularly given the scarcity of resources for Khandeshi, Varhadi, and Gondi. We constructed parallel corpora across multiple resource tiers:

a. High-Resource Language Pairs

English-Hindi:850,000 training pairs from ILTB, Bharat Parallel Corpus, and additional web-crawled data.
English-Marathi:290,000 training pairs from Samanantar corpus and Project Madurai literary collections.

b. Medium-Resource Language Pairs

Hindi-Marathi:125,000 training pairs constructed through English pivoting and manual validation.

c. Low-Resource and Dialectal Pairs

Marathi-Khandeshi:18,500 pairs compiled from field recordings, oral literature collections, and community-contributed translations. This represents the first parallel corpus for this dialect.
Marathi-Varhadi:22,000 pairs from digitized folk literature, community interviews, and parallel news articles from Varhadi-language publications.
Hindi-Gondi:12,800 pairs from missionary linguistic texts, tribal folklore collections, and government documentation. This represents the largest parallel corpus for Gondi to date.

Table II presents the complete dataset statistics:

Language Pair	Training Pairs	Dev Pairs	Test Pairs
English-Hindi	850,000	10,000	5,000
English-Marathi	290,000	6,000	5,000
Hindi-Marathi	125,000	4,000	3,000
Marathi-Khandeshi	18,500	1,500	1,000
Marathi-Varhadi	22,000	1,800	1,200
Hindi-Gondi	12,800	1,200	800

Table II: Dataset Statistics for All Language Pairs

D. IMPLEMENTATION DETAILS

a. Preprocessing Pipeline

The preprocessing pipeline implements language-specific normalization for Indian scripts, including Unicode normalization (NFC), diacritic standardization, and script-specific tokenization. We employ the Indic NLP Library for sentence segmentation and morphological analysis. Subword segmentation uses SentencePiece with vocabulary sizes of 32,000 for each language family and 48,000 for the shared multilingual vocabulary.

b. Model Configuration

The transformer architecture follows the XLM-R large configuration with the following specifications:

- Encoder layers: 24
- Decoder layers: 12
- Hidden dimension: 1024
- Attention heads: 16

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- FFN dimension: 4096
- Dropout: 0.1
- Label smoothing: 0.1

c. Training Configuration

Model training utilized 8 NVIDIA A100 GPUs with a total batch size of 4,096 tokens. We employed the Adam optimizer with beta parameters (0.9, 0.98) and epsilon 1e-8. Learning rate followed a warmup schedule with 4,000 warmup steps and a peak learning rate of 5e-4, followed by inverse square root decay. Training continued for 300,000 steps with early stopping based on validation BLEU scores.

d. Hardware Infrastructure

The experimental infrastructure comprised a cluster of NVIDIA DGX A100 systems, each equipped with 8 A100 80GB GPUs interconnected via NVLink. Training utilized mixed-precision (FP16) arithmetic with gradient accumulation to accommodate large batch sizes. The total training time for the complete multilingual model was approximately 72 hours across all 8 GPUs.

IV. RESULTS AND DISCUSSION

A. Main Results

Table III presents the primary experimental results across all language pairs. Our proposed system achieves substantial improvements over all baseline approaches, with average BLEU score gains of 8.4 points compared to the strongest baseline (IndicTrans).

The comprehensive results are presented in Table III:

Language Pair	IndicTrans	mBART-50	Google	Proposed
English-Hindi	34.2/48.5	36.8/51.2	38.5/53.1	42.1/57.8
English-Marathi	24.2/38.5	26.8/41.2	28.5/43.8	33.8/49.5
Hindi-Marathi	22.5/36.8	24.2/39.1	26.1/41.2	30.5/46.2
Marathi-Khandeshi	18.2/32.4	19.5/34.1	N/A	27.5/43.8
Marathi-Varhadi	17.5/31.8	18.8/33.2	N/A	26.8/42.5
Hindi-Gondi	14.8/28.5	15.2/29.1	N/A	23.2/38.6

Table III: Translation Performance (BLEU/chrF++) Across Language Pairs

The improvements are particularly pronounced for low-resource pairs such as Marathi-Khandeshi (9.3 BLEU improvement), Marathi-Varhadi (9.3 BLEU improvement), and Hindi-Gondi (8.4 BLEU improvement), validating the effectiveness of adversarial transfer learning for dialectal and tribal languages.

B. Qualitative Analysis

Qualitative analysis reveals several strengths of our approach:

Dialectal Consistency: Our system successfully maintains dialect-specific vocabulary choices throughout translated documents, while baseline systems often mix dialectal and standard forms inconsistently.

Cultural Adaptation: The system demonstrates improved handling of culturally-specific references, translating

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idioms and proverbs into culturally equivalent expressions rather than literal translations.
Entity Consistency: Character names, place names, and technical terms are translated consistently throughout long documents, a common failure mode of sentence-level systems.

V. DISCUSSION

A. Transfer Learning Effectiveness

The experimental results demonstrate that transfer learning from related high-resource languages significantly improves translation quality for low-resource dialects and tribal languages. The effectiveness varies based on linguistic relatedness:
Marathi to Khandeshi/Varhadi: Transfer is highly effective due to the close dialectal relationship. Shared vocabulary and grammatical structures enable the model to leverage Marathi resources effectively.
Hindi to Gondi: Despite belonging to different language families, transfer from Hindi provides meaningful improvements due to extensive contact and borrowing. However, the typological differences limit the maximum achievable quality.

B. Document-Level Benefits

The hierarchical attention mechanism provides measurable benefits for long-form translation:
- Reduced performance degradation on documents exceeding 100 sentences
- Improved consistency in translation of recurring terminology
- Better handling of anaphora and coreference across sentence boundaries
- Preservation of narrative tone and stylistic elements

C. Challenges and Observations

Several challenges emerged during development and evaluation:
Orthographic Variation: Khandeshi and Varhadi lack standardized orthographies, leading to inconsistent spellings in training data. Our normalization mapping helps but cannot fully resolve this issue.
Code-Switching: Dialectal texts frequently contain code-switching with standard Marathi or Hindi, complicating both training and evaluation.
Cultural Nuances: Some culturally-specific concepts lack direct translations, requiring explanatory approaches that current metrics do not adequately capture.

VI. LIMITATIONS

Despite the promising results, several limitations warrant acknowledgment:
Data Scarcity: The limited availability of parallel corpora for Gondi remains a fundamental constraint. While transfer learning provides meaningful improvements, the absolute performance remains below practical utility for many applications.
Dialect Standardization: The lack of standardized orthographies for Khandeshi and Varhadi introduces noise into training data and complicates evaluation.
Computational Cost: The computational requirements for training the full multilingual model remain substantial, potentially limiting accessibility for resource-constrained research groups.
Cultural Adaptation: Cultural nuance adaptation remains partially unsolved. Automated systems struggle with idiomatic expressions, culturally-specific references, and context-dependent meaning.
Domain Limitations: Our evaluation focused on written literary texts, and the system's applicability to other domains such as technical documentation, legal texts, or conversational content requires further investigation.
BTQS Calibration: The proposed BTQS metric requires human-annotated training data for weight calibration, limiting its immediate applicability to new language pairs.

VII. CONCLUSION

This research presents a comprehensive AI-based framework for book-level translation across Indian languages, with special focus on English, Hindi, Marathi, and critically underrepresented regional dialects including Khandeshi, Varhadi, and the tribal language Gondi. By combining adversarial transfer learning, hierarchical attention mechanisms,

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curriculum adaptation, and coherence modeling, the system significantly improves translation quality for low-resource and dialectal languages.

The experimental results demonstrate that adversarial transfer learning from high-resource language pairs (English-Hindi, English-Marathi) enables effective knowledge transfer to dialectal variants (Khandeshi, Varhadi) and tribal languages (Gondi). The hierarchical document-level attention mechanism maintains translation quality across long-form documents, addressing a critical gap in existing sentence-level approaches.

The introduction of the Book Translation Quality Score (BTQS) provides a more comprehensive evaluation framework for long-form document translation, complementing traditional sentence-level metrics. Human evaluation confirms that our system produces translations with superior narrative coherence, character consistency, and stylistic appropriateness.

VIII. FUTURE WORK

Several promising directions emerge from this research:

1. **Language Expansion:**Extension to additional tribal languages including Bhili, Kokborok, Santhali, and other underrepresented languages of India.
2. **Speech Integration:**Integration of speech-to-text capabilities for audiobook translation and oral literature preservation.
3. **Community Feedback:**Development of community-in-the-loop feedback systems that enable speakers of dialectal and tribal languages to contribute corrections and improvements.
4. **Multimodal Translation:**Extension to multimodal content including illustrated books, graphic novels, and educational materials with visual components.
5. **Open-Source Datasets:**Creation and release of open-source parallel corpora for Khandeshi, Varhadi, and Gondi to support future research.
6. **Unsupervised Methods:**Exploration of unsupervised and semi-supervised learning techniques to further reduce dependence on parallel corpora.
7. **Interactive Translation:**Development of interactive translation interfaces that incorporate human feedback during the translation process.

We believe that continued research in these directions will contribute to a more inclusive digital ecosystem that serves all of India's linguistic communities.

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