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Building Foundational Language Models for Marathi: Challenges and Opportunities

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Abstract

This research package examines the technical, linguistic, sociocultural, and ethical challenges involved in building foundational (large-scale, pre-trained) language models for Marathi and outlines practical opportunities for researchers, developers, and policymakers. We (1) map existing Marathi resources and open corpora, (2) identify major algorithmic and data-collection bottlenecks, (3) propose a reproducible methodology for creating and evaluating Marathi foundational models, and (4) present expected outcomes, evaluation strategies, risk mitigation, and recommendations for sustainable ecosystem development. The study blends a literature survey of recent Marathi corpora and Indic initiatives with an applied research design focused on dataset curation, model pretraining, fine-tuning, and release practices. Key contributions include a prioritized dataset construction roadmap, multilingual transfer strategies, evaluation benchmarks (intrinsic and extrinsic), and governance recommendations for inclusive, safe, and usable Marathi LLMs.

Keywords- Marathi, foundational models, low-resource languages, IndicNLP, L3Cube, AI4Bharat, OSCAR, CC100, dataset curation, multilingual transfer learning, evaluation benchmarks.

Introduction

Large foundational language models (FMs) have reshaped natural language processing across many languages. However, most progress has concentrated on English and a handful of high-resource languages; Marathi — spoken by tens of millions and among India's largest regional languages — remains comparatively underserved. Building robust Marathi FMs requires confronting data scarcity, script variety (Devanagari), domain imbalance (news vs. oral literature), sociolinguistic phenomena (code-mixing, dialectal variation), and computational constraints. At the same time, advances in transfer learning, open datasets (OSCAR, CC100), and local initiatives (AI4Bharat, L3Cube) create an actionable path toward sustainable Marathi LLMs. This research frames practical methods to convert these nascent opportunities into reliable models for downstream tasks like QA, summarization, ASR, NLU, and education technology.

Definitions

1. **Foundational Language Model (FM):** A large pre-trained model trained on broad data and adaptable to many downstream tasks via fine-tuning or prompting.
2. **Low-resource language:** A language for which large, high-quality digital corpora and NLP resources are limited relative to high-resource languages.
3. **Corpora types:** monolingual crawl corpora (e.g., OSCAR/CC100), curated curated corpora (news, Wikipedia), parallel corpora (bitext for translation), and speech corpora (for ASR).
4. **Intrinsic evaluation:** Evaluation of models using linguistic probes, perplexity, or masked-language accuracy.
5. **Extrinsic evaluation:** Task performance on downstream applications (e.g., NER, sentiment analysis, QA).

Need / Rationale

1. **Digital inclusion:** Marathi speakers require tools for information access, education, healthcare, and governance in their native language.
2. **Cultural preservation:** Digitizing diverse Marathi text (folk, literature, oral transcripts) helps preserve cultural heritage.

3. **Economic and social utility:** Localized AI can enable regional search, voice assistants, and domain-specific automation (agriculture, legal aid, education).
4. **Academic contribution:** Building Marathi FMs fills a research gap in low-resource modeling techniques and multilingual transfer.
5. **Policy alignment:** National initiatives and open science movements encourage creation of public datasets and models for Indian languages.

Aims

1. To design, build, and evaluate an open, ethically sourced foundational language model for Marathi.
2. To create a reproducible dataset and training pipeline that can be adopted and extended by the research community.
3. To measure model performance across intrinsic and extrinsic Marathi NLP tasks and identify failure modes.
4. To propose governance, licensing, and deployment guidelines enabling safe, equitable access.

Objectives

1. **Dataset mapping:** Catalog existing Marathi corpora (OSCAR, CC100, L3Cube MahaCorpus, IndicNLP subsets, HuggingFace datasets) and identify gaps.
2. **Curation pipeline:** Build a multilingual data processing pipeline (de-duplication, language identification, normalization, script handling, deduplication, and balancing).
3. **Model recipes:** Train baseline monolingual and multilingual transformer FMs (e.g., BPE/ unigram tokenizers; base → large scale) using transfer from multilingual checkpoints.
4. **Evaluation suite:** Develop intrinsic metrics (perplexity, MLM loss) and extrinsic tasks (NER, sentiment, QA, summarization, ASR pipeline integration).
5. **Ethics and governance:** Define licensing, harmful content filters, opt-out mechanisms, and documentation (model cards, data statements).

Hypotheses

1. H1: Augmenting Marathi monolingual corpora with targeted multilingual transfer from Indic multilingual checkpoints (and domain-matched corpora) yields statistically significant improvements over training from crawl data alone.
2. H2: Combining curated domain corpora (news, literature, subtitles) with filtered web crawl data reduces hallucination and improves factuality on Marathi QA benchmarks.
3. H3: Careful script normalization + dialectal sampling increases downstream performance for NER and ASR compared to naive preprocessing.
   (These hypotheses will be tested empirically in the methodology below; prior work suggests transfer learning and curated corpora materially improve low-resource language performance.)

Literature Search

A targeted literature search reveals key resources and initiatives:

- **AI4Bharat IndicNLP and models:** Ongoing collection and tools for multiple Indian languages; IndicTrans2 provides translation models across scheduled Indian languages.
- **L3Cube MahaCorpus / MahaBERT:** A Marathi monolingual corpus and early transformer experiments demonstrating that curated Marathi data significantly help downstream tasks.
- **OSCAR / CC100 / HuggingFace datasets:** Large web-crawl derived corpora include Marathi slices (OSCAR, CC100), useful for scale but requiring heavy filtering and cleanup.
- **IndicWav2Vec and speech models:** Multilingual speech models pretrained on many Indian languages (including Marathi) provide a speech–text bridge for multimodal systems.

- **Recent academic analyses:** Papers on challenges of adapting LLMs to low-resource languages and topic modeling for Marathi highlight domain imbalance and evaluation gaps.

Note: the references above are representative; the project will maintain a curated bibliography (see References & Bibliography).

Research Methodology

Overall approach

A mixed-method engineering and empirical evaluation plan combining data engineering, model pretraining, supervised fine-tuning, and user-centric evaluation.

1. Data acquisition & curation

A. **Inventory existing corpora:** Download and version CC100-Marathi, OSCAR-Marathi slices, L3Cube-MahaCorpus, AI4Bharat IndicNLP Marathi slices, subtitles and IndicDialogue Marathi subsets, and datasets from HuggingFace.

B. **Collect additional sources:** Crawl public Marathi news sites (respect robots.txt), Wikimedia Marathi dumps, public government content, digitized literature in public domain, subtitles, and community-contributed text after checking licenses.

C. **Speech data alignment:** Incorporate IndicWav2Vec-compatible speech corpora and transcriptions for multimodal experiments.

2. Cleaning and normalization

A. **Language identification:** Use robust langid + Indic-specific detectors to remove non-Marathi content and code-mixed noise.

B. **Script normalization:** Normalize Devanagari variants, Unicode normal forms, common orthographic variations, and expand common abbreviations.

C. **Deduplication & near-duplicate removal:** Shingled hashing and clustering to reduce repeated web crawl artifacts.

D. **Quality filtering:** Filter extremely short, boilerplate, and low-information documents; keep balanced domain proportions (news, literature, conversational).

3. Tokenization and vocabulary

- Compare tokenizer strategies: SentencePiece unigram vs. BPE, subword vocabulary size experiments (30k, 50k, 100k) and multilingual vs. monolingual tokenizers. For Marathi Devanagari script, subword tokenization with Unicode-aware normalization is critical.

4. Model training recipes

1. **Baselines:**
   A. *Monolingual Marathi FM* trained from scratch on curated Marathi corpora.
   B. *Multilingual adaptation* — continue pretraining from an Indic multilingual checkpoint (e.g., an AI4Bharat multilingual or mBERT-style checkpoint) then fine-tune on Marathi.
2. **Hyperparameters:** Standard transformer architectures (encoder-only and encoder-decoder variants) at different scales (100M, 500M, 1B+ parameters) with mixed precision and gradient accumulation for resource efficiency.
3. **Compute strategy:** Use progressive stacking (start with smaller models to iterate quickly), checkpointing, and parameter-efficient fine-tuning (LoRA, adapters) for downstream tasks.

5. Evaluation

1. **Intrinsic:** Perplexity on held-out Marathi validation sets, MLM accuracy, token prediction.

2. **Extrinsic:** Performance on Marathi NER, sentiment analysis, QA (extractive and generative), summarization, machine translation (Marathi↔English), and downstream ASR-to-text pipelines. Use cross-validation and human evaluation for naturalness and factuality.
3. **Robustness & safety:** Test for hallucinations, bias (gender, caste, region), offensive content detection, and adversarial prompts.

6. Human evaluation & user studies

1. Conduct crowd-sourced evaluations with Marathi speakers across age groups and regions to assess readability, utility, and cultural appropriateness for representative tasks.

7. Documentation & release

A. Create model cards, data statements, and clear licensing. Where possible, release datasets and models under permissive open licenses (or with clear usage restrictions for sensitive content).

Strong Points

1. **Growing ecosystem:** Availability of curated Marathi corpora (L3Cube, IndicNLP) and multilingual Indian initiatives (AI4Bharat) reduces the cold-start problem.
2. **Transfer methods:** Proven effectiveness of multilingual transfer/adaptation reduces compute and data needs.
3. **Multimodal opportunity:** Speech models (IndicWav2Vec) enable end-to-end voice applications for Marathi speakers.
4. **Community interest:** Academic and industry attention to Indic languages creates collaboration potential and crowd contributions.

Weak Points / Challenges

1. **Data quality & bias:** Web crawls contain noise, duplicates, and non-standard text; filtering is resource intensive.
2. **Domain imbalance:** Overrepresentation of news and formal text vs. conversational, dialectal, or oral literature limits generalization.
3. **Dialectal & colloquial variation:** Marathi has dialects and code-mixing with Hindi/English, complicating normalization and evaluation.
4. **Compute & cost constraints:** Training large FMs is expensive; resource-efficient methods will be necessary.
5. **Safety & misuse risks:** Misinformation, toxic outputs, and sociocultural harms must be mitigated through design and governance.

Current Trends

- **Open-source Indic models:** Growth of open libraries and Marathi-specific resources (MahaBERT, L3Cube).
- **Multilingual transfer & adapters:** Using multilingual checkpoints and parameter-efficient adapters to adapt to regional languages.
- **Speech + text integration:** Pretrained multilingual speech encoders like IndicWav2Vec facilitate multimodal pipelines.
- **Community datasets & reproducibility:** More datasets appearing on HuggingFace and GitHub; emphasis on transparent, reproducible training recipes.

History / Background

- **Pre-existing resources:** Earlier work assembled Marathi corpora (MahaCorpus) and fine-tuned transformer models (MahaBERT), demonstrating foundational feasibility. Web-crawl resources such as CC100 and OSCAR included Marathi slices that researchers have subsequently refined. AI4Bharat and L3Cube represent major institutional actors building indicators and toolsets for Indic languages.

Discussion

1. **Data vs. Model scale trade-off:** For Marathi, model performance gains plateau once data quality issues are not addressed. Therefore the project emphasizes smart curation and transfer learning rather than pure scale-up on noisy crawls.
2. **Evaluation complexity:** Traditional automatic metrics (perplexity, BLEU) do not fully capture cultural nuance or utility; thus, Mali metrics + human evaluation will be prioritized.
3. **Ethical governance:** Transparent documentation, provenance tracking, and selective redaction of sensitive content are crucial. Community opt-in crowdsourcing and a grievance mechanism for data removals should be integrated.
4. **Sustainability:** Encourage parameter-efficient models (adapters/LoRA) and public checkpoints to democratize access. Partnerships with local academic institutions and industry will lower maintenance costs.

Results (anticipated / hypothetical)

Because this document outlines a research plan rather than reporting completed experiments, we present **expected** outcomes based on existing literature and analogous projects:

- **Baseline monolingual FM** trained on curated Marathi corpus (≈50–100M tokens) will show measurable improvements in Marathi NER and sentiment tasks over multilingual baselines trained only on web crawls (expected relative F1 gains of 5–15%).
- **Multilingual continued pretraining** from Indic checkpoints plus Marathi fine-tuning is expected to outperform both monolingual from-scratch and naive multilingual baselines on low-data downstream tasks (especially translation and ASR integration).
- **Human evaluation** will likely show better fluency but persistent factuality/hallucination challenges for generative tasks; domain-specific retrieval-augmented generation (RAG) will reduce hallucinations notably.
- **ASR integration** using IndicWav2Vec checkpoints will enable higher WER improvements on Marathi speech tasks when fine-tuned with even modest transcribed corpora.

These expectations must be validated experimentally; the methodology section provides a pathway to generate empirical results with reproducible metrics.

Conclusions

Building foundational Marathi language models is both necessary and feasible. Key success factors include high-quality corpus curation, targeted multilingual transfer, emphasis on evaluation that includes human judgments, and robust governance. With coordinated community and institutional support, Marathi LLMs can power inclusive applications while respecting cultural and ethical constraints. The recommended approach balances pragmatism (use available open corpora and transfer learning) with ambition (curate new corpora, invest in multimodal datasets) to reach usable, safe models.

Suggestions & Recommendations

1. **Short term (0–6 months):**
    A. Assemble and version existing corpora (OSCAR, CC100, L3Cube, IndicNLP).
    B. Run baseline tokenizer and small-scale model experiments to establish initial metrics.
    C. Create model and data cards to document provenance.
2. **Medium term (6–18 months):**
    A. Scale to larger checkpoints using transfer from Indic multilingual models (AI4Bharat checkpoints) and explore adapters for targeted domains.
    B. Launch human evaluation panels across Marathi regions to test dialectal coverage.

3. **Long term (18+ months):**
    A. Develop multimodal Marathi models (text + speech + OCR of Marathi script). Integrate with IndicWav2Vec and text FMs.
    B. Work with government, libraries, and publishers to license and digitize Marathi literary resources ethically.
4. **Governance & ethics:**
    A. Publish transparent licensing, an opt-out mechanism for content takedown, and processes for harm mitigation.
    B. Engage linguists, sociologists, and community stakeholders when building dialectal or culturally sensitive datasets.

Future Scope

1. **Domain adaptation:** Agricultural advisory, legal aid, and local government automation for Marathi.
2. **Education tech:** Marathi tutoring assistants, automated grading, and content summarization for regional curricula.
3. **Healthcare:** Marathi conversational agents for triage and health literacy.
4. **Cross-lingual transfer studies:** Quantify how knowledge transfers between Marathi and closely related Indo-Aryan languages and evaluate multilingual continual learning strategies.

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