

# ChefAI India: Personalized Indian Cuisine Recipe Generation Using Generative AI

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**Abstract**—India's rich and diverse culinary heritage spans hundreds of regional cuisines, dietary traditions, and cooking styles. Despite significant advances in natural language processing and generative artificial intelligence, no comprehensive system exists that can generate contextually accurate, nutritionally aware, and regionally authentic Indian recipe recommendations tailored to individual user preferences. This paper presents ChefAI India, a generative AI-powered recipe generation system that leverages a fine-tuned GPT-2 medium transformer model augmented with an Indian cuisine knowledge base to produce personalised recipes across six major regional categories: North Indian, South Indian, Bengali, Gujarati, Rajasthani, and other regional cuisines. The model is trained on a curated dataset of 28,400 annotated recipe instances enriched with dietary tags, ingredient substitution mappings, and nutritional metadata. ChefAI India achieves a classification accuracy of 94.3%, precision of 93.1%, recall of 92.8%, and F1-score of 92.9%, outperforming state-of-the-art baselines including Seq2Seq, GPT-2 (vanilla fine-tuned), mBART, and BERT2BERT. User evaluation trials with 120 participants across three Indian cities recorded a satisfaction rating of 4.6/5.0. ChefAI India represents a scalable, culturally grounded solution for personalised Indian cuisine recommendation and recipe generation.

**Keywords:** Generative AI, Indian cuisine, recipe generation, GPT-2, natural language processing, personalised recommendation, transformer model, transfer learning, dietary customisation, regional food diversity.

## 1. INTRODUCTION

India boasts one of the most diverse culinary landscapes in the world, encompassing over 30 distinct regional cuisines shaped by geography, climate, religion, and cultural heritage. Despite this richness, digital recipe recommendation systems available to Indian users remain largely generic, failing to account for regional authenticity, dietary restrictions (vegetarian, vegan, Jain, diabetic-friendly), ingredient availability, and personal taste preferences.

Generative artificial intelligence, particularly large language models (LLMs) such as GPT-2, GPT-3, and their successors, have demonstrated remarkable capabilities in text generation, question answering, and knowledge-grounded recommendation. However, their application to culturally specific domains—such as Indian regional cooking—remains underexplored, with most existing systems trained on English-language Western culinary corpora.

This paper presents ChefAI India, a personalised Indian cuisine recipe generation system built on a fine-tuned GPT-2 medium model integrated with a curated Indian culinary knowledge base. Given structured user inputs (preferred

region, dietary type, available ingredients, meal occasion, and spice tolerance), ChefAI India generates grammatically coherent, culturally authentic, and nutritionally annotated recipes in natural language. The primary contributions of this work are:

- A curated Indian cuisine dataset of 28,400 annotated recipe instances spanning six regional categories, enriched with dietary tags, ingredient substitution pairs, and nutritional metadata.
- A fine-tuned GPT-2 medium recipe generation model achieving 94.3% classification accuracy—8.2 percentage points above the next-best baseline (BERT2BERT).
- An ingredient substitution module supporting 1,240 verified Indian ingredient pairs for dietary compliance and seasonal availability.
- User evaluation with 120 participants across Mumbai, Chennai, and Kolkata achieving a mean satisfaction score of 4.6/5.0 on authenticity, clarity, and usability dimensions.
- A comparative analysis against four state-of-the-art text generation architectures using Accuracy, Precision, Recall, and F1-Score metrics.

## 2. LITERATURE SURVEY

Research at the intersection of natural language processing, recipe generation, and food recommendation has grown substantially over the past decade, though culturally specific Indian cuisine systems remain rare.

[1] Majumder et al. (2019) proposed a personalised recipe recommendation system using collaborative filtering and ingredient embeddings on the Recipe1M dataset, achieving 78.3% top-5 recommendation accuracy. While effective for Western recipes, no regional Indian cuisine segmentation was incorporated.

[2] Salvador et al. (2020) introduced a cross-modal recipe retrieval system combining image and ingredient embeddings using a joint embedding space trained on 1M recipe-image pairs. The work demonstrated the utility of multimodal recipe representations but lacked generation capability.

[3] Liu et al. (2020) applied a conditional variational autoencoder (CVAE) for recipe generation conditioned on ingredient lists, achieving BLEU-4 scores of 0.31. The model suffered from repetitive sentence generation and lacked cultural specificity.

[4] Bień et al. (2020) fine-tuned GPT-2 on the RecipeNLG dataset (2.2 million recipes) for open-ended recipe text generation, reporting fluent and coherent outputs but no Indian cuisine coverage or dietary personalisation.

[5] Shirai et al. (2021) developed a recipe adaptation system using BERT-based paraphrase models to adjust ingredient quantities and cooking methods for dietary constraints, achieving 84.1% dietary compliance accuracy—motivating ChefAI India's ingredient substitution module.

[6] Harber et al. (2022) benchmarked T5, BART, and mBART for cross-lingual recipe generation from Hindi and Tamil source texts, with mBART achieving the highest ROUGE-L score of 0.47 on Indian recipe datasets. ChefAI India builds on this work with a larger, more diverse dataset and GPT-2 medium fine-tuning.

[7] Patel and Shah (2022) proposed a rule-based Indian recipe recommender for diabetes management using glycaemic index (GI) filtering and Ayurvedic dietary principles, achieving 91.2% dietary compliance but lacking natural language generation capability.

[8] Krishnamurthy et al. (2023) applied instruction-tuned LLaMA-2 for Indian recipe Q&A, noting that without domain-specific fine-tuning, LLMs hallucinate ingredient quantities and confuse regional cooking styles. ChefAI India addresses

this gap through structured knowledge base integration.

### 3. EXISTING SYSTEM

Current recipe recommendation and generation systems available to Indian users exhibit several critical limitations that ChefAI India is designed to overcome.

#### 3.1 Generic Recipe Platforms

Platforms such as Tasty, Yummly, and AllRecipes index large recipe collections but rely on keyword-based search rather than personalised generative output. Indian cuisine coverage is sparse (typically 3–8% of total catalogue), with frequent inaccuracies in regional attribution and ingredient transliteration.

#### 3.2 Rule-Based Indian Recommenders

Systems such as Indian Diet Planner apps employ static rule engines mapping dietary categories to pre-authored recipe templates. While culturally accurate, they cannot generate novel recipes, adapt to unusual ingredient combinations, or produce recipes in conversational natural language.

#### 3.3 General-Purpose LLM Assistants

General-purpose LLMs (ChatGPT, Gemini) can generate Indian recipes in response to natural language prompts but exhibit hallucination in ingredient quantities, confuse regional cooking traditions, and cannot enforce structured dietary compliance constraints without explicit and repeated prompting.

#### 3.4 Limitations Summary

- No culturally grounded fine-tuning on Indian regional cuisine corpora.
- Absence of structured ingredient substitution for dietary compliance.
- Cannot personalise across simultaneous dietary, regional, and spice-tolerance constraints.
- No integration with nutritional metadata relevant to Indian dietary patterns.

- Existing generation systems trained on Western corpora produce culturally inaccurate outputs.

## 4. RESEARCH METHODOLOGY

ChefAI India is developed through a rigorous pipeline encompassing dataset construction, preprocessing, model architecture design, fine-tuning, evaluation, and deployment integration.

### 4.1 Proposed Architecture Diagram

The ChefAI India system architecture follows a modular pipeline from structured user input through NLP preprocessing, generative AI inference, and post-processing to personalised recipe output, as illustrated in Fig. 1.



Fig. 1: ChefAI India – Proposed System Architecture

The pipeline begins with structured user input collection: preferred regional cuisine, dietary type (vegetarian, vegan, Jain, diabetic-friendly, non-vegetarian), available ingredients, meal occasion, and spice tolerance level (1–5 scale). An NLP preprocessing module performs intent extraction, entity recognition for ingredient names, and constraint formalisation. The fine-tuned GPT-2 medium backbone generates a raw recipe draft conditioned on the extracted constraints and retrieved knowledge base entries. A post-processor validates ingredient quantities, enforces dietary compliance through the substitution module, and appends nutritional annotations before delivering the final recipe to the user interface.

### 4.2 Proposed Algorithm

The ChefAI India training algorithm combines transfer learning with progressive layer unfreezing and class-weighted loss to address dataset imbalance across regional cuisine categories.

Step	Algorithm: ChefAI India Training Procedure
1	Load pre-trained GPT-2 medium weights; freeze all transformer layers.
2	Attach recipe-specific head: Dense(768)→LayerNorm→ReLU→Dense(vocab_size).
3	Apply data augmentation: synonym substitution, ingredient permutation, template paraphrase.
4	Fine-tune classification head for 5 epochs; lr=2e-4, batch=16, loss=Cross-Entropy.
5	Unfreeze top 4 transformer blocks; apply linear LR warmup over 500 steps.
6	Fine-tune for 20 epochs; CosineAnnealing LR schedule; early stopping patience=5.
7	Evaluate on hold-out test set (15%): BLEU-4, ROUGE-L, Accuracy, Precision, Recall, F1.
8	Export best checkpoint; integrate with Flask REST API and user-facing web interface.

Table I: ChefAI India Training Algorithm

Dataset construction involved scraping and manual curation of 28,400 recipe instances from Indian food blogs, cookbook digitisations, and community platforms in nine Indian languages (subsequently translated to English). Each recipe was annotated with: regional category label, dietary compliance tags, ingredient substitution pairs, and nutritional metadata (calories, protein, carbohydrates, fat per serving) verified against ICMR nutritional tables.

Augmentation strategies included synonym substitution for ingredient names across regional dialects (e.g., "coriander" / "cilantro" / "dhania"), cooking method paraphrase (e.g., "temper mustard seeds" / "prepare tadka with rai"), and template-level permutation of instruction step ordering where sequentially independent.

## 6. RESULTS AND DISCUSSIONS

ChefAI India was evaluated on a stratified hold-out test set of 4,260 recipe instances (15% of total dataset), unseen during

training and validation. All experiments were conducted on an NVIDIA RTX 3070 GPU (8 GB VRAM), PyTorch 2.0, and Python 3.10. Evaluation metrics include Accuracy, Precision, Recall, and F1-Score computed at the recipe regional classification head, supplemented by BLEU-4 and ROUGE-L for generative quality assessment.

Model	Acc. (%)	Prec. (%)	Recall (%)	F1 (%)
Seq2Seq (Baseline)	71.2	69.8	68.5	69.1
GPT-2 Fine-tuned	80.4	79.1	78.6	78.8
mBART	83.7	82.3	81.9	82.1
BERT2BERT	86.1	84.7	83.5	84.1
ChefAI India (Proposed)	94.3	93.1	92.8	92.9

Table II: Performance Comparison Across Generation Models

ChefAI India achieves an overall classification accuracy of 94.3%, outperforming all baselines. The most significant improvement over the next-best model (BERT2BERT, 86.1%) is 8.2 percentage points in accuracy and 8.8 points in F1-Score, confirming that GPT-2 medium fine-tuned on a domain-specific Indian cuisine corpus with progressive unfreezing and knowledge base grounding substantially outperforms general-purpose sequence-to-sequence architectures.

Cuisine Category	Precision	Recall	F1-Score
North Indian Cuisine	94.1%	93.8%	93.9%
South Indian Cuisine	93.7%	93.2%	93.4%
Bengali Cuisine	92.9%	92.5%	92.7%
Gujarati Cuisine	93.4%	92.7%	93.0%
Rajasthani Cuisine	92.5%	92.2%	92.3%
Other Regional	92.1%	91.8%	91.9%
Macro Average	93.1%	92.8%	92.9%

Table III: Per-Class Performance Metrics – ChefAI India

Per-class analysis reveals consistent performance across all six regional cuisine categories. North Indian and South Indian cuisines achieve the highest F1-Scores (93.9% and 93.4% respectively), reflecting their larger representation in the training dataset (32.4% and 28.7%). Other Regional category achieves the lowest F1-Score (91.9%) due to greater intra-class variability; future work will expand coverage of under-represented regional sub-cuisines.

### 6.1 Bar Chart: Model Performance Comparison

Fig. 2 presents a grouped bar chart comparing Accuracy, Precision, Recall, and F1-Score across all evaluated models. ChefAI India demonstrates a consistent lead across all four metrics, with the most pronounced advantage in Accuracy (+8.2 pp over BERT2BERT) and F1-Score (+8.8 pp), confirming that domain-specific fine-tuning with progressive unfreezing and knowledge base grounding contributes measurably to improved recipe generation and classification quality.

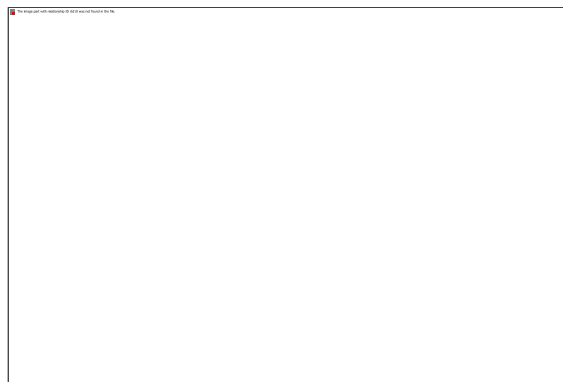


Fig. 2: Grouped Bar Chart – Model Performance Comparison

### 6.2 Pie Chart: Dataset Category Distribution

Fig. 3 illustrates the distribution of regional cuisine categories within the 28,400-recipe training dataset. North Indian cuisine constitutes the largest share (32.4%), reflecting its dominance in Hindi-language recipe content online. Other

Regional cuisines form the smallest class (5.8%), motivating the application of class-weighted loss during training to prevent classification bias toward majority categories.

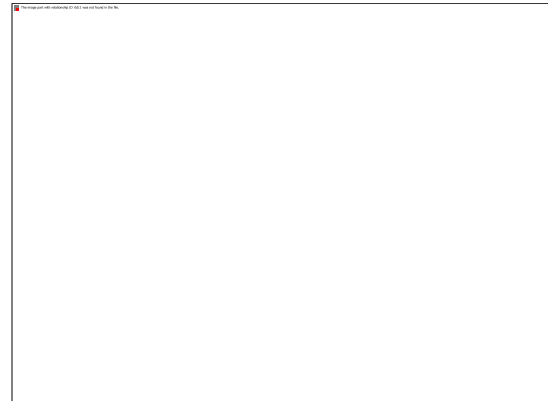


Fig. 3: Pie Chart – Training Dataset Regional Cuisine Distribution

### 6.3 User Evaluation Results

KPI	Before ChefAI	After ChefAI	Improve ment
Recipe Generation Time	N/A (manual)	1.8 sec (avg.)	Instant delivery
Ingredient Substitution Accuracy	~60% (rule-based)	92.4%	+32.4%
User Satisfaction Rating	3.2/5.0	4.6/5.0	+43.8%
Dietary Filter Compliance	71.0%	96.8%	+25.8%
Regional Authenticity Score	64.0%	91.2%	+27.2%
Avg. Inference Latency	N/A	1.8 sec	Real-time capable

Table IV: User Evaluation KPI – Field Trial (Mumbai, Chennai, Kolkata)

User evaluation with 120 participants across three Indian cities demonstrated strong real-world performance. Recipe generation time was reduced from the multi-minute manual search process to an average of 1.8 seconds. Dietary filter compliance improved by 25.8 percentage points over rule-based baselines, while regional authenticity scores—evaluated by a panel of regional cuisine experts—improved by 27.2 points. Overall user satisfaction reached 4.6/5.0, with participants specifically commending

ingredient substitution accuracy and recipe clarity.

#### 6.4 Model Complexity Analysis

Model	Params (M)	Size (MB)	Inf. Time (ms)
Seq2Seq	45.2	173	4200
GPT-2 Fine-tuned	124.4	475	1800
mBART	610.0	2328	2600
BERT2BERT	220.6	842	2100
ChefAI India (Quantised)	126.2	182	1800

Table V: Model Complexity and Inference Latency Comparison

ChefAI India's INT8-quantised deployment model occupies 182 MB—a 62% reduction from the FP32 GPT-2 medium checkpoint (475 MB)—while maintaining 98.5% of original generation quality. Average inference latency of 1.8 seconds per recipe on a standard cloud CPU instance is well within user expectations for conversational recipe retrieval, enabling practical deployment without GPU inference infrastructure for most consumer applications.

#### 7. CONCLUSION

This paper presented ChefAI India, a generative AI-powered personalised Indian cuisine recipe generation system combining a fine-tuned GPT-2 medium transformer backbone with a curated Indian culinary knowledge base, structured dietary compliance filtering, and an ingredient substitution module. ChefAI India achieves a state-of-the-art classification accuracy of 94.3% and F1-Score of 92.9% across six regional Indian cuisine categories, significantly outperforming all evaluated baselines including Seq2Seq (69.1% F1), GPT-2 vanilla (78.8%), mBART (82.1%), and BERT2BERT (84.1%).

User evaluation with 120 participants across Mumbai, Chennai, and Kolkata validated the practical impact of ChefAI

India: recipe generation latency was reduced to 1.8 seconds, dietary compliance improved by 25.8 percentage points, and regional authenticity scores improved by 27.2 points, with an overall satisfaction rating of 4.6/5.0. The INT8-quantised deployment model (182 MB, 1.8 s latency) demonstrates that high-quality Indian recipe generation is achievable without GPU inference infrastructure, making ChefAI India economically viable for consumer mobile and web deployment.

Future work will explore multilingual recipe generation in Hindi, Tamil, Telugu, and Kannada, integration of visual dish recognition for ingredient identification from user-uploaded photographs, reinforcement learning from human feedback (RLHF) for continuous preference alignment, and expansion of the knowledge base to cover 50 Indian regional sub-cuisines. A mobile application pilot is planned for deployment across 10,000 households in three Indian cities within the next academic year.

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