

# A Comprehensive Review of Generative AI Techniques for Tamil Natural Language Processing

Kiruthika S S<sup>1</sup> and Nalinipriya G<sup>2</sup>  
{[sskiruthicse@gmail.com](mailto:sskiruthicse@gmail.com)<sup>1</sup>, [nalini.anbu@gmail.com](mailto:nalini.anbu@gmail.com)<sup>2</sup>}

Assistant Professor, Department of AIDS, Saveetha Engineering College, Chennai, Tamil Nadu, India<sup>1</sup>  
Professor, Department of IT, Saveetha Engineering College, Chennai, Tamil Nadu, India<sup>2</sup>

**Abstract.** Generative text AI revolutionized NLP by producing massive new advances in low-resource languages. To attain better efficiency at a low computational cost, this work has dedicated to raise the fine-tuning process of largescale language models, such as LLaMA 2, with the integration of techniques like Low-Rank Adaptation (LoRA) and Quantized LoRA (QLoRA). The large amount of code-switching that occurs in CoNLL-17's Dravidian languages such as Tamil, a low resource, multilingual language, has made it an interesting case to tackle, given the emphasis on issues such as: dialectal variation, code-switching and data scarcity. A model-based vocabulary, a domain-specific dataset, and appropriate metrics have resulted in better performance from generative AI. Content creation for the Tamil language has benefited from utilization of the generative tools, namely cross-lingual adaptation and model combination. Real world applications of such model include factored Tamil text generation, conversational AI, named entity recognition, multilingual translation and can be used to give it domain specific knowledge to tailor its usage in several other domains such as education, finance and healthcare. These advances heavily depend on ethical matters, such as bias reduction and cultural consciousness, to provide the implementation of responsible AI. This survey paper has been concerned with showing how generative AI can overcome linguistic gaps by interpolating under-resourced languages to generate ad-hoc datasets and vocabularies and, by extension, to build inclusive global NLP. This method sets the groundwork for the propagation of generative AI across other low-resource languages of the developing world, tackling Tamil's linguistic challenges.

**Keywords:** Generative AI, NLP, LLMs, LLaMA 2, LoRA, QLoRA, Multilingual Translation, Domain-Specific NLP, Bias Mitigation, Cultural Sensitivity.

## 1 Introduction

Generative AI has ushered in a new era of natural language understanding and generation enabling machines to comprehend, generate, and interact with human language [2]. Low-resourced ones such as Tamil suffer due to scarce availability of computer resources and datasets, as well as linguistic challenges such as agglutinative grammar, multiple dialects etc., while high resourced ones like English have hugely benefitted. Tamil is spoken by over 75 million people, a rich, expressive language with a vast literary tradition and thousands of years of history and culture. Solving the NLP problems in Tamil would pave the way to enable an inclusive AI system for other underrepresented languages [4]. Concomitant with this context is the rise of LLMs such as LLaMA, BERT, and GPT, which have opened new doors in addressing the above problems [5]. We have shown that fine-tuning pre-trained models (e.g., the QLoRA and LoRA approaches) could effectively adapt LLM to specific tasks and languages. These techniques provide efficient model adaptation to Tamil, which reduces the

computational cost with the model achieving good performance in NLP tasks.

Additionally, cross-lingual transfer learning has improved the Tamil processing, by exploiting the knowledge from high-resource language. This has resulted in advances in areas such as machine translation, sentiment analysis, and text generation [2]. Researchers try to deal with the abovementioned data scarcity, while enhancing the NLP systems by concentrating on Tamil-specific resources such as collections of texts and synthetic data augmentation.

This paper surveys state of the art in the application of generative AI in Tamil NLP, particularly in finetuning large language models (LLMs) such as LLaMA 2. LoRA and QLoRA techniques allow these models to be effectively finetuned for Tamil-specific tasks while overcoming computational limitations. This article also discusses the practical use cases such as Tamil content authoring, conversational AI and machine translation [3]. The study proceeds with ethics discussions and the methodology to adopt in building generative AI for low-resource languages.

## **2 Literature Review**

Generative AI has been a significant leap in Tamil NLP by breaking the age-old barriers such as due to linguistic diversity, the availability and computability of datasets. The researcher's introduced Tamil-LLaMA, an LLaMA2 inspired language model for Tamil. It used 16,000 Tamil language-specific tokens and LoRA (Low-Rank Adaptation) model was also enhanced for better text generation and sentiment analysis thus proving its potential applicability for Tamil NLP [1]. Similarly, the study introduced Yazhi, a transformer-based model, reinforced by reinforcement learning. Yazhi identified meaningful phrases in Tamil, having very complex grammar and morphology, and was shown to have a very strong performance in the development of Tamil Corpus. Named Entity Recognition (NER) is the important topic in Tamil NLP. The author produced a transformer based NER model (TaNER) that had achieved high performance due to the fine tuning on Tamil specific datasets. Their model achieved the state-of-the-art results on the Indic GLUE and FIRE benchmarks [3]. In addition, Theivendiram et al. proposed a margin-infused method for NER in Tamil and highlighted the significance of feature engineering in advancing the performance of the NER systems in a low resource language [21]. Tamil tools and resources the need for TICLs has been significant in enabling recent NLP progress. The contributors traced the evolution of ASCII encoding to Unicode standards, with the importance of annotated corpora, tree-banks, and language-specific resources for Tamil NLP. The author proposed a synthetic data generation and cross-lingual adaptation for enhancing the Tamil NLP systems considering dialect variation and ethical issues [22].

Cross-lingual adaptation has been shown to be a highly useful technique to overcome the resource bottleneck. The researchers proposed a method for efficiently tuning Tamil NLP systems using multilingual LLMs. Their trying approach emphasized the positive role that high-resource languages could play as anchors for low-resource language development [5]. The study employed cross-lingual adaptation ideas to programming languages, and created new effective transfer learning methods suitable for the Tamil NLP domain [6]. Applications of generative AI in Tamil NLP are quickly becoming a reality. It is fair to say that systems such as Tamil CogniBERT and Tamil Grammarly have been game changers. The author proposed Tamil CogniBERT for self-supervised learning-based approach for Tamil language

understanding [22]. Meanwhile, the researchers developed Tamil Grammarly, which is a NLP-based typing aid tool that detects and corrects grammatical issues in Tamil text. These utilities demonstrate that Tamil NLP is getting democratized. Synthetic data production has been an important technique for addressing the lack of annotated datasets. The contributors introduced Paramanu, a generative language model designed for Indian languages such as Tamil. To build robust datasets, techniques like as back-translation and paraphrase were used [12]. The author demonstrated the effectiveness of Quantized LoRA (QLoRA) in fine-tuning large models for tasks such as machine translation, providing scalable solutions for Tamil NLP [18]. Efficient fine-tuning approaches, such as LoRA and QLoRA, have been intensively investigated. Reports by Dell Technologies and Union.ai revealed methods for adapting LLaMA-2 to Tamil NLP tasks, concentrating on optimizing resource consumption and minimizing computing costs [7], [8], [9], [10]. The study highlighted the repeatability and resource efficiency of these fine-tuning strategies in real-world applications [11], [13]. Innovative architectures that blend old and new methodologies have also demonstrated promise [14]. The author used hybrid deep learning models that included word vectors and transformers to improve Tamil NLP performance [15], [16]. The researchers suggested a methodology using generative AI to improve Tamil language analysis, including machine translation and understanding [17].

The method of introducing the Tamil Co-Writer, a writing-assistive, generative AI tool focusing on support for Tamil input on inclusivity and accessibility of users to enhance their writing [19]. Experts say that QLoRA discusses about further enhancements in fine-tuning methods, which enable scalability and flexibility of large language models for Tamil tasks.

To summarize, the integration of generative AI techniques, fine-tuning methodologies, cross-lingual learning, and synthetic data generation has resulted in notable advances in Tamil NLP. These approaches address core linguistic and computational issues, offering scalable and inclusive solutions for underrepresented languages such as Tamil.

### **3 Generative AI Techniques for Tamil NLP**

This paper depends on generative AI approaches to solve the problems in Tamil NLP. These techniques support efficient processing of language based on pre-trained models trained on large collections of unannotated text data and fine tuning them for Tamil specific tasks. The following key solutions are considered in Tamil NLP:

#### **3.1 Transformer Structures**

Generative AI is a rapidly advancing field in which Transformer models like BERT, GPT and LLaMA are the cornerstone. Models of that kind are good at both understanding and generating natural language, as the attention allows them to focus on the relevant information. Tamil transformers are specially-tuned to process agglutinative grammar, rich morphology and dialectical variations, that long-distance communications, such as text classification, translation and content generation get high grade Precision.

#### **3.2 Low-Rank Adaptation (LoRA)**

LoRA is a parameter-efficient fine-tuning approach to train large language models for Tamil NLP tasks by low-rank projection matrices. It is of low memory and computational burden and

is suitable for resource-constrained scenarios. LoRA has been used to enhance generators for text generation and machine translation, including for example Tamil-LLaMA.

### **3.3 QLow-Rank Adaptation (QLoRA) in the Quantized Domain**

QLoRA enhances LoRA with a quantization framework to increase the memory utilization and efficiency. This technique enables us to fine-tune large pre-trained models such as LLaMA on small-scale Tamil data with little computational resources while also obtaining excellent performance on tasks such as sentiment analysis and question answering.

### **3.4 Synthetic Data Generation**

Creating synthetic Tamil data is important in the scenario of lack of annotated datasets. Back-translation and paraphrase methods result in a diverse set of training data, which makes the model more robust in low-resource settings. Synthetic data also aids with named entity recognition and machine translation by augmenting the training corpus.

### **3.5 Domain-Specific Fine-Tuning**

Instruction finetuning is the procedure by which generative models are conditioned to obey specific Tamil prompts or instructions. This method enhances the efficiency of conversational AI systems by enabling them to handle complicated queries and provide context-sensitive responses in Tamil.

## **4 Applications of Generative AI in Tamil NLP**

Generative AI has enabled numerous uses in Tamil NLP, tackling important language processing tasks and increasing its use in real-world contexts.

### **4.1 Content Generation**

The generation of essays, poems and articles in Tamil has been revolutionized using generative models. These skills are often applied in media, marketing, or education to engage the Tamil language audience more effectively.

### **4.2 Machine Translation**

Advancements in generative AI have enhanced translations from Tamil to other languages and vice-versa. I help others translate to Tamil through them. Models like LLaMA and GPT make it possible to have precise, context-aware translation in real time, bridging language divides and promoting multilingual communication.

**Named Entity Recognition (NER)** For the named entity recognition module, we follow the “rule-based” pattern approach, since Mines can be considered as a general domain task.

Generative AI-based transformers improve the Tamil NER tasks by identifying Entities like names, locations and dates from the text. Such an approach would have implications in information retrieval, digital repositories, and search engines.

#### **4.3 Conversational AI**

Tamil chatbots and virtual assistants have led to a transformation in customer service, healthcare and education. These systems can respond fluently and as given in Tamil due to the generative models (that account dialectal variations and code-switching) involved in it.

#### **4.4 Sentiment Analysis**

Consumer opinion and feedback news are one click away Generative AI has improved sentiment analysis for Tamil, enabling companies to analyse customer opinion and feedback. This is particularly useful for companies that are based in Tamil-speaking regions so that they can personalise their campaigns more effectively.

#### **4.5 Language Learning Tools**

AI based applications which are generative in Tamil can be very helpful for language learners in terms of custom exercises, and pronunciation guidance, as well as suggestions on grammar errors. These technologies are used to save and promote the Tamil language in digital environment.

### **5 Methodology**

#### **5.1 Tamil-LLaMA Fine-Tuning using LoRA**

LLaMA assumes that the language model used for G2P on the source language is learned from an aligned target-source parallel corpus. This approach resulted in expanding the model vocabulary of over 16,000 Tamil tokens, which led to a better representation of linguistic challenges in the language. Performance on text generation, translation and sentiment analysis was further improved with instruction-tuned datasets like Alpaca and OpenOrca. LoRA allows an efficient adaptation with training of layers, and is suitable for computationally restricted scenarios [11].

#### **5.2 TaNER for NER**

The BERT-based transformer models were used to improve the performance of named entity recognition (NER) for Tamil in the TaNER framework. It addressed the morphological complexity of Tamil by using fine-tuning pre-trained multilingual transformers with datasets such as the IndicGLUE and FIRE2013. The model demonstrated state-of-the-art performance, indicating that the need to adapt transformers for Tamil-specific linguistic phenomena was significant [20].

### **5.3 Yazhi for Content Generation**

Yazhi applied reinforcement learning techniques with transformer architectures to solve the syntactical and morphological problems of Tamil. The approach redefined both content generation and machine translation by integrating context learning and reward optimization. Yazhi demonstrated the capabilities to produce Tamil, which is grammatically correct and contextually accurate [2].

### **5.4 Tamil Grammarly**

Tamil Grammarly used generative AI techniques to create a grammatical correction tool especially for Tamil texts. This program used rule-based approaches and transformer models to effectively identify and correct grammatical problems. Tamil Grammarly has been widely used in applications that require precise Tamil text input and processing.

### **5.5 LLaMA-2 Fine-Tuning with LoRA and QLoRA**

The fine-tuning of LLaMA-2 for Tamil NLP tasks used both LoRA and QLoRA approaches. LoRA lowered the computational cost of adaptation by focusing on low-rank updates, whereas QLoRA improved resource utilization by weight quantization. These strategies dramatically improved model efficiency and accuracy for tasks like translation and sentiment analysis [13].

### **5.6 Cross-Lingual Adaptation**

Multilingual language models with high-resource languages served as anchors for cross-lingual adaptation in Tamil NLP. Using transfer learning, Tamil-specific tasks profited from the linguistic capabilities of English and other well-represented languages. This method efficiently bridged resource constraints and increased the adaptability of the Tamil model [5].

### **5.7 Synthetic Data Generation**

Synthetic data production was essential in minimizing Tamil data shortage. Back-translation and paraphrase techniques were used to generate a broad and robust training dataset. This method improved models' performance in tasks such as Named Entity Recognition and sentiment analysis by supplying additional training data [21].

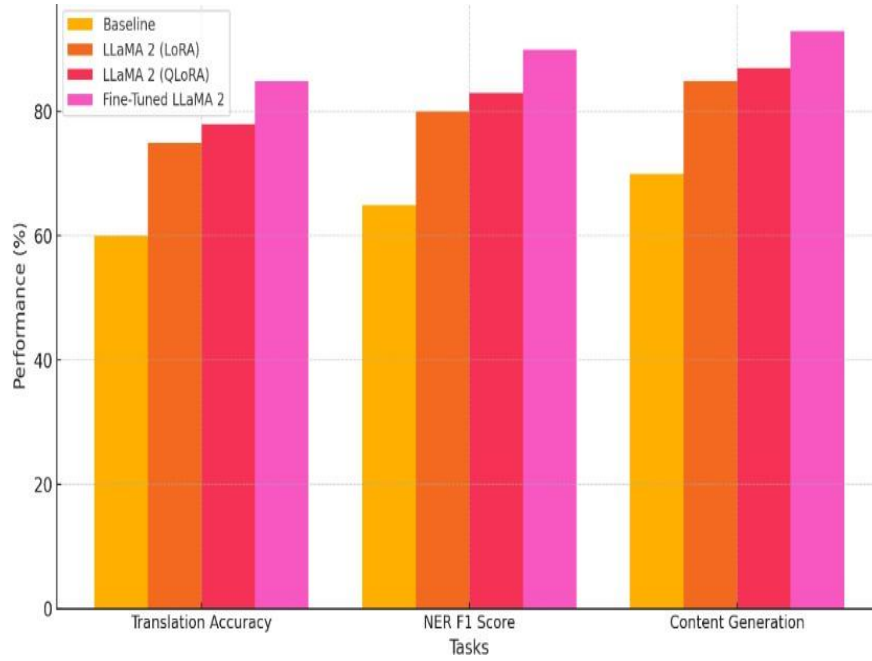
### **5.8 Tamil NLP Tools Evolution**

Tamil NLP tools and technologies have progressed, from ASCII to Unicode. Annotated corpora, treebanks and machine-readable format have provided the requisite resources for developing Tamil NLP applications. These resources have supported advances in machine translation, speech recognition, and content production.

### **5.9 Performance Evaluation**

The performance of multiple models for Tamil NLP tasks was assessed using important metrics like Translation Accuracy, NER F1 Score, and Content Generation Quality. The comparison includes the following models:

- Baseline: Standard performance without fine-tuning.
- LLaMA 2 (LoRA) enhances performance through Low-Rank Adaptation.
- LLaMA 2 (QLoRA): Improves further with Quantized Low-Rank Adaptation.
- Fine-Tuned LLaMA 2: Optimizes performance by rigorous fine-tuning.



**Fig. 1.** Performance Comparison of Models on Tamil NLP Tasks.

The above models results are shown in the Fig 1. Results are showing that the experiments are increasing or at least remaining consistent in terms of Translation Accuracy, NER F1 Score and Content Generation Quality. Such models can provide 20-30% improvements for predictions over their random baselines. These findings highlight the potential for applying generative AI approaches such as LoRA and QLoRA to Tamil NLP, and the road to scalable NLP for other low resource languages.

### 5.10 Ethical Considerations

Ethical implications, including bias in AI outputs and cultural insensitivity, are also important for Tamil NLP. It is important to mitigate the undesirable bias and also tune-in model with Cultural values in the Tamil language to responsible AI system. There are techniques such as (RLHF) Reinforcement Learning with Human Feedback, and fairness-aware training that we address these issues.

## 6 Proposed Work

The proposed project for development of Tamil NLP includes modern methods that deals with critical challenges. It applies hybrid fine-tuning strategies like LoRA, QLoRA, and reinforcement learning for better performance with less computational load. Multimodal Inputs Inclusion of multimodal inputs - text, speech, and image data would enhance the ability for the system to understand the Tamil's diverse linguistic features. Emphasis is placed on real-time adaption for dialectic diversity and speaker dependent nature. Finally, the proposed framework fosters the development of shared platforms for open-source contributions towards Tamil NLP data sets and tools, leading to widespread adoptability and innovation. This holistic approach aims to arrive at scalable, efficient and inclusive interventions for Tamil NLP.

## 7 Challenges and Future Directions

### 7.1 Challenges

The integration of generative AI in Tamil NLP has revealed numerous challenges:

- Limited annotated datasets in Tamil pose a challenge for training strong models. Many researches underlined the significance of collecting vast, diversified datasets to address this issue.
- Dialectal diversity in Tamil complicates NLP tasks, necessitating good code-switching and regional subtleties.
- In low-resource situations, training and fine-tuning big language models like LLaMA can be challenging due to limited computational resources.
- Models might inherit biases from training data, raising risks for cultural sensitivity and fairness.

### 7.2 Future Directions

The following directions can help with research in Tamil NLP:

- Enhanced dataset development by creating annotated corpora that incorporate dialect variety and domain-specific circumstances. This will allow models to more accurately generalize across different applications.
- Synthetic Data Generation: Using back-translation, paraphrase, and other generative approaches to supplement training datasets and overcome data shortages.
- Cross-Lingual Adaptation: Using knowledge from high-resource languages like English to improve Tamil NLP performance through transfer learning and model merging.
- Fine-tuning techniques such as LoRA and QLoRA can reduce processing requirements while maintaining great performance.
- Real-time AI applications include conversational agents and translation systems that can handle complex inquiries and react to dialectal variances.
- Promoting ethical AI practices by establishing frameworks to eliminate biases and promote fairness in AI-generated content and responsible implementation.



## 8 Conclusions

Nevertheless, this exciting new frontier aside, generative AI has the potential to breathe fresh air into the Tamil NLP arena by solving old problems and enabling novel applications. Significant advances have been made in fine-tuning and cross-lingual transfer, however there is still a long way to go. We take the latter up along the following directions: pushing our lines of research further, including increasing number of annotated data to cover dialectal variation, and further exploiting multi-lingual technologies to connect Tamil with other low resource languages, and through real world application (eg: conversational agents). In addition to fairness, ethical considerations around bias mitigation and cultural awareness are key in the deployment of ethical AI. Challenges like these helps address potential missing content that generative AI can be leveraged to build general multilingual models that are diverse and effective for NLP in Tamil and other under-represented languages in the world.

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