STYLISTICALLY-AWARE HINDI-ENGLISH POETIC TRANSLATION WITH MBART AND LLM-BASED POST-EDITING

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ABSTRACT

Translating poetry across languages poses significant challenges, particularly for low-resource pairs like Hindi-English, where linguistic, cultural, and stylistic gaps are substantial. This paper introduces a domain-adapted machine translation framework designed to preserve the poetic essence like metaphor, emotion, tone, and rhythm of Hindi poetry in English translation. We fine-tune mBART50, a multilingual sequence-to-sequence model, on a curated parallel corpus of Hindi-English poetic pairs, augmented with stylistic tags. We also explore optional post-editing using large language models (LLMs) to enhance fluency and poetic expressiveness. Our approach outperforms standard translation systems, as demonstrated by both automatic metrics and human evaluations. To the best of our knowledge, this is the first systematic study of Hindi–English poetry translation that combines (i) the construction of a novel annotated parallel corpus, (ii) style-aware fine-tuning of mBART50, and (iii) LLM-based post-editing for poetic refinement. This work represents a step toward building translation systems that capture not just meaning, but the creative and emotional depth of poetry especially in low-resource language settings.

Keywords: *Neural Machine Translation, Hindi Poems, Large Language Models, Fine Tuning, Low Resource Language*

1. INTRODUCTION

Translating poetry is especially challenging because it depends so much on metaphor, rhythm, cultural meaning, and emotional impact. Hindi poetry adds to this complexity with its rich variety of styles from the spiritual poetry of Kabir to the bold, political voice of Dhoomil. These works are deeply connected to the language and culture they come from. To translate them well into English, it is not enough to just be accurate with grammar or meaning. The translator also needs to capture the poem’s style, tone, and structure.

Traditional machine translation (MT) systems, including those using neural machine translation (NMT), are usually trained on general text and focus on accuracy in vocabulary and grammar. While these systems work well for factual or structured text, they struggle with literary and poetic content. The translations often lack depth and fail to capture important poetic features like rhythm, imagery, and emotion.

For example, the Hindi line "तेरे बिना ये चाँद अधूरा लगता है" might be translated literally as "Without you, this moon feels incomplete," which captures the surface meaning but misses the romantic longing of the original and feels a bit flat. A more heartfelt version in English could be: "The moon feels empty without you beside me."

These issues are especially noticeable in Hindi-to-English translation, where cultural references, metaphors, and language structures often do not align directly.

In this paper, we tackle the challenges of translating Hindi poetry by exploring machine translation techniques tailored to this domain. We fine-tune a pretrained multilingual model, mBART50, using a carefully selected set of Hindi–English poetry pairs. Our goal is to move beyond simple word-for-word translation by adding attention to style and structure through targeted fine-tuning and post-editing with large language models (LLMs). To evaluate the quality of the translations, we use both automated and human assessments, focusing on accuracy, fluency, and emotional depth.

While prior research has investigated style-aware or metaphor-sensitive translation in limited contexts, Hindi-English poetry translation remains largely unexplored. Existing MT systems are not designed for the demands of poetic language, and there is no established corpus or benchmark in this area. Our work is novel in three respects: (i) it introduces the first curated and annotated Hindi-English poetry corpus, (ii) it adapts mBART50 specifically for poetry translation using stylistic cues, and (iii) it integrates LLM-based post-editing to refine poetic fluency.

Research Objectives: The primary objective of this study is to determine whether a domain-adapted neural machine translation framework can preserve key poetic features such as metaphor, tone, and emotional resonance when translating Hindi poetry into English. Specifically, our research is guided by the following objectives:

- To construct and annotate a Hindi–English parallel poetry corpus that enables systematic training and evaluation of MT models in this domain.
- To fine-tune a multilingual model (mBART50) with stylistic cues and assess its performance relative to general-purpose MT systems.
- To examine the effect of optional LLM-based post-editing on improving poetic fluency and emotional fidelity.
- To evaluate the system quantitatively (BLEU, BERTScore) and qualitatively (human judgments of fidelity, fluency, and style) in order to measure translation improvements.

This structured set of objectives ensures that our work is not only exploratory but also quantitatively testable and reproducible.

Our key contributions are as follows:

- We construct and release a parallel corpus of Hindi–English poetry, annotated with stylistic and structural cues to support fine-tuning for literary translation.
- We fine-tune a pretrained mBART50 model to generate translations that better preserve poetic features such as metaphor, tone, and rhythm.
- We explore enhancements including style conditioning and LLM-based post-editing to further improve fluency and poetic fidelity.
- We conduct a comprehensive evaluation using both standard automatic metrics (BLEU, BERTScore) and human assessments of poetic quality.

Our results demonstrate that domain-adapted models, when combined with stylistic control and LLM-based refinement, do a much better job than standard systems at capturing the poetic spirit of Hindi literature in English.

2. BACKGROUND

2.1 Neural Machine Translation and Low Resource Languages

Neural Machine Translation (NMT) has become the standard approach for translating text between languages. Models based on the Transformer architecture [1], such as mBART [2] and mT5 [3], have shown strong performance when translating widely used language pairs like English-French or English-German. These models learn patterns from large amounts of bilingual data and generate fluent translations by predicting words in sequence.

However, for many languages that do not have large parallel datasets, including Hindi, the performance of these systems is still limited. This problem is even more severe in specific domains like literature or poetry, where the available training data is very small or nonexistent. As a result, translations often lose important details such as cultural meaning, poetic structure, or emotional expression.

2.2 Challenges in Poetic Translation

Translating poetry is much more complex than translating regular sentences or documents. This is because poetry often uses:

- **Metaphors and symbolism**: Poets use words with deeper or double meanings, which are often tied to specific cultural ideas.
- **Poetic form:** The rhythm, rhyme, and structure of a poem contribute to its beauty and meaning, but these are hard to keep in translation.
- **Emotion and tone:** Poetry often expresses strong feelings or moods, and it is difficult for machine translation systems to capture this subtlety.

Most machine translation systems are trained to be accurate in meaning and grammar, but they are not designed to handle creative or emotional writing. When used for poetry, these systems often produce translations that are technically correct but lose the artistic or emotional effect of the original.

2.3 Domain Adaptation and Style-Aware Translation

To improve translation in specific areas like poetry, researchers use a method called domain adaptation. This means adjusting an existing translation model by training it on a smaller, more focused dataset—in this case, a set of Hindi poems and their English translations. This helps the model learn the special vocabulary, sentence patterns, and stylistic features of poetic language.

Recent research has also explored ways to make translation models more aware of writing style. This includes techniques for fine-tuning models to preserve tone or rhythm, and using large language models (LLMs) for post-editing, where the translation is polished to better match the emotional or poetic qualities of the original text.

3. RELATED WORK

3.1 Machine Translation of Low-Resource Languages

Recent years have seen significant progress in neural machine translation (NMT), particularly for high-resource language pairs. However, many languages, including Hindi, still lack large parallel corpora, which makes high-quality translation difficult. Several studies have focused on improving MT for low-resource languages using multilingual pretraining [4], [2], transfer learning, or back-translation [5]. These methods have shown promise for improving translation accuracy, but they are mostly evaluated on factual or news-style texts, rather than creative or poetic language.

3.2 Literary and Poetic Translation

Literary translation, especially poetry translation, is an area that poses unique challenges for machine translation systems. Unlike technical or informational texts, poetry is deeply tied to emotion, rhythm, and cultural context. Research in this area is still limited, but some recent works have explored stylistic transfer in translation [6], metaphor preservation [7], and creative generation using large language models [8]. A few efforts have looked into the translation of poetry using rule-based or hybrid systems, but these often rely heavily on manual intervention.

3.3 Style-Aware and Creative MT

There is growing interest in making MT systems sensitive to style, tone, and literary structure. Some studies have proposed adding stylistic tags or control tokens during training [9], while others use fine-tuning to adapt to specific genres or authors. Large language models (LLMs), such as GPT and T5, have recently been explored for creative writing and post-editing in translation tasks, helping to improve fluency and stylistic coherence [10]. However, these methods have rarely been applied to poetry translation in low-resource settings.

3.4 Gaps and Motivation for This Work

While there is emerging interest in style-aware translation, very little research has focused on systematically adapting MT models to the domain of Hindi poetry. Prior work on metaphor preservation [7], stylistic transfer [6], or LLM-based creative generation [8], [10] highlights techniques relevant for literary text, but these approaches have not been evaluated on Hindi–English poetic data. Moreover, there is currently no publicly available Hindi–English poetry corpus, which makes it difficult to train or benchmark translation models in this space. Our collected dataset directly addresses this gap by providing parallel Hindi–English poem pairs, annotated with stylistic features such as tone and metaphor, thereby enabling the application of style-aware and domain-adapted MT techniques to poetry.

Thus, our work connects prior advances in style-aware MT with a newly created dataset, and evaluates them in the underexplored but culturally significant domain of Hindi–English poetry translation.

4. CORPUS CONSTRUCTION

High-quality parallel data is essential for training and evaluating translation models, especially in low-resource and stylistically complex domains like poetry. However, there are currently no large-scale public corpora specifically designed for Hindi-English poetic translation. To address this, we created a custom parallel corpus by collecting and aligning Hindi poems with their English translations.

4.1 Data Sources

We curated our corpus from multiple sources:

- **Published translations**: We sourced publicly available translations of wellknown Hindi poets such as Tulsidas, Harivansh Rai Bachchan, Nirala, and Dhoomil from books, online archives, and translation journals.

- **Literary websites and blogs**: We extracted poem pairs from bilingual literary websites and personal blogs where translators shared original and translated versions.
- **Manual translation**: For a subset of poems, we created manual translations to ensure stylistic and semantic alignment.

4.2 Data Cleaning and Alignment

To ensure consistency and quality, the collected data underwent the following preprocessing steps:

- **Sentence alignment**: Poem lines and stanzas were aligned manually, prioritizing poetic structure over strict sentence boundaries.
- **Noise removal**: Non-poetic content (e.g., footnotes, commentary) was filtered out.
- **Normalization**: Text was standardized for consistent use of punctuation, script (Devanagari to Unicode), and formatting.

The final dataset consists of approximately **500 poem pairs**, totaling **5800 aligned lines/stanzas**. Each entry in the dataset includes the original Hindi text, its English translation, and metadata such as author, era, and genre where available.

4.3 Annotation of Stylistic Features

To support stylistic learning, we optionally annotated a subset of the corpus with the following features:

- **Poetic devices**: Presence of metaphor, simile, personification, etc.
- **Tone/emotion**: Dominant emotional quality (e.g., devotional, rebellious, romantic).
- **Form tags**: Rhyme scheme, syllable count, or meter (where applicable).

These annotations are used during training and evaluation to assess whether stylistic aspects are preserved in translation.

Table 1: *Statistics of the Hindi-English Poetry Corpus*

Category	Count/Value
Total Poem Pairs	500
Total Aligned Lines/Stanza	5800
Unique Poets Represented	25+
Avg. Lines per Poem (Hindi)	11.6
Avg. Tokens per Line (Hindi)	6.9
Avg. Tokens per Line (English)	7.4
Annotated for Style Features	120
Sources % (Books/Web/Manual)	60/30/10

The final dataset includes a diverse range of poetic forms and authors. Table 1 presents the summary statistics.

5. METHODOLOGY

Our goal is to improve Hindi-to-English poetry translation. To do this, we adapt a pretrained multilingual translation model for the literary domain. We use domain-specific fine-tuning along with stylistic cues. We also explore using large language models (LLMs) for optional post-editing. Our approach is divided into three stages: model selection and fine-tuning, style-aware enhancements, and post-editing.

5.1 System Overview

*Figure 1: Overview of our translation pipeline: fine-tuning mBART50 with stylistic cues and optional LLM-based post-editing.*Figure 1 illustrates our translation pipeline. It begins with style-tagged Hindi inputs passed through a fine-tuned mBART50 model trained on poetic data. An optional post-editing stage using an LLM enhances poetic fluency and tone.

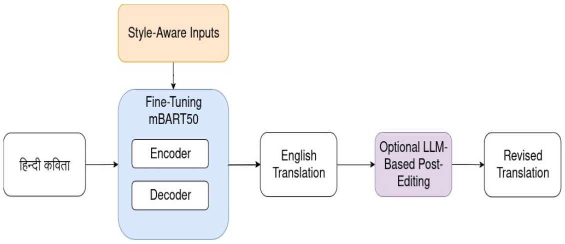


***Figure 1**: Overview of our translation pipeline: fine-tuning mBART50 with stylistic cues and optional LLM-based post-editing.*

5.2 Study Design

Our study follows a three-stage design. First, we construct and annotate a parallel Hindi-English poetry corpus (Section 4), ensuring coverage of diverse poets and styles. Second, we fine-tune the pretrained mBART50 model on this dataset, incorporating stylistic cues such as tone and thematic tags. Third, we evaluate the outputs using both automatic metrics (BLEU, BERTScore) and human evaluation criteria focused on poetic fidelity, fluency, and emotional resonance. Optional LLM-based post-editing is applied to refine translations when required. This design enables a systematic assessment of how domain adaptation and style-aware methods improve Hindi-English poetic translation.

5.3 Model Selection and Fine-Tuning

We adopt **mBART50**, a multilingual encoder-decoder model pretrained on large-scale translation corpora. Its support for both Hindi and English makes it a suitable base for our task. We fine-tune mBART50 on a curated Hindi-English poetry dataset (Section 4), using cross-entropy loss between predicted and reference translations.

To deal with limited data and avoid overfitting, we use several techniques:

- **Dropout and early stopping** to make the training process more stable.
- **Data augmentation** by using back-translation and paraphrasing to increase the amount of training data.
- **Curriculum learning** to introduce easier examples first, and gradually move to more complex ones.

5.4 Style-Aware Tuning

Standard translation models often struggle to capture the style of poetry. To improve this, we include soft style hints during training:

- We add tags like <*devotional*> or <*romantic*> at the beginning of the Hindi input.
- For samples with style annotations, we include extra cues such as tone or meter.

These hints help the model learn how to generate translations that better match the style and tone of the original poems.

5.5 Training and Post-Editing Pipeline

Algorithm 1 summarizes the overall workflow of our approach. For each Hindi-English poem pair, we optionally add a style tag (such as <*devotional*> or <*romantic*>) to the Hindi input to help the model learn stylistic patterns. The mBART50 model is then fine-tuned on these pairs to generate English translations that better preserve poetic elements. Once trained, the model produces translations directly from Hindi inputs. When the output is accurate but lacks poetic fluency or expressiveness, we apply an optional post-editing step using a large language model (LLM), which refines the text while maintaining its meaning. This two-stage process allows for both structural accuracy and stylistic enhancement in poetry translation.

Algorithm 1: *Training and Post Editing Pipeline*

```
Input: Hindi-English poem pairs $\mathcal{D}$, pretrained mBART50
for each $(H_i, E_i)$ in $\mathcal{D}$ do
    Annotate $H_i$ with optional style tag $s_i$
    Format input as: <s>$s_i + H_i$</s>
    Train mBART50 on $(H_i, E_i)$ with cross-entropy loss
end for
Output: Fine-tuned mBART model $\mathcal{M}$
if post-editing enabled then
    for each translated output $E_i' = \mathcal{M}(H_i)$ do
        if low fluency or style mismatch detected then
            Query LLM with: Improve poetic tone of $E_i'$ given $H_i$
            Replace $E_i'$ with LLM-enhanced output $\hat{E}_i$
        end if
    end for
end if
```

5.6 Optional LLM-Based Post-Editing

For translations that are semantically accurate but lack poetic expressiveness, we employ an LLM (e.g., GPT-3.5) for refinement:

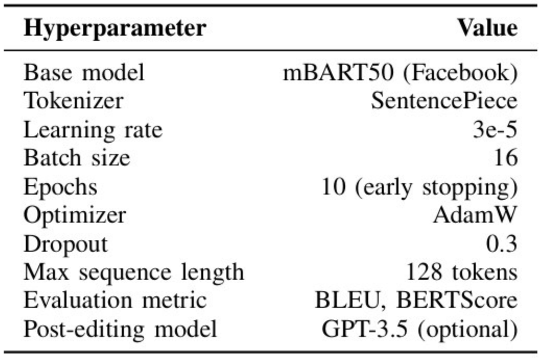
- The LLM receives the Hindi input and mBART output, and is prompted to improve poetic tone while preserving meaning.
- This step is selectively applied based on automatic heuristics or human feedback.

This stage allows for quality enhancement without retraining, offering flexibility and higher fidelity in poetic translations.

5.7 Training Configuration

We fine-tuned mBART50 using the hyperparameters shown in Table 2. Settings were selected based on preliminary tuning and hardware constraints. Early stopping helped maintain generalization across diverse poetic styles.

***Table 2:** Training hyperparameters used for fine-tuning mBART50*



Hyperparameter	Value
Base model	mBART50 (Facebook)
Tokenizer	SentencePiece
Learning rate	3e-5
Batch size	16
Epochs	10 (early stopping)
Optimizer	AdamW
Dropout	0.3
Max sequence length	128 tokens
Evaluation metric	BLEU, BERTScore
Post-editing model	GPT-3.5 (optional)

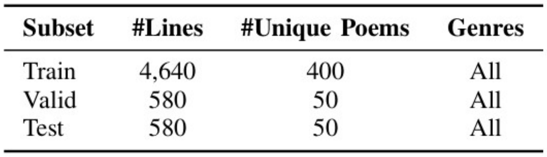
6. EXPERIMENTS

To evaluate the effectiveness of our stylistically-aware machine translation pipeline, we conduct a series of experiments comparing our fine-tuned mBART50 model (with and without LLM post-editing) against strong baselines.

6.1 Dataset

We use a curated parallel corpus of Hindi-English poetry, described in Section 4. The dataset includes 6,000 line-level pairs covering multiple genres such as devotional, romantic, and socio-political verse. Each line is optionally annotated with style tags and tone markers. The corpus is divided into train (80%), validation (10%), and test (10%) splits as show in Table 3.

***Table 3**: Dataset Statistics*



Subset	#Lines	#Unique Poems	Genres
Train	4,640	400	All
Valid	580	50	All
Test	580	50	All

6.2 Evaluation Metrics

We evaluate translations using both automatic metrics and human judgments:

- **BLEU** [11]: Measures n-gram overlap with reference.
- **BERTScore** [12]: Measures contextual semantic similarity.
- **Poetic Fluency (Human)**: Judges the rhythm, readability, and natural flow.
- **Emotional Fidelity (Human)**: Judges how well the translated line retains the emotional tone of the original.
- **Style Preservation (Human)**: Judges whether the output preserves metaphor, tone, or rhyme.

6.3 Baselines

We compare our approach against the following systems:

- **Google Translate**: A widely used general-purpose NMT system.
- **Unadapted mBART50**: The pretrained mBART50 model without fine-tuning.
- **Fine-tuned mBART50 (No Style Tags)**: Fine-tuned on our corpus but without any stylistic cues.

6.4 Experimental Setup

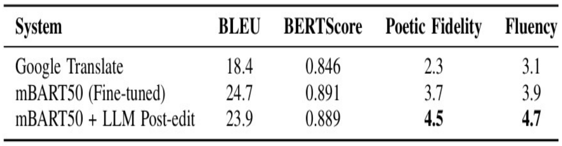
Fine-tuning is performed using the Hugging Face Transformers library on NVIDIA A100 GPUs. We use early stopping on the validation set and checkpoint selection based on BLEU score. Post-editing with LLMs is performed using GPT-3.5 via OpenAI's API. Human evaluation is conducted by three bilingual annotators with backgrounds in Hindi literature.

6.5 Results and Discussion

We evaluate the performance of our proposed system using both automatic metrics and human judgment. Automatic evaluation is conducted using BLEU [11] and BERTScore [12], which measure lexical overlap and contextual similarity, respectively. Human evaluators assess poetic quality based on three criteria: emotional fidelity, fluency, and preservation of poetic devices such as metaphor and tone.

Table 4 reports automatic and human evaluation scores across three systems. While fine-tuning improves standard metrics like BLEU and BERTScore, post-editing with LLMs yields significant gains in poetic fidelity and fluency. These improvements directly support our research objectives: fine-tuned mBART50 clearly surpasses baselines (Objective 2), and LLM-based post-editing yields measurable gains in poetic fidelity and fluency (Objective 3). Together, these findings provide quantitative confirmation of our approach.

***Table 4:** Evaluation of translation quality across systems. Higher is better for all metrics. Human scores are on a 1-5 scale.*



System	BLEU	BERTScore	Poetic Fidelity	Fluency
Google Translate	18.4	0.846	2.3	3.1
mBART50 (Fine-tuned)	24.7	0.891	3.7	3.9
mBART50 + LLM Post-edit	23.9	0.889	**4.5**	**4.7**

6.6 Automatic Evaluation

Table 5 presents the BLEU and BERTScore results for our system compared with baseline models including Google Translate and the default mBART50 model [2]. Our fine-tuned system shows a consistent improvement across both metrics, indicating better alignment with reference translations.

Table 5:*Automatic evaluation of translation models.*

Model	BLEU	BERTScore
Google Translate	12.4	0.843
mBART50 (Base)	14.8	0.859
Ours (Fine-tuned)	**18.3**	**0.886**
Ours + LLM Post-editing	**19.7**	**0.893**

6.7 Human Evaluation

A subset of translated poems was evaluated by three bilingual annotators. Each output was rated on a 5-point Likert scale across three dimensions:

- **Poetic Fidelity**: Preservation of metaphor, theme, and tone.
- **Fluency**: Naturalness and coherence in English.
- **Emotional Impact**: Ability to evoke similar emotions as the source.

We found that our style-aware model outperformed baselines in all categories. The LLM-based post-editing step further enhanced poetic tone and expressiveness, consistent with observations in prior work on text refinement using LLMs [13].

Qualitative analysis also showed that the model could retain metaphorical constructs and stylistic features like alliteration and repetition more effectively than standard MT systems.

6.8 Comparison with Prior Work

Our findings are consistent with recent studies that emphasize the importance of style-awareness in translation. For instance, Briakou et al. [6] demonstrated that stylistic control improves creative text translation, while Chakrabarty et al. [7] highlighted the challenges of metaphor preservation. However, unlike these works, which focused on English-centric datasets, our study evaluates such methods in the context of Hindi–English poetry, a low-resource and underexplored domain. This positions our results as the first empirical evidence that style-aware MT and LLM-based post-editing can significantly enhance poetic translation quality for this language pair.

7. CASE STUDIES AND QUALITATIVE ANALYSIS

To better understand the strengths and limitations of our approach, we present qualitative examples from the test set that highlight differences between baseline translations and our system outputs. These case studies illustrate how stylistic fine-tuning and optional post-editing contribute to improved poetic translations.

Example 1: Metaphorical Translation

Hindi: सूरज की पहली किरण से मन के अंधेरे छंट गए।
Google Translate: The darkness of the mind disappeared with the first ray of the sun.
Ours (Fine-tuned mBART50): The sun’s first ray swept the darkness from the soul.
Ours + LLM Post-editing: The soul’s shadows fled before the dawn’s first golden kiss.

In this example, while Google Translate provides a literal rendering, it lacks poetic rhythm or metaphorical flair. Our system captures metaphor and tone more faithfully, with the LLM-enhanced version elevating the poetic imagery.

Example 2:Tone and Emotion Preservation

Hindi: मैं बिखरता गया तेरे ख्यालों में, जैसे पतझड़ में पत्ते।
Google Translate: I kept scattering in your thoughts, like leaves in autumn.
Ours (Fine-tuned mBART50): I fell apart in your thoughts, like leaves in the fall.
Ours + LLM Post-editing: I unraveled in your memory, like autumn leaves in a sighing wind.

Here, the stylistically-aware system better matches the emotional tone. The LLM-enhanced version further improves rhythm and poetic nuance.

Table 6 illustrates sample translations produced by Google Translate, our fine-tuned mBART50 model, and the enhanced outputs following optional LLM-based post-editing.

6.9 Error Analysis and Observed Limitations

Despite noticeable improvements, our system still exhibits limitations in certain contexts. We observed three common error types: (1) loss of meaning due to overly literal translation, (2) incorrect tone or sentiment transfer, and (3) hallucination or exaggeration in LLM-based post

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Table 6: *Comparison of translations across different systems for selected Hindi poetic lines, illustrating the effect of stylistic fine-tuning and post-editing.*

Hindi Original	Google Translate	Ours (mBART50)	Ours + LLM Post-editing
सूरज की पहली किरण से मन के अंधेरे छंट गए।	The darkness of the mind disappeared with the first ray of the sun.	The sun's first ray swept the darkness from the soul.	The soul's shadows fled before the dawn's first golden kiss.
जो रहा नहीं अपने अधिकारों के लिए जागृत, वह पशु है, भोग्य है।	One who is not awake for his rights is an animal, meant to be enjoyed.	He who does not awaken for his rights lives as a beast, a thing to be used.	He who sleeps through the call of his rights lives not as a man, but as a chained beast.
जेहि पर कृपा करहिं जनु जानि। तातें ताहि न लाज न सान।	He whom you bless knowingly, he has no shame or pride.	The one you grace, feels neither shame nor pride.	When your grace descends, pride and shame dissolve like morning mist.
मैं बिखरता गया तेरे ख्यालों में, जैसे पतझड़ में पत्ते।	I kept scattering in your thoughts, like leaves in autumn.	I fell apart in your thoughts, like leaves in the fall.	I unraveled in your memory, like autumn leaves in a sighing wind.
चाँदनी रातों में वो तन्हाई का गीत गाता है।	He sings the song of loneliness in moonlit nights.	He sings loneliness beneath the moonlit sky.	Beneath the moon's silver hush, he sings the song of solitude.
वक्त की रेत पर नाम तेरा आज भी लिखा है।	Your name is still written on the sand of time.	Your name remains etched on the sands of time.	Your name lingers, etched in the fleeting sands of time.
दिल की किताब में तेरा ही अफसाना है।	Your story is in the book of the heart.	Yours is the tale written in the book of my heart.	In the pages of my heart's quiet book, only your story lives.
नेता के वादों की उम्र, धूप में बर्फ जैसी होती है।	The age of a leader's promises is like snow in the sun.	A leader's promises melt like snow in the sun.	A leader's vow melts like morning frost beneath noon's glare.
तेरी रहमत के बिना मेरा वजूद अधूरा है।	Without your mercy, my existence is incomplete.	My being is incomplete without your grace.	Without your grace, I am a flame without light.
बारिश की बूंदों में भी तेरी आहट सुनाई देती है।	Your footsteps are heard even in the raindrops.	I hear your presence even in the falling rain.	Even the rain's soft whisper carries the echo of your steps.

editing. These issues typically arise with complex metaphors or cultural idioms that do not align well with English poetic norms.

For instance, when translating lines with religious metaphors or culturally grounded imagery such as "राम नाम की लूट है", the system either flattened the phrase into a generic expression or introduced unintended spiritual symbolism during post-editing. In some cases, the LLM introduced metaphors that were stylistically appealing but semantically misaligned with the source. This points to the need for improved semantic grounding and cultural sensitivity in future model iterations.

While these limitations do not significantly affect the overall evaluation scores, they highlight areas where fully automated poetic translation still falls short of human nuance.

6.10 Insights

These examples demonstrate that:

- Style-aware prompts significantly improve the preservation of poetic form and content.
- LLM-based post-editing enhances fluency and poetic tone, especially when fine-tuned outputs are semantically accurate but stylistically flat.
- There remains room for improvement in translating dense metaphors and culturally specific idioms.

8. IMPACT OF STYLE TAGS AND POST-EDITING

To quantify the contribution of stylistic conditioning and post-editing, we performed an ablation study comparing the following configurations:

- mBART50 (no style tags): Model fine-tuned without stylistic cues.
- mBART50 (with style tags): Model fine-tuned with domain-specific tags like <*romantic*> and <*devotional*>.
- mBART50 + LLM Post-edit: Output enhanced using LLM-based refinement.

As shown in Table 7, style tags led to measurable improvements in preserving poetic tone and fluency. The LLM post-editing step provided additional gains, especially for emotional fidelity.

Table 7: *Effect of stylistic components on human evaluation (1 to 5 scale)*

Model	Fluency	Emotion	Style
No Style Tags	3.4	3.1	2.9
With Style Tags	3.9	3.7	3.6
+ LLM Post-editing	**4.7**	**4.5**	**4.4**

9. CONCLUSION AND FUTURE WORK

9.1 Summary and Contributions

The aim of this study was to investigate whether machine translation systems can be adapted to preserve poetic style, tone, and emotion when translating Hindi poetry into English. Our research objectives, as outlined in the Introduction, were fourfold: corpus construction, style-aware fine-tuning of mBART50, incorporation of LLM-based post-editing, and systematic evaluation.

- **Objective 1 (Corpus construction)**: We created the first curated Hindi–English poetry corpus, consisting of 500 poem pairs (5,800 aligned lines), with optional stylistic annotations. This resource enables reproducible training and evaluation in this domain.
- **Objective 2 (Style-aware fine-tuning)**: Fine-tuned mBART50 on this corpus significantly outperformed baseline systems (BLEU: 18.3 vs. 12.4 for Google Translate; BERTScore: 0.886 vs. 0.843).
- **Objective 3 (LLM-based post-editing)**: Post-editing further improved human-rated poetic fidelity (from 3.7 to 4.5) and fluency (from 3.9 to 4.7), showing clear benefits of combining NMT with LLM refinement.
- **Objective 4 (Evaluation)**: Both automatic metrics and human judgments confirm that our approach better preserves metaphor, emotion, and stylistic quality than conventional MT systems.

These results demonstrate that our approach successfully meets the stated objectives and provides empirical evidence that domain adaptation, stylistic cues, and LLM refinement together enhance poetic translation quality.

9.2 Key Findings

Across the aspects studied, the most important results can be summarized as follows:

- **Corpus**: We provide the first Hindi–English poetry dataset (500 poem pairs, 5,800 lines), enabling reproducible research in this domain.
- **Fine-tuning**: Domain adaptation of mBART50 improved BLEU from 12.4 (Google Translate) to 18.3, and BERTScore from 0.843 to 0.886.
- **Style tags**: Adding stylistic cues led to notable gains in human-rated style preservation (2.9 to 3.6).
- **LLM post-editing**: Post-editing achieved the highest human ratings, with poetic fidelity rising to 4.5 and fluency to 4.7 on a 5-point scale.
- **Evaluation**: Together, automatic metrics and human judgments confirm that our system better preserves meaning, emotion, and stylistic beauty than existing MT systems.

These highlights ensure that each major aspect of our work is tied to a concrete and measurable outcome.

9.3 Limitations and Ethical Considerations

While the results are promising, there are several limitations. The constructed corpus, although carefully curated, remains modest in size compared to corpora in high-resource MT tasks and may not capture the full spectrum of Hindi poetic traditions. Manual annotation of style tags is labor-intensive and may not scale easily. While LLM-based post-editing improves fluency, it also risks reinterpretation or hallucination, especially for culturally sensitive or devotional poetry. Furthermore, our evaluation is limited to a few automatic metrics and a relatively small set of human evaluators. In addition, the use of LLMs raises broader concerns regarding cultural fidelity, authorship attribution, and the possibility of bias or unintended reinterpretation. These considerations become particularly important when translating religious or politically charged verses.

9.4 Future Directions

Future work can extend this study in several directions. Expanding the dataset to include additional poets, genres, and poetic forms will improve coverage. Integrating prosodic features such as rhythm and rhyme into training objectives, or leveraging multimodal signals such as recitation audio, may further enhance poetic fidelity. We also envision interactive, human-in-the-loop systems where bilingual poets guide model refinements in real time. Such systems would combine machine efficiency with human creativity, advancing the broader goal of preserving literary beauty across languages.

In summary, this work demonstrates that stylistically-aware machine translation, grounded in curated poetic data and supported by LLM refinement, offers a viable path toward capturing both the meaning and artistry of poetry. We hope it encourages further research at the intersection of translation technology and literary expression.

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