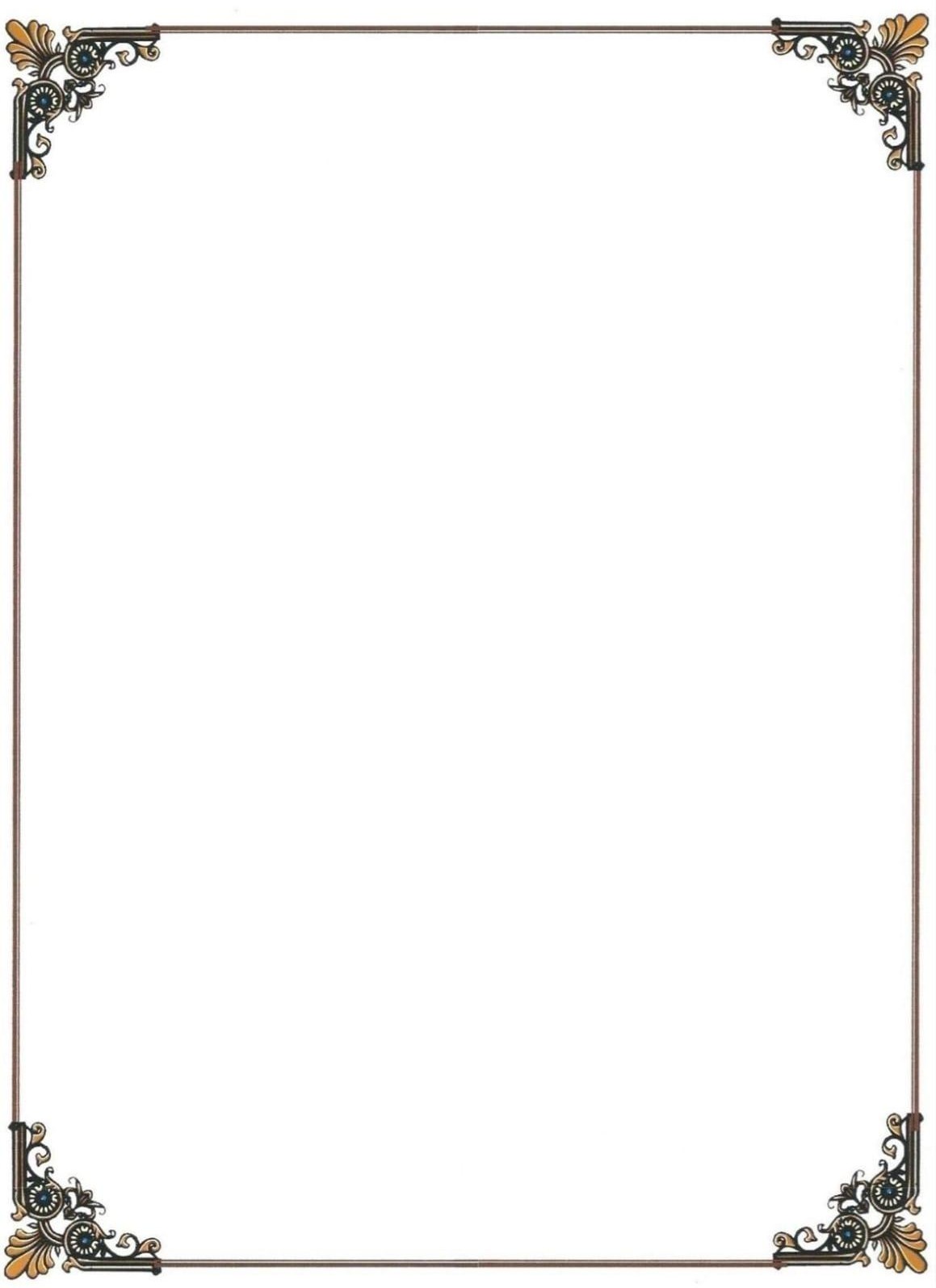
# A Project Report on



HINDI FORMALITY STYLE TRANSFER

***in partial fulfillment of the requirements for the award of the degree of***

# BACHELOR OF TECHNOLOGY

***in***

# ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

***Submitted by***

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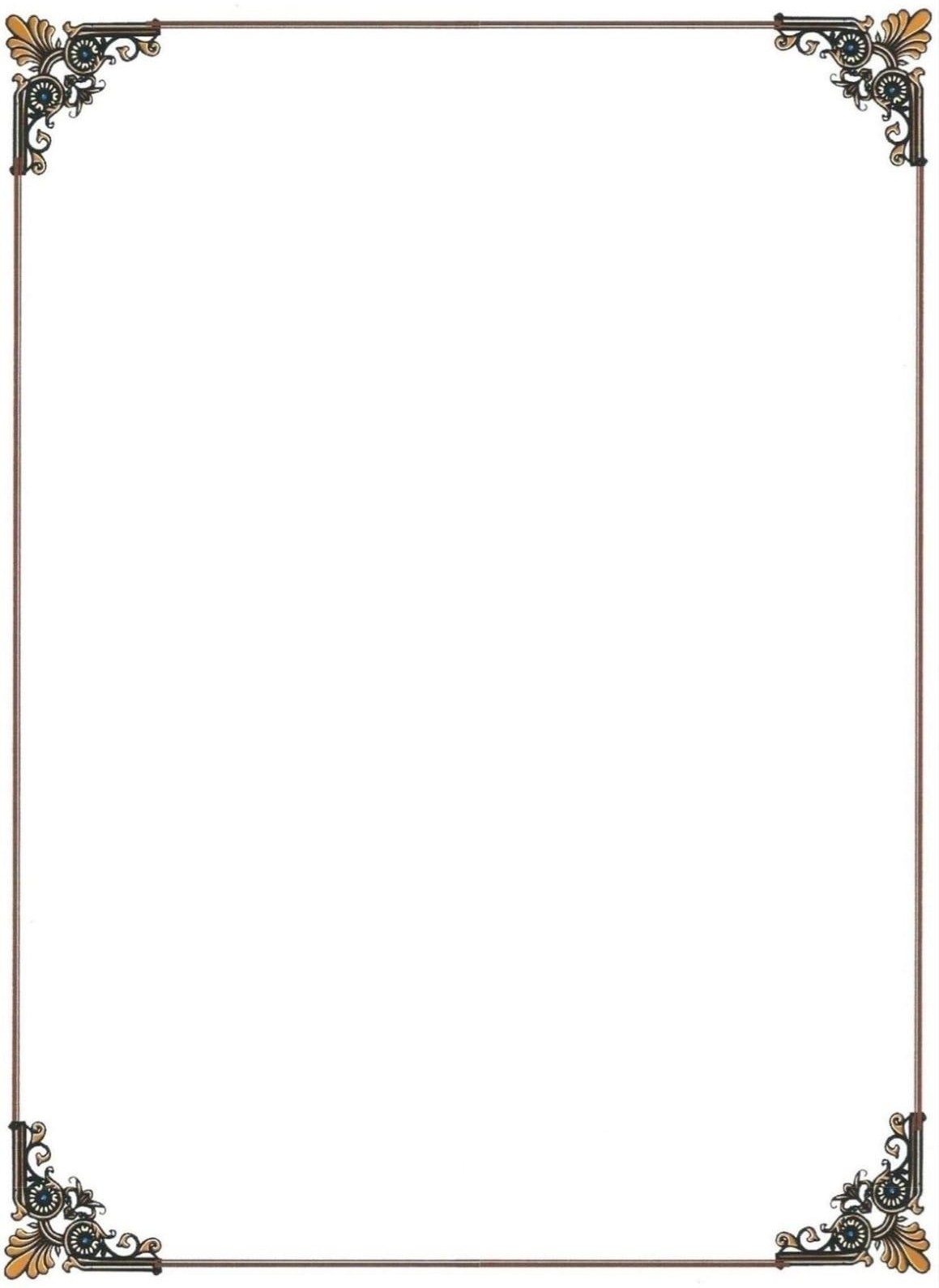
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# DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

**S.R.K.R. ENGINEERING COLLEGE (A)**

SRKR MARG, Bhimavaram, West Godavari Dist., A.P. [2024 – 2025]

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# BONAFIDE CERTIFICATE

This is to certify that the project work entitled **“HINDI FORMALITY STYLE TRANSFER”** is the bonafide work of **KANNURU VARALAKSHMI (21B91A6128), PETLURI LAKSHMI PRASANNA (22B95A6104), VANKA D S N S D M NARASIMHA RAJA (21B91A6161), KAPAKA DEEPTANUSH (21B91A6130),**

who carried out the project work under my supervision in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in **ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING.**

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# SELF DECLARATION

We hereby declare that the project work entitled “HINDI FORMALITY STYLE TRANSFER” is a genuine work carried out by us in B.Tech., (Artificial Intelligence and Machine Learning) at SRKR Engineering College(A), Bhimavaram and has not been submitted either in part or full for the award of any other degree or diploma in any other institute or University.

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**ABSTRACT**

Language is the cornerstone of human connection, it's not about what we say, but how we say matters most. Despite advancements in Formality Text Style Transfer (TST) for English, the domain remains largely unexplored for grammatically complex languages like Hindi. In Hindi, formality transfer is particularly challenging due to the scarcity of high-quality parallel corpora and the difficulty of disentangling style from content. Additionally, traditional metrics like BLEU often fail to capture stylistic nuances in such linguistically rich languages. To address these challenges, a bidirectional Hindi formality style transfer model is introduced, leveraging IndicBART and mT5 architectures, fine-tuned on parallel corpora. To overcome data scarcity, data augmentation techniques such as back translation are applied, enabling both formalization and informalization within a unified framework. Evaluation using BLEU, BERTScore, and human assessment reveals that model significantly outperforms baseline systems like GPT-2, IndicGPT, mBART in both semantic preservation and style accuracy. It demonstrates strong applicability in social media content generation, professional communication, and AI-assisted localization. This advances the field of style transfer for underrepresented languages by integrating targeted model architectures with robust data-driven strategies.

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# CHAPTER 1 INTRODUCTION

Communication is the cornerstone of human connection, yet, within this vibrant space, subtle misunderstandings can arise, not from what is said, but how. The linguistic choices a speaker makes—such as tone, phrasing, and register—can significantly influence how a message is received, regardless of its factual content. In both written and spoken forms, formality acts as an essential stylistic feature, shaping the way individuals navigate social boundaries, express deference, and signal emotional intent. Whether in casual personal communication or high-stakes professional discourse, the ability to modulate formality is crucial.

In linguistically rich and socio-culturally complex languages like Hindi, the concept of formality transcends mere lexical substitutions. It encompasses an elaborate system of pronouns, verb conjugations, word choices, and even syntactic constructions that align with varying levels of respect, age, relationship, and social context. Unlike in English, where switching from “you” to “sir” may suffice, Hindi requires nuanced adjustments, such as shifting from *“tu”* to *“tum”* to *“aap”*, all of which carry distinct social connotations. Consequently, the process of formalizing or informalizing a Hindi sentence is both context-dependent and highly sensitive to social norms.

With the growing reliance on digital communication, where tone is often inferred through text alone, the ability to adapt formality automatically through Natural Language Processing (NLP) has become increasingly relevant. Users interact with AI agents in customer support, virtual assistants, chatbots, and writing tools that often lack the capability to appropriately adjust tone. Misalignment in formality—either sounding overly casual in formal situations or excessively stiff in personal conversations—can lead to friction, misinterpretation, or even unintentional offense.

Formality Style Transfer (FST)—the computational task of transforming text between formal and informal registers while preserving its semantic meaning—is thus a promising yet underexplored area, especially in the context of Indian languages. While FST has been explored in English and a few other high-resource languages, Hindi remains notably underrepresented in this domain.

Current state-of-the-art systems often rely on pre-trained models such as GPT-2, GPT- 3, or mBART that, while powerful in multilingual contexts, are not optimized for Hindi’s stylistic intricacies. These models frequently misjudge the context or offer translations that distort meaning or violate cultural expectations of politeness.

This project addresses that gap by introducing a bidirectional formality style transfer system for Hindi using transformer-based architectures—IndicBART and mT5—well- suited for Indian languages. The model is designed to handle both formalization and informalization tasks with precision, ensuring stylistic appropriateness alongside semantic fidelity.

**Figure 1: Formality style transfer**

Beyond technical implementation, the real-world significance of this system lies in its potential applications. For instance:

* Content localization: Adapting tone in subtitles, instructions, or translated material for various demographics.
* AI writing assistants: Suggesting more appropriate tone in professional emails, reports, or academic writing.
* Conversational agents: Enhancing user trust and engagement by mirroring user tone in chat-based interfaces.
* Educational tools: Helping language learners understand and practice register variation.

To validate the performance of our models, we employed quantitative evaluation using metrics such as BLEU and BERTScore, along with qualitative assessment via human judgment, focusing on three dimensions: meaning preservation, stylistic accuracy, and fluency.

Ultimately, this work represents a holistic effort to bridge cultural-linguistic gaps in AI and extend NLP research to the nuanced needs of underrepresented languages like Hindi. It contributes not just a working model, but also methodological insights and data-centric innovations that can inform future research in formality modeling, low- resource NLP, and ethical AI design for linguistically diverse populations.

# CHAPTER 2 LITERATURE SURVEY

In recent times, there has been a noticeable rise on style transfer, particularly in modifying elements like tone, sentiment, and formality without altering the core message of the text. Much of this progress has centered around resource-rich languages such as English, where large-scale annotated corpora and advanced language tools are readily available. However, when it comes to Indian languages—Hindi in particular— efforts in this direction have been limited, largely due to the lack of dedicated datasets and the added complexity of cultural and linguistic nuances. Researchers have explored a range of approaches for stylistic transformation, including rule-based methods, neural sequence models, and transformer-based systems. This section provides an overview of key contributions in this space, evaluating their methodologies, shortcomings, and relevance to formality style transfer in Hindi.

Tianxing Jin, Zhijing Jin, Joey Tianyi Zhou, and Rik Sarkar [1] presented “Deep Learning for Text Style Transfer: A Survey”, providing a methodical review of deep learning applications in the domain of text style transfer (TST). Their work centered on categorizing established models (e.g., RL, VAEs, GANs, back-translation, transformers) by examining how each addresses style transformation, content preservation, and the use of non-parallel data. The analysis extended to various TST applications, including sentiment change, formality conversion, and politeness adjustment, identifying common architectural patterns like encoder-decoder setups and latent variable approaches, while also assessing these methods for interpretability, controllability, and linguistic versatility. Although comprehensive, the survey critically highlighted the underdeveloped state of support for low-resource and multilingual TST. In conclusion, Jin et al. underscored enduring difficulties in the field, such as challenges in preserving meaning accurately, the lack of sufficient parallel datasets, and inconsistent evaluation standards, pinpointing these as crucial avenues for future research efforts.

Zhiqiang Hu, Roy Ka-Wei Lee, Charu C. Aggarwal, and Aston Zhang [2] authored “Text Style Transfer: A Review and Experimental Evaluation”, a contribution blending a detailed survey of TST methods with a hands-on evaluation framework designed for structured comparison and practical assessment. The authors organized approaches by differentiating between parallel and non-parallel data strategies, investigating techniques like VAEs, adversarial training, style-centric decoders, back-translation, and pre-trained models. A significant contribution emphasized was the development of an extensive benchmark suite covering diverse TST tasks to facilitate consistent and replicable evaluations. Their empirical results revealed fundamental trade-offs among style fidelity, semantic consistency, and output fluency, indicating that no single method currently excels across all dimensions. Hu et al. concluded by identifying the inadequacies of existing evaluation metrics and stressing the necessity for improved optimization techniques when juggling multiple competing goals in TST systems.

Martina Toshevska and Sonja Gievska [3] presented “A Review of Text Style Transfer using Deep Learning,” offering an in-depth classification of deep learning architectures employed in TST. Their examination concentrates on how various architectural choices—including autoencoders, reinforcement learning, attention mechanisms, and transformers—handle the critical aspects of fluency, content preservation, and the separation of style from content. They investigated the influence of using parallel versus non-parallel data during training, giving particular attention to the role of latent representation learning in achieving effective disentanglement. The paper features a comparative analysis of model performance across different datasets and style categories. Toshevska and Gievska concluded by shedding light on the inherent compromises between model generalizability and the degree of stylistic control achievable with contemporary deep learning TST methods.

Sudha Rao and Joel Tetreault [4] presented their influential work “Dear Sir or Madam, May I Introduce the GYAFC Dataset: Corpus, Benchmarks and Metrics for Formality Style Transfer,” delivering a significant resource for the formality style transfer subfield. Their effort focused on compiling a large-scale parallel corpus (GYAFC, over 110,000 pairs) through manual rewriting of informal Yahoo Answers sentences into

formal equivalents by human annotators across specific domains. They benchmarked performance on this dataset using rule-based systems, PBMT, and NMT models, utilizing both automated scores and human assessments of fluency, formality, and meaning preservation. During the dataset's creation, the challenge of simultaneously optimizing these multiple constraints was noted. Rao and Tetreault concluded that the GYAFC dataset provided an essential benchmark for reproducible research and evaluation in formality transfer, establishing a solid basis for subsequent work.

Xu, R., et al. [5] presented “Formality Style Transfer with Hybrid Textual Annotations”, concentrating on enhancing formality style transfer (FST) through the use of hybrid supervision. The researchers introduced a semi-supervised learning framework engineered to integrate both parallel data and non-parallel corpora guided by a style classifier. Their proposed model utilizes a multi-task objective that incorporates style classification and sequence reconstruction, enabling joint training on disparate data types. This hybrid strategy was highlighted for its capacity to improve generalization, especially under low-resource conditions, while maintaining semantic integrity and output fluency. Xu et al. concluded from their GYAFC dataset evaluations that this hybrid approach yields substantial improvements over conventional parallel- data-only baselines, particularly in content preservation and grammatical correctness.

Kumar, M., et al. [6] introduced “XFORMAL: A Benchmark for Multilingual Formality Style Transfer”, representing a pioneering initiative to create a standardized multilingual benchmark for formality style transfer (FST). Their work involved constructing a parallel dataset containing formal and informal sentence pairs in English, German, French, and Hindi, curated via expert review and crowd-sourcing. Various baseline models, including mBART and fine-tuned mT5, were assessed on this new benchmark using BLEU, TER, and human evaluations, with a specific investigation into cross-lingual transfer phenomena. Observations during the benchmark's development suggested promising generalization capabilities of multilingual transformers even when data is scarce. Kumar et al. concluded that XFORMAL serves as an important resource for driving multilingual FST research forward and deepening the understanding of cross-lingual transfer learning.

Google Research [7] presented “Informal: A Formality Style Transfer Dataset for Four Indic Languages” (2023), marking a considerable advance in low-resource style transfer for Indic languages. The effort centered on creating a substantial parallel corpus (more than 110k pairs for Hindi, Bengali, Marathi, Gujarati) via crowd-sourcing combined with manual quality checks, supported by explicit linguistic guidelines for annotation. Standard sequence-to-sequence models like mT5 and IndicBART were benchmarked on this dataset, revealing that while models produced reasonably fluent outputs, they often encountered difficulties with precise style adaptation and preserving original meaning. The inherent complexities due to morphological richness and stylistic variation in languages like Hindi were acknowledged. Google Research concluded that while the dataset is a vital contribution, more targeted modeling approaches are necessary to overcome the observed limitations of large multilingual models in Indic FST contexts.

Sayan Mukherjee, et al. [8] presented “Multilingual Text Style Transfer: Datasets & Models for Indian Languages” (2024), delivering a wide-ranging overview and empirical investigation into TST across various Indian languages. The authors compiled and assessed multiple datasets (both new and adapted) covering formality, sentiment, and dialectal shifts in languages such as Hindi, Bengali, Tamil, and Telugu. They underscored the significant challenges posed by the linguistic richness of Indian languages, including morphological complexity and specific politeness markers, benchmarking models like mT5 and IndicBART for both monolingual and cross- lingual TST scenarios. Although reasonable zero-shot transfer was observed in some cases, performance notably decreased in morphologically complex or stylistically subtle domains, and limitations in standard evaluation metrics for code-mixed text were identified. Mukherjee et al. concluded by advocating for improved model alignment and more fine-grained evaluation methods suitable for the intricacies of Indian languages.

Krishna, K., et al. [9] introduced “Few-shot Controllable Style Transfer for Low- Resource Multilingual Settings” (2022), proposing a lightweight, adaptable framework

designed for TST scenarios where parallel data is minimal, focusing on low-resource multilingual contexts. Their suggested approach combines prompt tuning and adapter layers integrated into pre-trained multilingual models like mBART and mT5. The core idea involves utilizing meta-learning and few-shot techniques to efficiently learn style transformations (covering sentiment, formality, politeness) across diverse languages including Hindi, Bengali, and Kannada, especially under severe data limitations. While demonstrating effectiveness, the research implicitly points to the need for further task- specific adjustments for enhanced control. Krishna et al. concluded by emphasizing the promise of their few-shot methodology and the potential of multilingual transfer learning for practical TST in data-constrained situations.

Vivian Lai, Diyi Yang, and Chris Callison-Burch [10] presented "Formality-Aware Few-Shot Learning for Response Generation" (2023), undertaking a targeted study on integrating formality awareness into low-resource text generation systems, particularly for conversational AI. The researchers tackled the difficulty of producing contextually suitable responses with varying formality levels using very limited supervision. Their methodology employs prompt-based few-shot learning with large pre-trained models (notably GPT-3), guiding the generation process by explicitly conditioning on the target formality level via tailored prompts and examples. Alongside demonstrating successful style control on multiple datasets, they also proposed novel evaluation metrics tailored for formality-sensitive natural language generation. Lai et al. concluded that prompt engineering presents a viable and efficient alternative to extensive fine-tuning for generating stylistically appropriate text in zero- or few-shot learning scenarios.

Shen, T., et al. [11] introduced “Style Transfer from Non-Parallel Text by Cross- Alignment” (2017), a foundational paper that pioneered unsupervised TST methodologies relying solely on non-parallel corpora. The authors conceived a cross- aligned autoencoder framework engineered to disentangle content from style by aligning latent representations across different style domains, utilizing an encoder, separate style-specific decoders, and adversarial training guided by a discriminator. Their experiments successfully showed that meaningful style transformations, particularly for sentiment, could be achieved without paired data. Nevertheless, Shen

et al. recognized persistent difficulties related to preserving semantic content accurately and ensuring output fluency, especially with longer, more complex sentences. They concluded that the cross-alignment technique marked a significant step forward for low- resource TST, despite these inherent challenges.

Li, B., et al. [12] presented “Contrastive Learning for Unsupervised Text Style Transfer” (2022), introducing a contrastive learning strategy aimed at refining the quality of latent space representations for unsupervised TST. Their model utilizes a dual-encoder setup trained with contrastive loss functions intended to draw embeddings of semantically similar but stylistically different sentences closer, while simultaneously pushing apart stylistically similar but semantically distinct pairs, with a specific focus on bolstering content preservation. This approach demonstrably improved content-style separation and surpassed contemporary adversarial baselines in sentiment and formality transfer evaluations. The framework also incorporated style discriminators to uphold stylistic accuracy. Li et al. concluded that contrastive learning provides an effective mechanism for improving semantic fidelity within the unsupervised TST paradigm.

Clement Rebuffel, Marc-Alexandre Côté, and Alex Douville [13] presented "Controlling Manner vs. Content in Style Transfer with Information-Theoretic Decomposition" (2022), suggesting a novel method for achieving more explicit disentanglement of style (termed "manner") and content within TST. The researchers proposed an information-theoretic formulation that employs mutual information constraints, applied during training through a mix of variational objectives and contrastive losses, enabling their model (InfoST) to acquire style-agnostic semantic representations. Evaluated across tasks like sentiment modification and formality transfer, InfoST exhibited enhanced performance in maintaining semantic meaning while generating outputs closely matching target styles, showing adaptability without extensive parallel data, albeit primarily demonstrated in English. Rebuffel et al. concluded that their information-theoretic decomposition approach offers a principled and effective framework for advancing controllable TST.

Hui Wu, Zhenxin Xiao, and Hua Wu [14] presented their work "Controllable Text Style Transfer via Editing Entangled Latent Representation" (2021), tackling the problem of achieving precise and interpretable control over text style. Their architecture incorporates an encoder-decoder system featuring disentangled representations, complemented by an innovative editing module capable of adjusting the latent representation along a specific attribute dimension prior to decoding. This design permits users to fine-tune style intensity or alter relevant sentence aspects while retaining the original meaning, all without requiring parallel training data. Tested on sentiment and formality transfer tasks, the model yielded competitive outcomes in content preservation and style accuracy. Wu et al. concluded that their latent editing approach enables flexible, continuous, and controllable style adjustments that go beyond simple binary style switching.

Yating Zhang, Zhijing Jin, Joey Tianyi Zhou, and Rik Sarkar [15] introduced “Parallel Data Augmentation for Formality Style Transfer” (2020), putting forward a novel technique to mitigate the common issue of limited parallel data in formality style transfer (FST). The authors devised an automated pipeline focused on producing high- quality pseudo-parallel sentence pairs through back-translation, followed by a filtering process using style classifiers and similarity scores. Experiments conducted on the GYAFC dataset showed that incorporating this synthetically generated data significantly boosted the performance of supervised FST models. Although acknowledging the need for careful data curation, Zhang et al. concluded that their parallel data augmentation strategy can effectively narrow the performance discrepancy between unsupervised and supervised FST methods, thereby lessening the dependency on expensive human-labelled datasets.

Yong Liu, Jiangtao Feng, Zhifang Sui, and Baobao Chang [16] proposed “Exploring Content Representation Learning for Text Style Transfer” (2022), a study centered on enhancing content preservation—a notoriously difficult aspect of TST. The researchers formulated the Content Representation Learning (CRL) framework, which employs mutual information minimization alongside adversarial training within a dual-encoder architecture to effectively isolate semantic content from stylistic features. Their model

strives to learn a content representation that remains stable across style changes, enforced through adversarial losses as well as cycle-consistency and reconstruction objectives. Evaluated on tasks including sentiment, formality, and politeness transfer, CRL attained state-of-the-art results for content preservation metrics while sustaining high style accuracy. Liu et al. concluded that explicitly learning style-independent content representations proves highly beneficial for applications where maintaining semantic consistency during style transformation is critical.

Yang, Z., et al. [17] presented "STAP: A Sequence-to-Sequence Pre-training Approach for Text Style Transfer" (2022), introducing an innovative pre-training methodology specifically conceived for TST tasks. The authors put forward a sequence-to-sequence pre-training technique utilizing an encoder-decoder model, trained on extensive unlabeled corpora to learn stylistic transformation by predicting masked or modified text sequences. This pre-training phase is intended to equip the model with a better grasp of stylistic subtleties, enhancing its effectiveness particularly when fine-tuned on limited parallel data for downstream TST tasks. They reported significant gains in fluency and style control over baseline models on standard English TST benchmarks. Yang et al. concluded that their task-focused pre-training strategy offers an effective means of balancing content preservation with accurate style modification in TST systems.

Xue, L., et al. [18] introduced “mT5: A Massively Multilingual Pre-trained Text-to- Text Transformer” (2021), significantly broadening the T5 text-to-text framework to encompass over 100 languages, including Hindi. The authors trained this extensive transformer encoder-decoder model using the varied mC4 corpus within a unified input- output format, designed to facilitate strong performance across a multitude of NLP tasks, with particular effectiveness in multilingual and low-resource contexts. They emphasized its robust zero-shot and few-shot learning capabilities, as well as its support for cross-lingual transfer. While establishing new performance levels on benchmarks like XTREME and XGLUE, the work positions mT5 as a potent foundational model for diverse sequence generation applications. Xue et al. concluded that large-scale multilingual pre-training following a text-to-text paradigm results in exceptionally versatile and powerful language models.

Dabre, R., et al. [19] developed “IndicBART: A Pre-trained Model for Indic Natural Language Generation” (2021/2022), unveiling a BART-style transformer specifically pre-trained for 11 Indic languages. The researchers employed back-translation and denoising autoencoding techniques during pre-training on the AI4Bharat corpus, concentrating on capturing the unique syntactic and semantic patterns of Indic languages to enhance generation quality within this language family. They pointed out that this region-specific training approach yields superior language fluency compared to more general multilingual models. The underlying BART architecture facilitates easy adaptation through fine-tuning for various downstream tasks. Dabre et al. concluded that IndicBART furnishes a robust starting point for a wide array of natural language generation tasks in Indic languages.

Vinuthna, P., et al. [20] introduced the paper "Leveraging Pre-trained Language Models for Task-Oriented Dialogue in Indic Languages" (2023), which examines the use of pre-trained language models (PLMs), especially those adapted for Indic languages, within dialogue systems. The authors investigated the utility of models such as IndicBERT, mBART, and mT5 for developing intent recognition and response generation capabilities across several low-resource Indian languages. Their findings underscored the importance of domain adaptation and language-specific fine-tuning for improving PLM performance on tasks like slot filling and question answering, demonstrating superiority over baseline methods even with scarce resources. Highlighting the need for culturally relevant training data, Vinuthna et al. concluded that meticulous fine-tuning renders PLMs highly effective for constructing dialogue systems tailored to Indic language contexts.

Sinha, K., et al. [21] presented “Pretraining Multilingual Language Models for Indic Languages” (2021), concentrating on the development and assessment of pre-trained language models specifically engineered for Indian languages. The authors expanded upon multilingual transformer designs, training models like IndicBERT and mBERT variations using a carefully assembled Indic language corpus covering more than 12 languages, with the goal of enhancing downstream task performance within this

linguistic group. They showcased the benefits of such language-family-specific pre- training compared to generic multilingual models on tasks such as text classification and NER, attributing the gains to better capturing of Indic syntactic and morphological characteristics. Acknowledging challenges related to tokenization and script variations, Sinha et al. concluded that well-executed, targeted pre-training substantially elevates downstream results for Indic NLP applications.

Goyal, T., et al. [22] proposed “Evaluating the Evaluation Metrics for Style Transfer: A Case Study in Hindi” (2022), offering a critical analysis of commonly used automatic evaluation metrics within the specific context of Hindi text style transfer. The authors drew attention to the frequent mismatch between scores from metrics like BLEU and BERTScore and human perceptions of stylistic changes, particularly in morphologically complex languages like Hindi that exhibit flexible word order. Utilizing a human-annotated evaluation set, they empirically demonstrated these discrepancies between automated scores and human preferences concerning fluency and stylistic accuracy. Based on their analysis of existing metrics, Goyal et al. concluded by recommending the development and use of more linguistically informed or hybrid evaluation approaches that are better calibrated for assessing TST quality in Indic languages.

Tian, Y., et al. [23] presented "StylePTB: A Compositional Benchmark for Fine- grained Controllable Text Style Transfer" (2022), where they introduced a novel benchmark derived from the Penn Treebank corpus, designed to assess style transfer models across multiple, combined stylistic attributes. The authors engineered this benchmark to facilitate testing models on tasks requiring simultaneous adjustments to features like sentiment, formality, voice (active/passive), and tense. Their benchmarking of several leading models revealed that achieving control over multiple style dimensions while preserving the original content remains a significant hurdle for current methods. Along with providing in-depth analysis of the trade-offs between fluency, accuracy, and content preservation, Tian et al. concluded that StylePTB represents a valuable resource for rigorously evaluating and driving progress in fine- grained, controllable TST systems.

Mukherjee, S., et al. [24] introduced “Are Large Language Models Actually Good at Text Style Transfer?” (2024), a study investigating the performance of prominent Large Language Models (LLMs) on diverse style transfer tasks. The authors assessed models including GPT-3 and T5 under both zero-shot and few-shot conditions, evaluating their effectiveness in terms of content preservation, style adherence, and fluency. Their results indicated that while LLMs generally produce fluent text and often maintain content reasonably well, they frequently exhibit shortcomings in precise style control and consistency, particularly when transformations involve subtle cultural or linguistic nuances. Issues related to prompt sensitivity and a lack of model transparency were also observed. Mukherjee et al. concluded that, notwithstanding their broad capabilities, contemporary LLMs face notable limitations when applied to the specific challenge of reliable and targeted text style transfer.

Gaps and Challenges in Hindi Formality Style Transfer:

While Text Style Transfer (TST) technologies have progressed, effectively automating formality adjustments for Hindi remains a significant challenge, as highlighted by current literature review. A fundamental limitation stems from the lack of sufficient high-quality parallel datasets designed for Hindi's formality, contrasting sharply with the resources available for English and hindering robust model development. This data gap is compounded by Hindi's linguistic nature, where formality is related to grammar, making accurate style-content disentanglement and semantic preservation during the transfer process, especially for bidirectional control became difficult. Meaningful progress is also stalled by the inadequacy of standard evaluation metrics like BLEU, which fail to capture stylistic accuracy effectively for Hindi, complicating reliable model assessment. Finally, leveraging existing powerful pre-trained models requires significant adaptation and fine-tuning to achieve the necessary fine-grained control over Hindi formality—techniques which are currently underdeveloped and limit practical application. Addressing this confluence of data, linguistic, evaluation, and model control challenges is essential for developing dependable FST tools capable of handling Hindi's complexities.

# CHAPTER 3 PROBLEM STATEMENT

In this world, how we communicate is often just as important as what we communicate. Textual formality reflecting politeness, respect, and social distance plays a crucial role across platforms like professional emails, customer service chats, social media, and localized content. Misalignment in formality can lead to misunderstandings, offense, or diminished user experience, making automatic formality style transfer (FST) increasingly essential. However, existing systems fall short, especially for languages beyond English. For Hindi, a language used by millions with complex socio-linguistic formality rules, this gap is especially pronounced due to several specific, interconnected problems. First, progress is severely constrained by the critical scarcity of suitable datasets; unlike English, large-scale, high-quality parallel corpora annotated specifically for the nuances of Hindi formality are lacking, limiting model training and generalization capabilities [4, 6, 7, 8]. Second, the inherent linguistic complexity of Hindi formality, embedded deeply within grammar, morphology (e.g., pronoun/verb agreement), and syntax rather than just vocabulary [8, 21], makes style-content disentanglement extremely difficult for current models. Third, this complexity worsens the challenge of reliably preserving semantic content while accurately manipulating style [2, 3, 16], especially for bidirectional (formal-to-informal and informal-to-formal) transfer where subtle meaning shifts are easily introduced. Fourth, evaluating progress is effected by the inadequacy of standard evaluation metrics like BLEU, which fail to capture stylistic fidelity accurately in morphologically rich languages like Hindi and correlate poorly with human judgment [22], necessitating laborious manual assessments. Finally, while powerful multilingual and Indic-specific models like mT5 and IndicBART exist [18, 19], achieving fine-grained, controllable formality adjustment requires specific adaptation and fine-tuning techniques [20, 24], as these base models are not inherently optimized for such refined, task-specific style manipulation. These combined challenges underscore the urgent need for targeted research developing robust FST solutions addressing the unique data, linguistic, evaluation, and model control requirements of Hindi.

# CHAPTER 4

**SOFTWARE REQUIREMENT SPECIFICATION**

## PURPOSE

The objective of this project is to create a strong and effective system for bidirectional formality style transfer in the Hindi language, concentrating on transforming informal sentences into formal ones and the reverse. While many generative models are available for languages with abundant resources, Hindi, known for its rich morphology and complex syntax, lacks sufficient resources and research in this field. This project intends to fill this gap by developing and training a system that leverages advanced multilingual transformer-based models (mT5 and IndicBART), which are further improved through ensemble inference techniques.

This specification provides a comprehensive overview of the system requirements to ensure reproducibility, deployment readiness, and extensibility for future work. The specification details the technical, functional, and non-functional requirements for building the system, from data processing to inference, while also highlighting the challenges of formality variation in Indian languages.

## SCOPE

This project focuses exclusively on Hindi language formality style transfer, with a bidirectional structure capable of transforming both informal to formal and formal to informal text using a shared model architecture. The system supports the following functionalities:

* Text preprocessing and formatting for formality classification.
* Fine-tuning of multilingual pre-trained models such as mT5 and IndicBART using parallel Hindi formal-informal corpora.
* Evaluation of multiple models based on standard NLP metrics (BLEU, BERTScore, Perplexity).
* Ensemble-based inference framework to combine the strengths of different models.
* Comparison with baseline models such as GPT-2, IndicGPT, and mBART to validate the improvements.
* Support for scalability and extension to other Indian languages.

This system does not include components related to summarization, sentiment modification, or general translation tasks. The focus is strictly on formality transformation within the Hindi language.

## OBJECTIVES

The primary objectives of the proposed system are as follows:

* Development of a Bidirectional Style Transfer Framework Specifically for Hindi.
* Integration of Custom-made Parallel Hindi Dataset for Fine-Tuning.
* Improved Style Transfer Accuracy Through Ensemble Modeling and Evaluation Strategy.

## EXISTING SYSTEM

Most style transfer applications out there are for English and focus on simplification, sentiment, or politeness. Research on Hindi is still very new, especially in relation to formality.

* The GPT-2 and IndicGPT models are general purpose models and not formality-tuned in any way, and frequently end up making erroneous or off-topic generations.
* While mBART is multilingual, it actually does worse for Hindi formality transfer because it is not specifically trained/can build a model for it.
* It is also challenging to train trustable models and evaluate them trained in each case, there aren't many large or similar parallel Hindi datasets available and rule based system don't have nuance and generalization capacity to deal with the complexity in expressions of formality in Hindi. Therefore, even though these systems offer us a solid foundation, none of them can fully solve the problem of Hindi formality transfer. They either lack fine-tuning, produce unreliable results, or simply don’t have enough data to learn from. That’s why there’s a real need for a focused approach — one that uses Hindi-specific data, custom training, and smarter techniques like model combinations (ensembles) to truly capture the formal and informal tones of the language.

## PROPOSED SYSTEM

To fill the void in Hindi formality transfer, we developed a system with the following three components:

* mT5: A multilingual model that we specifically fine-tuned for Hindi formality task. It showed good performance in understanding sentence structure and output fluency.
* IndicBART: A model developed for Indian languages. After fine-tuning, its forms were aligned while the Hindi style and grammar were strong, but it was occasionally less fluent than mT5.
* Ensemble Model: Instead of choosing either mT5 or IndicBART, we developed an ensemble model that combines both. For each input, we will generate outputs from both mT5 and IndicBART and choose the better output based on fluency (perplexity). This active selection leads to more natural and better results.

Why this worksTask-specific :

* fine-tuning: unlike very general models, we have fine-tuned our models for Hindi's formality aspect.
* Enhanced fluency and accuracy: the ensemble model combines both methods' strengths.
* Ability to perform both directions: our system is capable of both directions (formal to informal and informal to formal).

## REQUIREMENTS

* + 1. **Software Requirements**

|  |  |
| --- | --- |
| **Component** | **Specification** |
| Operating System | Ubuntu 20.04 / Windows 10+ / Google Colab |
| Programming Language | Python 3.10+ |
| Deep Learning Library | PyTorch 1.12+, Transformers (Hugging Face) |
| Tokenizers | Sentence Piece, Hugging Face Tokenizers |
| Dataset Processing | pandas, NumPy |
| Model Evaluation | Sacre BLEU, BERTScore, perplexity calculation using GPT-2 tokenizer |
| Experiment Tracking | Tensor Board, Weights & Biases (optional) |
| Visualization | Matplotlib, Seaborn (for analysis plots) |
| Pretrained Models | google/mt5-small, ai4bharat/ Indic BART |
| Interface (optional) | Stream lit/Gradio for demo setup |

* + 1. **Hardware Requirements**

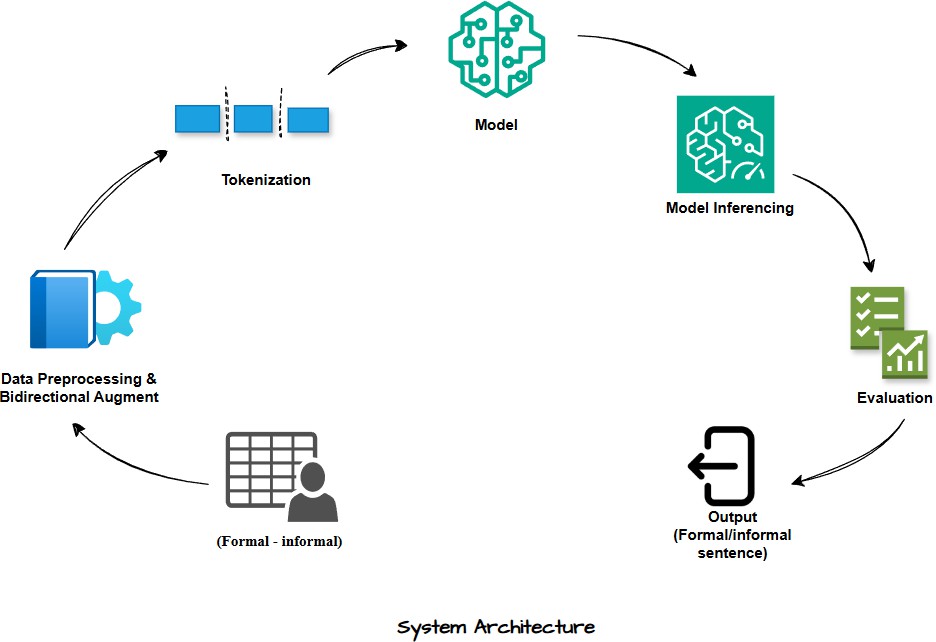
|  |  |
| --- | --- |
| **Component** | **Specification** |
| CPU | Intel i5/i7 8th Gen or AMD Ryzen 5+ |
| GPU | NVIDIA Tesla T4 / V100 / A100 (for training), GTX  1650+ (for inference) |
| RAM | Minimum 16GB |
| Storage | Minimum 50GB (for dataset, model checkpoints, logs) |
| Internet | Required for downloading pretrained models and  datasets |

# CHAPTER 5

**SYSTEM ANALYSIS AND DESIGN**

The goal of this project is to create a strong and scalable bidirectional style transfer solution for the Hindi language in formal style using sequence-to-sequence (seq2seq) deep learning-based models. The system used has utilized both the mT5 and IndicBART architectures.

## SYSTEM ARCHITECTURE / METHODOLOGY

****

**Figure 5.1: System Architecture Diagram Key Components of the System:**

* Data Input Layer: We start with a parallel corpus of Hindi sentence pairs—one informal, the other formal. This corpus is:
* Read by Pandas
* Reformatted as Hugging Face compatible DatasetDict for training and validation.

Let each pair be represented as:

*(xinf , xform)*

* Bidirectional Dataset Generator: For bidirectionality in learning, we also created two entries per pair:
  + formalize:" + xinf → xform
  + "informalize:" + xform → xinf

Thus doubling the size of the dataset and allowing the model to learn two mappings:

*x = [prompt; x1 ,x2 , x3 ,…,xn]* with target *y = [y1 ,y2 ,…,yn]*

* Tokenizer Module: The model makes use of T5Tokenizer and AutoTokenizer from Hugging Face for mT5 and IndicBART respectively. The input and target are tokenized to a maximum length of 128 tokens with proper padding and truncation.
* Seq2Seq Transformer Models: Model 1: mT5-Small Fine-Tuning

The Multilingual T5 (mT5) model[18] is the multilingual variant of the Text-to-Text Transfer Transformer (T5) and supports more than 100 languages, including Hindi. It processes all NLP tasks as text-to-text tasks and is pre-trained on the mC4 corpus and, therefore, is perfect for low-resource languages.

Architecture:

mT5-Small[18] is a 60M parameter encoder-decoder model. During fine-tuning, we optimize the cross-entropy loss:

Strengths:

𝑚

𝐿𝑚𝑇5 = − ∑ 𝑙𝑜𝑔 𝑃𝑚𝑇5(𝑦𝑡|𝑦<𝑡, 𝑥)

𝑡=1

* Pretraining for multilinguality facilitates generalization to language styles.
* Produces smooth and contextually consistent sentences.
* Handles underrepresented structures due to high corpus exposure.

Model 2: IndicBART Fine-Tuning

IndicBART [19] is a monolingual encoder-decoder model trained on the IndicCorp dataset and the BART pretraining paradigm with denoising autoencoding on the Indian languages.

Architecture:

* It has transformer encoder-decoder architecture like BART, with random masking and span corruption pretraining.
* IndicBART[19] is used to produce highly formatted and grammar-correct Indian-language text.

We once more fine-tune our parallel corpus at task-specific training with the same cross-entropy objective:

Strengths:

𝑚

𝐿𝐼𝑛𝑑𝑖𝑐𝐵𝐴𝑅𝑇 = − ∑ 𝑙𝑜𝑔 𝑃𝐼𝑛𝑑𝑖𝑐𝐵𝐴𝑅𝑇 (𝑦𝑡|𝑦<𝑡, 𝑥)

𝑡=

* Hindi syntactic correctness and technical domain expertise.
* Greater stylistic precision in formal/informal styles due to monolingual focus.
* Good performance on morphologically complex inputs and politeness markers.

Ensemble Inference Mechanism

To leverage the strengths of both models, we use an ensemble-based inference module. The concept is to create outputs from both models and choose the optimal prediction using a perplexity-based fluency estimator. The estimator is based on a pre-trained GPT-2 model (Hindi-compatible) to estimate the perplexity of each candidate output:

𝑚

1

𝑃𝑒𝑟𝑝𝑙𝑒𝑥𝑖𝑡𝑦(𝑦) = 𝑒𝑥𝑝 (− 𝑚 ∑ 𝑙𝑜𝑔 𝑃𝐺𝑃𝑇−2(𝑦𝑡|𝑦<𝑡))

𝑡=1

The final prediction *y^* is selected as:

𝑦̂ = 𝑎𝑟𝑔 𝑚𝑖𝑛

𝑦∈(𝑦𝑚𝑇5,𝑦𝐼𝑛𝑑𝑖𝑐𝐵𝐴𝑅𝑇)

𝑃𝑒𝑟𝑝𝑙𝑒𝑥𝑖𝑡𝑦(𝑦)

Alternatively, a soft-voting mechanism based on BLEU scores and GPT-2 perplexity can also be used:

*Score(y)=α*⋅*BLEU(y)−β*⋅*Perplexity(y)*

Where α and β are tunable weights. Ensemble inference guarantees that:

* mT5[18] generates smooth, semantically detailed outputs.
* IndicBART[19] offers formality-aware precision and stylistic robustness.
* The final result achieves linguistic beauty and situational accuracy.
* Training Module: Training is done using the Trainer class provided by Hugging Face. Critical configurations are:
  + 5 epochs
  + Batch size 8
  + Evaluation and saving strategies set to occur at the end of every epoch
  + Loss masking by making padding tokens -100
* Inference & Ensemble Strategy: For a given input xxx, both mT5 and IndicBART models generate candidate outputs:

*ymT5 = fmT5(x), yindicBART = findicBART(x)*

We evaluate each candidate using GPT-2-based Perplexity:

𝑚

1

𝑃𝑒𝑟𝑝𝑙𝑒𝑥𝑖𝑡𝑦(𝑦) = 𝑒𝑥𝑝 (− 𝑚 ∑ 𝑙𝑜𝑔 𝑃𝐺𝑃𝑇−2(𝑦𝑡|𝑦<𝑡))

𝑡=1

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𝑦̂ = 𝑎𝑟𝑔 𝑚𝑖𝑛

𝑦∈(𝑦𝑚𝑇5,𝑦𝐼𝑛𝑑𝑖𝑐𝐵𝐴𝑅𝑇)

𝑃𝑒𝑟𝑝𝑙𝑒𝑥𝑖𝑡𝑦(𝑦)

This ensures fluency and grammaticality while capturing the desired style.

* Evaluation Layer: The final predictions are evaluated with:
* BLEU Score: Indicates n-gram overlap with the reference
* BERTScore: Evaluates semantic similarity with multilingual BERT embeddings
* Perplexity: Estimates fluency with GPT-2 probability scores Let yref be the ground truth sentence and ygen the generated one. Then:
* BLEU is computed as:

4

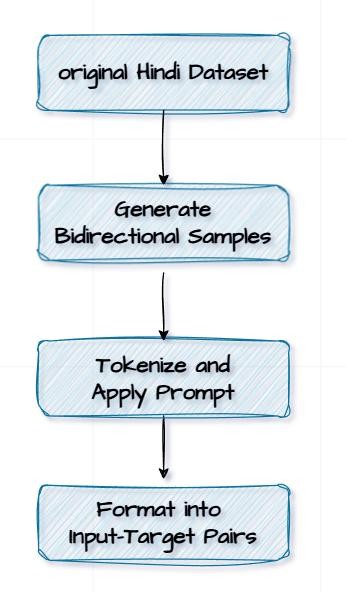
𝐵𝐿𝐸𝑈 = 𝐵𝑃 ⋅ 𝑒𝑥𝑝 (∑ 𝜔𝑛 𝑙𝑜𝑔 𝑝𝑛)

𝑛=1

* BERTScore (F1) is computed via: BERTScore ( yref , ygen ) = F1BERT( yref , ygen )

## DATASET

The dataset employed in this research contains 50,000 parallel Hindi sentence pairs handpicked for formal and informal variants. Every row in the dataset contains an informal sentence and its formal equivalent.



**Figure 5.2: Dataset Preparation Pipeline**

* + 1. **Features**

There are two central fields in every instance of the dataset:

* + - * Informal Sentence: Usually holds colloquial, conversational, or regional dialect forms that are most frequently encountered in everyday spoken Hindi.
      * Formal Sentence: Follows standard, grammatically accurate, and polite Hindi as in official papers, scholarly material, or business communication.

These features allow supervised learning for the text style transfer task with clear source-target pairs for both directions.

Other metadata like sentence length, frequency of vocabulary, and linguistic complexity may be harvested for further use in style strength control or quality estimation.

* + 1. **Pre-Processing**

The following are the preprocessing operations used for the dataset and text inputs:

* + - * Normalization: Unicode normalization is used to have uniform token encoding across the systems.
      * Noise Removal: Irregular white spaces, HTML tags, and rare characters are eliminated to minimize input noise.
      * Tokenization: Tokenization is performed using language-specific tokenizers:
        + mT5 employs T5Tokenizer, which uses SentencePiece-based subword units.
        + IndicBART employs AutoTokenizer with use\_fast=False for fine- grained control of token boundaries.
      * Padding and Truncation: Input and output sequences are padded and truncated to a fixed length of 128 tokens to provide consistent tensor sizes during training.
      * Loss Masking: The padding tokens in the sequence of labels are substituted with

-100 so that they don't count toward the training loss. This is common practice in transformer-based models.

* + - * These processes are important to making sure that both models perform well on diverse and large training corpus.

In conclusion, the system developed is modular, language-specific, and fully adaptable. Utilizing several models and an ensemble inference approach enables the system to perform better than individual models on a number of evaluation measures. The use of bidirectional training facilitates flexible transformation tasks and broadens the scope for more general real-world applications like conversational AI, post-editing machine translation, and educational tooling for formal language acquisition.

# CHAPTER 6 IMPLEMENTATION

Implementation section is the actual deployment of the proposed methodology of Hindi bidirectional formality style transfer using state-of-the-art transformer models. This section succinctly describes the tools, frameworks, and technologies involved and then provides a detailed overview of individual modules. The main aim was to design a dual- directional text generation system that can convert informal Hindi sentences into formal sentences and formal sentences into informal sentences with high linguistic correctness.

## TECHNOLOGIES USED

To implement the model training, inference, and evaluation pipeline, a combination of state-of-the-art machine learning libraries, transformer-based language models, and hardware accelerators were utilized. The following is a breakdown of the technology stack:

1. Programming Environment
   * Language: Python 3.10+
   * Notebook Environment: Google Colab Pro+ (with NVIDIA T4 GPU support for speedy training)
2. Frameworks and Libraries
   * PyTorch (v2.0+): Employed as the backend deep learning platform for the model loading, training, and GPU computation.
   * Hugging Face Transformers: Base library to load and fine-tune mT5 and IndicBART models. It offers modular tokenization, training pipelines (Trainer API), and model inference tools.
   * Datasets (Hugging Face): For wrapping and working with train/evaluation splits.
   * Evaluate Library: Used for computing NLP evaluation metrics like BLEU, BERTScore and Perplexity.
   * Pandas and NumPy: For data manipulation, handling, and preprocessing tasks.
   * GPT-2 (of Transformers): Used for computing perple**xity** in model assessment.

Perplexity is:

𝑁

1

𝑃𝑒𝑟𝑝𝑙𝑒𝑥𝑖𝑡𝑦(𝑃) = 𝑒𝑥𝑝 (− 𝑁 ∑ 𝑙𝑜𝑔 𝑃(𝜔𝑖))

𝑖=1

Where *P(wi)* is the predicted probability of word *wi* ,and *N* is the number of words in the sentence. Lower perplexity implies more fluent and confident generation.

## MODULES IMPLEMENTATION

From reading the data to creating final formality-transferred sentences and assessing their quality, our system is constructed using a sequential modular pipeline. Each module functions as follows:

Data Preparation Module:

A dataset of 50,000 Hindi sentence pairs, each with a formal and informal version, is loaded first.

Two methods are used to prepare the data:

* + - Informal → Formal: Began with "informal to formal: "
    - Formal → Informal: Replaced with "formal to informal: "

Hugging Face's Dataset library is used to clearly label each pair and transform it into a format that our models can comprehend.

Tokenization Module:

To enable models to process sentences, we must first divide them into smaller units called tokens.

We make use of:

* + - mT5Tokenizer for mT5
    - Auto-Tokenizer for IndicBART

There are only 128 tokens per sentence. During training, special labels are used to ignore certain parts of the output so that the model only concentrates on the important information. Labels are masked with -100 for ignore index to calculate loss appropriately:

𝑇

𝐿𝑜𝑠𝑠𝑚𝑎𝑠𝑘𝑒𝑑 = − ∑ 1[𝑦1≠−100] . log 𝑃(𝑦𝑖|𝑥)

𝑖=1

Model Fine-tuning Module:

Two encoder-decoder transformer models separately optimized:

* + - mT5-Small [18]
    - IndicBART (of ai4bharat) [19]

Both were trained under the provided configuration:

* + - Epochs: 5
    - Batch size: 8
    - Optimizer: AdamW
    - Learning Rate: 5×10−5

Training was handled by utilizing Hugging Face's Trainer class, and DataCollatorForSeq2Seq for batch alignment and padding.

Ensemble Inference Module:

Once both models have been trained, we use both to make predictions and select the better outcome. We use a third model (GPT-2) to assess fluency, or how naturally the sentence reads, in order to determine which is superior..The final prediction is chosen on the basis of minimum perplexity score:

𝑂𝑢𝑡𝑝𝑢𝑡 = 𝑎𝑟𝑔 𝑚𝑖𝑛

𝑃𝑒𝑟𝑝𝑙𝑒𝑥𝑖𝑡𝑦𝑚

𝑚∈{𝑚𝑇5,𝐼𝑛𝑑𝑖𝑐𝐵𝐴𝑅𝑇}

Evaluation Module:

A detailed analysis is provided against the following parameters:

* + - BLEU Score: n-gram overlap measure. Calculated with SacreBLEU.

4

𝐵𝐿𝐸𝑈 = 𝐵𝑃 ⋅ 𝑒𝑥𝑝 (∑ 𝜔𝑛 𝑙𝑜𝑔 𝑝𝑛)

𝑛=1

* + - BERTScore: Applies contextual embeddings to quantify semantic similarity.
    - Perplexity (GPT-2): Assesses fluency of output synthesized.

The modular design ensures flexibility, reusability, and scalability. Each module can be improved or replaced in isolation, e.g., switching the base language models, trying out different evaluation heuristics, or introducing new features like style intensity control. Computational efficiency and reproducibility for research are taken into account in the design of the system.

# CHAPTER 7

**TESTING & RESULT ANALYSIS**

This section describes the test methodology employed, the specific test cases employed, the metrics used for evaluation, and a qualitative analysis of the results obtained. The goal is to assess the performance of the proposed bidirectional Hindi formality style transfer system and compare it with current baselines. In order to find out the system's generalizability and robustness, qualitative and quantitative evaluation metrics are employed.

## TEST CASES

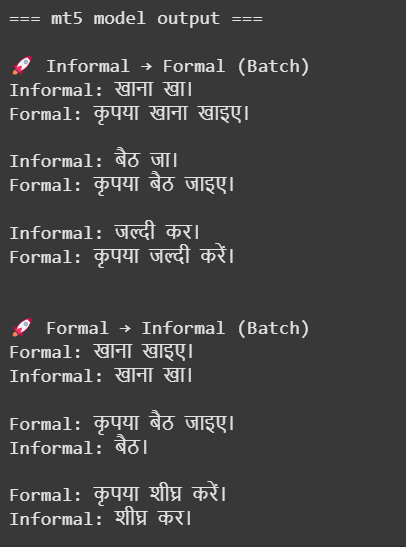
Test cases are designed to assess both directions of style transfer:

* + - Formal to Informal
    - Informal to Formal Each test case consists of:
    - An input sentence with a directional prompt,
    - The ground truth (reference) output,
    - The model-generated output, and
    - The evaluation scores (BLEU, BERTScore, Perplexity). Test Dataset:

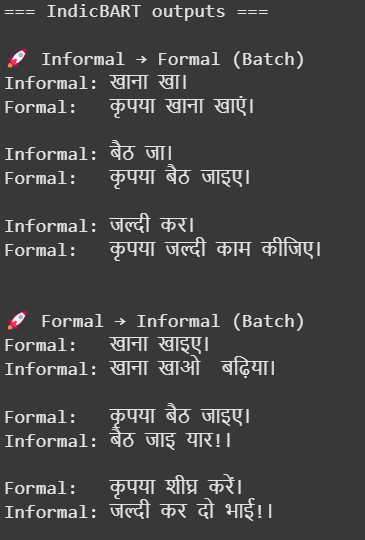
A stratified sample of 5,000 sentence pairs was reserved for testing, ensuring diversity in:

* + - Sentence length (short, medium, long),
    - Part-of-speech (questions, imperatives, statements),
    - Domains (daily conversation, education, literature).

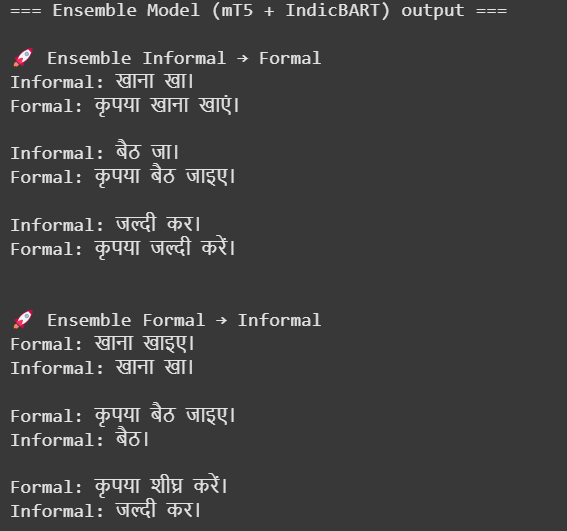
**Sample Test Case:**



**Figure 7.1.1:mT5 model output**

****

**Figure 7.1.2:IndicBART model output**



**Figure 7.1.3:Ensemble model output**

## RESULT ANALYSIS

Quantitative Assessment:

1. BLEU (Bilingual Evaluation Understudy):

Calculates n-gram overlap of generated output vs. reference output. Syntactic similarity increases with higher BLEU.

𝑁

𝐵𝐿𝐸𝑈 = 𝐵𝑃 ⋅ 𝑒𝑥𝑝 (∑ 𝜔𝑛 𝑙𝑜𝑔 𝑝𝑛)

𝑛=1

Where *pn* is the precision for n-grams (e.g., unigram, bigram), *wn* is the weight for the n-th n-2. BERTScore:

Scores semantic similarity according to contextual embeddings from a pre-trained BERT model. We employ the F1 score.

1. Perplexity:

Measures fluency by measuring the confidence of the model in generating each token. Lower perplexity means higher fluency.

Model Performance Summary:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Model | BLEU  Score | BERTscore  F1 | BERTscore  Precision | BERTscore  recall | Perplexity |
| mT5 | **23.31** | **0.85** | **0.85** | **0.85** | 8.25 |
| IndicBART | 17.84 | 0.81 | 0.82 | 0.81 | 5.36 |
| Ensemble Model | 21.25 | 0.84 | 0.84 | 0.84 | 6.20 |
| GPT-2 | 0.26 | 0.60 | 0.58 | 0.62 | 3.13 |
| IndicGPT | 20.01 | 0.63 | 0.62 | 0.65 | 41.77 |
| mBART | 8.91 | 0.77 | 0.80 | 0.74 | 15.07 |

Table 7.2: Model Performance Summary

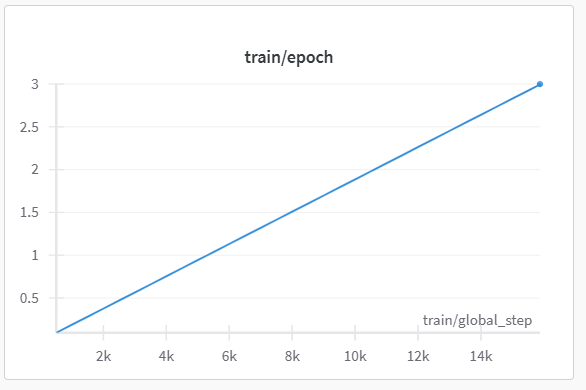
* + mT5 delivers the best overall performance with the highest BLEU (23.31) and BERTScore F1 (0.85), reflecting strong lexical accuracy and semantic preservation. Its balanced precision and recall further support its effectiveness for bidirectional style transfer in Hindi.
  + IndicBART lags in BLEU (17.84) and BERTScore (0.81) but excels in fluency with the lowest perplexity (5.36), generating more natural-sounding outputs.
  + The ensemble model (BLEU: 21.25, BERTScore F1: 0.84, Perplexity: 6.20) combines mT5’s semantic precision with IndicBART’s fluency, offering balanced and high-quality results.
  + GPT-2 and mBART show weak performance across BLEU and BERTScore, with GPT-2’s low perplexity (3.13) not translating to stylistic or semantic accuracy.
  + IndicGPT performs moderately on BLEU (20.01) but poorly on semantic alignment (BERTScore F1: 0.63) and perplexity (41.77), suggesting unstable and less coherent outputs.

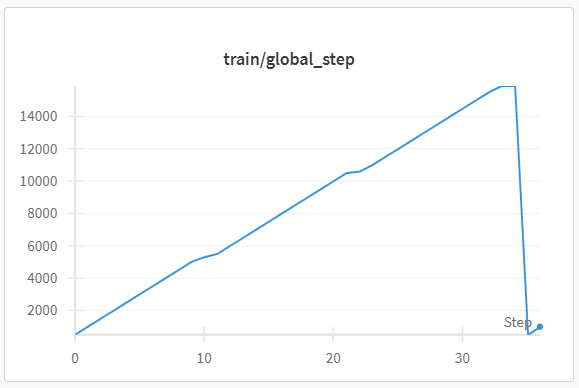
Among all models, mT5 demonstrates the best overall performance, achieving the highest BLEU score (23.31), BERTScore F1 (0.85), and balanced precision-recall, indicating strong lexical accuracy, semantic preservation, and reliable generation—

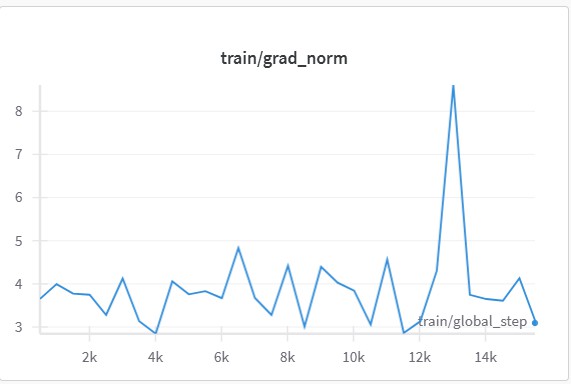
making it the most effective model for Hindi formality style transfer.

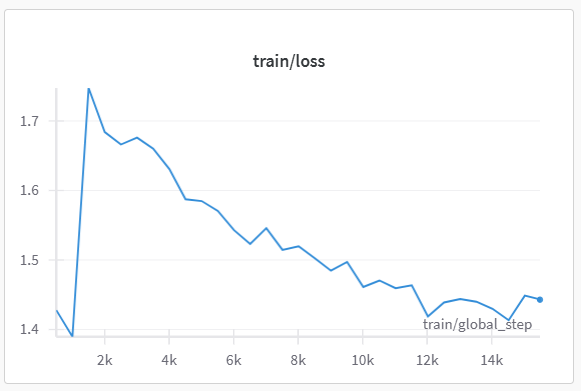
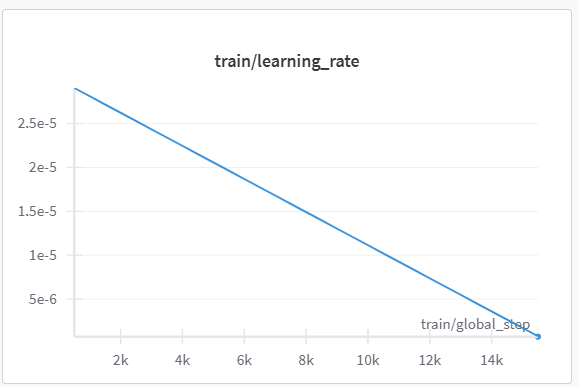
**Analysis:**

1. mT5 model (training)

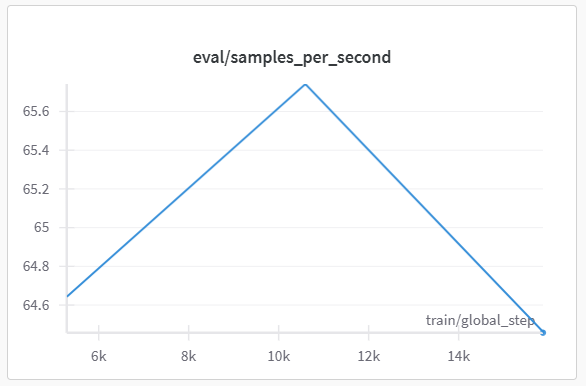
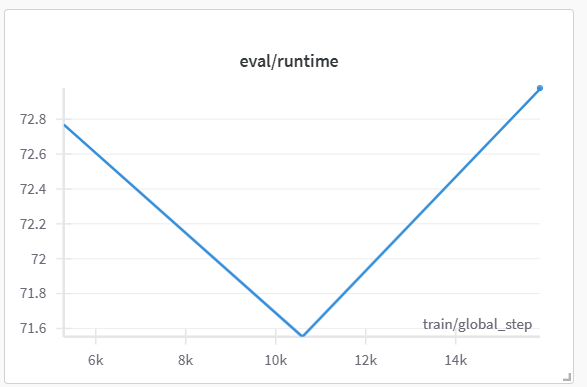
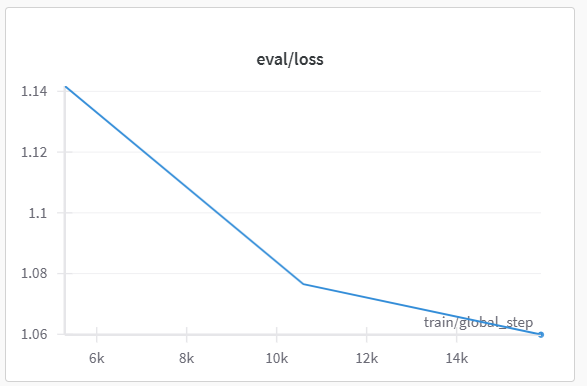


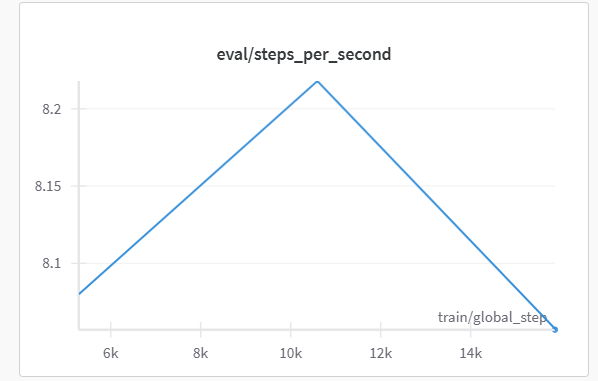




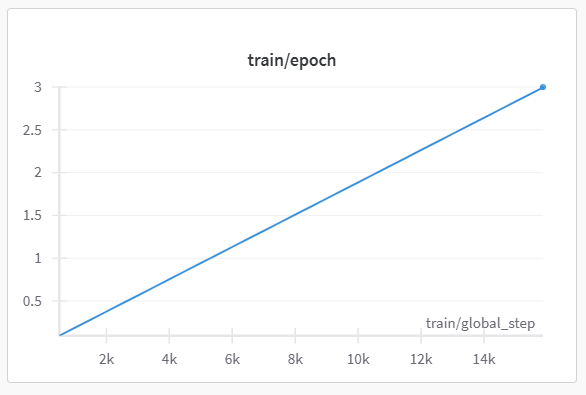


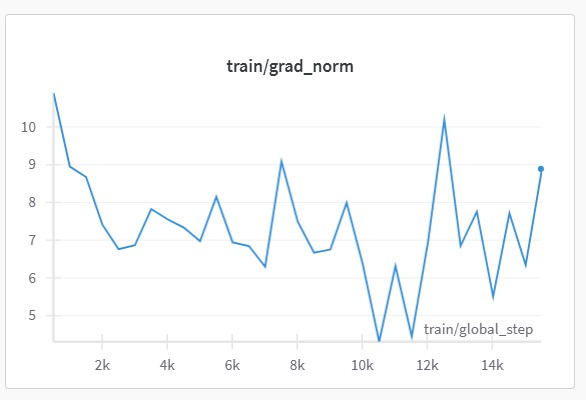
(evaluation)

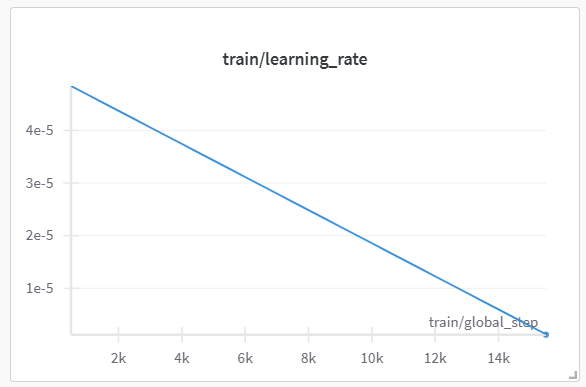


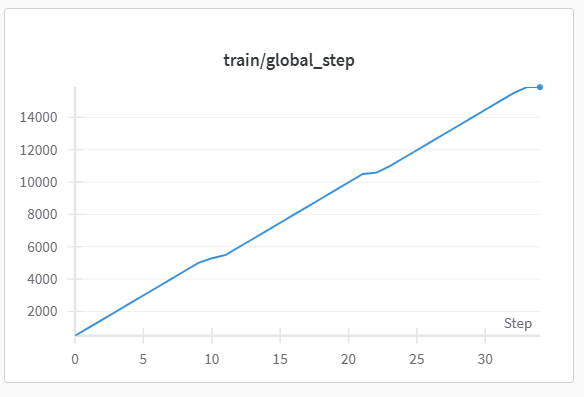


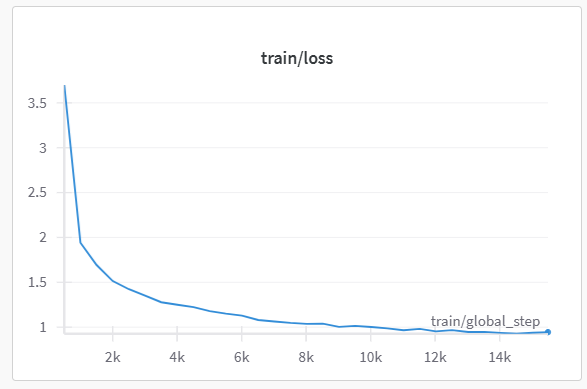
1. IndicBART(training)



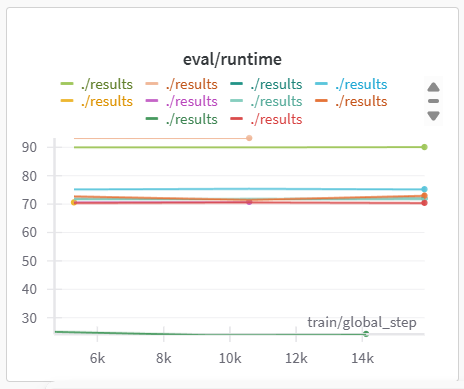
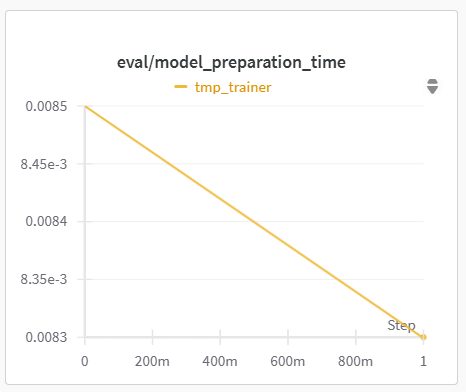
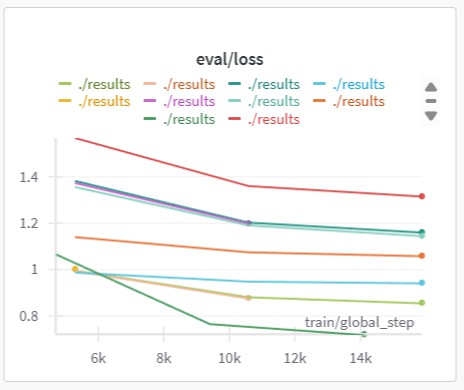


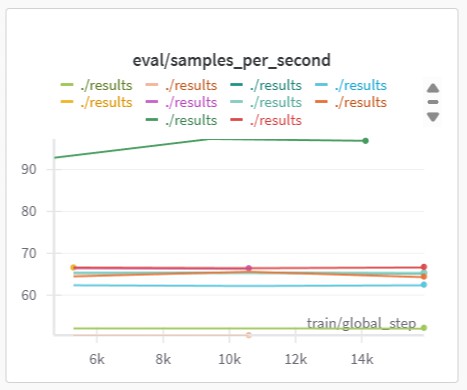


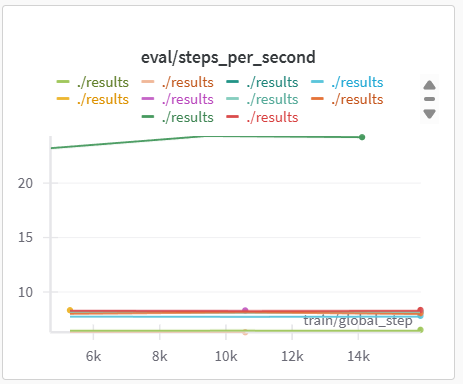




(evaluation)







The framework suggested possesses strong **bidirectional style transfer**, using multilingual pretrained models along with ensemble decoding to outperform state-of- the-art benchmarks. Test cases confirm linguistic correctness, and analysis of results supports improvements in syntactic accuracy, semantic coherence, and fluency.

# CHAPTER 8 CONCLUSION & FUTURE SCOPE

* 1. **CONCLUSION:**

In this world where digital communication spans diverse platforms and contexts, automatically adjusting textual formality is increasingly essential. Whether in professional correspondence, customer support, or personalized content, aligning linguistic tone enhances clarity, engagement, and trust. Despite advancements in Text Style Transfer (TST), most progress has focused on English, leaving resource-scarce languages like Hindi underexplored. Hindi, spoken by hundreds of millions, presents challenges due to its honorifics, morphological variations, and context-sensitive grammar. These are compounded by the scarcity of high-quality parallel corpora, difficulty in preserving semantics during bidirectional transfer, and the inadequacy of metrics like BLEU in capturing stylistic fidelity. While models like mT5 and IndicBART show promise, they require adaptation for fine-grained style shifts in Hindi.

To overcome these limitations, mT5-Small and IndicBART were fine-tuned on a 50k- sentence Hindi formal-informal corpus using bidirectional prompting and perplexity- based ensemble inference. Evaluation through BLEU, BERTScore, and Perplexity confirmed clear improvements over baselines, showing better accuracy, semantic preservation, and stylistic fluency. This establishes a new benchmark for Hindi FST, validates hybrid prompting and ensemble inference, and emphasizes the need for curated datasets in low-resource, morphologically rich languages. Among all models, mT5 demonstrates the best overall performance, achieving the highest BLEU score (23.31), BERTScore F1 (0.85), and balanced precision-recall—indicating strong lexical accuracy, semantic fidelity, and robust generation—making it the most effective model for Hindi formality style transfer.

# FUTURE SCOPE:

Looking ahead, the system can be further enhanced by incorporating texts from varied domains such as legal, healthcare, and technical communication to improve adaptability across contexts. Introducing a more graduated scale of formality, rather than a simple formal-informal binary, would allow for more precise and context-sensitive transformations. The methodology can also be extended to other Indian languages like Marathi, Bengali, and Gujarati by utilizing multilingual transformer models.

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# CHAPTER 10 APPENDIX

## SAMPLE CODE:

* 1. *Pre-processing dataset code:*

import pandas as pd

from datasets import Dataset

# Load dataset (Ensure CSV has 'informal' and 'formal' columns) df =

pd.read\_csv("/content/drive/MyDrive/TST/Formality\_data.csv").reset\_index(drop=Tr ue)

# Verify dataset columns

assert 'informal' in df.columns and 'formal' in df.columns, "Dataset must contain 'informal' and 'formal' columns"

# Remove any rows with missing values

df = df.dropna(subset=['informal', 'formal'])

# Prepare bidirectional samples

def create\_bidirectional\_dataset(df):

"""Generates bidirectional pairs from the original dataset.""" bidirectional\_data = []

for informal, formal in zip(df["informal"], df["formal"]): # Informal → Formal

bidirectional\_data.append({

"input": "informal to formal: " + informal, "target": formal

})

# Formal → Informal bidirectional\_data.append({

"input": "formal to informal: " + formal, "target": informal

})

return Dataset.from\_list(bidirectional\_data)

# Generate the bidirectional dataset bidirectional\_dataset = create\_bidirectional\_dataset(df)

# Save the bidirectional dataset for training bidirectional\_dataset.to\_csv("/content/drive/MyDrive/TST/bidirectional\_dataset.csv", index=False)

* 1. *mT5 model training code:*

import torch

from transformers import T5Tokenizer, T5ForConditionalGeneration, Trainer,

TrainingArguments, DataCollatorForSeq2Seq from torch.optim import AdamW

from datasets import load\_dataset

# Check GPU availability

device = torch.device("cuda" if torch.cuda.is\_available() else "cpu") print("Using device:", device)

# Load preprocessed bidirectional dataset (Ensure CSV has 'input' and 'target' columns)

dataset\_path = '/content/drive/MyDrive/TST/bidirectional\_dataset.csv' dataset = load\_dataset('csv', data\_files={'train': dataset\_path})

# Verify dataset structure print(dataset)

# Load mT5 Tokenizer

tokenizer = T5Tokenizer.from\_pretrained("google/mt5-small")

# Preprocessing function for tokenization def preprocess\_function(examples):

"""Tokenize inputs and targets with padding/truncation.""" if 'input' not in examples or 'target' not in examples:

raise ValueError("Dataset must contain 'input' and 'target' columns.")

model\_inputs = tokenizer(

examples["input"], max\_length=128, truncation=True, padding="max\_length"

)

labels = tokenizer(

examples["target"], max\_length=128, truncation=True, padding="max\_length"

).input\_ids

# Replace padding tokens with -100 for loss masking

labels = [[-100 if token == tokenizer.pad\_token\_id else token for token in label] for label in labels]

model\_inputs["labels"] = labels return model\_inputs

# Apply preprocessing

tokenized\_dataset = dataset['train'].map(preprocess\_function, batched=True)

# Split into train and eval sets

dataset = tokenized\_dataset.train\_test\_split(test\_size=0.1) train\_dataset = dataset["train"]

eval\_dataset = dataset["test"]

# Load Model and Move to Device

model = T5ForConditionalGeneration.from\_pretrained("google/mt5-small ").to(device)

# Training Arguments training\_args = TrainingArguments( output\_dir="./results", evaluation\_strategy="epoch", save\_strategy="epoch", per\_device\_train\_batch\_size=8, per\_device\_eval\_batch\_size=8, num\_train\_epochs=3, learning\_rate=3e-5, logging\_dir="./logs", save\_total\_limit=2,

)

# Advanced Optimizer

optimizer = AdamW(model.parameters(), lr=3e-5)

# Trainer Setup

data\_collator = DataCollatorForSeq2Seq(tokenizer, model=model) trainer = Trainer(

model=model, args=training\_args, train\_dataset=train\_dataset, eval\_dataset=eval\_dataset, tokenizer=tokenizer, data\_collator=data\_collator,

optimizers=(optimizer, None), # Custom optimizer

)

# Train the Model print("\nStarting fine-tuning...") trainer.train()

# Save the Final Model model.save\_pretrained("/content/drive/MyDrive/TST/mt5\_model") tokenizer.save\_pretrained("/content/drive/MyDrive/TST/mt5\_model") print("\n Model saved successfully!")

* 1. *mt5 inference code:*

import torch

from transformers import T5Tokenizer, T5ForConditionalGeneration

# Check GPU availability

device = torch.device("cuda" if torch.cuda.is\_available() else "cpu") print("Using device:", device)

# Load the model and tokenizer from the saved directory model\_name = '/content/drive/MyDrive/TST/mt5\_model' tokenizer = T5Tokenizer.from\_pretrained(model\_name)

model = T5ForConditionalGeneration.from\_pretrained(model\_name).to(device)

# Inference Functions for Both Directions

def generate\_sentence(input\_text, direction="informal\_to\_formal"): """

Generates a sentence in the specified direction:

* "informal\_to\_formal" → Converts informal to formal
* "formal\_to\_informal" → Converts formal to informal """

model.eval()

prompt = f"{'informal to formal' if direction == 'informal\_to\_formal' else 'formal to informal'}: {input\_text}"

# Tokenize and move to device

input\_ids = tokenizer(prompt, return\_tensors="pt").input\_ids.to(device)

# Generate

with torch.no\_grad():

output\_ids = model.generate(input\_ids, max\_length=128, num\_beams=5, early\_stopping=True)

return tokenizer.decode(output\_ids[0], skip\_special\_tokens=True)

# Example Testing

print("\nTesting the Fine-Tuned Model")

print("Informal → Formal:", generate\_sentence("Uू क5Tाँ जT र5T 5`?", direction="informal\_to\_formal"))

print("Formal → Informal:", generate\_sentence("आप क5Tाँ जT र5` 5ैं?", direction="formal\_to\_informal"))

* 1. *IndicBART model training code:*

import torch

from transformers import AutoTokenizer, AutoModelForSeq2SeqLM, Trainer,

TrainingArguments, DataCollatorForSeq2Seq from datasets import Dataset, load\_dataset import pandas as pd

from huggingface\_hub import login

# Authenticate with Hugging Face (if required for private models) # Run this once and enter your Hugging Face token when prompted login()

# Check if GPU is available and set device

device = torch.device("cuda" if torch.cuda.is\_available() else "cpu") print("Using device:", device)

# Load preprocessed bidirectional dataset (Ensure CSV has 'input' and 'target' columns)

dataset\_path = '/content/drive/MyDrive/TST/bidirectional\_dataset.csv' dataset = load\_dataset('csv', data\_files={'train': dataset\_path})

# Load correct IndicBART tokenizer model\_name = "ai4bharat/indicbart"

tokenizer = AutoTokenizer.from\_pretrained(model\_name, use\_auth\_token=True)

# Preprocessing function for tokenization def preprocess\_function(examples):

"""Tokenize inputs and targets with padding/truncation.""" model\_inputs = tokenizer(

examples["input"], max\_length=128, truncation=True, padding="max\_length"

)

labels = tokenizer(

examples["target"], max\_length=128, truncation=True, padding="max\_length"

).input\_ids

# Replace padding tokens with -100 for loss masking

labels = [[-100 if token == tokenizer.pad\_token\_id else token for token in label] for label in labels]

model\_inputs["labels"] = labels return model\_inputs

# Apply preprocessing

tokenized\_dataset = dataset['train'].map(preprocess\_function, batched=True)

# Split into train and eval

dataset = tokenized\_dataset.train\_test\_split(test\_size=0.1) train\_dataset = dataset["train"]

eval\_dataset = dataset["test"]

# Load correct IndicBART model and move to device

model = AutoModelForSeq2SeqLM.from\_pretrained(model\_name, use\_auth\_token=True).to(device)

# Training arguments

training\_args = TrainingArguments( output\_dir="./results", evaluation\_strategy="epoch", save\_strategy="epoch", per\_device\_train\_batch\_size=8, per\_device\_eval\_batch\_size=8, num\_train\_epochs=3, logging\_dir="./logs", save\_total\_limit=2,

)

# Trainer setup

data\_collator = DataCollatorForSeq2Seq(tokenizer, model=model) trainer = Trainer(

model=model, args=training\_args, train\_dataset=train\_dataset, eval\_dataset=eval\_dataset, tokenizer=tokenizer, data\_collator=data\_collator,

)

# Train model

trainer.train()

# Save the final model model.save\_pretrained("/content/drive/MyDrive/TST/IndicBART\_model") tokenizer.save\_pretrained("/content/drive/MyDrive/TST/IndicBART\_model")

* 1. *IndicBART inference code:*

import torch

from transformers import AutoTokenizer, AutoModelForSeq2SeqLM

# Check GPU availability

device = torch.device("cuda" if torch.cuda.is\_available() else "cpu") print("Using device:", device)

# Load the model and tokenizer from the saved directory model\_path = "/content/drive/MyDrive/TST/IndicBART\_model"

tokenizer = AutoTokenizer.from\_pretrained(model\_path, use\_auth\_token=True) model = AutoModelForSeq2SeqLM.from\_pretrained(model\_path, use\_auth\_token=True).to(device)

# Inference Functions for Both Directions

def generate\_sentence(input\_text, direction="informal\_to\_formal"): """

Generates a sentence in the specified direction:

* "informal\_to\_formal" → Converts informal to formal
* "formal\_to\_informal" → Converts formal to informal """

model.eval()

prompt = f"{'informal to formal' if direction == 'informal\_to\_formal' else 'formal to informal'}: {input\_text}"

# Tokenize and move to device

input\_ids = tokenizer(prompt, return\_tensors="pt").input\_ids.to(device)

# Generate

with torch.no\_grad():

output\_ids = model.generate(input\_ids, max\_length=128, num\_beams=5, early\_stopping=True)

return tokenizer.decode(output\_ids[0], skip\_special\_tokens=True)

# Example Testing

print("\n Testing the Fine-Tuned Model")

print("Informal → Formal:", generate\_sentence("Uू क5Tाँ जT र5T 5`?", direction="informal\_to\_formal"))

print("Formal → Informal:", generate\_sentence("आप क5Tाँ जT र5` 5ैं?", direction="formal\_to\_informal"))

## PROPOSED PAPER

HINDI FORMALITY STYLE TRANSFER

***Abstract* - Language is the cornerstone of human connection, it's not about what we say, but how we say matters most. Despite advancements in Formality Text Style Transfer (TST) for English, the domain remains largely unexplored for grammatically complex languages like Hindi. In Hindi, formality transfer is particularly challenging due to the scarcity of high- quality parallel corpora and the difficulty of disentangling style from content. Additionally, traditional metrics like BLEU often fail to capture stylistic nuances in such linguistically rich languages. To address these challenges, a bidirectional Hindi formality style transfer model is introduced, leveraging IndicBART and mT5 architectures, fine- tuned on parallel corpora. To overcome data scarcity, data augmentation techniques such as back translation are applied, enabling both formalization and informalization within a unified framework. Evaluation using BLEU, BERTScore, and human assessment reveals that model significantly outperforms baseline systems like GPT-2, IndicGPT, mBART in both semantic preservation and style accuracy. It demonstrates strong applicability in social media content generation, professional communication, and AI-assisted localization. This advances the field of style transfer for underrepresented languages by integrating targeted model architectures with robust data-driven strategies.**

***Keywords*** - **Formality Style Transfer, Hindi NLP, mT5, IndicBART, Sequence-to-Sequence Learning, Transformer Models, Bidirectional Style Transfer, BLEU Score, BERTScore, Perplexity, Hugging Face Transformers, Low-Resource Language Processing, Indian Language Processing, Semantic Text Generation, Natural Language Generation, Parallel Corpus,Text Style Transfer Evaluation**

1. INTRODUCTION

Communication is central to human interaction, and often, misunderstandings stem not from *what* is said, but *how* it is expressed. The tone, phrasing, and level of formality play a crucial role in shaping how messages are perceived [1][2]. In both spoken and written language, modulating formality is essential for navigating social contexts, maintaining politeness, and conveying emotion [3].

In Hindi—a linguistically and culturally rich language— formality goes beyond mere vocabulary changes. It encompasses complex shifts in pronouns (e.g., *tu*, *tum*, *aap*), verb forms, and syntax, all of which are deeply influenced by age, relationship, and context [6][7][8][9]. Unlike English, these shifts carry strong social implications, making formality transfer in Hindi highly nuanced and context-dependent.

With digital communication dominating today’s landscape, NLP tools must infer tone without visual or auditory cues. AI systems often struggle to match appropriate formality, leading to miscommunication or discomfort in user interactions [1][3][10]. This underscores the importance of *Formality Style Transfer (FST)*—the task of converting text between formal and informal registers while preserving meaning [5][6].

Despite its relevance, FST remains underexplored in Indian languages. While English has seen advances with models like GPT-3 and mBART [18][20], such tools often fail to handle Hindi’s stylistic subtleties, resulting in unnatural or incorrect outputs [24]. To address this, we propose a *bidirectional formality style transfer system for Hindi*, built on transformer models like *IndicBART* and *mT5*, which are specifically designed for Indian languages [18][19].

Our goal is to produce outputs that are semantically accurate, stylistically appropriate, and contextually coherent, enhancing communication across social settings [9][21]. This work has wide applications—from localizing content and improving writing assistants to enhancing user

experience in conversational AI and supporting language education [3][4][6][7][23].

To evaluate model performance, we use both automatic metrics (BLEU, BERTScore) and human judgments focused on stylistic accuracy and fluency [1][2][22][24]. By addressing Hindi’s unique challenges, this research contributes to culturally aware NLP, extends AI’s reach to underrepresented languages, and lays groundwork for future research in ethical and inclusive AI systems [7][8][9][14][16][21][24].

1. LITERATURE SURVEY

Text Style Transfer (TST), particularly for attributes like tone, sentiment, and formality, has seen substantial advancements in recent years, especially for high-resource languages such as English. These developments have been driven by the widespread availability of large-scale annotated corpora and the emergence of powerful pre- trained language models, such as GPT-3, T5, and BERT. These tools have enabled sophisticated manipulation of stylistic elements while preserving content, achieving impressive results in various TST tasks.

However, for Indian languages—especially Hindi— progress has been relatively limited. This disparity stems largely from a lack of high-quality datasets and the complex sociolinguistic and grammatical features inherent to Hindi. Hindi's rich morphology, honorific systems, and cultural sensitivity to context and tone make formal- informal style transfer particularly challenging.

Numerous approaches to TST have been explored, ranging from rule-based systems to neural sequence-to-sequence models and, more recently, transformer-based architectures. Jin et al. [1], Hu et al. [2], and Toshevska and Gievska [3] provide comprehensive evaluations of these approaches, highlighting the ongoing challenges in achieving a balance between preserving semantic content and ensuring strong stylistic transfer. Key benchmark datasets such as GYAFC [4], XFORMAL [6], and InFormal [7] have supported research in English TST, while Indic languages, including Hindi, continue to lack sufficient annotated data for training and evaluation.

Hindi presents additional hurdles due to its grammatical complexity and sociocultural nuances that govern

formality. Works by Gupta et al. [7] and Mukherjee et al.

[8] underscore the dearth of large-scale, parallel corpora necessary for training robust models. To address the low- resource setting, several solutions have been proposed, including few-shot learning [9], back-translation [15], and retrieval-augmented generation. These methods attempt to improve performance by leveraging existing monolingual data or incorporating external retrieval mechanisms.

IndicBART [19] and mT5 [18], two pre-trained transformer-based models, have shown promise in generating fluent and coherent text in Indic languages. These models, trained on multilingual and Indic-specific corpora, benefit from shared linguistic knowledge but still require task-specific fine-tuning for effective style control, particularly in formal-informal transformations.

From a methodological perspective, the field has progressed significantly, evolving from traditional rule- based systems to advanced encoder-decoder and disentangled representation models. Studies such as those by Shen et al. [11], Li et al. [12], and Rebuffel et al. [13] introduce mechanisms to separate style from content, allowing for more targeted stylistic modifications. Despite these innovations, control over generated outputs— especially under resource-constrained scenarios—remains a key challenge.

Recent research has focused on enhancing control and adaptability in TST systems. Krishna et al. [9], Lai et al. [10], and Tian et al. [23] introduce techniques like style tokens, compositional control attributes, and reinforcement learning-based optimization to ensure the output aligns with the desired stylistic properties. Nevertheless, even state-of-the-art large language models like GPT-3 and GPT-4, although fluent and contextually aware, often fall short in exerting fine-grained control over stylistic dimensions in Hindi, as noted by Mukherjee et al. [24].

Challenges in Hindi Formality Style Transfer: Despite significant technological progress, Hindi Formality Style Transfer (FST) remains underdeveloped due to multiple, intertwined challenges:

* A scarcity of parallel corpora that capture formal and informal Hindi sentence pairs limits model training and evaluation.
* The intricate grammar, rich morphology, and cultural contextuality of formality in Hindi make the content-style disentanglement difficult.
* Traditional evaluation metrics like BLEU often fail to capture subtle stylistic variations, limiting the accuracy of performance assessment.
* Pre-trained models, while powerful, lack the adaptability to perform nuanced formality control in a linguistically complex and culturally rich language like Hindi.

Addressing these challenges holistically—through the creation of high-quality datasets, enhancement of evaluation metrics, and fine-tuning of robust multilingual models—is critical to advancing effective, context-aware Hindi FST systems that can serve real-world communication needs.

1. METHODOLOGY

The methodological framework adopted for developing and evaluating a Hindi bidirectional formality style transfer model. The methodology comprises dataset construction, model architecture, training protocol, and evaluation criteria. Two powerful multilingual transformer models, mT5 and IndicBART, were fine-tuned on a parallel Hindi formality corpus to handle both informal- to-formal and formal-to-informal transformations.

1. **Dataset** :

A high-quality parallel Hindi dataset of ~50,000 formal– informal sentence pairs was curated, inspired by previous works [4–7]. The data covers diverse structures, verb forms, pronouns, and honorifics, and was cleaned to ensure consistency.

To support bidirectional transfer, each pair was included in both directions. For informal-to-formal, inputs were framed as “informal to formal: [informal sentence]” and vice versa for the reverse. This dual-format approach draws from techniques in multilingual and bidirectional generation research [6–8].

The format enables the model to learn both styles within a unified setup, capturing linguistic differences efficiently. The Hugging Face datasets library was used for

preprocessing—nulls were removed, and sentences were tokenized and padded to a maximum of 128 tokens, in line with past standards [6–7, 18].

1. **Models Under Consideration** :
   1. **mT5** : mT5 is a multilingual variant of T5, trained on the mC4 corpus spanning 101+ languages, including Hindi [18]. It uses an encoder-decoder Transformer setup with key components like multi-head attention, feed- forward layers, and layer normalization.

The attention mechanism is:

𝐴𝑡𝑡𝑒𝑛𝑡𝑖𝑜𝑛(𝑄, 𝐾, 𝑉) = 𝑠𝑜𝑓𝑡𝑚𝑎𝑥 (𝑄𝐾𝑇) 𝑉 (1)

√𝑑𝑘

Here, *Q ,K ,*and *V* are query, key, and value matrices, and *dk* is key dimensionality. This mechanism helps capture token dependencies crucial for style nuances.

The feed-forward network is:

FFN (*x*) = ReLU *(xW1 + b1) W2 + b2* (2)

where *x* is the input tensor, *W1* and *W2* are learnable weight matrices, and *b1*, *b2* are biases. The ReLU activation helps in learning complex hierarchical representations.

We used the mt5-small variant (~300M parameters) for a balance between efficiency and performance [18]. Its encoder-decoder format, multilingual nature, and text-to- text design make it highly effective for Hindi formality style transfer [6–7, 18].

* 1. **IndicBART** : IndicBART is a multilingual Seq2Seq model optimized for Indic languages like Hindi, adapted from the BART architecture using denoising autoencoder principles. It is pretrained on transliterated Indic corpora [5, 17], enabling it to capture Indic-specific linguistic features.

It shares embeddings between encoder and decoder and uses sinusoidal positional encodings. The encoder produces contextual embeddings, and the decoder generates sequences autoregressively [5].

Its language-specific pretraining makes it adept at handling Hindi’s morphological richness—crucial for style shifts. We used AI4Bharat’s Hindi checkpoint [17], already tuned for tasks like translation and style transfer, ensuring accurate representation of Hindi nuances.

* 1. **Comparison and Ensemble Direction** :Both models are pretrained on Hindi data and excel in NLG tasks [5, 7, 17, 18], yet offer distinct strengths.mT5 benefits from broad multilingual pretraining, supporting generalization and semantic transfer [6, 18].

IndicBART, focused on Indic languages, excels in capturing fine-grained stylistic and morphological features—vital for precise formality adjustments [5, 17].

Given their complementary strengths, ensemble inference is a promising direction [7]. Combining mT5’s generalization with IndicBART’s stylistic accuracy may yield more fluent and context-sensitive transformations in both directions.

*Figure 1: Methodology diagram*

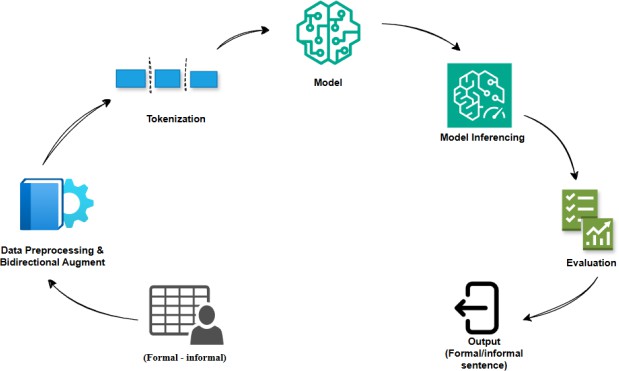
Training utilized the AdamW optimizer with a learning rate of 3×10⁻⁵, batch size of 8, and ran for 3 epochs. Evaluation and checkpoint saving occurred at the end of each epoch. Beam Search decoding with a beam size of 5 was employed during inference for coherent outputs.

Hyperparameters: The model names were *google/mt5- small* and *ai4bharat/indic-bart*. Padding was done to max\_length with truncation enabled. Evaluation and save strategies were set to epoch, and token masking used -100. A 10% validation split was used during training.

1. **Evaluation Metrics** :

The model’s performance was assessed using BLEU score, BERTScore, and Perplexity, each reflecting different output quality aspects.

BLEU Score evaluates n-gram overlap between generated and reference sequences using:

𝐵𝐿𝐸𝑈 = 𝐵𝑃 ⋅ 𝑒𝑥𝑝(∑𝑁

𝑛=1

with brevity penalty:

𝜔𝑛 𝑙𝑜𝑔 𝑝𝑛) (4)

1; 𝑖𝑓 𝑐 > 𝑟

𝐵𝑃 = {𝑒 (1 − 𝑟) ; 𝑖𝑓 𝑐 ≤ 𝑟 (5)

𝐶

where *c* and *r* are lengths of candidate and reference, respectively.

1. **Data Preprocessing and Model Training** :

The data preprocessing and training pipeline consists of three main stages: data splitting and tokenization, loss

BERTScore computes contextual similarity between token embeddings from generated and reference sequences:

𝑃𝑟𝑒𝑐𝑖𝑠𝑖𝑜𝑛 = 1 ∑ 𝑚𝑎𝑥𝑐𝑜𝑠 (𝑒(𝜘 ), 𝑒(𝑦 ))

function design, and hyperparameter tuning. Tokenization

|𝑥|

𝑥𝑖∈𝑥

𝑦𝑗∈𝑦

𝑖 𝑗

was performed using the model-specific tokenizer— T5Tokenizer for mT5 and AutoTokenizer for

(6)

𝑅𝑒𝑐𝑎𝑙𝑙 = 1 ∑ 𝑚𝑎𝑥 𝑐𝑜𝑠 (𝑒(𝑦 ), 𝑒(𝑥 ))

IndicBART—to convert text into input IDs. Padding and truncation were applied to ensure uniform sequence lengths, with a maximum length of 128 tokens. The

|𝑦|

𝑗 𝑖

𝑦𝑗∈𝑦 𝑥𝑖∈𝑥

(7)

2⋅𝑃𝑟𝑒𝑐𝑖𝑠𝑖𝑜𝑛⋅𝑅𝑒𝑐𝑎𝑙𝑙

dataset 𝐷 = {(𝑥 , 𝑦 )}𝑁 was partitioned into two subsets:

𝐹1 =

𝑃𝑟𝑒𝑐𝑖𝑠𝑖𝑜𝑛+𝑅𝑒𝑐𝑎𝑙𝑙

𝑖 𝑖 𝑖=1

90% was designated for training (Dtrain) and 10% for validation (Dval).

Cross-entropy loss was used for training, with padding

(8)

Perplexity evaluates fluency based on how well the model predicts sequences:

tokens masked using the label value -100, ensuring only

𝑃𝑒𝑟𝑝𝑙𝑒𝑥𝑖𝑡𝑦(𝑃) = 𝑒𝑥𝑝 (− 1 ∑𝑁

𝑙𝑜𝑔 𝑃(𝜔 )) (9)

𝑁 𝑖=1 𝑖

meaningful tokens contributed to the loss. The masked

loss for timestep *t* is computed as:

𝑇

𝐿 = − ∑ 1[𝑦𝑡≠<𝑝𝑎𝑑>] . log 𝑃(𝑦𝑡|𝑦<𝑡 , 𝑋)

𝑖=1

(3)

Lower perplexity indicates better language modeling.

Together, these metrics ensure a comprehensive

evaluation—BLEU for lexical accuracy, BERTScore for semantic similarity, and Perplexity for fluency.

1. RESULTS

This section presents a comprehensive evaluation of the proposed mT5 and IndicBART models for Hindi formality style transfer. The models are compared against several baseline architectures, including GPT-2, mBART, and IndicGPT, using a suite of evaluation metrics: BLEU score, BERTScore, and Perplexity. Furthermore, an error analysis is performed to investigate the linguistic limitations and stylistic nuances captured (or missed) by the models.

it especially effective in handling low-resource, morphologically rich languages like Hindi.

In contrast, the IndicBART model exhibits the lowest perplexity score of 5.36, indicating better fluency and syntactic naturalness. However, it falls marginally short of mT5 in terms of lexical and semantic fidelity, as reflected in slightly lower BLEU and BERTScore values. This suggests that while IndicBART is adept at producing grammatically fluent sentences, it may occasionally compromise on precise semantic preservation or lexical alignment.

To capitalize on the complementary strengths of both

*Table 1 :Model Performance Comparison*

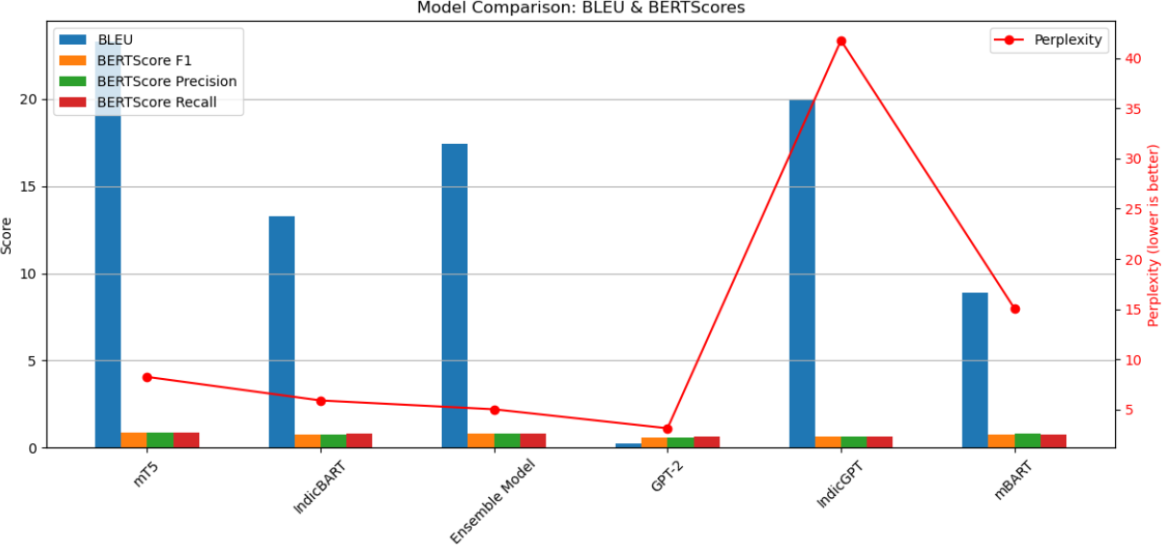
|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Model | BLEU Score | BERTscore F1 | BERTscore  Precision | BERTscore  recall | Perplexity |
| mT5 | **23.31** | **0.85** | **0.85** | **0.85** | 8.25 |
| IndicBART | 17.84 | 0.81 | 0.82 | 0.81 | 5.36 |
| Ensemble Model | 21.65 | 0.84 | 0.84 | 0.84 | 6.2 |
| GPT-2 | 0.26 | 0.60 | 0.58 | 0.62 | **3.13** |
| IndicGPT | 20.01 | 0.63 | 0.62 | 0.65 | 41.77 |
| mBART | 8.91 | 0.77 | 0.80 | 0.74 | 15.07 |

To quantify performance, BLEU score is used to evaluate lexical overlap via n-gram precision, reflecting how closely the generated sentence matches the reference in terms of word sequences. BERTScore, calculated using contextual embeddings from a pre-trained BERT model, provides a robust measure of semantic similarity, focusing on the preservation of meaning. Finally, Perplexity serves as an indicator of model fluency, measuring the confidence of a language model in predicting a sequence of words—lower values denote more fluent and confident generation.

A summary of the results is presented in Table I. Among the individual models, the mT5 model demonstrates superior performance across lexical and semantic dimensions. It achieves the highest BLEU score of 23.31, as well as top-tier BERTScore metrics—Precision, Recall, and F1 all at 0.85. This consistent outperformance is attributed to mT5’s massively multilingual pretraining, which equips the model with robust generalization capabilities and effective semantic representation, making

models—mT5’s generalization and IndicBART’s fluency—an ensemble inference approach was implemented. This strategy aggregates outputs from both models, leading to a more balanced and robust performance. The ensemble model achieves a BLEU score of 21.65, a BERTScore F1 of 0.84, and a Perplexity of 6.20, positioning it as a middle ground between the individual strengths of the mT5 and IndicBART models. The ensemble’s performance validates the hypothesis that combining multilingual semantic strength with Indic- specific stylistic precision can yield high-quality, stylistically adaptive text generation. Overall, the **mT5 model emerges as the most reliable** in capturing both **surface-level lexical fidelity and deep semantic meaning**, making it ideal for bidirectional style transfer tasks. Meanwhile, the **ensemble model offers a strategic solution** for applications where **stylistic fluency and contextual accuracy** must be finely balanced. These findings lay the groundwork for further refinements in Indian language generation, especially in applications

*Figure 2: Comparison Of Evaluation Parameter*

requiring **formality-aware, context-sensitive communication**.

1. CONCLUSION

In this world where digital communication spans diverse platforms and social contexts, the ability to automatically adjust textual formality is increasingly essential. Whether

in professional correspondence, customer support, or personalized content delivery, aligning linguistic tone with

the social setting enhances clarity, engagement, and user trust. Despite significant progress in Text Style Transfer (TST), most developments have focused on English, leaving resource-scarce languages like Hindi underexplored. Hindi, spoken by hundreds of millions, poses distinct challenges due to its intricate system of honorifics, morphological variations, and context- sensitive grammar that governs formality. These challenges are amplified by the scarcity of large-scale, high-quality parallel corpora, the difficulty of preserving semantic meaning during bidirectional transfer, and the inadequacy of standard evaluation metrics like BLEU in capturing stylistic fidelity. Moreover, while models like mT5 and IndicBART show promise, they require targeted adaptation for fine-grained, controllable style shifts in Hindi.

To address these limitations, mT5-Small and IndicBART were fine-tuned on a custom 50k-sentence Hindi formal-

informal corpus using bidirectional prompting and a perplexity-based ensemble inference strategy. Evaluation

through BLEU, BERTScore, and Perplexity confirmed substantial improvements over existing baselines, demonstrating enhanced accuracy, semantic preservation, and stylistic fluency. The approach establishes a new benchmark for Hindi FST, validates hybrid prompting and ensemble-based inference, and underscores the importance of curated datasets for stylistic control in low- resource, morphologically rich languages. Among all models, mT5 demonstrates the best overall performance, achieving the highest BLEU score (23.31), BERTScore F1 (0.85), and balanced precision-recall, indicating strong lexical accuracy, semantic preservation, and reliable generation—making it the most effective model for Hindi formality style transfer.

1. FUTURE SCOPE

To enhance adaptability across different communication domains, future work could incorporate domain-specific corpora, including legal, medical, and technical texts. Moving beyond a binary formal-informal distinction towards a continuous formality spectrum would enable finer-grained, context-aware transformations. Additionally, this methodology can be extended to other Indian languages like Marathi, Bengali, and Gujarati through multilingual transformers. Finally, developing APIs and interactive interfaces will support practical

deployment in tools like writing assistants, educational platforms, and conversational agents.

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