RESEARCH ARTICLE

INTERNATIONAL RESEARCH JOURNAL OF
MULTIDISCIPLINARY TECHNOVATION

Asian Research Association

DOI: 10.54392/irjmt2633

G-Transgan: Semantic Translation of Gujarati Texts using GAN-based Augmentation and Optimized Transformer Models in Low-Resource Settings

Mehulkumar Dalwadi [a,*], Abhishek Mehta [a]

[a] Faculty of IT and Computer Science, Parul University, Waghodia, Vadodara, Gujarat-391760, India
* Corresponding Author Email: mehulkumardalwadi.phd@gmail.com
DOI: https://doi.org/10.54392/irjmt2633
Received: 28-09-2025; Revised: 25-03-2026; Accepted: 08-04-2026; Published: 20-04-2026

Abstract: Gujarati is an Indo-Aryan language with more than 55 million speakers, making it an important language to consider in machine translation. It has limited parallel corpora, complex morphology, and no context preservation. The typical neural machine translation methods tend to fail in low-resource settings, resulting in syntactic errors and semantic drifts. To overcome these shortcomings, this paper presents Gujarati-Translation with Generative Adversarial Network (G-TransGAN), a new hybrid model that combines conditional Generative Adversarial Networks (cGANs), morphology-sensitive Sentence Piece tokenization, multilingual transformer embeddings (XLM-RoBERTa and Indic BERT), and optimization techniques such as Sharpness-Aware Minimization (SAM) and Low-Rank Adaptation (LoRA). The main goal is to maximize fluency, semantic retention, and domain flexibility in low-resource Gujarati-English translation. The workflow includes five steps: data augmentation, pre-processing and tokenization, contextual embedding, semantic translation, and optimization. The experimental findings indicate that G-TransGAN had better performance on various measures, including BLEU (38.4), METEOR (0.76), and TER (0.46). Such results support the model as able to produce high-quality, human-like translations and yet remain computationally feasible in low-resource real-world settings.

Keywords: Low-Resource Translation, Gujarati-English, GAN-Based Augmentation, Transformer Models, Semantic Preservation, Optimization.

1. Introduction

As an Indo-Aryan language spoken worldwide by more than 55 million speakers, Gujarati faces challenges for its speakers in terms of digital and natural language processing, especially in the area of machine translation. Resources for Gujarati differ significantly from those for high-resource languages like English and Spanish, where large-scale parallel corpora exist, which have driven advances in automated translation and language tools as well. The gap in textual resources also results in varying degrees of information available for Gujarati speakers, while ultimately, it demonstrates a clear drive for better translation alternatives when assessing Gujarati in low-resource contexts. While it showed promise, the advancement of transformer-based architectures, such as XLM-RoBERTa and IndicBERT, is challenged due to a lack of data [1-2]. These transformer-based models are restricted by the quantity of training data available for them, but they are also challenged when their outcomes must preserve semantics and cultural nuance, especially for low-resource contexts. A need for more approaches to leverage the resource gap and optimize for the semantic translation of Gujarati is increasingly required. Standard neural machine translation systems perform poorly when resources are low. In low-resource conditions, limited data implies limited exposure to many (different) linguistic representations, and the resulting machine translation may be syntactically shallow or semantically incorrect. Pretrained multilingual transformers often need a large amount of finetuning data and either overfit or generalize poorly if there is insufficient data to finetune from [3-4]. Furthermore, performing translation from language(s) with rich morphology (e.g., Gujarati) while resolving issues of subword segmentation is problematic (and naive tokenization results in interruptions to meaning and does not represent valid morphological features) [5]. Previous work on data augmentation (i.e., through back-translation or paraphrasing) has shown improvement (potentially for fine-tuning), but the process of preserving semantic fidelity is weak [6-7]. In the case of regular finetuning regimes, there can be problems of instability of training and thus non-reproducibility when translating low-resource values [8].

This paper presents G-TransGAN, a novel deep learning (DL) pipeline for Gujarati–English translation in low-resource scenarios. These goals are fourfold: (1) reduce data sparsity by using cGANs to generate realistic Gujarati sentences that have been trained to use both character- and sentence-level embeddings; (2) properly tokenize for morphology by using a sentence-piece model specifically trained for Gujarati; (3) use multilingual transformer models (XLM-RoBERTa, IndicBERT 2) that have been fine-tuned to provide semantically rich, context-dependent embeddings; and (4) improve finetuning stability and generalization, using recent optimization algorithms, in particular, SAM and LoRA. A conditional GAN is created and deployed to synthesise a diverse and realistic Gujarati sentence pair, significantly expanding the usable training dataset and enhancing linguistic diversity, an original undertaking for low-resource translation [9-10]. Using a sentence-piece model harnessed to Gujarati's morpho-syntactic features, a subword semantics that is better than just using a BPE model as a sentence piece is achieved, producing more coherent representations [11]. XLM-RoBERTa and IndicBERT 2 are fine-tuned on this augmented corpus to create strong, contextually-enriched embeddings that preserve both syntactic and cultural shade [12-13]. To manage overfitting and improve finetuning efficiency, SAM and LoRA are incorporated into the training loop; augmenting the training with this dual optimization process improves convergence stability while preserving generalization with limited data [14-15]. In contrast to the current GAN-assisted NMT systems, where GANs are mainly used to expand data, the proposed G-TransGAN proposed a single learning system, which combines conditional GAN-based data augmentation with multilingual contextual embeddings (XLM-RoBERTa and IndicBERT) and jointly trains translation robustness via Sharpness-Aware Minimization and parameter-efficient adaptation via LoRA. This integrates architecture and optimization level that allows stable adversarial learning and enhanced generalization in the most low-resource Gujarati-English translation conditions. Besides, previous hybrid GAN Transformer approaches, the proposed framework jointly optimizes adversarial augmentation, semantic alignment, as well as parameter-efficient fine-tuning within a single training objective, rather than applying these components independently.

The main contribution of this research is as follows:

- Introduced G-transGAN, a single architecture, which combines conditional GAN-based data augmentation models with multilingual Transformer encoders (XLM-RoBERTa and IndicBERT 2) and parameter-efficient training methods (SAM and LoRA) to enhance low-resource Gujarati-English neural machine translation.
- Invented a Gujarati-specific SentencePiece tokenization scheme, which uses the high morphology of the language and minimizes cases of out-of-vocabulary words, and improves semantic coherence during translation.
- Proposed a dual-level contextual embedding approach, which integrates character-level and sentence-level features into a GAN-Transformer model to more effectively represent linguistics, semantic detail, and cultural background in low-resource translation environments.

Section 2 provides the literature survey on low-resource language translation and augmentation; Section 3 describes the G-TransGAN methodology, Section 4 discusses the results and analysis of the experiments, while Section 5 concludes the study in terms of future directions.

2. Literature Survey

Saxena *et al.* [16] developed an Unsupervised Statistical Machine Translation (USMT) system for ten MT tasks in four Dravidian languages and an endangered language, Kangri, under low-resource conditions. This study aimed to evaluate the translation quality of automated translations in morphologically rich languages using automatic evaluation metrics and tokenizers. The study reported a reasonable level of efficiency in Indic–English translation, with statistical significance testing indicating valid outcomes.

Khatri *et al.* [17] investigated Unsupervised Neural Machine Translation (UNMT) for six Indic and four European language pairs, using lexical divergence as the focus. And proposed adding bilingual Byte Pair Encoding (BPE) embedding and pre-training of dictionary-based word substitution so as to gain more out of the cross-lingual learning of low-overlap language pairs. Nevertheless, the study focused on lexical divergence and mentioned syntactic divergence as a recommended future research avenue.

Raulji *et al.* [18] followed a rule-based machine translation framework for Sanskrit to Gujarati and recognized the diversity of grammatical considerations in morphologically heavy languages. A detailed evaluation using both the ALPAC manual scale and BLEU found that the results were able to meet both intelligibility and fidelity robustness. Limitations identified in this research were limited dictionary coverage and exception handling.

Onan *et al*. [19] proposed an ensemble-based text augmentation strategy for Turkish sentiment analysis, combining a series of transform functions to improve classification performance. It considered the linguistic properties of Turkish and proposed ethical considerations for augmentation methods, such as bias and privacy. Limitations included dataset size and complexity of the language, which indicate that future work is needed to better define augmentation methods and target a wider variety of use cases.

Benayas *et al.* [20] introduced the notion of LLM-based data augmentation to train an intent classifier in NLU tasks. The intention of using LLM-based data augmentation was to address data scarcity and improve end model robustness. LLM-based data augmentation produced realistic and diverse labeled data that exceeded what is possible with traditional methods. The results showed similar LLM-based data augmentation performance in both low- and high-resource conditions. The research provided ethical discussions and considerations, and a suggestion for advanced debiasing methods that ensured equity and reliability of products based on LLM usage.

Chen *et al*. [21] developed a data augmentation and classification framework for spatially referenced text data that incorporated LLMs, semantic vector indexing, and advanced augmentation methods to tackle the issues of data sparsity and high costs of annotation in EO methods. Overall, the new approach increased predictive accuracy and computational efficiency while minimizing dependence on manual labeling. To continue advancing the work, improvements could be made through domain-specific fine-tuning of the models used.

Kowsher *et al.* [22] presented a Bangla-specific BERT model that has been properly pre-trained on the largest available Bangla text corpus with a standard version of the BERT architecture. The objectives were to increase NLP developments in the Bangla language regions and provide a model to initiate domain-specific fine-tuning in various domains.

Mishra *et al*. [23] introduced the Context-Aware Embedded Language Transformers model to produce a scalable and flexible climate change knowledge graph using public data from its raw state, intending to work around the challenges of the world's limited resources and promote informed decision-making in the areas of risk assessment and sustainability.

Tejero *et al.* [24] introduced a SAM Decoder Adapter for semantic segmentation as a means to provide an efficient solution with a small computational overhead. An image embedding was used as the query in our attention modules to improve mask prediction and zero-shot generalization.

Table 1. Comparative Analysis of Low-Resource Translation and Augmentation Approaches

Author(s) & Year	Technique Introduced	Achievements	Limitations
Saxena *et al.* [16]	USMT	Achieved reasonable translation quality for morphologically rich languages with valid statistical significance	Poor structural handling, lexicalized reordering issues, and low-quality data
Khatri *et al*. [17]	UNMT	Improved translation for both related and distant language pairs	Did not address syntactic divergence; future work suggested
Raulji *et al.* [18]	Rule-based MT framework	Robust translations considering grammar diversity	Limited dictionary coverage
Onan *et al.* [19]	Ensemble-based text augmentation	Better classification performance across datasets	The dataset size & linguistic complexity limited broader applicability
Benayas *et al.* [20]	LLM-based data augmentation	Produced realistic, diverse labeled data in low & high-resource settings	Biases in LLM outputs; lack of generalizability to proprietary datasets
Chen *et al*. [21]	LLM + semantic vector indexing	Improved predictive accuracy & efficiency in EO data tasks	Dependent on the quality of embedding models & LLMs
Kowsher *et al.* [22]	Bangla-specific pre-trained BERT model	High efficiency in storage, complexity, and processing power for Bangla NLP	Limited to mono-lingual Bangla; lacks mixed-lingual capability
Mishra *et al.* [23]	Context-Aware Embedded Language Transformers	Generated rich ontologies for multi-domain sustainability applications	Publicly available data limit completeness & granularity
Tejero *et al.* [24]	SAM Decoder Adapter	Outperformed large model adapters in zero-shot & TTA tasks	Needs optimization for architecture compatibility & real-time use
Müller *et al*. [25]	Data-focused fine-tuning of SLMs	Matched GPT-4-turbo performance in privacy-centric settings; cost savings	Manual prompt design & LLM-generated label scaling challenges

Müller *et al.* [25] presented a data-focused fine-tuning practice for small language models (SLMs) to obtain automated extraction of technical requirements, consequently in data data-scarce and privacy-centric manner. In addition, training data through prompt generation and augmentation achieved performance levels on par with GPT-4-turbo and outside commercially available sources of knowledge. Future work intends to automate prompt refinement and expand the process across varying domains and tasks.

Existing GAN-based MT systems are mostly based on adversarial loss to enhance fluency or synthetic data quality. Nonetheless, they are not based on language-specific tokenization strategies, dual-level contextual embeddings, and parameter efficient fine-tuning mechanisms that are specific to low-resource Indic languages. Moreover, the use of semantic consistency constraints in a single adversarial-Transformer optimization system is rarely combined with previous research.

Table 1 provides a summary of the recent works in the field of low-resource machine translation, data augmentation, and multilingual transformer-based models. The current methods are mainly directed to unsupervised statistical or neural MT, rule-based systems, or language-specific pretrained models. Although augmentation strategies and pretrained transformers have enhanced performance, there are still weaknesses in managing structural divergence, semantic preservation, adversarial stability, and low-resource Gujarati-English translation. Besides, there is a scarcity of literature that combines adversarial data augmentation with semantic consistency constraints in a single Transformer-based system. These shortcomings serve as the inspiration of the proposed G-transGAN model, which integrates conditional GAN augmentation, semantic regularization, and optimization techniques to improve the quality of translation in the low-resource situation.

2.1 Problem Statement

Although there has been improvement in Gujarati language machine translation applications based on Transformer and GAN models, existing models have limitations like small parallel corpora, ineffective processing of morphologically rich words, limited context maintenance in long sentences, and poor domain adaptability. Such constraints adversely affect fluency and semantic precision and strength of translation, particularly in low-resource and dialect-heavy environments.

3. Proposed Methodology

The present study targets the issue of Gujarati language machine translation, which suffers from shortcomings in parallel corpora, morphology complexity, and context, which reduce the accuracy and fluency of translation.

The primary goal is to increase the accuracy, fluency, semantic preservation, understandability and robustness when performing translation tasks in low-resource situations. To achieve this, a hybrid model, G-TransGAN, is proposed that combines cGAN-based data augmentation, transformer-based contextual embeddings based on cGAN architecture, and optimization methods including SAM and LoRA, along with mixed precision to overcome the current limitations by providing a coherent, fluent, and domain-adaptive Gujarati language translation.

The System Architecture Overview is presented in Figure 1. G-TransGAN pipeline combines data augmentation based on GANs with optimized transformer models to enable robust low-resource Gujarati-to-English semantic translation. The end-to-end architecture includes five main stages: (1) Data Augmentation, (2) Preprocessing and Tokenization, (3) Contextual Embedding and Understanding, (4) Semantic Translation, and (5) Optimization Strategies. The system takes advantage of synthetic and real data to overcome the problem of data scarcity and maintains semantic fidelity by fine-tuning advanced transformers.

3.1 Data Augmentation

To alleviate data sparsity within Gujarati-English translation, a cGAN is used to produce realistic Gujarati text sequences. Here, has taken advantage of two levels of embeddings:

- Character-level embeddings serve to capture morphological variations,
- Sentence-level embeddings depict semantic context.

The augmented dataset consists of synthetic data produced by the cGAN and whatever real parallel corpora are available. There is much diversity in terms of linguistic patterns, idioms, syntactic structures, and similar features, ensuring that the conditioned model generalizes better [26].

3.2 Preprocessing and Tokenization

The preprocessing phase is an essential step in normalizing and structuring the Gujarati text to ensure that the downstream models are being fed normalized, standard, clean, consistent, and context-rich input. This phase reduces inconsistencies that have been introduced by a variety of styles, orthographic variety and selection of author-related noise in text drawn and collated from a variety of text sources. Figure 2 shows the process of pre-processing and tokenization.

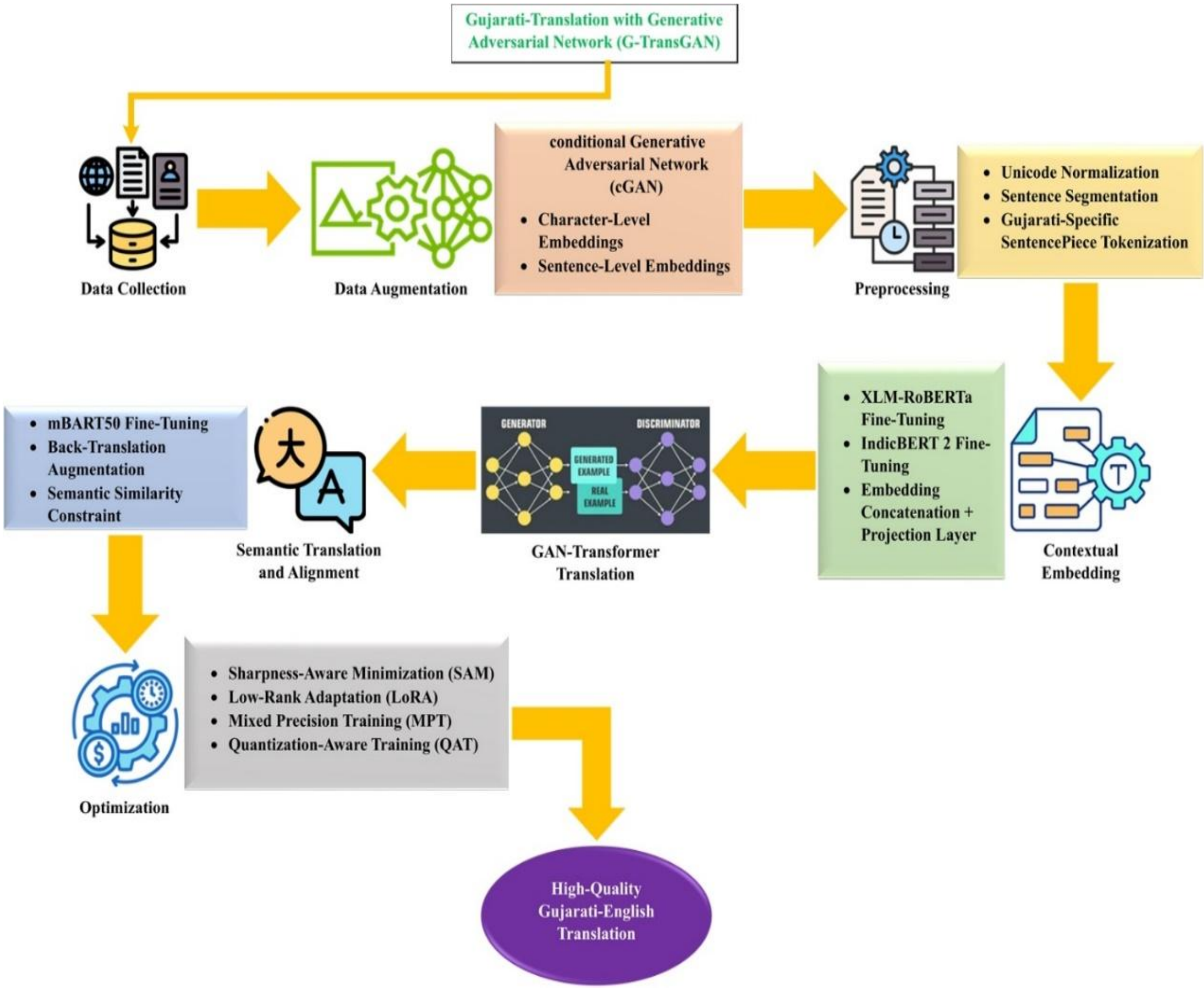

Figure 1. Architecture of the proposed G-TransGAN.

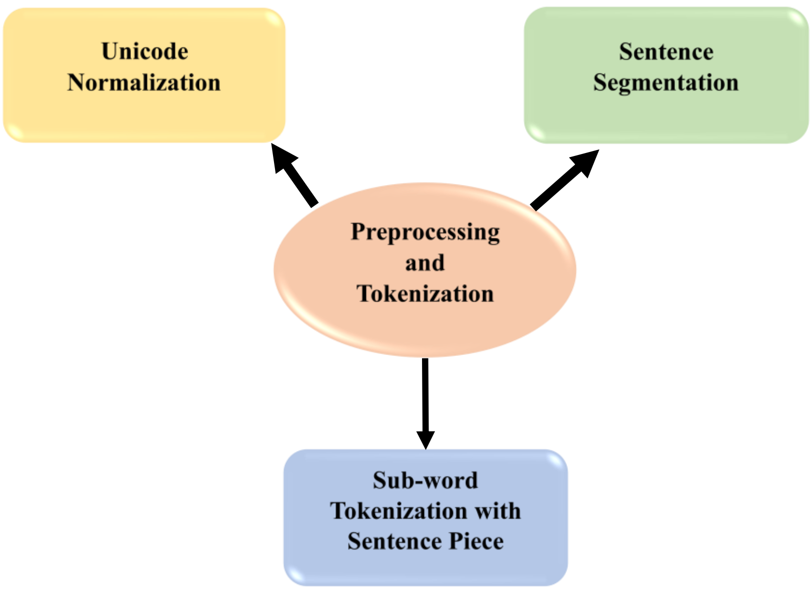

Figure 2. Structure of pre-processing and tokenization

Raw text - ગુજરાત ભારતનો પશ્ચિમ રાજ્ય છે।

(Translation: Gujarat is a western state of India.)

3.2.1 Unicode Normalization

Gujarati text sometimes uses visually similar characters that differ in code point, due to variations in encoding. Unicode normalization maps these similar visual encodings into canonical form and ensures consistency. An application of Normalization Form C (NFC) is applied to the Gujarati text according to equation (1):

$$T_{norm} = NFC(T_{raw}) \quad (1)$$

Where T_{raw} is the raw Gujarati text and T_{norm} is the normalized Gujarati text.

ગુજરાત ભારતનો પશ્ચિમ રાજ્ય છે। (Visually unchanged, but internally standardized in Unicode.)

3.2.2 Sentence Segmentation

To achieve coherent boundary detection, segmentation of sentences uses punctuation, whitespace patterns and Gujarati-specific delimiters like "।" (Danda). The segmentation function is expressed as in equation (2):

$$S = \{ s_i \mid s_i \in Split(T_{norm}, D) \} \quad (2)$$

where D is the set of Gujarati sentence delimiters and S is the set of segmented sentences.

["ગુજરાત ભારતનો પશ્ચિમ રાજ્ય છે।"]

3.2.3 Sub-word Tokenization with Sentence Piece

Gujarati has a rich morphology, as there are regularly occurring compound words and inflections. Thus, prior tokenization at the word-level leads to a very large vocabulary size, as well as out-of-vocabulary issues. In this regard, SentencePiece provides a method for tokenization using either a Byte-Pair Encoding (BPE) or a Unigram LM model, which has been trained on Gujarati text. The tokenization is represented as defined in equation (3):

$$X = SP_\theta(S) \quad (3)$$

where SP_θ is the trained SentencePiece model with parameters θ, and X is the sequence of subword tokens. SentencePiece seeks to maximize the likelihood of the training corpus for the selected vocabulary V according to equation (4):

$$\hat{\theta} = \arg\max_{\theta} \prod_{i=1}^{N} P_\theta(S_i \mid V) \quad (4)$$

["ગુ", "જરા", "ત", " ", "ભાર", "ત", "નો", " ", "પ", "શ્ચિ", "મ", " ", "રાજ્ય", " ", "છે", "।"]

By encoding text at a subword level, the model encounters uncommon words (e.g., "પશ્ચિમ") and breaks them up into potentially meaningful smaller pieces. This improves vocabulary efficiency and reduces out-of-vocabulary (OOV) errors in translation models.

This step enhances generalization of previously unseen words, reduces vocabulary size, and provides a method to capture morphological subtleties within Gujarati, which ultimately results in better quality of translations in subsequent Transformer-based modelling.

3.3 Contextual Embedding and Understanding

The purpose of this phase is to capture deep contextual relations between the Gujarati text and its associated translations. Contextual embeddings are created by fine-tuning XLM-RoBERTa and IndicBERT 2 on the augmented parallel dataset. These frameworks utilize multilingual pre-training to model both the syntactic (word order, grammar) and semantic (meaning) aspects of the language, improving the cross-lingual alignment. IndicBERT 2 is trained on a sample of Indic languages and develops language-specific embeddings that are enriched with morphological, orthographic, and cultural markers that help to accurately capture the subtle use of Gujarati expressions.

The Contextual Embedding and Understanding is displayed in Figure 3. The embeddings from both models are concatenated, and a projection layer reduces the dimensions to be congruent according to equation (5):

$$E_{combined} = W_c \cdot [E_{XLM-R} \oplus E_{IndicBERT}] + b_c \quad (5)$$

where E_{XLM-R} is the embeddings from XLM-RoBERTa, $E_{IndicBERT}$ is the embeddings from IndicBERT 2, $\oplus$ is the concatenation operation, and W_c and b_c are the trainable projection weights and bias. The contextual dependency between tokens t_i and t_j is learned through self-attention according to equation (6):

$$Attention(Q, K, V) = softmax\left(\frac{QK^{\top}}{\sqrt{d_k}}\right)V \quad (6)$$

Q, K, V are query, key, and value matrices taken from $E_{combined}$, d_k is the dimension of the key for scaling, V denotes the actual representations of the tokens that is weighted ,$K^{\top}$ refers the transpose of the Key matrix. This permits similarity of dot product between Q and K. In merging multilingual generalization with context learning specific to Gujarati, this step is critical for both guaranteeing semantic preservation during translation and adaptability in terms of domain, and it results in considerably fewer mistranslations with sentence structures that are morphologically rich or context-dependent.

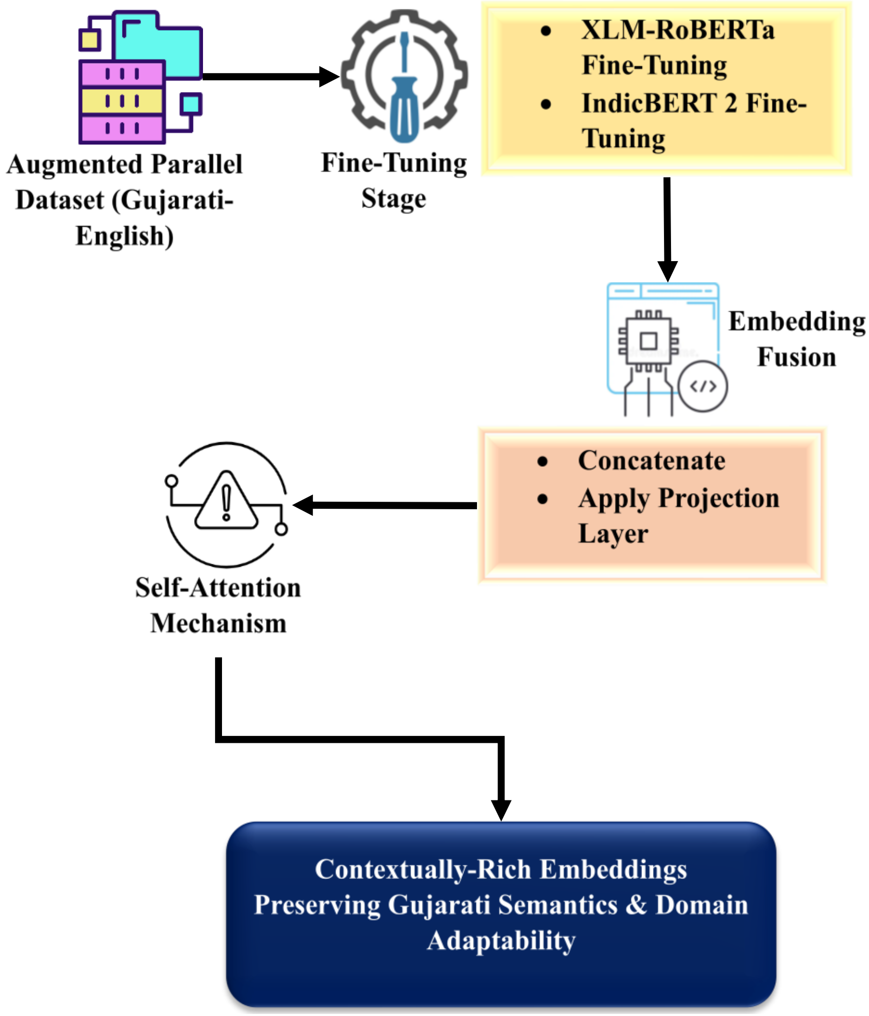

Figure 3. Contextual Embedding and Understanding

3.4 Translation with GAN-Transformer

This phase introduces the use of Generative Adversarial Networks (GANs), combined with a Transformer-based Neural Machine Translation (NMT) model, to improve fluency and accuracy for Gujarati-English translation. The GAN framework acts as a game between the generator (translation model) and the discriminator (in this case, overlapping human translations). The framework instructs the generator to produce translations that are not dissimilar to the human translation.

Figure 4 shows the architecture of the GAN-Transformer for Gujarati-English translation. The generator G_θ is based on a transformer encoder–decoder architecture, which, as outlined in equation (7), accepts the contextual embeddings output by phase 3, $E_{combined}$, as input to generate a translation sequenceY':

$$Y' = G_\theta(E_{combined}) \tag{7}$$

The transformer leverages multi-head self-attention as outlined in equation (8) to model long-range dependencies.

$$MultiHead(Q, K, V) = Concat(head_1, \ldots, head_h)W^O \tag{8}$$

Each head is defined according to the following equation (9):

$$head_i = Attention(QW_i^Q, KW_i^K, VW_i^V) \tag{9}$$

Discriminator D_ϕ is a deep sequence classifier that distinguishes real human translations, Y, from generated translations Y' as in equation (10):

$$D_\phi(Y) \to 1(real),\ D_\phi(Y') \to 0(generated) \tag{10}$$

The GAN objective is the sum of the generator loss, L_G, and the discriminator loss, L_D, as in equations (11) and (12):

$$L_D = -E_{Y \sim p_{data}}[logD_\phi(Y)] - E_{Y' \sim G_\theta}\left[log\left(1 - D_\phi(Y')\right)\right] \tag{11}$$

$$L_G = -E_{Y' \sim G_\theta}[logD_\phi(Y')] \tag{12}$$

The final generator loss is a hybrid loss, levelled with cross-entropy translation loss, L_{CE}, to sustain linguistic fidelity as in equation (13):

$$L_{final} = \lambda_1 L_G + \lambda_2 L_{CE} \tag{13}$$

Where λ_1 and λ_2 are weight coefficients balancing fluency (adversarial) and fidelity (cross-entropy).

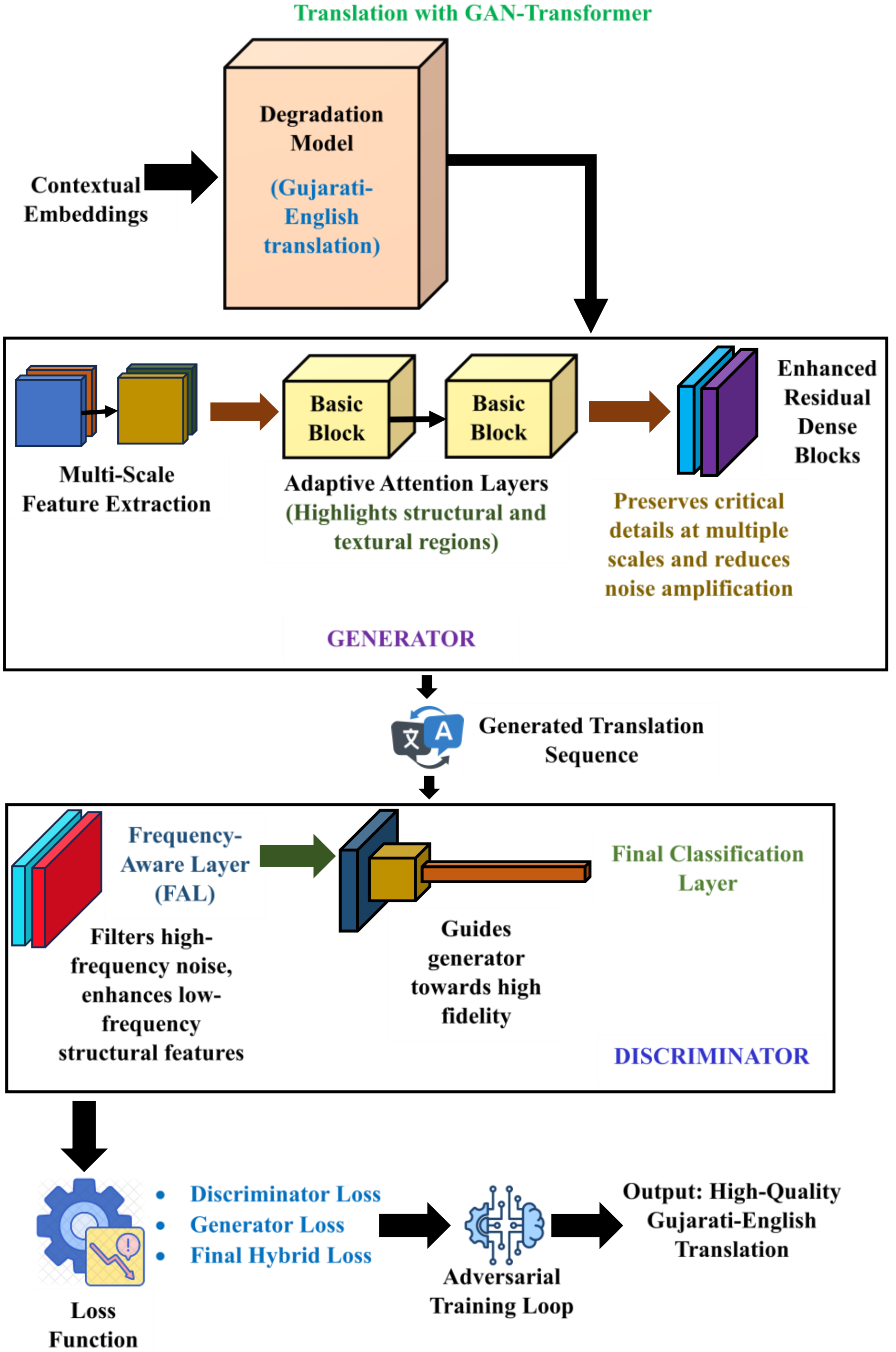

Figure 4. GAN-Transformer for Gujarati-English translation.

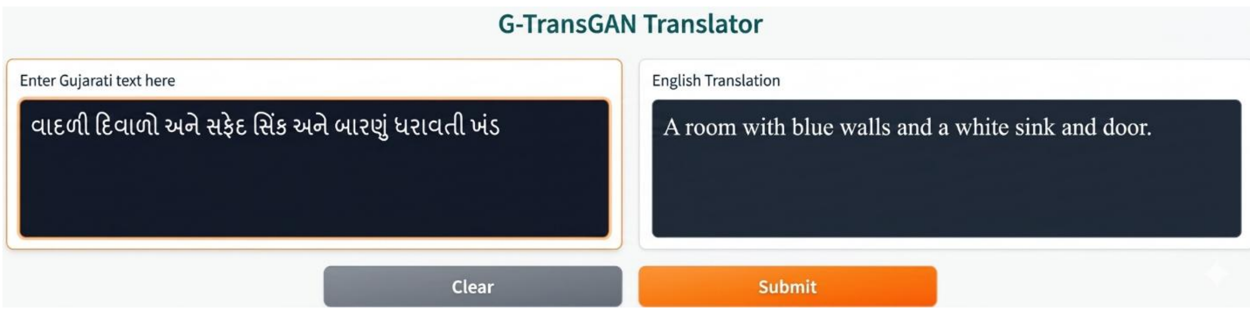

Figure 5. Sample image of the Translation with GAN-Transformer

This two-way training allows the system to launch into translation, producing skilled and grammatically correct outputs and also generating outputs that are indistinguishable from human references, particularly with culture-specific or idiomatic language. Figure 5 shows the sample image of the Translation with GAN-Transformer.

Algorithm 1. Training Procedure of G-TransGAN

Input: Gujarati–English parallel corpus D
Output: Trained G-TransGAN model

1. Preprocess D (cleaning, normalization, tokenization)
2. Train conditional GAN on D to generate synthetic sentence pairs
3. Combine real and synthetic data $\rightarrow D_{aug}$
4. Apply Gujarati-specific $\mathrm{SentencePiece}$ tokenization
5. Generate contextual embeddings using $\mathrm{XLM-RoBERTa\ and\ IndicBERT2}$
6. Initialize Transformer encoder–decoder
7. For each training epoch:
    a. Compute translation loss (cross-entropy)
    b. Compute adversarial loss
    c. Compute semantic similarity loss
    d. Combine losses with weighted sum
    e. Update parameters using SAM
    f. Apply LoRA fine-tuning
8. Repeat until convergence
9. Return trained model

3.4.1 GAN Architecture and Training Configuration

The conditional GAN is used in this work is composed of a Transformer-based generator and a neural discriminator. The generator is based on the encoder decoder transformer architecture that consists of 6 encoder and 6 decoder layers with an embedding dimension of 512 and 8 attention heads. A position-wise feed-forward network with a hidden dimension of 2048 and GELU activation is contained in each of the layers. Addition of positional encodings is done to maintain sequence order. The generator is trained to work on Gujarati source sentences and generates synthetic English translations with a linear projection layer and then softmax. The discriminator is trained as a 3-layer feed-forward neural network having 512 and ReLU activation functions as hidden dimensions. It is given concatenated source-target sentence representations and gives a probability score through a sigmoid layer to differentiate between real and synthetic pairs of sentences. The general training goal is a combination of the standard translation loss, adversarial and semantic similarity derived in equation (14),

$$L = L_{MT} + \lambda_{adv} L_{adv} + \lambda_{sem} L_{sem} \tag{14}$$

where L_{MT} refers the cross-entropy translation loss, L_{adv} specifies the adversarial loss, and L_{sem} denotes the semantic consistency. The hyperparameters are set to $\lambda_{adv} = 0.5$ and $\lambda_{sem} = 0.3$ based on validation performance. Adam optimizer and a learning rate of 0.0002 (b1 = 0.5, b2 = 0.999) is used to train the models. The 1:1 training schedule is followed in which the generator and discriminator are updated alternately and had 100 epochs with a batch size of 32. Adversarial training is stabilized using gradient clipping (maximum norm 1.0) and dropout (rate 0.1). The experiments are all run on an NVIDIA Tesla V100 32GB memory. The training is done with a fixed learning rate. The results are reproducible, random seeds are fixed (seed = 42) in Python, NumPy, and PyTorch. The mean time spent on training is about 35 minutes per epoch.

3.5 Semantic Translation

At this point, the translation process is accomplished using a purely Transformer-based encoder-decoder architecture that is fine-tuned from mBART50, a multilingual encoder-decoder sequence-to-sequence model. The encoder translates the contextual embeddings from Phase 3 into a deep intermediate representation, and the decoder generates the translated target sequence in either Gujarati or English while still capturing the semantic meaning. To alleviate low-resource limitations, synthetic parallel data is obtained by first translating monolingual Gujarati text into English and then converting it back to Gujarati. This firstly brings added training diversity, along with increasing robustness. The loss function that is used incorporates the forward (L_f) and back-translated (L_b) translations depicted in equation (15):

$$L_{total} = \lambda_f L_f + \lambda_b L_b \tag{15}$$

In this scenario, λ_f and λ_b are the weights for forward and back-translation losses. To facilitate minimizing meaning drift, a semantic similarity constraint is incorporated using cosine similarity between the source (e_s) sentence embeddings and the generated target (e_t) sentence embeddings, as given by the overall equation (16):

$$Sim(e_s, e_t) = \frac{e_s \cdot e_t}{\|e_s\| \|e_t\|} \tag{16}$$

A semantic loss term is defined as well by the overall equation (17):

$$L_{semantic} = 1 - Sim(e_s, e_t) \tag{17}$$

This loss term is added to the final loss to maintain meaning consistency given by equation (18):

$$L_{final} = L_{total} + \beta L_{semantic} \tag{18}$$

Where β defines the weight for semantic alignment. The final stage of the proposed framework ensures that translations retain both fluency, accuracy, and cultural sensitivity through attention-weighted translation, back-translation augmentation, and semantic alignment.

3.6 Optimization Strategies

The last step was to make sure it runs as efficiently, calmly and hardy as possible in low-resource settings using a mixture of SAM and LoRA and precision-aware training methods. SAM promotes generalization by locating parameters residing in neighbourhoods of low loss instead of sharp minima, therefore reducing the sensitivity of the model to perturbations.

Figure 6 shows the architecture of Optimization Strategies. Given the training loss function $L(w)$, SAM is optimized as in equation (19):

$$\min_{w} \max_{\|\epsilon\|_2 \le \rho} L(w + \epsilon) \tag{19}$$

Where w is the parameters of the model, ρ is the perturbation radius, and ϵ is the adversarial perturbation vector. The optimization process consists of two steps: the perturbation step and the update step using perturbed weights as presented in equations (20 and 21):

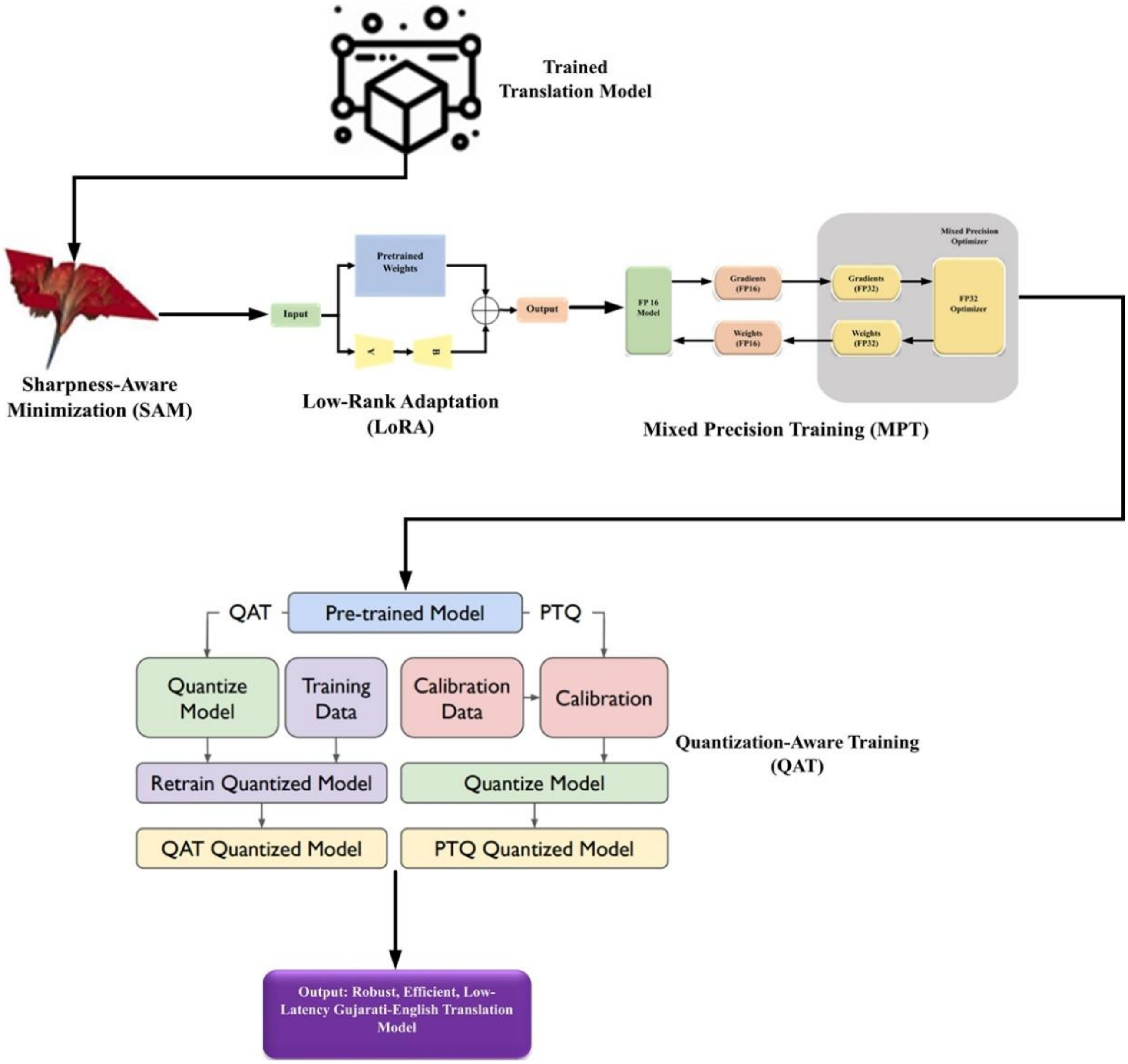

Figure 6. Optimization Strategies

$$\epsilon = \rho \cdot \frac{\nabla_w L(w)}{\|\nabla_w L(w)\|_2} \tag{20}$$

$$w \leftarrow w - \eta \cdot \nabla_w L(w + \epsilon) \tag{21}$$

This pushes towards flatter minima and therefore reduces overfitting. LoRA incorporates low-rank matrices in the weight updating procedure as a method for parameter-efficient fine-tuning. If the weight matrix $W_0 \in R^{d \times k}$, then the weight after fine-tuning is given by equation (22):

$$W = W_0 + \Delta W \tag{22}$$

Where,

$$\Delta W = AB, \;\; A \in R^{d \times r}, \;\; B \in R^{r \times k}, \;\; r \ll min(d, k) \tag{23}$$

Here, r is the rank factor determines the number of trainable parameters. With LoRA, freeze the weight W_0 while only training A and B, saving memory and computing. The Mixed Precision Training (MPT) method accelerates the training process and reduces memory usage via a combination of 32-bit floating-point (FP32) and 16-bit floating-point (FP16) operations as defined in equation (24):

$$x_{FP32} \approx cast(x_{FP16}) \quad \text{for stability} \tag{24}$$

and to avoid underflow through loss scaling as defined in equation (25):

$$\hat{L} = L \cdot s \tag{25}$$

where s refers to the scaling factor, which is modified dynamically. Similar to this is Quantization-Aware Training (QAT), which trains with a simulated inference low-bit (e.g. INT8) representation to allow model accuracy to be retained during its intended deployment as defined in equation (26):

$$x_q = round\left(\frac{x}{\Delta}\right) \cdot \Delta \tag{26}$$

where Δ is the quantization step size. This allows for the best possible robustness and adaptation to working in low specification (low resources) operational conditions, such as the use of mobile or embedded devices. This optimization stage ensures the Gujarati text translation model performs with robust accuracy, low latency, and low memory usage without increasing any loss of semantic fidelity.

G-TransGAN is a multi-phased framework to solve Gujarati-English translation under low-resource settings. First, a conditional GAN is used to produce a wide variety of realistic Gujarati text based on character- and sentence-level embeddings to address the sparsity of data. Then, morphological shades are captured by preprocessing and Gujarati-specific SentencePiece tokenization, shrinking vocabulary size and out-of-vocabulary problems. IndicBERT 2 and fine-tuned XLM-RoBERTa models offer deep contextual embeddings with syntax and semantics, as well as cultural distinction. A transformer translation model with a GAN integration guarantees outputs that are similar to human translation, and back-translation enhances robustness. The semantic similarity constraints preserve the meaning. Lastly, optimization techniques SAM, LoRA, mixed precision, and quantization-aware training improve generalization, efficiency, and deployment to low-resource devices without compromising the quality of translation. The performance evaluation of the proposed model is explained in the next section.

4. Results and Discussion

The results and discussion section bring out the performance of the proposed G-TransGAN framework in comparison with the existing methods of Gujarati to English translation in low-resource conditions. Different assessment measures, such as BLEU, METEOR, accuracy, precision, recall, and error rates, are used to justify the gains in fluency, semantic preservation, efficiency, and robustness.

4.1 Experimental Setup

Gujarati-English parallel corpora with synthetic data created using cGAN were used in the experimental setup. XLM-RoBERTa, IndicBERT, and mBART architectures were fine-tuned on models. SAM, LoRA, and mixed-precision training optimization methods were applied to guarantee better efficiency, accelerated convergence, and resilient low-resource performance.

The experiments use Gujarati-English parallel corpus that is found on Kaggle and has about 65,000 sentence pairs that are aligned. The data is mostly general domain bilingual text that is gathered via publicly available sources. The preprocessing steps consist of Unicode normalization, noisy and duplicate sentence pair's removal, length filtering, and the use of a Gujarati-specific SentencePiece tokenizer.

The dataset is then cleaned and divided into 70% training and 30% testing data. Since the corpus is built using publicly available sources, there is a possibility of bias due to domain imbalance and different quality of translation that influences generalization to highly specialized domains.

4.2 Comparison of the Proposed Model

To set a proper comparison, G-TransGAN was contrasted with other well-known models, including mBART [16], mT5 [17], and M2M-100 [18]. These baselines gave a clue on efficiency, accuracy and fluency.

Figure 7 shows the comparison of BLEU score of mBART, mT5, M2M-100 and proposed Full G-TransGAN model. The highest BLEU score of 38.4 is attained by the proposed model, which is better compared to M2M-100 (36.2), mBART (35.9), and mT5 (34.8). The fact that the improvement is about 2.2 BLEU compared to M2M-100 and 2.5 BLEU compared to mBART prove that the proposed framework produces translations with a higher degree of n-gram accuracy and closer to the reference translation. This means that there is enhanced fluency and adequacy in the translation of Gujarati to English.

Figure 8 shows the comparison of METEOR score in all models. Full G-TransGAN has a score of 0.76 on METEOR, which is better than M2M-100 (0.73), mBART (0.72), and mT5 (0.71). As METEOR takes into account the synonym matching and semantic alignment, the enhancement suggests that the given model is more effective in terms of semantic meaning and contextual relevance of the translated sentences than the baseline multilingual models.

Figure 9 presents the comparison of Translation Error Rate (TER) with a lower value being a better performance. The G-transGAN has the lowest TER of 0.46, which is lower than M2M-100 (0.48), mBART (0.49), and mT5 (0.51). The TER decrease indicates that it needs fewer edits to convert the generated translation into the reference sentence, which validates a higher accuracy and structural quality of translation.

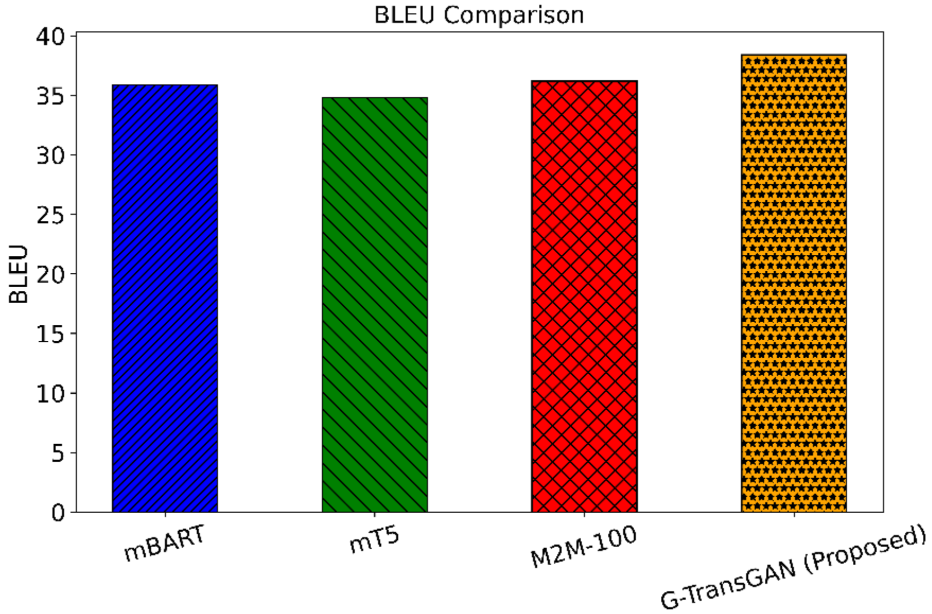

Figure 7. BLEU of the proposed model

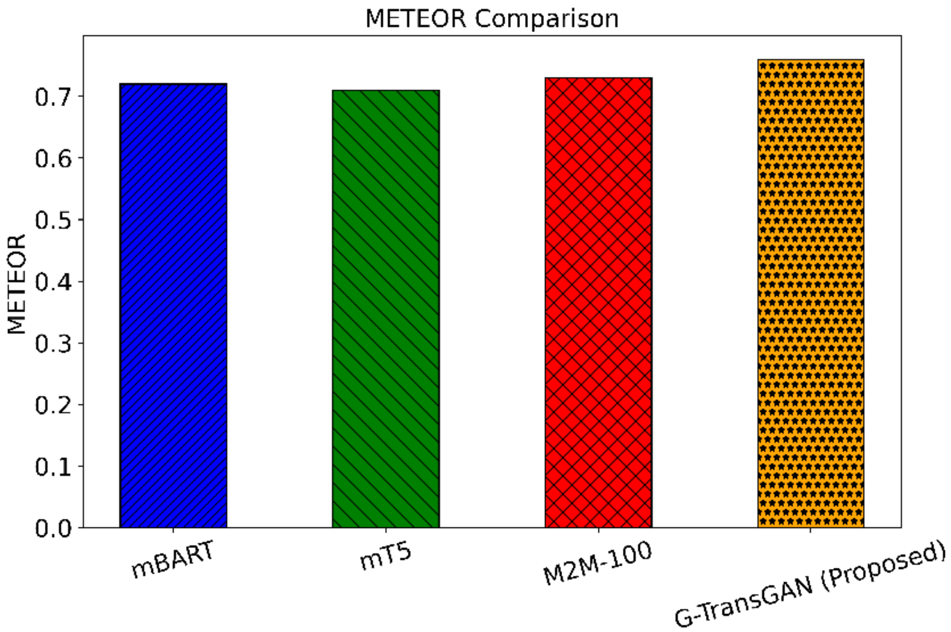

Figure 8. METEOR of the proposed model

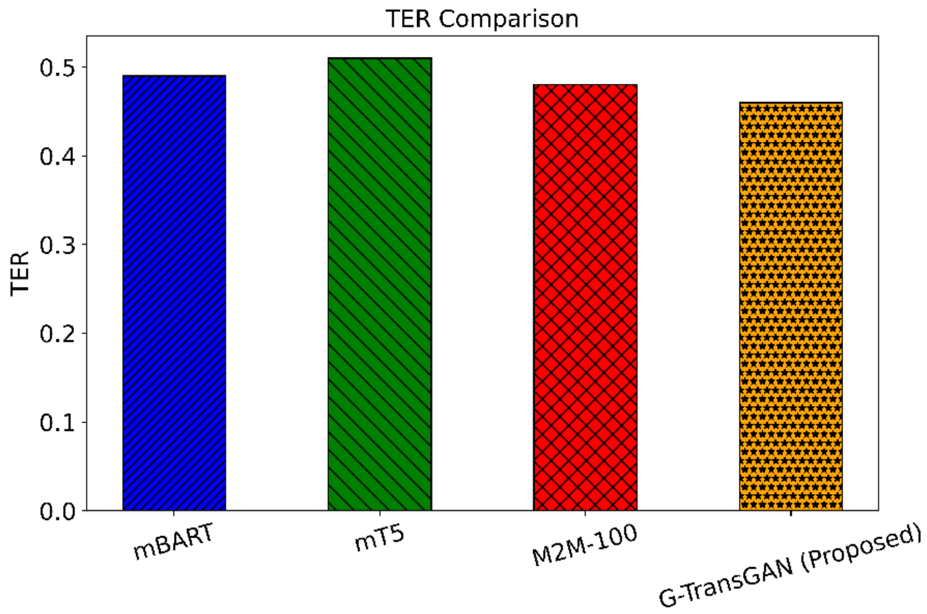

Figure 9. TER of the proposed model

4.3 Performance Evaluation of the Proposed Model

Standard translation metrics such as BLEU, METEOR, accuracy, F-measure and error rates were used in performance evaluation. These steps confirmed the success of the proposed framework in the improvement of Gujarati-English translation in low-resource set-ups.

Figure 10 shows the decrease in training loss over the course of 100 epochs in Normal Training and SAM-based Training. First Normal Training begin at a loss of approximately 1.05, and SAM begin a little lower at 0.95. At the last step, Normal Training has a convergence of about 0.08, whereas SAM has a lower loss of about 0.02. This shows that SAM optimization allows smoother convergence and generalization by not falling into sharp minima, which is consistent with the objective of the proposed G-TransGAN framework to improve stability and efficiency of low-resource Gujarati-English translation.

Figure 11 contrasts the accuracy of validation after 100 epochs of Full Fine-Tuning and LoRA Fine-Tuning. First, Full Fine-Tuning is initialized at a low value of 0.62, whereas LoRA is initialized at a higher value of 0.65. At the last stage, Full Fine-Tuning is approximately 0.92, and LoRA exceeds it with 0.96. This gain shows the parameter-efficient fine-tuning property of LoRA, which has a higher generalization ability with fewer parameters to train. Consistent with the G-TransGAN framework, LoRA guarantees faster convergence, less resource consumption, and higher accuracy, which is especially useful in low-resource Gujarati-English translation tasks

The ablation results indicate that Full G-TransGAN model (GAN + Transformer + LoRA + SAM) performs the best in terms of a BLEU score of 38.4, METEOR of 0.76, and the lowest TER of 0.46, which proves the effectiveness of the integrated framework. The deletion of GAN makes BLEU drop to 35.9 and TER rise to 0.49, which indicates the value of adversarial augmentation. On the same note, the removal of SAM (BLEU 36.7) or LoRA (BLEU 34.8, TER 0.52) leads to worse performance, which shows that optimization and parameter-efficient fine-tuning are important.

The baseline Transformer does not have any augmentation, and its results are much worse (BLEU 31.2, TER 0.56), which proves the weakness of low-resource training. Although back-translation (BLEU 34.6) and GAN augmentation alone (BLEU 36.8) are better than the plain Transformer, none of them is as good as the full integrated model. These results show that the results of the improvements observed are not only due to augmentation volume increase, but due to the synergetic combination of GAN-based augmentation, back-translation, and high-level optimization methods in a single architecture. Table 3 displays the Five-Fold Cross-Validation Performance of G-TransGAN.

Table 3 shows the results of 5-fold cross-validation of the proposed G-transGAN model. The data is separated into five subsets with four subsets being trained and one being a validation in each fold. The folds are consistent in terms of performance with less difference in the BLEU, METEOR and TER. The small values of standard deviation show that the model is stable and reliable in the performance of the model in various data splits, which proves the strength and the ability to generalize the proposed framework.

Table 4 provides qualitative examples of translation results of various multilingual NMT baselines as opposed to the proposed Full G-TransGAN model.

The examples show semantic fidelity, grammatical correctness, lexical precision and preserving context. The translations generated by the proposed model across the samples are always the ones that are the closest to the human reference in their structure and meaning. As an example, in the former, the suggested production perfectly matches the reference sentence, but the baseline models introduce small lexical changes like the model, which is used in place of replica.

In the same way, in the second and fifth examples, the offered system coincides with the reference translation, which indicates high lexical accuracy and fluency.

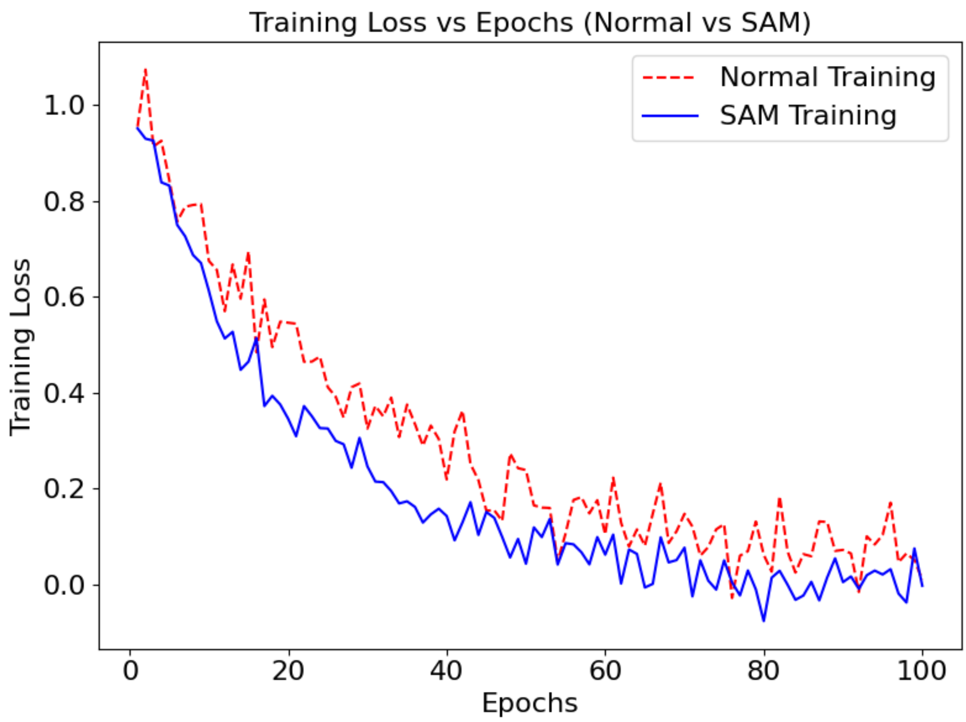

Figure 10. Training Loss Convergence with SAM vs Normal Optimization

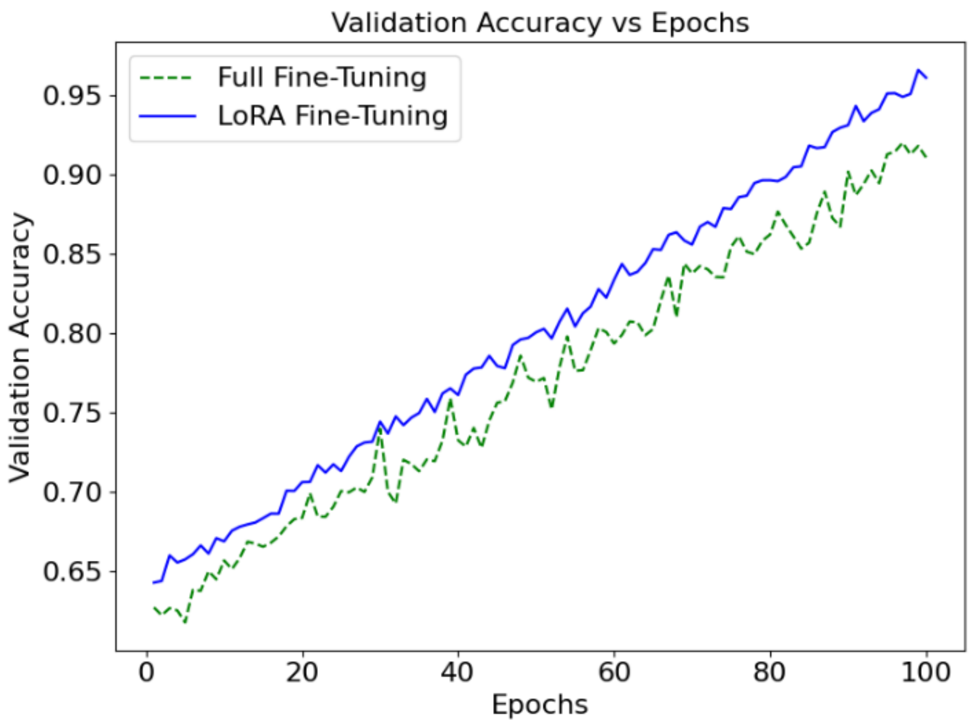

Figure 11. Validation Accuracy Progression with LoRA vs Full Fine-Tuning

Table 2. Ablation study of the proposed model

Metric / Model	Full Model (GAN + Transformer + LoRA + SAM)	Without GAN	Without SAM	Without LoRA	Transformer (No Augmentation)	Transformer + Back-Translation	Transformer + GAN Augmentation	Without Back-translation	Back-translation Only	GAN Only	GAN + BT
BLEU	38.4	35.9	36.7	34.8	31.2	34.6	36.8	32.8	34.6	36.8	33.5
METEOR	0.76	0.72	0.74	0.71	0.67	0.71	0.74	0.74	0.71	0.74	0.75
TER	0.46	0.49	0.48	0.52	0.56	0.52	0.48	0.49	0.52	0.59	0.5

Table 3. Five-Fold Cross-Validation Performance of G-TransGAN

Fold	BLEU	METEOR	TER
Fold 1	37.9	0.75	0.47
Fold 2	38.2	0.76	0.46
Fold 3	38.5	0.76	0.45
Fold 4	38.1	0.75	0.46
Fold 5	38.3	0.76	0.46
Mean ± Std	**38.2 ± 0.2**	**0.756 ± 0.005**	**0.46 ± 0.01**

Table 4. Qualitative Comparison of Gujarati–English Translation Outputs Across Baseline Models and the Proposed G-TransGAN

Source (Gujarati)	Reference (English)	mBART	mT5	M2M-100	Full G-TransGAN (Proposed)
ફ્રન્ટ વ્હીલ તરીકે ઘડિયાળ સાથે સાયકલ પ્રતિકૃતિ.	A bicycle replica with a clock as the front wheel.	A bicycle model with a clock as the front wheel.	A bicycle with a clock as its front wheel.	A bicycle replica having a clock as the front wheel.	A bicycle replica with a clock as the front wheel.
ગેરેજની સામે પાર્ક કરેલી બ્લેક હોન્ડા મોટરસાયકલ	A black Honda motorcycle parked in front of a garage.	A black Honda bike parked in front of the garage.	A black Honda motorcycle parked before a garage.	A black Honda motorcycle parked in front of a garage.	A black Honda motorcycle parked in front of a garage.
વાદળી દિવાલો અને સફેદ સિંક અને બારણું ધરાવતી ખંડ	A room with blue walls and a white sink and door.	A room having blue walls with a white sink and a door.	A room with blue colored walls and a white sink and door.	A room with blue walls and white sink and door.	A room with blue walls and a white sink and door.
એક કાર કે જે કાનૂની રીતે પાર્ક કરેલી કારની પાછળ ગેરકાયદેસર રીતે પાર્ક કરવામાં આવે તેવું લાગે છે	A car that seems to be parked illegally behind a legally parked car.	A car appears to be illegally parked behind another car.	A car that looks illegally parked behind a parked car.	A car that seems to be parked illegally behind a legally parked vehicle.	A car that appears to be illegally parked behind a legally parked car.
હવામાં ઉડતી મોટી પેસેન્જર વિમાન.	A large passenger airplane flying through the air.	A big passenger airplane flying in the sky.	A large passenger aircraft flying in the air.	A large passenger airplane flying through the air.	A large passenger airplane flying through the air.

In more structurally complex sentences, as in the case of illegal parking, the baseline models simplify or lose contextual information (another car, rather than a legally parked car), whereas the model proposed does not. In descriptive sentences with objects and attributes (description of the room), some basic grammatical omissions occur in certain baselines (white sink and door without article), but the proposed model does not have such omissions. Altogether, these qualitative findings contribute to the quantitative ones by proving the better semantic preservation, contextual clarity, and grammatical consistency due to the combined adversarial augmentation and optimization strategy of G-TransGAN.

5. Discussion

The results of the experiments indicated that the suggested G-transGAN model is always better performance than traditional translation models and even modern multilingual Transformer baselines like mBART, mT5, and M2M-100. Although these pretrained models perform well on multilingual tasks by using the large scale training, their performance in translating to Gujarati is limited by the lack of language specific adaptation and reliance on massive parallel corpora. In comparison, G-TransGAN solves low-resource issues by using conditional GAN-based data augmentation to increase linguistic depth and allow better morphologically rich Gujarati structures to be learnt. Architecturally, the current models of baselines are based mainly on the standard encoder-decoder Transformer learning, but the model proposed incorporates the adversarial learning, which generator to generate translations that are more aligned with the human linguistic patterns. At the methodological level, Gujarati-specific SentencePiece tokenization, dual contextual embeddings, semantic similarity constraints and back-translation mechanisms facilitate contextual knowledge and reduce semantic drift that is often achieved via multilingual pretrained systems. The augmentation with the use of the GAN is integrated with the Transformer architecture, which enhanced the performance of translation but raises the complexity of calculations as a result of adversarial training and combined optimization. Despite the fact that SAM and LoRA improved convergence and efficiency of generalization, the hybrid GAN-Transformer model has a greater computational cost than the conventional Transformer models. Although this results in better BLEU, METEOR and TER scores, it is scaled in resource-constrained environments. The next step in the direction of work will be to integrate lightweight or compact Transformer architectures and more effective adversarial stabilization methods to decrease the number of computations and still achieve the same quality of translation.

6. Conclusion

This research presented a hybrid GAN-Transformer-based framework, referred to as G-TransGAN, which aims at solving the problem of Gujarati-English translation in a low-resource setting. The method is effective in enhancing the fluency of translation, semantic transfer, and strength through a combination of adversarial data augmentation, multilingual contextual embedding, and optimization methods, including SAM and LoRA. The efficacy of augmentation-based learning coupled with parameter-efficient optimization was experimentally proved by comparative analysis of morphologically rich languages over conventional and multilingual Transformer-based baselines. In addition to the performance gains, the suggested framework also addresses the technical viability of creating effective machine translators that operate on low-resource languages, which leads to the increase in digital accessibility and multilingual communication. The findings show that focused augmentation and domain-conscious optimization are used as plausible alternatives to scale-sensitive multilingual pretraining methods. Further research will involve domain-adaptive translation in specialized settings, minimizing the computational complexity of edge deployment, and generalizing the framework to other Indic and low-resource language pairs. The use of bias-conscious augmentation and better adversarial stabilization can also be useful in enhancing generalization and practical applicability.

References

[1] F. Eranpurwala, P. Ramane, B. K. Bolla, Comparative Study of Marathi Text Classification using Monolingual and Multilingual Embeddings. International Conference on Advanced Network Technologies and Intelligent Computing, 1534, (2021) 441–452. https://doi.org/10.1007/978-3-030-96040-7_35

[2] A. Nandi, K. Sarkar, A. Mallick, A. De, A survey of Hate Speech Detection in Indian languages. Social Network Analysis and Mining, 14(1), (2024) 70. https://doi.org/10.1007/s13278-024-01223-y

[3] H. Huang, H. Zhang, Y. Wang, H. Liu, X. Chen, Y. Chen, Y. Liang, Integrated Robust Optimization for Lightweight Transformer Models in Low-Resource Scenarios. Symmetry, 17(7), (2025) 1162. https://doi.org/10.3390/sym17071162

[4] F. Z. El-Alami, S. O. El Alaoui, N. E. Nahnahi, A Multilingual Offensive Language Detection Method based on Transfer Learning from Transformer Fine-Tuning Model. Journal of King

Saud University – Computer and Information Sciences, 34(8), (2022) 6048–6056. https://doi.org/10.1016/j.jksuci.2021.07.013

[5] K. Manohar, R. Rajan, Improving speech Recognition Systems for the Morphologically Complex Malayalam Language using Subword Tokens for Language Modeling. EURASIP Journal on Audio, Speech, and Music Processing, 2023(1), (2023) 47. https://doi.org/10.1186/s13636-023-00313-7

[6] P. Prasada, M. V. P. Rao, Reinforcement of low-resource language translation with neural machine translation and backtranslation synergies. IAES International Journal of Artificial Intelligence, 13(3), (2024) 3478–3488. https://doi.org/10.11591/ijai.v13.i3.pp3478-3488

[7] J. W. Brook, (2023). Towards improving Neural Machine Translation Systems for Lower-Resourced Languages: Optimising Preprocessing and Data Augmentation Techniques. https://doi.org/10.13140/RG.2.2.27649.26721

[8] H. Hua, X. Li, D. Dou, C. Z. Xu, J. Luo, Improving Pretrained Language Model Fine-Tuning with Noise Stability Regularization. IEEE Transactions on Neural Networks and Learning Systems, 36(1), (2023) 1898–1910. https://doi.org/10.1109/TNNLS.2023.3330926

[9] F. Farahanipad, M. Rezaei, M. S. Nasr, F. Kamangar, V. Athitsos, A Survey on GAN-based Data Augmentation for Hand Pose Estimation Problem. Technologies, 10(2), (2022) 43. https://doi.org/10.3390/technologies10020043

[10] C. Koç, F. Özyurt, L. B. Iantovics, Survey on Latest Advances in Natural Language Processing Applications of Generative Adversarial Networks. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 15(1), (2025) e70004. https://doi.org/10.1002/widm.70004

[11] S. Dey, S. Thakur, A. Kandwal, R. Kumar, S. Dasgupta, P. P. Roy, BharatBhasaNet—a Unified Framework to Identify Indian code mix languages. IEEE Access, IEEE, 12, (2024) 68893–68904. https://doi.org/10.1109/access.2024.3396290

[12] M. Rehan, M. S. I. Malik, M. M. Jamjoom, Fine-tuning Transformer Models using Transfer Learning for Multilingual Threatening text Identification. IEEE Access, IEEE, 11, (2023) 106503–106515. https://doi.org/10.1109/access.2023.3320062

[13] D. Ganatra, D. Domadiya, Toward Accurate English to Gujarati Language Translation: An Artificial Intelligence Framework using Neural Machine Translation. International Conference on Deep Learning and Visual Artificial Intelligence, (2024) 183–190. https://doi.org/10.1007/978-981-97-4533-3_14

[14] B. Wang, D. Liu, J. Wu, SSNFNet: An Enhanced Few-Shot Learning Model for Efficient Poultry Farming Detection. Animals, 15(15), (2025) 2252. https://doi.org/10.3390/ani15152252

[15] Y. Yu, C. H. H. Yang, J. Kolehmainen, P. G. Shivakumar, Y. Gu, S. R. R. Ren, I. Bulyko, (2023). Low-Rank Adaptation of Large Language Model Rescoring for Parameter-Efficient Speech Recognition. IEEE Automatic Speech Recognition and Understanding Workshop (ASRU), IEEE, Taipei, Taiwan. https://doi.org/10.1109/ASRU57964.2023.10389632

[16] Y. Liu, J. Gu, N. Goyal, X. Li, S. Edunov, M. Ghazvininejad, M. Lewis, L. Zettlemoyer, Multilingual denoising Pre-Training for Neural Machine Translation. Transactions of the Association for Computational Linguistics, 8, (2020) 726–742. https://doi.org/10.1162/tacl_a_00343

[17] L. Xue, N. Constant, A. Roberts, M. Kale, R. Al-Rfou, A. Siddhant, C. Raffel, mT5: A Massively Multilingual Pre-Trained Text-To-Text Transformer. Proceedings of the North American Chapter of the Association for Computational Linguistics (NAACL), (2021) 483–498. https://doi.org/10.18653/v1/2021.naacl-main.41

[18] A. Fan, S. Bhosale, H. Schwenk, Z. Ma, A. El-Kishky, S. Goyal, M. Baines, O. Celebi, G. Wenzek, V. Chaudhary, N. Goyal, T. Birch, V. Liptchinsky, S. Edunov, M. Auli, A. Joulin, Beyond English-Centric Multilingual Machine Translation. Journal of Machine Learning Research, 22(107), (2021) 1–48. https://www.jmlr.org/papers/v22/20-1307.html

[19] A. Onan, K. F. Balbal, Improving Turkish text Sentiment Classification through Task-Specific and Universal Transformations: An ensemble Data Augmentation Approach. IEEE Access, IEEE, 12, (2024) 4413–4458. https://doi.org/10.1109/ACCESS.2024.3349971

[20] A. Benayas, S. Miguel-Ángel, M. Mora-Cantallops, Enhancing Intent Classifier Training with Large Language Model-Generated Data. Applied Artificial Intelligence, 38(1), (2024) 2414483.

https://doi.org/10.1080/08839514.2024.2414483

[21] Z. Chen, L. Zhao, HierLabelNet: A Two-Stage LLMs Framework with Data Augmentation and Label Selection for Geographic Text Classification. ISPRS International Journal of Geo-Information, 14(7), (2025) 268. https://doi.org/10.3390/ijgi14070268

[22] M. Kowsher, A. A. Sami, N. J. Prottasha, M. S. Arefin, P. K. Dhar, T. Koshiba, Bangla-BERT: Transformer-based Efficient Model for Transfer Learning and Language Understanding. IEEE Access, IEEE, 10, (2022) 91855–91870. https://doi.org/10.1109/ACCESS.2022.3197662

[23] P. Mishra, S. K. Narayanasamy, K. Srinivasan, Context-Aware Embedded Language Transformers for Evaluating Climate Change-Based Sustainable Development Goals. IEEE Access, IEEE, 13, (2025) 65757–65775. https://doi.org/10.1109/ACCESS.2025.3559548

[24] J. G. Tejero, M. Schmid, P. M. Neila, M. S. Zinkernagel, S. Wolf, R. Sznitman, (2025). SAM-DA: Decoder Adapter for Efficient Medical Domain Adaptation. IEEE/CVF Winter Conference on Applications of Computer Vision (WACV), IEEE, Tucson, AZ, USA. https://doi.org/10.1109/WACV61041.2025.00659

[25] L. Müller, N. Schwarz, L. Böcking, A. Bereczuk, H. Stagge, W. Kratsch, N. Kühl, Data-centric Fine-Tuning of Small Language Models for Automatic Extraction of Technical Requirements. IEEE Access, IEEE, 13, (2025) 135301–135315. https://doi.org/10.1109/ACCESS.2025.3591739

[26] Kaggle, Gujarati to English translation dataset. (n.d.). https://www.kaggle.com/datasets/utsav7vanodiya/gujarati-to-english-translation

Authors Contribution Statement

Mehulkumar Dalwadi: Conceptualization, Methodology, Software, Writing- Original draft preparation, Visualization, Writing- Reviewing and Editing. Abhishek Mehta: Investigation, Supervision. Both authors have read and agreed to the published version of the manuscript.

Acknowledgement

The authors would like to express their sincere gratitude to Parul University, Vadodara, Gujarat, India, for providing the necessary resources, research facilities, and academic support to carry out this study.

Funding

The authors declare that no funds, grants or any other support were received during the preparation of this manuscript.

Has this article screened for similarity?

Yes

Competing Interests

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

About the License