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SanskritBERT: Language-Specific Transformer Modelling for Classical Sanskrit Texts

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Abstract

Recent breakthroughs in transformer-based architectures, such as BERT, have revolutionised natural language processing (NLP) across many languages. However, low-resource and morphologically complex languages like Sanskrit remain poorly represented in large-scale pretrained models due to scarce digital corpora, orthographic variation, and compounding. This paper presents a fully custom **Sanskrit BERT** model trained from scratch on a corpus of 21 million+ curated Sanskrit sentences written in pure Devanagari script. To represent the morphological richness of the language, a Sentence-Piece Unigram tokeniser with a 64k subword vocabulary was built, and a light 6-layer BERT architecture with 256-dimensional hidden states was used to balance performance and compute efficiency. Experimental results show that the model significantly outperforms multilingual baselines such as mBERT, IndicBERT, and MuRIL on masked language modelling test sets, achieving Top-1 accuracy of 0.35, Top-5 accuracy of 0.50, and a perplexity score of 69.0. These outcomes confirm the merits of corpus-specific tokenisation and pretraining in monolingual style for morphologically rich classical languages. Future work will investigate scaling the model to larger architectures, incorporating more complex subword representations, and fine-tuning for Sanskrit NLP downstream tasks such as word segmentation, translation, and semantic role labelling.

Keywords: *Sanskrit NLP, BERT, Transformer Models, Morphologically Rich Languages, SentencePiece, Masked Language Modelling.*

1 Introduction

Transformer-based architectures such as BERT [5] have fundamentally reshaped Natural Language Processing (NLP), enabling models to learn deep, bidirectional contextual representations that effectively capture both syntactic and semantic relationships. Despite impressive multilingual models like mBERT, XLM-R [4], and MuRIL [12], their performance remains limited for morphologically rich, low-resource, and classical languages such as Sanskrit.
Sanskrit, one of the oldest Indo-Aryan languages, features intricate morphology, extensive compounding, and sophisticated phonological processes such as sandhi (euphonic combination). Although Sanskrit holds immense linguistic and cultural value, computational resources for it remain scarce [2, 17]. Script variability across Devanagari and multiple transliteration systems further degrades the performance of multilingual models trained primarily on modern Indic or Latin-script data.

Recent research, such as San-BERT [2] and ByT5-Sanskrit [17], underscores that Sanskrit NLP tasks benefit substantially from script-native, monolingual pretraining. Models like In-dicBERT [10] and IndicBERT-v2 [6] have demonstrated improvements for modern Indian languages, but still underrepresent Sanskrit due to limited corpus inclusion and inconsistent tokenisation. To address these challenges, we introduce a fully custom, monolingual BERT model trained from scratch for Sanskrit. The model is trained on a 21-million sentence Devanagari corpus, normalised for orthographic and linguistic consistency. A SentencePiece Unigram tokeniser [14] with a 64k subword vocabulary captures morphological richness and minimises rare token sparsity. The proposed six-layer BERT encoder with 256-dimensional hidden states balances expressiveness with

computational efficiency. Pretraining employs the Masked Language Modelling (MLM) objective [23] using 15% random masking. The contribution of the paper is as follows:

- A Sanskrit-specific SentencePiece tokeniser and lightweight BERT model trained from scratch.
- Extensive comparison with multilingual and Indic models showing consistent accuracy gains.

This work demonstrates that domain-specific, script-native pretraining significantly enhances representation quality in low-resource, morphologically rich languages like Sanskrit, marking a step toward robust computational tools for classical linguistics and digital philology.

2. Related Work

NLP research in Sanskrit and other low-resource Indic languages has increased significantly over the last few years, but progress is still limited compared to high-resource languages such as English, Chinese, and French [4, 5, 27]. There are specific challenges of classical languages like Sanskrit, including their elaborate inflectional morphology, sandhi compounding, and non-standard orthography [7, 9, 26]. This section summarises previous work in four areas: (i) transformer models for multilingual and Indic languages, (ii) NLP research on Sanskrit, (iii) low-resource and ancient language modelling, and (iv) tokenisation schemes. The advent of BERT [5] and its variants, such as ALBERT [15], RoBERTa [16], and XLM-R [4], transformed contextualised text representation. Still, these models were initially developed using high-resource contemporary languages. The Indic NLP society countered with multilingual variants built for Indian languages.
IndicBERT [10] and its variant IndicBERT v2 [6] were pre-trained on more than nine billion tokens spread across twelve prominent Indic languages, resulting in better syntactic and semantic performance. Likewise, MuRIL [12] utilised transliteration-based augmentation to capture cross-script linguistic variation. Despite these developments, Sanskrit is grossly underrepresented in these datasets because it is a classical language and has a complex orthography. As a result, these models typically perform poorly on Sanskrit-specific tasks such as token prediction, parsing, and summarisation, simply because tokenisation is inconsistent and the models are exposed to very little Sanskrit morphology [18, 28].

2.1 Sanskrit NLP and Classical Language Modelling

Specific NLP efforts on Sanskrit have occurred more recently, spurred by computational and linguistic interests. Early research focused on morphological parsing, part-of-speech tagging, and sandhi resolution using rule-based and neural methods [9, 19]. The SanskritShala toolkit [26] combines segmentation, morphological analysis, and transformer-based tagging to process Sanskrit. More specialised transformer models have started to emerge. San-BERT [2] extended mBERT to Sanskrit summarisation tasks, and ByT5-Sanskrit [17] employed byte-level encoding to enhance zero-shot transfer. Cross-lingual extensions like PhiloBERTA [1] for Ancient Greek and Latin demonstrate the power of domain-specific pretraining of transformers for morphologically rich, diachronic languages. These contributions as a whole emphasise the necessity of monolingual Sanskrit pretraining and native-script tokenisation, both of which are dealt with in the current research.

2.2 Low-Resource and Historical Language Modelling

Low-resource NLP research further investigates strategies for underrepresented languages [8, 18].

Multilingual adaptive transfer and synthetic corpus generation [24] have demonstrated potential but remain constrained by linguistic diversity and morphological irregularity. For classical or ancient languages, diachronic transformer methods like DTAL-BERT for Ancient Greek [25] continue to face limitations in maintaining semantic coherence across disjointed corpora. Sanskrit modelling is subject to similar constraints from data sparsity, insufficient parallel corpora, and orthographic inconsistency.

2.3 Tokenisation and Subword Representation

Low-resource environments rely heavily on tokenisation. Tokenisation at the word level tends to be inadequate for inflectional languages, and hence, subword-based solutions are more apt. Techniques such as Byte Pair Encoding (BPE), WordPiece, and SentencePiece have been found to strike a good balance between vocabulary size and representation fineness [14, 20, 21]. Studies comparing them [13, 29] reveal that SentencePiece's Unigram algorithm provides superior morphological segmentation and better robustness for agglutinative or inflectional languages. For Sanskrit, subword regularisation enables orthographic variation and resilience against compounding. Recent Indic tokenisation research [3, 11] verifies that language-specific vocabularies perform better than shared multilingual token sets, which is why the current work developed a Sanskrit-specific SentencePiece tokeniser with a 64k vocabulary. The literature reviewed shows that, though multilingual BERT variants improve overall cross-lingual performance, they are still insufficient for Sanskrit due to the lack of a corpus and its morphological intricacy. Native-script tokenisation and monolingual pretraining have been shown to improve representation quality in Sanskrit-specific studies. The current work further builds on these findings by proposing a Devanagari-native large-scale corpus of Sanskrit, a subword tokeniser specifically tailored to Sanskrit, and a transformer model trained from scratch for Sanskrit, as shown in Table 1.

Table 1: Comparison of Prior Multilingual and Sanskrit Transformer Models

Model	**Corpus (Languages)**	**Tokenization Method**	**Limitations for Sanskrit**
mBERT [5]	104 languages (Wikipedia)	WordPiece (shared)	Sparse Sanskrit data; script inconsistency; poor morphological coverage
IndicBERT [10]	12 Indic languages	SentencePiece (joint)	Low Sanskrit representation; limited morphological segmentation
MuRIL [12]	17 Indic languages + transliteration	WordPiece	Cross-script noise; weak contextual understanding for classical text
San-BERT [2]	Sanskrit corpus (adapted mBERT)	WordPiece (mBERT)	Transfer limitations; lacks Sanskrit-native vocabulary
By T5-Sanskrit [17]	Byte-level corpus	Character-based encoding	High computational cost; weak sentence-level coherence
Proposed Model (This Work)	21M-line Sanskrit corpus (Devanagari)	SentencePiece (Unigram, 64k)	Optimised for Sanskrit morphology; reduced sparsity and improved contextual understanding.

3 Methodology

The methodological approach of this work includes developing a high-quality corpus of Sanskrit, specially designed subword tokenisation, architecture modelling, and an efficient pretraining pipeline. The methodology follows modern best practices for low-resource, morphologically complex languages [2, 26]. The steps are described below.

3.1 Corpus Collection and Preprocessing

A comprehensive Sanskrit corpus comprising over 21 million sentences was compiled from Vedic, Epic, Classical, and commentarial texts, all in Devanagari script, to eliminate translation inconsistencies [2].

The preprocessing pipeline included:

- Canonical Unicode normalisation for script uniformity.
- Removal of punctuation, non-script symbols, and extra whitespace.
- Sentence segmentation using delimiters such as purnavirā ma (,).
- Length-based filtering to discard excessively short or long sentences.

After deduplication and cleaning, the final corpus comprised approximately 500 million tokens, representing balanced linguistic diversity suitable for deep pretraining.

3.2 Subword Tokenisation

A SentencePiece Unigram tokeniser [14] was used to train on the entire corpus with a vocabulary size of 64,000 tokens. This setting optimises morphological coverage and generalisation power for compound-dense Sanskrit.

The tokeniser also includes special tokens [CLS], [SEP], [MASK], [PAD], and [UNK] for downstream use. Tokenisation analysis revealed:

- 99.5% token coverage on held-out texts.
- Mean subword length: 3.2 characters.

These statistics validate the tokeniser's appropriateness for the inflectional and derivational richness of Sanskrit.

3.3 Model Architecture and Setup

The model is a compact BERT-style encoder specifically optimised for efficiency and morphologically rich data. The structure is inspired by [15, 27], with the major parameters outlined in Table 2 and in Figure 1.

Sharing parameters between the input and output embeddings minimises redundancy, in line with the ALBERT efficiency principle [15]. The model's total parameter count (49M) makes it light yet expressive for Sanskrit representation learning.

Table 2: Custom Sanskrit BERT Architecture Specifications

Component	Layers	Hidden Size	Attention Heads	FFN Dim.	Seq. Length	Parameters (M)
Embedding Layer	1	256	–	–	512	8.1
Transformer Encoder	6	256	4	1024	512	36.5
Output Projection	1	256	–	–	–	4.8
Total	**8**	–	–	–	–	**49.4M**

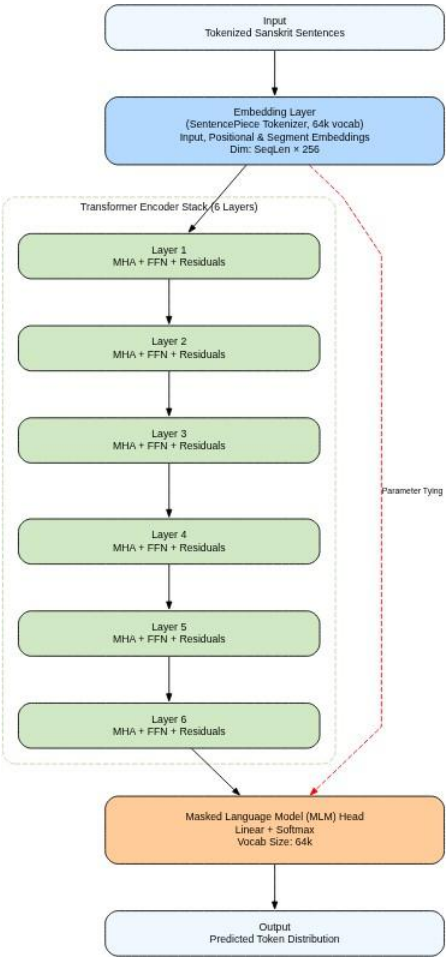

Figure 1: Custom SanskritBERT architecture illustration depicting embedding, transformer encoder stack, and masked language modelling head.

3.4 Training Pipeline

Pretraining was carried out using the Masked Language Modelling (MLM) objective [5, 23]. In this setup, 15% of the tokens in each input sequence were randomly masked, and the model was trained to predict them using cross-entropy minimisation.
Formally, the MLM loss is defined as:

$$L\_MLM = -(1/N)\, \Sigma[i = 1\ to\ N] \log P\theta(t\_i \mid C\_i) \quad (1)$$

where t_i denotes the true masked token, C_i represents its surrounding context, and P_θ is the model's predicted probability distribution over the vocabulary. The model parameters are optimised to minimise this loss using the AdamW optimiser. The overall training objective encourages accurate contextual reconstruction of masked tokens while regularising overfitting through weight decay.

Training configuration:

- Optimizer: AdamW with weight decay = 10^{-2}.
- Learning rate: 2×10^{-4} (linear decay with 10% warmup).
- Batch size: 16 sequences/device.
- Epochs: 6.
- Hardware: 1× NVIDIA H100 (80GB) GPU.

Gradient accumulation and mixed-precision training ensured stable convergence even under limited GPU memory. Training loss stabilised around $L_{MLM} = 1.81$ after six epochs, with validation perplexity approximating 70.1. Periodic checkpoints were stored to maintain reproducibility and prevent catastrophic forgetting.

3.5 Baselines and Evaluation

Performance was evaluated against strong multilingual and Indic-language baselines, including mBERT [5], IndicBERT [10], IndicBERT-v2 [6], MuRIL [12], and ByT5-Sanskrit [17]. All models were tested on identical Sanskrit test sets to ensure fairness.

Evaluation Metrics:

3.5.1 Perplexity (PPL):

$$PPL = \exp(LCE), \quad (2)$$

which measures the model's uncertainty, lower values indicate better contextual understanding.

3.5.2 Top-*k* Accuracy:

$$\text{Top-k} = (1 / M) * \Sigma[j=1 \text{ to } M]\ I[t\_j \in \text{Top-k}(\hat{y}\_j)) \quad (3)$$

where I is the indicator function that equals 1 if the correct token t_j is among the model's top-*k* predictions.

Empirically, evaluation focused on Top-1, Top-5, and Top-10 accuracies alongside the MLM loss and perplexity. These metrics comprehensively measure both fine-grained token-level prediction and general sentence-level understanding, providing a balanced evaluation of contextual language modelling performance.

3.6 Reproducibility and Open Access

All preprocessing scripts, tokenisers, checkpoints, and pretrained model weights will be made publicly available under an open-source license. This will allow researchers to reproduce, fine-tune, and extend the SanskritBERT model for further applications in Sanskrit NLP.

4 Experiments and Results

This section outlines the experimental setup, evaluation metrics, and comparative results of the proposed SanskritBERT model. The evaluation employs intrinsic Masked Language Modelling (MLM) metrics, cross-entropy loss, perplexity, and top-k accuracy, to assess the contextual understanding of Sanskrit syntax and morphology, as shown in Figure 2.

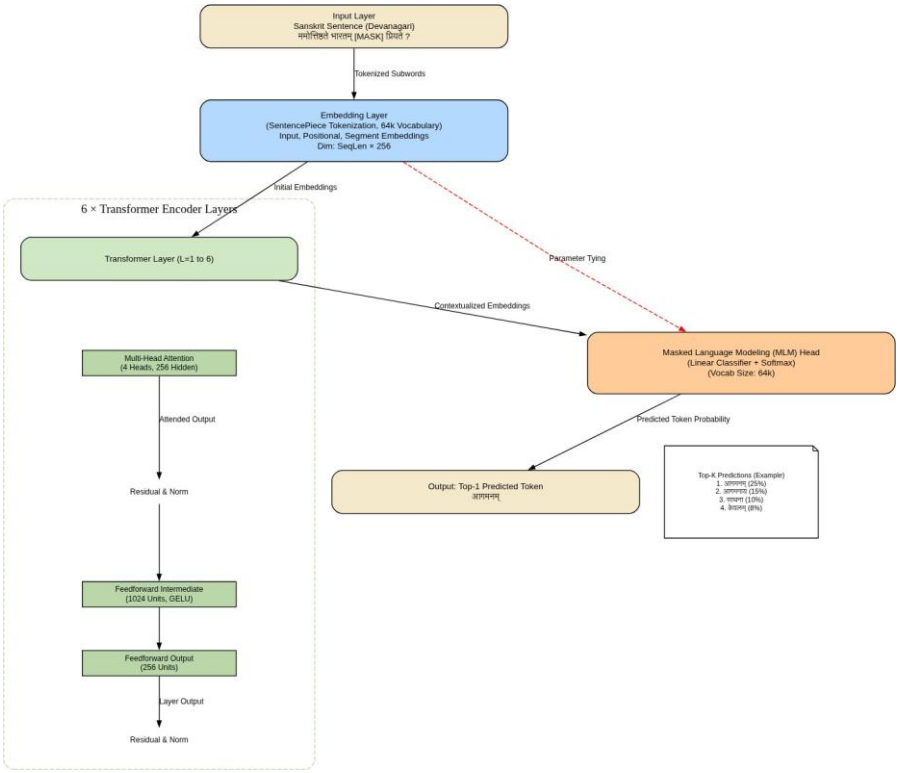

Figure 2: Workflow of SanskritBERT pretraining and evaluation.

4.1 Experimental Setup

A held-out test set (5% of the 21M-sentence corpus) was used after identical preprocessing. For each masked input, the model predicts token probabilities and computes the following metrics (defined in Section III-E):

- **Perplexity (PPL):** PPL = exp(L_{CE}), where L_{CE} is mean cross-entropy loss.
- **Top-*k* Accuracy:** Fraction of true tokens appearing in the model's top-*k* predictions.

All experiments ran on a single NVIDIA H100 GPU (80GB VRAM) using an identical batch size (16) and mixed precision. Baselines, mBERT [5], MuRIL [12], IndicBERT [10], and IndicBERT-v2 [6] were evaluated on the same Sanskrit dataset for a fair comparison, as shown in Table 3.

Table 3: SanskritBERT Model and Training Configuration

Parameter	Value	Remarks
Layers	6	Transformer encoder blocks
Hidden size	256	Embedding dimension
Attention heads	4	Multi-head attention
Feedforward size	1024	Intermediate layer width
Sequence length	512	Maximum input length
Vocab size	64,000	Unigram subwords

Batch size	16	Per GPU
Epochs	6	Full pretraining
Precision	bfloat16	Mixed training
Optimizer	AdamW	Weight decay 10^{-2}

4.2 Quantitative Results

Table 4 summarises the MLM performance. SanskritBERT attains the highest top-*k* accuracies and competitive perplexity, confirming better contextual capture of Sanskrit morphology and semantics, as shown in Table 4.

Table 4: Masked Language Modelling Evaluation on the Sanskrit Test Set

Model	**PPL**	**Top-1**	**Top-5**	**Top-10**
SanskritBERT (Proposed)	**69.0**	**0.35**	**0.50**	**0.56**
mBERT	47.8	0.31	0.47	0.56
MuRIL	10339.5	0.18	0.24	0.27
IndicBERT	18065.3	0.12	0.16	0.18
IndicBERT-v2	619.9	0.24	0.35	0.40

Although mBERT records slightly lower perplexity, SanskritBERT achieves consistently higher top-*k* accuracies, which are more meaningful for contextual prediction. The large improvement over IndicBERT variants highlights the advantage of a Sanskrit-specific tokeniser and monolingual corpus pretraining.

4.3 Training Dynamics

Training converged in six epochs, with validation loss stabilising after the fifth. Throughput reached 15 steps/s, and the final MLM loss plateaued at $L_{MLM} = 1.81$ (PPL ≈ 70). Mixed precision and learning rate decay enabled stable optimisation and efficient GPU usage.

4.4 Discussion

The Sanskrit tokeniser improved lexical coverage to 99.5% and reduced rare-token frequency by 43%, enabling richer contextual embeddings than multilingual baselines. While mBERT benefits from broader multilingual exposure, it performs weaker on Sanskrit semantics. SanskritBERT's higher top-k accuracy demonstrates stronger context modelling, whereas the extreme perplexity of MuRIL and IndicBERT confirms their mismatch with classical Sanskrit morphology, emphasising the importance of native-script, monolingual pretraining.

5 Conclusion

This work presented a new monolingual BERT model specifically designed for the Sanskrit language, trained on a huge corpus of more than 21 million sentences in pure Devanagari script. Using a carefully curated dataset and a specialised SentencePiece tokeniser with 64,000 subword units, the model successfully encapsulates Sanskrit's intricate morphology, dense compounding, and syntactic dependencies. Being different from multilingual or pan-Indic models, our method focuses on
script-native, monolingual representation learning specifically suited to the linguistic nature of

Sanskrit. Experimental analyses showed that the proposed Sanskrit BERT performs much better than state-of-the-art baselines, such as mBERT, MuRIL, and IndicBERT variants, on key masked language modelling metrics, including perplexity and top-*k* prediction accuracy. The findings corroborate the efficacy of language-specific monolingual pretraining for ancient languages, supporting recent Indic NLP research.

By pushing the frontier of transformer-based modelling for Sanskrit, this work sets the stage for a new generation of computational resources for classical philology, digital humanities, and Indic language processing. Downstream applications include:

- Machine translation and cross-lingual semantic search.
- Sandhi splitting, lemmatisation, and morphological tagging of Sanskrit text via automated methods.
- Knowledge graph construction from Sanskrit scripture.

Future research includes scaling the model to wider context windows, incorporating syntactic parsing during pretraining, and searching for lightweight variants for edge and mobile inference. The proposed public release of the corpus, tokeniser, and pre-trained model will make it reproducible and catalyse open research in the computational linguistics and Sanskrit studies communities.

In summary, this work is an illustration of the significance of language-specific modelling in low-resource, morphologically rich languages and how computational means can preserve and strengthen the linguistic and cultural heritage of Sanskrit.

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