IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

BOUNDARY-AWARE EVALUATION FOR TAMIL EXTRACTIVE QUESTION ANSWERING USING MULTILINGUAL TRANSFORMERS

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Abstract: Extractive Question Answering (QA) systems have been highly developed in resource-rich languages like English mainly thanks to the existence of big annotated datasets and well-established evaluation frameworks. Nevertheless, there is still a lack of investigation on the evaluation of morphologically rich language such as Tamil. Conventional QA evaluation measures, EM and token-level F1 score, are mostly used, which are not able to measure the boundary-level prediction behaviour especially when the answer involves the inflectional suffix or compound expressions.

This paper proposes a boundary-aware evaluation framework for Tamil extractive question answering for a detailed understanding of span prediction tendencies. The proposed framework assesses the performance of several Multilingual transformer models for Tamil: Tamil-BERT, MuRIL, XLM-RoBERTa, and IndicBERT on a Tamil QA dataset represented in a SQuAD-similar format. Besides the conventional EM and F1 measures, the paper reports extended evaluation measures: Strict EM, Relaxed EM, Span Calibration Accuracy (SCA), Character F1, Character Overlap and Average Length Deviation. Errors in structure prediction are divided into expansion, truncation and wrong-region errors. Performance differences are statistically validated through two-proportion Z-test and confidence intervals. The experimental results indicate that span calibration behavior of the multilingual transformer models differs, while they are fairly close based on EM/F1 scores.

Index Terms - Tamil Question Answering, Extractive Question Answering, Multilingual Transformers, Span Boundary Detection, Boundary-Aware Evaluation, Morphologically Rich Languages, Natural Language Processing.

I. INTRODUCTION

Extractive Question Answering (QA) is a fundamental problem in Natural Language Processing (NLP), where given a context paragraph and a question, the goal is to locate the relevant span of text in the context that answers the question. Recent transformer-based language models have led to a large jump in QA performance on a number of benchmarks. Pre-trained models like BERT and other multilingual transformers understand the contextual associations between questions and passages which helps in the precise answer span prediction. Yet, the majority of QA research has been in resource-rich languages, notably English, facilitated by the existence of extensive, manually annotated datasets and robust evaluation methodologies.

Conventional evaluation standards like EM (Exact Match) and token F1 have grown to be the leading evaluation methodologies for extractive QA systems on the SQuAD benchmark. However, the assessment of QA systems for morphologically rich languages like Tamil is still difficult. Tamil is agglutinative — a Dravidian language that encodes grammatical features by suffixing them to the stem. Therefore, answer spans can be realized in different surface forms according to inflectional or syntactic differences. Such morphological features complicate the precise span boundary recognition relative to languages with a more simple morphology. Consequently, models that have similar EM and F1 scores can display significantly different behaviors in span calibration.

To tackle this issue, this research introduces a boundary-aware evaluation framework specifically for Tamil extractive question answering. This framework assesses various multilingual transformer models — XLM-RoBERTa, Tamil-BERT, MuRIL, and IndicBERT — using a Tamil QA dataset formatted in a SQuAD-style manner. Alongside conventional evaluation metrics, the framework incorporates boundary-sensitive measures: Strict Exact Match, Relaxed Exact Match, Span Calibration Accuracy (SCA), Character-level F1, Character Overlap, and Average Length Deviation. The study also conducts structural error analysis and statistical significance testing using two-proportion Z-tests.

II. LITERATURE SURVEY

Recent developments in transformer-based architectures have greatly enhanced the effectiveness of extractive question answering systems. Numerous studies have concentrated on refining answer span localization through improved contextual modeling and boundary detection techniques. Methods that focus on context-aware span selection and boundary-aware modeling have been suggested to boost the accuracy of answer span predictions in reading comprehension tasks [1]–[3].

Additionally, multilingual and cross-lingual question answering has garnered more attention, especially concerning low-resource languages. Previous research has investigated the application of multilingual transformer models to facilitate question answering in Indic and other less-represented languages [5]–[8]. These studies indicate that multilingual pretraining can enhance contextual comprehension across different languages while allowing for transfer learning in low-resource scenarios.

Another area of research aims to enhance evaluation methodologies for extractive QA systems. Conventional metrics like Exact Match and token-level F1 are commonly utilized but may not adequately reflect subtle boundary variations in predicted spans. Recent studies have proposed refined evaluation strategies and boundary-aware analysis methods to better understand span prediction behavior [13], [14], [21]. Despite these advancements, evaluation frameworks specifically crafted for morphologically rich languages such as Tamil are still scarce, which the current work addresses.

III. PROPOSED SYSTEM

The proposed system is an extractive QA model tailored for Tamil questions, leveraging transformer-driven comprehension. Rather than depending only on pretrained language understanding tools, this method pairs retrieved documents with deep reading mechanisms to boost precision. The design operates efficiently without massive vector stores, pulling key parts from an organized collection and using a transformer-driven reader to pinpoint responses. The approach handles everyday language questions efficiently while tying each response closely to source material, combining document retrieval with deep reading steps for stronger fact alignment.

IV. SYSTEM ARCHITECTURE OVERVIEW

The suggested system operates as follows. Starting at the front, raw inputs go through several steps before results appear. First, each Tamil question is paired with its related paragraph. These pairs split into smaller pieces so machines can handle them easily. When text runs long, overlapping chunks step in to catch every possible answer section. At the core, transformers turn words into rich meaning vectors. From there, likely answer segments emerge based on learned patterns. Finally, precision adjusts around predicted edges using a custom scoring method.

Starting with encoded tokens, a multilingual transformer encoder turns them into contextual embeddings. These representations feed into a span predictor that locates where an answer begins and ends. From there, the system checks the proposed span against standard question-answering benchmarks along with specialized metrics sensitive to boundary precision.

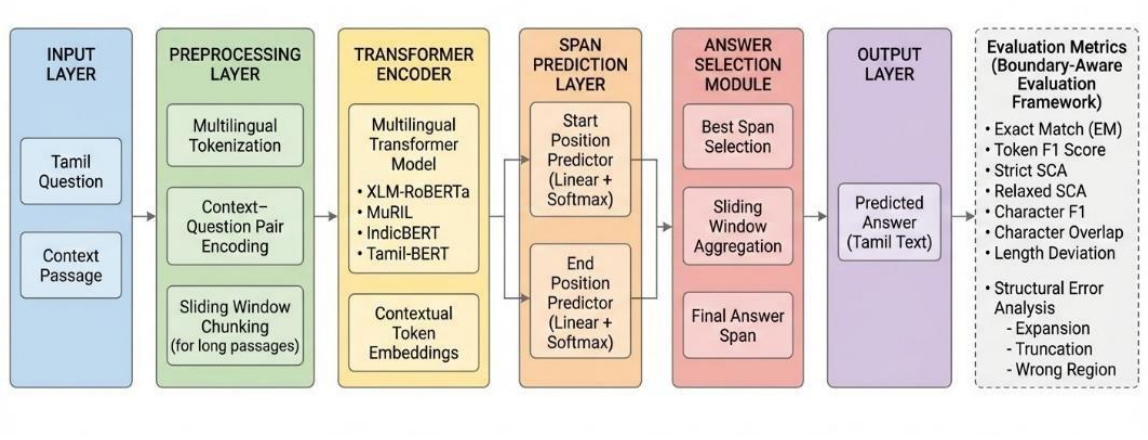


Fig. 1: Architecture of the proposed boundary-aware extractive question answering evaluation framework.

V. TRANSFORMER ENCODER

Starting with token processing, the transformer encoder builds meaning-aware embeddings for each element in the input. Because they track connections across distant parts of a sentence, transformer-driven systems grasp how questions relate to background text — key for pinpointing answer spans. Four multilingual setups entered testing here: XLM-RoBERTa, MuRIL, IndicBERT, and Tamil-BERT. Having learned from vast collections of global language data through word-masking exercises, these frameworks later adapted specifically to pull answers from passages.

Notably, XLM-RoBERTa delivers robust understanding across diverse languages. Built for Indian languages, MuRIL uses cross-lingual cues to boost results in local language applications. IndicBERT learns from varied Indian texts to deliver context-aware word meanings in multiple tongues. Tamil-BERT focuses only on Tamil, shaped entirely by native text to reflect its distinct grammar and usage. Once input arrives, the transformer encoder handles split pieces of question and context together, generating rich meaning vectors per unit. From those vectors, the system pinpoints where answers begin and end through a dedicated span detection step.

VI. SPAN PREDICTION LAYER

Starting at the output stage, the system pinpoints where an answer begins and finishes inside the given text. Once the transformer processes both question and context, representations emerge that capture how meaning connects across them. From these, likelihoods are assigned per token — marking potential beginning or ending points of the correct span. Two separate output layers estimate likelihoods for where an answer begins and ends across each token. Though derived independently, these predictions combine when choosing a beginning-end token set:

$$(i^*, j^*) = \arg\max \; P\_start(i) \cdot P\_end(j), \quad \text{subject to } i \leq j$$

where P_start(i) and P_end(j) represent the predicted probabilities of tokens i and j being the start and end positions of the answer span, respectively. The tokens between i* and j* are extracted from the context as the final predicted answer.

VII. BOUNDARY-AWARE EVALUATION FRAMEWORK

Lexical similarity forms the basis of standard assessment tools in extractive question answering. Although helpful for gauging correctness, such methods often overlook small shifts in answer span limits. In languages like Tamil — where word endings frequently change form — these minor displacements matter less semantically yet still impact scores unfairly. Instead of relying solely on classic benchmarks, this work brings in supplementary techniques that pay closer attention to span edges.

A. Exact Match (EM)

Exact Match measures whether the predicted answer span exactly matches the ground-truth answer span:

$$EM = 1 \text{ if } A\_p = A\_g, \text{ else } 0$$

where A_p denotes the predicted answer span and A_g represents the ground-truth answer span. Although Exact Match provides a strict evaluation criterion, it fails to reward partially correct predictions where the predicted span overlaps with the ground truth but differs slightly in boundaries.

B. Token-Level F1 Score

Token-level F1 evaluates the overlap between predicted and ground-truth tokens by combining precision and recall:

$$F1 = (2 \times \text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$$

where precision represents the fraction of predicted tokens that appear in the ground truth, and recall represents the fraction of ground-truth tokens that are correctly predicted.

C. Strict Semantic Containment Accuracy (Strict SCA)

Strict Semantic Containment Accuracy evaluates whether the predicted span is fully contained within the ground-truth span or vice versa, capturing cases where minor boundary deviations still preserve the correct semantic content:

$$SCA_{strict} = 1 \text{ if } A_p \subseteq A_g \text{ or } A_g \subseteq A_p, \text{ else } 0$$

D. Structural Error Classification

One way to study how models make predictions is by sorting mistakes into three kinds based on structure. When a forecast stretches beyond the right answer, grabbing extra words nearby, that is called an expansion error. If the output falls short, missing key parts of the true span, it becomes a truncation mistake. Another type happens when the system pulls text from the wrong section entirely — no match at all — which counts as a wrong-region case.

E. Additional Boundary-Aware Metrics

Relaxed SCA picks up cases where parts of a predicted span touch the correct answer, allowing some overlap. Character-level F1 checks how closely individual characters align between what was predicted and what is expected. Character Overlap Ratio calculates how much shared content exists across spans by counting common letters. Average Length Deviation shows whether model outputs tend to run longer or fall short compared to true spans, highlighting consistent shifts in boundary placement.

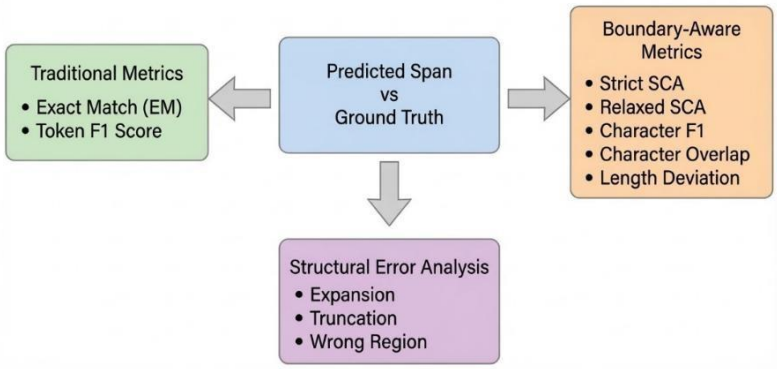


Fig. 2: Boundary-aware evaluation framework used to analyze answer span predictions.

VIII. EXPERIMENTAL SETUP

A. Tamil QA Dataset

Running tests involved a Tamil extractive QA set modeled on SQuAD's layout. Within every entry sits a background paragraph, a query in Tamil, followed by the exact answer drawn from that text. Holding close to 390 entries, it marks correct responses clearly — both the phrase and where it begins in characters. Content came from Tamil Wikipedia pages along with school-level learning material across diverse real-world themes. Structured similarly to SQuAD, the collection includes context, question, answer text, starting index of the answer, along with a reference tag. Because of this layout, integration into transformer-driven question-answering frameworks happened without structural adjustments.

B. Models Evaluated

Four transformer models were selected for evaluation. XLM-RoBERTa stands out due to broad training across many languages. Tamil-BERT focuses only on Tamil data, sharpening sensitivity to Tamil structure. MuRIL and IndicBERT target Indian language families through tailored pretraining, leaning into regional variation rather than global scale. Each system adapted during testing by adjusting weights for question-answering tasks, locating spans using start-end markers within passages. Fine-tuning shaped their responses without altering core pretrained knowledge.

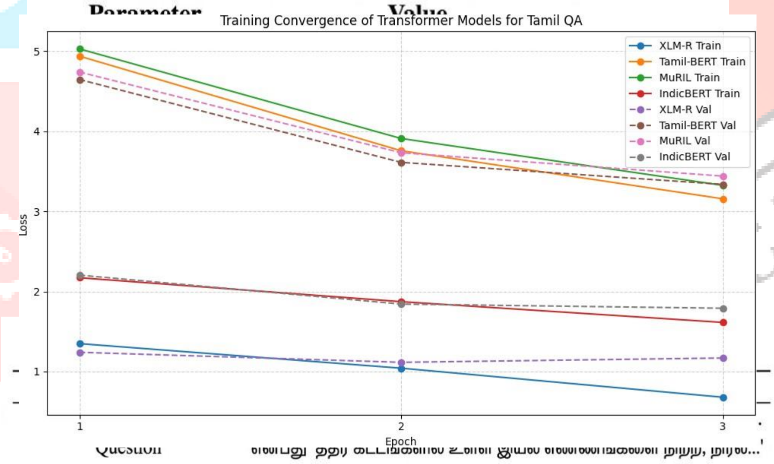
C. Training Configuration

Fine-tuning took place within Google Colab's GPU setup, leveraging the HuggingFace Transformers library. Each context-question combination was transformed through dedicated tokenizers into unified sequences. The tables below show the hyperparameter settings used across models. Prediction relied on cross-entropy loss, aiming at pinpointing both start and stop tokens for answers simultaneously.

Table 5: Training and Validation Loss Comparison Across Models

Model	Epoch	Training Loss	Validation Loss
XLM-RoBERTa	1	1.3489	1.2406
	2	1.0421	1.1153
	3	0.6793	1.1692
Tamil-BERT	1	4.9394	4.6474
	2	3.7574	3.6124
	3	3.1573	3.3375
MuRIL	1	5.0299	4.7410
	2	3.9108	3.7325
	3	3.3251	3.4408
IndicBERT	1	2.1718	2.2045
	2	1.8728	1.8427
	3	1.6136	1.7906

Table 3: Hyperparameter Configurations for Input Preprocessing



Parameter	Value
Question	[illegible]
Answer Text	மாயச் சதுரம்
Answer Start	82
Source	XQA_DEV

Table 4: Training Parameters and Hyperconfigurations

Parameter	Value
Framework	HuggingFace Transformers
Training Environment	Google Colab GPU
Optimizer	AdamW
Learning Rate	3×10^{-5}
Batch Size	16
Training Epochs	3
Maximum Sequence Length	384
Sliding Window Stride	128
Loss Function	Cross-Entropy Loss
Task Formulation	Start and End Token Prediction

Fig. 3: Training convergence curves illustrating training and validation loss across epochs for the evaluated multilingual transformer models.

D. Evaluation Protocol

Evaluation of model performance combined conventional extractive QA measures with the boundary-sensitive methods outlined in Section VII. While EM and Token-level F1 formed the core of standard assessment, techniques like Strict SCA and its relaxed variant measured how well predictions contained correct meanings. Character-level F1 tracked fine-grained similarity down to individual letters. Character Overlap Ratio revealed proportional alignment at the character string level. Average Length Deviation exposed systematic shifts in output span size compared to reference answers. Alongside numerical assessment, researchers examined structural mistakes by expansion, truncation, or misplaced region patterns.

E. Statistical Significance Testing

A closer look at model performance used pairwise tests to check if gaps in accuracy matter much. Starting from Exact Match scores, each comparison relied on a two-proportion Z-test. This method judges if observed splits in results likely reflect real ability gaps rather than chance:

$$Z = (p1 - p2) / \sqrt{[\ p(1-p)(1/n1 + 1/n2)\ ]}$$

where p1 and p2 denote the Exact Match proportions for two models, n1 and n2 represent the number of evaluation samples, and p is the pooled proportion. To account for multiple pairwise comparisons, Bonferroni correction was applied to control the family-wise error rate.

IX. RESULTS AND DISCUSSION

This part shares findings from testing four multilingual transformer systems on a Tamil extractive question answering challenge. Performance is examined through three lenses: general accuracy, metrics sensitive to answer boundaries, and recurring structural mistakes. Multiple trials were conducted per model to confirm reliability.

Table 6: Performance Comparison of Transformer Models on Tamil QA

Model	S-EM	R-EM	T-F1	C-F1	C-O	S-SCA	R-SCA
XLM-R	34.62	79.23	42.85	39.41	61.83	35.38	47.95
Tamil-BERT	30.26	73.85	41.92	39.21	72.85	33.08	55.90
MuRIL	27.95	71.03	39.36	39.19	65.87	30.77	45.90
IndicBERT	7.95	74.36	14.48	18.57	40.14	10.51	25.64

Note: S-EM: Strict EM, R-EM: Relaxed EM, T-F1: Token F1, C-F1: Char F1, C-O: Char Overlap, S-SCA: Strict SCA, R-SCA: Relaxed SCA.

Despite varying architectures, outcomes differ noticeably among tested systems. Leading the group, XLM-RoBERTa posts top numbers — its Exact Match lands at 34.62%, alongside a Token F1 of 42.85%. Close behind, Tamil-BERT shows promise, especially where character alignment matters: it hits 72.85% on Character Overlap, plus 55.90% on relaxed scoring. In contrast, MuRIL manages only mid-tier results. Meanwhile, IndicBERT trails far behind, struggling most to pinpoint correct answer segments in Tamil texts.

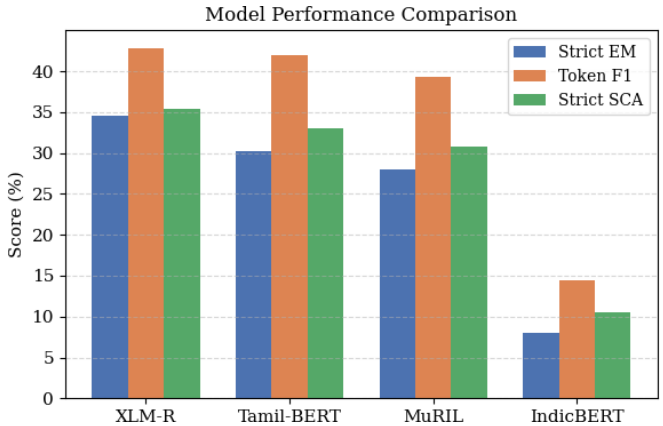


Fig. 4: Performance comparison of multilingual transformer models across Exact Match, Token F1, and Strict SCA metrics.

Performance is compared in Figure 4 using Exact Match, Token F1, and Strict SCA. With top rankings often held by XLM-R, its edge in span detection stands out. Though not leading overall, Tamil-BERT handles tokens well. Results sit mid-range for MuRIL regardless of measure used. Where answers must be precisely located in Tamil texts, IndicBERT struggles — its weaker outcomes point to clear constraints.

A. Boundary-Aware Metric Analysis

Looking closer at how answers align by their edges reveals more than just counting matching tokens. Different models behave uniquely when measured through Character F1, Character Overlap, Relaxed SCA, and Length Deviation. While Tamil-BERT leads in both character overlap and Relaxed SCA, its strength lies in capturing the core meaning — even if spans stretch a bit past exact limits. XLM-RoBERTa spreads its accuracy more evenly across these criteria, showing tighter alignment between locating relevant content and marking accurate start-end points. MuRIL manages a middle ground, while IndicBERT trails far behind on each of these span-based criteria.

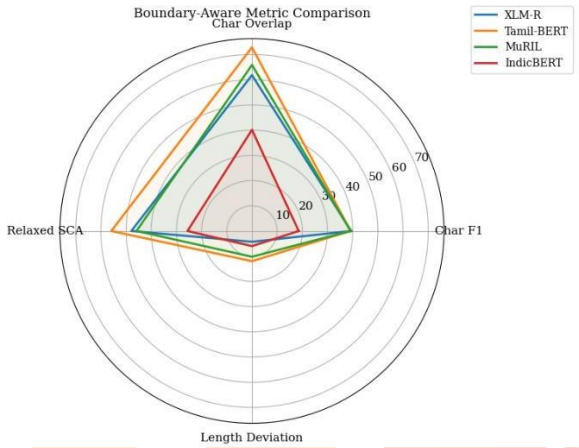


Fig. 5: Comparison of boundary-aware evaluation metrics across models.

These findings emphasize why boundary-sensitive metrics matter when assessing span predictions. Although standard approaches like Exact Match and Token F1 reflect general correctness, newer methods focused on edges show how models differ — some prioritize exact limits, others favor including the right content within looser bounds.

B. Structural Error Analysis

Looking closer at how models perform, mistakes fell into three groups — expansion, truncation, and wrong-region. Most common by far: guesses landing in entirely incorrect parts of the text, especially with IndicBERT. Tamil-BERT expands most aggressively — its outputs frequently stretch into neighboring tokens. Despite weaker edge accuracy, such stretches typically keep the true answer within range. XLM-RoBERTa spreads mistakes more evenly; it commits fewer wide misses and locates spans with greater consistency. Moderate in every category, MuRIL sits midway between the others.

Table 7: Structural Error Analysis of Model Predictions (%)

Model	EM %	Exp. %	Trun. %	W. Reg. %
XLM-R	35.38	12.56	7.69	44.36
Tamil-BERT	33.08	22.82	6.15	37.95
MuRIL	30.77	15.13	6.92	47.18
IndicBERT	10.51	15.13	1.28	73.08

Note: EM: Exact Match, Exp.: Expansion, Trun.: Truncation, W. Reg.: Wrong Region.

Table 8: Semantic Containment vs Boundary Calibration Trade-off

Indicator	XLM-R	Tamil-BERT	MuRIL	IndicBERT
Strong Boundary Precision	**Yes**	No	No	No
High Expansion Bias	No	**Yes**	Moderate	Moderate
Best Semantic Localization	Moderate	**Yes**	Moderate	Weak
Region Localization Failure	Moderate	Low	Moderate	**High**

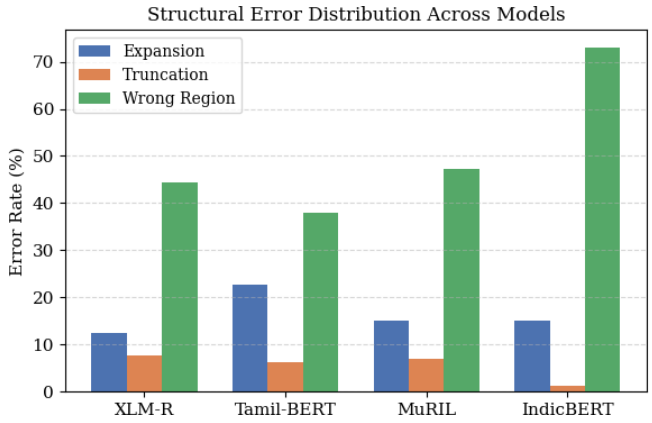


Fig. 6: Distribution of structural prediction errors across transformer models.

Examining structural mistakes reveals a key tension: sharp boundaries often come at the cost of meaning preservation in multilingual transformers. Because of this, assessing spans through boundary-sensitive measures proves especially useful when studying languages like Tamil, where word forms carry heavy grammatical weight.

C. Statistical Significance Analysis

To check if model performance gaps matter, statistical tests were applied using the two-proportion Z-test on Exact Match scores. Outcomes show XLM-RoBERTa does better than MuRIL and IndicBERT by a clear margin. When measured against Tamil-BERT, XLM-R still holds an edge that counts under standard thresholds.

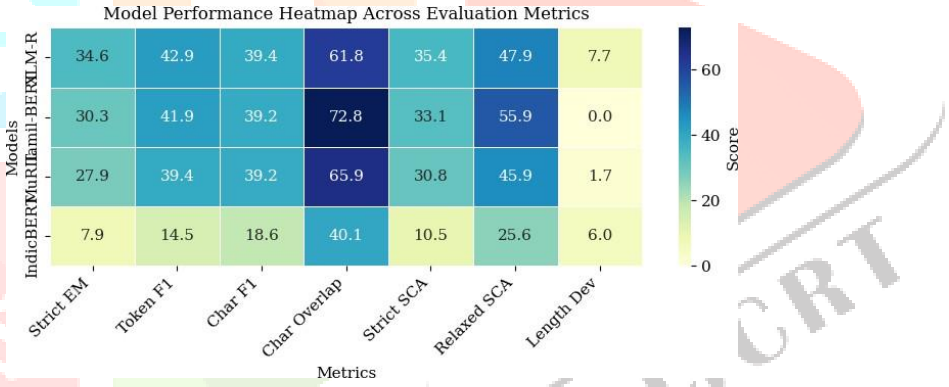


Fig. 7: Heatmap visualization summarizing model performance across evaluation metrics. Darker colors indicate higher metric values, while lower length deviation reflects better span boundary calibration.

TABLE 9: PAIRWISE Z-TEST RESULTS FOR EXACT MATCH COMPARISON

Table 9: Statistical Significance Testing (Z-test) for Model Comparison

Comparison	Z-statistic	p-value	Significant ($\alpha = 0.05$)
XLM-R vs. MuRIL	2.91	0.0036	Yes
XLM-R vs. IndicBERT	9.23	¡0.001	Yes
XLM-R vs. Tamil-BERT	2.68	0.0073	Yes

TABLE 10: PERFORMANCE IMPROVEMENTS UNDER BONFERRONI-CORRECTED SIGNIFICANCE THRESHOLD

Table 10: Bonferroni-Corrected Significance

Comparison	p-value	Significant (Bonferroni α')
XLM-R vs. MuRIL	0.0036	Yes
XLM-R vs. IndicBERT	¡ 0.001	Yes
XLM-R vs. Tamil-BERT	0.0073	Yes

To control for multiple comparisons, Bonferroni correction was applied. As shown in Table 10, the performance improvements of XLM-R remain statistically significant under the corrected significance threshold. Despite similar overall trends, XLM-R outperforms others consistently in statistical tests.

TABLE 11: EXAMINATION OF INCORRECT REGION PREDICTIONS ACROSS MODELS

Table 11: Statistical comparison of wrong-region prediction rates across models

Comparison	Z-Statistic	p-value	Significant ($\alpha = 0.05$)	Significant (Bonferroni $\alpha' \approx 0.0167$)
XLM-R vs. Tamil-BERT	-1.4177	0.1570	No	No
XLM-R vs. MuRIL	-1.3642	0.1726	No	No
XLM-R vs. IndicBERT	-4.0380	5.82×10^{-5}	Yes	Yes

Notably, IndicBERT makes far more localization mistakes than XLM-R, a gap confirmed by significance testing. On the other hand, when comparing XLM-R to Tamil-BERT and MuRIL, observed gaps disappear after adjusting for multiple comparisons. Statistical thresholds prevent strong conclusions about those pairs.

D. Qualitative Analysis of Model Predictions

Looking more closely at how models behave, researchers used example questions and answers from the Tamil QA set to carry out a descriptive review. These cases reveal recurring ways models respond when answering. Well-defined answer segments often come from XLM-R, showing it grasps context quite effectively despite occasional boundary shifts. Tamil-BERT occasionally delivers predictions covering the right content yet spills slightly past the exact limits. MuRIL pinpoints useful sections fairly well, though small edge shifts appear now and then. Unlike other models, IndicBERT often misplaces the right answer segment.

TABLE 12: QUALITATIVE COMPARISON OF MODEL PREDICTIONS ON SAMPLE TAMIL QA INSTANCES

Table 12: Model Prediction Comparison (Tamil Dataset)

Question (Tamil)	Gold Answer	XLM-R	Tamil-BERT	MuRIL	IndicBERT
எந்த ஆண்டு செயர்பஸ் ஐரோப்பிய ஒன்றியத்தில் சேர்ந்தது?	2004	2004 ஆம் ஆண்டு...	1 மே 2004	1 மே 2004	2004
தேவாரத் திருப்பதிகளில் பாடப்பட்டுள்ள 276.	தேவாரத் திருத்தலங்கள்	தேவாரத் திருத்தலங்கள்	தேவாரத் திருத்தலங்கள்	தேவாரத் திருத்தலங்கள்	—
உற்சாகமில்லாத கதாபாத்திரங்களை யார் தேர்ந்தெடுத்தார்கள்?	மங்கோலியர்கள்...	மங்கோலியர்கள்...	மங்கோலியர்கள்...	மங்கோலியர்கள்...	—
தமிழ்நாட்டின் பழைய பெயர் என்ன?	சென்னை மாகாணம்	—	சென்னை மாகாணம்	மெட்ராஸ் ஸ்டேட்	சென்னை மாகாணம்
பெரிய இடங்கள் சில முக்கிய மல்யுத்த நிகழ்ச்சிகள் எங்கே நடத்தப்படுகின்றன?	மேடிசன் ஸ்கொயர் கார்டன்...	கால்பந்து மைதானங்கள்	மேடிசன் ஸ்கொயர் கார்டன்...	கால்பந்து மைதானங்கள்	—

X. CONCLUSION

This research focuses on boundaries when evaluating Tamil question answering systems built with multilingual transformers. Though common measures like Exact Match and Token F1 show how close predictions are, they miss nuances tied to where answer spans begin or end — especially in complex forms found in Tamil. The proposed framework adds finer tools: Strict SCA, Relaxed SCA, character-based F1, overlap ratios between predicted and true answers, plus average shifts in length. These join deeper checks into structural mistakes made during output generation.

When tested on four transformer setups, results showed noticeable variation — not just in correctness but also in how each model handles span edges. XLM-R maintains the most stable results across tasks, while Tamil-BERT captures meaning more effectively, reflected in greater alignment scores. MuRIL performs modestly, and IndicBERT struggles notably with incorrect spatial predictions.

What stands out is how crucial boundary-sensitive assessment becomes when judging answer span accuracy in languages with complex forms and scarce data. While promising, conclusions are shaped by a modest-sized dataset. Expanding tests to include broader Tamil collections could clarify whether improvements hold under varied conditions. Adjusting search techniques alongside custom-built transformers might push performance even further. Beyond that, applying these refined measures to wider sets of languages opens new paths forward. Testing such metrics on generative approaches would stretch their usefulness significantly.

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