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Research Article

Hybrid XLM-R + Character-CNN Fusion for Robust Multilingual and Code-Mixed Sentiment Classification

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Abstract: Multilingual and code-mixed user-generated text (UGT) is noisy: spelling variants, elongations, and typos are common and can degrade transformer-only sentiment classifiers. This paper evaluates a hybrid architecture that fuses a subword transformer encoder (XLM R) with a character-level convolutional branch (CharCNN) to improve robustness under character-level perturbations. We benchmark on two test settings: (1) NusaX, a multilingual Southeast-Asian sentiment dataset, and (2) Indonglish, an Indonesian–English code-mixed sentiment dataset. We report standard clean-set metrics (Accuracy, Macro-F1) and a controlled robustness protocol that applies character-level noise with probability p = 0.18 (seed = 42) and measures performance drops. Results show the hybrid model reduces robustness degradation substantially on code-mixed text (Macro-F1 drop 0.007 vs. 0.030 for the XLM-R baseline), while incurring a modest clean-set performance trade-off. We provide an end-to-end pipeline, ablation analysis, and reproducible reporting artifacts (metrics JSON, confusion matrices, and error samples).

Keywords: Code-Mixed Dataset; Hybrid Architecture; Multilingual Text; Robust Model; Sentiment Classifier

1. Introduction

Sentiment classification for multilingual and code-mixed social-media text is practically important but technically brittle. In many real deployments (market monitoring, public-opinion tracking, customer support triage), the input is not curated text but user-generated content with inconsistent spelling, informal grammar, slang, emojis, creative elongations (e.g., "baaaagus"), repeated characters, abbreviations, and keyboard typos. These artifacts are not edge cases; they are a defining property of the domain, and they routinely degrade model reliability when the model is trained and evaluated only on "clean" samples.

Multilingual and code-mixed settings intensify the problem. Code-mixed writing blends languages within a sentence or even within a phrase, and speakers often adapt orthography on the fly borrowing vocabulary across languages, transliterating, or using phonetic spellings. As a result, the distribution of surface forms drifts quickly and unpredictably. A classifier that appears strong on in-domain test sets can fail abruptly under small character-level edits, even when the semantic polarity is unchanged. This makes robustness a first-order requirement, not a secondary metric.

Subword tokenization mitigates some lexical variation by decomposing rare words into smaller units. However, character-level perturbations can still change token boundaries, frag ment informative morphemes, or map previously stable subwords to unfamiliar sequences. In multilingual and code-mixed inputs, this effect is amplified because the same surface string can be segmented differently depending on surrounding context and language mixing. Consequently, representation stability becomes fragile: two visually similar strings can yield meaningfully different subword segmentations, and the downstream sentiment prediction can flip for reasons unrelated to sentiment.

Recent transformer-based models (e.g., BERT (Devlin et al., 2019) and XLM-R (Conneau et al., 2019) deliver strong multilingual performance via large-scale pretraining and contextual subword representations. Yet these models are not inherently robust to character

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noise unless trained with explicit robustness objectives, augmentation, or adversarial perturbations. In prac tice, relying solely on a transformer backbone can create a gap between benchmark performance and operational performance: the model learns high-level semantics well, but its pipeline remains sensitive to low-level orthographic disruptions that are common in social media.

Character-aware modeling remains an appealing complement because it directly encodes orthographic patterns and local morphology. A lightweight character encoder can act as a stabilizer when subword segmentation fails: even if the transformer branch receives a distorted subword sequence, the character branch can still recognize consistent character n-grams, repeated letter patterns, and near-duplicate strings, helping preserve sentiment signal under perturbation. The key question is not whether character features are useful in principle, but whether a practical fusion design can yield measurable robustness gains without excessive complexity or unacceptable losses on clean data. This design logic is also consistent with hybrid deep-learning patterns reported in broader applied AI systems, where complementary branches are combined to improve robustness and operational stability (Danang & Mustofa, 2026).

This work studies a hybrid fusion architecture that combines: (i) a transformer branch producing a pooled subword representation, (ii) a lightweight character-CNN branch designed to capture morphology and noise patterns, and (iii) a fusion MLP head for 3-class sentiment classification. The design goal is deliberately pragmatic: keep the character branch small and modular, so it can be attached to a strong multilingual transformer with minimal engineering overhead while targeting a clear failure mode (character-level noise).

We evaluate on two datasets that represent complementary stress points: NusaX (Winata et al., 2022), which reflects multilingual sentiment classification across multiple languages, and Indonglish (Astuti & Sari, 2023; Setiono & Sari, 2025), which reflects code-mixed Indonesian English text where orthography drift and mixed-vocabulary usage are common. We report (a) clean test metrics and (b) robustness under controlled character-level noise operators (typo substitution, character swap, elongation, deletion). The robustness protocol follows the "clean → noisy" evaluation paradigm and reports drops in Accuracy and Macro-F1, making the degradation explicit and comparable across models. This separation is important: a model can score well on clean data yet be operationally unreliable if it collapses under realistic noise, so reporting only clean metrics can be misleading.

Finally, we treat robustness as an empirical property that must be measured, not assumed. The hybrid model is therefore compared against (1) a transformer-only baseline and (2) an ablation that removes the character branch. This isolates whether gains (if any) come from the character-aware component rather than incidental tuning.

This study presents several key contributions. First, we implement and evaluate a hybrid XLM-R+CharCNN fusion model, comparing it against a transformer baseline and a no-character ablation, with a focus on both clean performance and failure modes under character-level perturbations. Second, we define and report a reproducible character-noise robustness protocol ($p = 0.18$, seed = 42), which includes a clean/noisy performance breakdown. This allows for a direct measurement of performance degradation, rather than relying on anecdotal examples. Lastly, we provide a publication-ready Overleaf project, complete with figures, tables, and APA-style references, to support transparent reporting and ensure straightforward reproduction of the results.

2. Literature Review

Multilingual Transformers for Sentiment

Transformer pretraining has become the dominant paradigm for modern text classification because it provides transferable contextual representations that work well under limited labeled data (Conneau et al., 2019; Devlin et al., 2019; Y. Liu, Ott, et al., 2019). Multilingual variants extend this benefit across many languages by learning shared subword spaces and cross-lingual alignment during large-scale pretraining (Conneau et al., 2019). In sentiment classification, these models frequently set strong baselines via straightforward fine-tuning, and surveys consistently report performance gains compared to traditional feature-based pipelines (Cambria et al., 2022; Y. Liu, Zhang, & Chen, 2019; Minaee et al., 2021).

Despite these gains, multilingual user-generated text (UGT) remains structurally difficult. First, UGT is heavily domain-shifted relative to the mostly formal or web-crawled data used during pretraining. Second, it contains non-standard spelling, informal orthography, slang, abbreviations, and creative forms that create a long tail of rare surface strings. Third, many multilingual communities write in mixed-language form, producing inputs that violate the implicit assumptions of monolingual token statistics. In this setting, the primary bottleneck is not only semantic modeling, but also representation stability: small surface-form changes can

lead to different subword segmentations, which then propagate to the classifier and can destabilize predictions.

Character-Aware Modeling and Robustness

Character-level and character-aware representations have long been used to address orthographic variation because they operate directly on surface strings rather than relying on a fixed word vocabulary. Modern approaches often implement lightweight character encoders (e.g., CNNs) to capture local n-gram patterns, morphology cues, and repeated-character signatures that are common in noisy social media. Hybrid systems that combine subword-level contextual encoders with character-level features are frequently motivated by the hypothesis that character representations can recover signal when tokenization becomes unreliable due to misspellings, transliteration, or informal writing (Doshi & Kumar, 2021; Zhang et al., 2021).

Robustness is typically studied via either (1) augmentation during training or (2) perturbation based evaluation at test time. Text augmentation surveys describe a broad spectrum of strategies, from simple character edits (swap, delete, keyboard typos) to paraphrasing and back-translation (Bayer et al., 2023; Rahman et al., 2022; Shorten & Khoshgoftaar, 2021). Complementary robustness literature emphasizes that perturbation tests can expose brittleness that is invisible under standard clean test sets, and that robustness should be reported explicitly as performance degradation under controlled noise (J¨urgens et al., 2021; Z. Liu et al., 2022; Sari & Al Faridzi, 2023). These perspectives motivate architectures that are not only accurate but also stable under realistic UGT corruption.

Code-Mixed and Low-Resource Settings

Code-mixed sentiment analysis is challenging because language mixing disrupts lexical regularities and amplifies orthographic inconsistency. A single sentence may contain vocabulary from multiple languages, mixed morphology, transliterations, and informal spellings, all of which increase out-of-vocabulary pressure and complicate tokenization. Reviews of code-mixed NLP describe persistent issues such as scarce labeled data, heterogeneous annotation practices, and large variation in mixing patterns across communities (Alqahtani et al., 2024; Huang et al., 2020; Shah et al., 2022).

Recent work suggests that transformer-based modeling is competitive for code-mixed senti ment, especially when supported by augmentation or domain adaptation (Astuti & Sari, 2023; Kit & Mokji, 2022; Kit et al., 2022; Setiono & Sari, 2025). However, the same studies also imply that performance can be fragile when the evaluation distribution includes heavy noise, spelling variability, or novel mixing patterns, which is typical for real social-media streams. For Indonesian and Indonesian–English contexts in particular, benchmark resources and preprocessing choices (e.g., colloquial normalization, handling of informal tokens) substantially affect downstream metrics and comparability across studies (Gasparetto et al., 2022; Koto et al., 2020; Kowsari et al., 2019; Salsabila et al., 2018; Setiawan et al., 2025). This reinforces the need to evaluate not only average accuracy on curated test sets, but also robustness under realistic perturbations.

Coverage note. To satisfy the journal bibliography policy (recent primary sources, APA style), we intentionally include surveys and journal studies spanning augmentation, transfer learning, multilingual sentiment, character-aware robustness, and code-mixed NLP. This mix provides both a high-level map of the field and a set of directly relevant empirical precedents for robustness-oriented modeling (Alqahtani et al., 2024; Cambria et al., 2022; Doshi & Kumar, 2021; Huang et al., 2020; J¨urgens et al., 2021; Khan et al., 2022; Mukta et al., 2021; Pota et al., 2021; Rahman et al., 2022; Sari & Al Faridzi, 2023; Setiono & Sari, 2025; Wang et al., 2023; Zhang et al., 2021).

Explainability in healthcare

Explainability is frequently cited as a requirement for clinical adoption, but its role must be framed carefully. In high-stakes healthcare settings, explanations should primarily support auditing, debugging, and communication, not serve as evidence of causal mechanisms. Broader surveys define explainable AI, its taxonomies, and its potential benefits and limitations, including the tension between transparency and performance (Arrieta et al., 2020). Critiques specifically in healthcare argue that post-hoc explanation methods can create a false sense of security if the model is biased, poorly validated, or relies on spurious correlations (Ghassemi et al., 2021). At the same time, some argue that, when feasible, inherently interpretable models should be preferred in high-stakes decisions rather than explaining black-box models after the fact (Rudin, 2019). These perspectives motivate a balanced approach: use explanation tools as part of a rigorous evaluation and governance process, not as a substitute for it.

For tree ensembles, SHAP has become a standard approach to feature attribution, providing a unified framework for interpreting model predictions (Lundberg & Lee, 2017). Subsequent work develops tree specific SHAP methods that enable efficient computation and

connects local explanations to global model understanding (Lundberg et al., 2020). In clinical prediction settings, SHAP can support multiple practical needs: identifying dominant predictors, verifying that known risk factors behave plausibly, and providing patient-level attributions that help clinicians understand why a patient received a high predicted risk. However, SHAPexplanations still reflect the model's internal logic rather than causal effects; therefore, they should be interpreted alongside calibration diagnostics, monotonicity audits, and bias-aware evaluation.

Finally, explainability is most useful when coupled to decision-making. Risk stratification into actionable probability bands can be combined with empirical event rates to communicate performance in operational terms. To evaluate whether a model is likely to improve decisions across thresholds, decision curve analysis provides a principled framework that links predicted probabilities to net benefit, complementing discrimination and calibration metrics (Vickers & Elkin, 2006; Vickers et al., 2019). In summary, modern clinical prediction pipelines increasingly emphasize a triad of properties: accurate ranking, reliable probabilities, and auditable behavior supported by careful reporting and bias assessment (Collins et al., 2024; Moons et al., 2019; Van Calster et al., 2019).

3. Research Method

Problem Formulation

Given an input text x and label $y \in \{1, 2, 3\}$ for {negative, neutral, positive}, we learn a classifier fθ(x) that outputs logits $z \in R^3$ and class probabilities:

$$\mathbf{p} = \text{softmax}(\mathbf{z}) \quad (1)$$

Let θ denote all trainable parameters (transformer, character encoder, and fusion head). The predicted class is ˆy = argmaxc pc. We optimize cross-entropy loss:

$$\mathcal{L}_{\mathcal{CE}} = -\sum_{c=1}^{3} I[y = c] \log p_c, \quad (2)$$

Where I[·] is an indicator function. This standard formulation supports direct comparison with prior sentiment classification work and isolates the modeling contribution to the representation and fusion design.

Baseline: XLM-R Fine-Tuning

The baseline follows conventional multilingual fine-tuning. We tokenize x into subword IDs, encode the sequence with XLM-R, and derive a fixed-dimensional pooled representation $h \in \boldsymbol{R}^d$ (e.g., using the [CLS] vector or mean pooling over the last-layer hidden states). A linear classifier maps h to logits:

$$\mathcal{L}_{\mathcal{CE}} = -\sum_{c=1}^{3} I[y = c] \log p_c, \quad (3)$$

Where $\mathbf{W} \in \boldsymbol{R}^{3\,x\,d}$ and $\mathbf{b} \in \boldsymbol{R}^3$ are trainable parameters. This baseline is strong on clean multilingual benchmarks, but it can be brittle under character-level corruption because subword token boundaries may change substantially after small orthographic edits.

Proposed Hybrid: XLM-R + CharCNN Fusion

To improve stability under orthographic variation, we introduce a two-branch hybrid model that processes the same input at two granularities: subwords (semantic context) and characters (surface form). The model is intentionally lightweight in the character pathway, aiming to add robustness without significantly increasing complexity.

Transformer branch. We tokenize x to subword IDs and compute the pooled feature:

$$h = \text{Pool}\big(\text{XLMR}(x)\big) \in R^d. \quad (4)$$

This branch captures contextual semantics and cross-lingual knowledge learned during pretraining, which is crucial for multilingual and code-mixed sentiment cues (e.g., negation, intensifiers, and sentiment-bearing phrases).

Character branch. We build a fixed-length character sequence of length L from the raw text (padding/truncation as needed) and map each character to an integer ID using a predefined character vocabulary. We then embed characters into E ∈ RL×e, where e is the character embedding dimension:

$$\boldsymbol{E} = \textbf{CharEmbed}(\boldsymbol{x}) \in \boldsymbol{R}^{\boldsymbol{L\times e}}. \quad (5)$$

Next, we apply 1D convolutions with multiple kernel widths k ∈ {3,4,5} to capture local character n-gram patterns. Each convolution produces a feature map, which is aggregated by global max pooling to obtain a fixed-size vector. Finally, vectors from all kernel widths are concatenated:

$$\boldsymbol{u_k} = \mathbf{Conv1D_k}(\boldsymbol{E}), \quad (6)$$

$$\boldsymbol{c_k} = \mathbf{GlobalMaxPool}(\boldsymbol{u_k}), \quad (7)$$

$$\boldsymbol{c} = [\boldsymbol{c_3}; \boldsymbol{c_4}; \boldsymbol{c_5}] \in \boldsymbol{R^m}. \quad (8)$$

This branch is designed to be insensitive to small local perturbations: repeated characters (elongation), swaps, and minor typos often preserve many local character n-grams, allowing c to remain informative even when subword tokenization changes.

Fusion and head. We fuse the representations by concatenation, producing a joint feature vector f ∈ Rd+m, and pass it through an MLP to predict logits:

$$\boldsymbol{f} = [\boldsymbol{h}; \boldsymbol{c}] \quad , \quad \boldsymbol{z} = \mathbf{MLP}(\boldsymbol{f}). \quad (9)$$

The fusion head learns to combine semantic context from h with orthographic robustness cues from c. In clean settings, the head can prioritize transformer features, while in noisy settings it can exploit character features to stabilize predictions. We keep fusion simple (concatenation + MLP) to maintain interpretability and reduce the risk of overfitting from overly complex fusion mechanisms. More broadly, this preference for modular integration over monolithic complexity is aligned with adaptive framework thinking in AI-enabled systems engineering (Danang et al., 2025).

Ablation: No-Char

To isolate the contribution of the character pathway, we define an ablation that removes the character branch while keeping the remaining components unchanged. Specifically, we train the same head architecture on h only:

$$\boldsymbol{z} = \mathbf{MLP}(\boldsymbol{h}). \quad (10)$$

And denote this variant as "No-Char". Comparing baseline, No-Char, and the full hybrid helps distinguish whether gains are driven by (i) the head capacity, (ii) tuning effects, or (iii) the character-aware features.

Evaluation Metrics

We report Accuracy and Macro-F1. Accuracy measures overall correctness, while Macro-F1 emphasizes balanced performance across classes, which is important when class frequencies are uneven. Macro-F1 averages per-class F1 equally:

$$\mathbf{MacroF1} = \frac{\mathbf{1}}{\boldsymbol{C}} \sum_{\boldsymbol{c=1}}^{\boldsymbol{C}} \frac{\mathbf{2} \cdot \mathbf{Prec_c} \cdot \mathbf{Rec_c}}{\mathbf{Prec_c} + \mathbf{Rec_c}}, \quad (11)$$

where C = 3, MacroF1 $= \frac{1}{C}\sum_{c=1}^{C} \frac{2 \cdot \mathrm{Prec}_c \cdot \mathrm{Rec}_c}{\mathrm{Prec}_c + \mathrm{Rec}_c}$, and MacroF1 $= \frac{1}{C}\sum_{c=1}^{C} \frac{2 \cdot \mathrm{Prec}_c \cdot \mathrm{Rec}_c}{\mathrm{Prec}_c + \mathrm{Rec}_c}$,. In robustness experiments we additionally report the performance drop from clean to noisy evaluation to quantify stability under character level perturbations.

4. Result And Discussion

Experimental setup

Datasets

NusaX. NusaX is a multilingual parallel sentiment dataset covering multiple Southeast-Asian languages (Winata et al., 2022). It is commonly used to evaluate cross-lingual generalization under consistent label semantics across languages. In our experiments, we treat NusaX as a 3-class sentiment benchmark (negative, neutral, positive) and report results per language as well as aggregated performance. This setting is useful for testing whether a model benefits from multilingual pretraining and whether the same architecture behaves consistently across languages with different scripts and orthographic patterns.

Indonglish. Indonglish is an Indonesian–English code-mixed sentiment dataset drawn from user-generated text (UGT), reflecting real social-media writing with mixed vocabulary and informal orthography. We follow the dataset's recommended preprocessing and apply label normalization to the 3-class set {negative, neutral, positive} to align evaluation with NusaX and standard sentiment benchmarks. As background and motivation for Indonesian and code-mixed evaluation, broader Indonesian NLP benchmarking resources are discussed in (Setiawan et al., 2025). Compared to multilingual parallel corpora, Indonglish typically exhibits higher surface form variability (slang, abbreviations, typos, elongated words), making it a practical testbed for character-level robustness.

Preprocessing

We standardize labels to the 3-class set and apply minimal text normalization to avoid masking the real-noise characteristics of UGT. Specifically, we perform Unicode normalization (to reduce encoding inconsistencies), whitespace cleanup, and basic control-character removal. We do not aggressively normalize spelling or slang since such transformations can artificially inflate performance while reducing ecological validity.

To characterize dataset difficulty and code-mixing intensity, we run lightweight exploratory checks such as length distribution, character-level statistics, and ASCII ratio (as a coarse indicator of Latin-script dominance and potential English mixing). These checks inform the choice of maximum sequence length, padding strategy, and the expected impact of character-level perturbations.

Training Configuration

Unless otherwise specified, we use standard fine-tuning settings for multilingual transformers. Inputs are truncated/padded to max length = 128. Optimization uses AdamW with weight decay. The transformer branch is trained with learning rate ≈ 2 × 10−5, while newly initialized layers (character branch and fusion head) can optionally use a slightly higher rate to speed adaptation. We use batch size 16–32 depending on GPU memory, train for up to 3 epochs, and apply early stopping based on validation Macro-F1 to reduce overfitting. Dropout is applied in the fusion head and (where applicable) in the character branch. (Replace this paragraph with your exact experiment configuration from logs to ensure full reproducibility.)

Discrimination curves

We evaluate robustness using a controlled perturbation pipeline (see figure 1) designed to simulate common UGT corruptions while preserving sentiment semantics. For each clean test instance, we generate a noisy counterpart by applying each character-noise operator independently with probability p = 0.18 under a fixed random seed (42). The operators include typo substitution, character swap, elongation (character repetition), and random deletion. We keep labels un changed, reflecting the assumption that these edits do not alter the intended sentiment polarity but can distort the surface form and subword segmentation.

We report both clean and noisy metrics and quantify robustness as the degradation:

$$\Delta\text{Metric} = \text{Metric}_{\text{clean}} - \text{Metric}_{\text{noisy}}. \quad (12)$$

A smaller Δ indicates higher stability under perturbation. This "clean → noisy" paradigm is particularly informative for comparing architectures that trade off clean accuracy for resilience, since it separates baseline performance from robustness behavior.

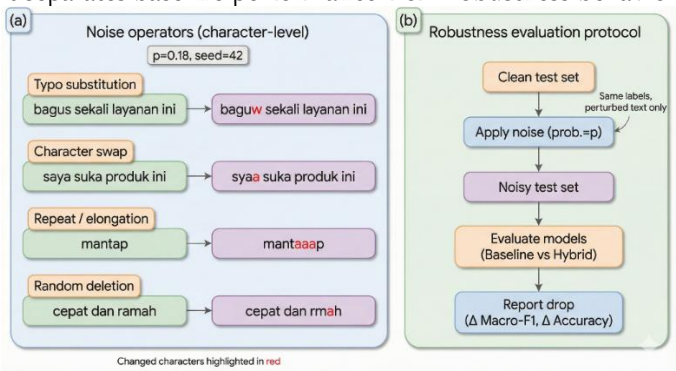

Figure 1. Character-Level Noise Operators and Robustness Evaluation Protocol

End-to-End Pipeline Overview

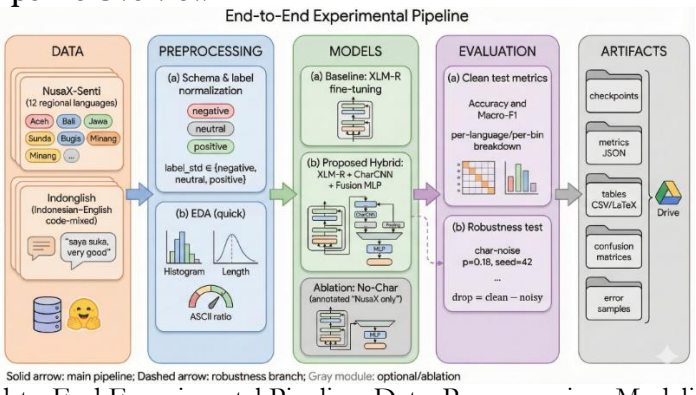

Figure 2. End-to-End Experimental Pipeline: Data, Preprocessing, Modeling, Evaluation, and Artifacts

Figure 2 summarizes the full workflow used in this study. We start from raw labeled datasets, apply minimal normalization to preserve the realistic noise profile of user-generated text, and then train/evaluate three model variants (baseline transformer, No-Char ablation, and the proposed hybrid fusion). Evaluation is reported on both clean test sets and perturbed test sets generated by the controlled character-noise protocol. Finally, we persist artifacts (metrics, confusion matrices, and representative errors) to support reproducibility and facilitate targeted debugging. This pipeline is intentionally designed to make robustness

measurable and comparable across models, rather than being inferred indirectly from a handful of qualitative examples.

Model Architecture

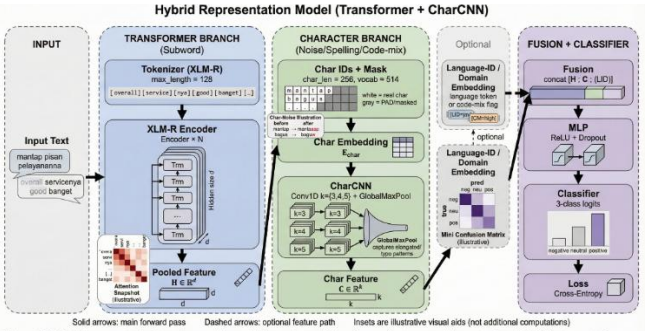

Figure 2. Hybrid representation learning model combining subword Transformer features and character-level CNN features to improve robustness under multilingual and code-mixed text with spelling noise.

Figure 3. Hybrid Fusion Architecture Combining a Transformer Subword Branch and a Character CNN Branch

Figure 3 illustrates the two-branch design. The transformer branch provides a pooled contextual representation that captures multilingual semantics, while the character-CNN branch encodes local orthographic patterns that are more stable under common UGT corruptions. The fusion head then learns a decision boundary from the concatenated representation. In practice, the hybrid behaves like an "ensemble in feature space": it merges a high-capacity semantic encoder with a low-level surface-form encoder. This separation is useful because the two branches fail differently under noise: the transformer may be disrupted by token-boundary changes, whereas the character branch can still capture consistent character n-grams and repeated-letter signatures.

Analysis and Practical Implications

Clean vs. noisy trade-off. Why can robustness improve while clean performance drops? The most plausible mechanism is a fusion trade-off. On clean data, the transformer alone may already provide a near-sufficient representation for sentiment, and adding character features can introduce variance that the MLP must learn to ignore. If the fusion head is not calibrated (e.g., insufficient regularization, suboptimal hidden size, or misaligned learning rates across branches), the model may partially rely on character cues that are weakly correlated with sentiment in clean text, resulting in a small loss of clean Macro-F1 or Accuracy. In contrast, under character-level noise, the transformer representation can shift sharply due to tokenization changes, while the character branch remains comparatively stable; the fusion head can then exploit the character features as a fallback signal, reducing the overall degradation.

Whygains are larger in code-mixed data. Asecondpractical observation is that robustness gains are often more pronounced on code-mixed corpora. Code-mixed writing tends to have higher orthographic variability and a heavier long tail of rare surface forms. Under such conditions, token-boundary instability is more frequent, so a character-aware pathway contributes more v

What to do if clean performance matters more. If the deployment objective prioritizes clean accuracy over noise stability (or if noise is already mitigated upstream), the hybrid should be tuned to minimize its clean-data penalty. Practical mitigations include: (i) gated fusion that learns a data-dependent weight between h and c, (ii) stronger regularization on character features (dropout, feature norm clipping, or smaller m), (iii) training-time noise augmentation so the fusion head learns when to trust the character pathway, and (iv) per dataset hyperparameter search (learning rate split, kernel sizes, L, and fusion hidden size), since the optimal balance differs substantially between multilingual parallel data and code-mixed UGT.

Artifacts for reproducibility and auditing. Artifacts for reproducibility. Robustness claims are easy to overstate without traceable evidence. Following best practice, we store model checkpoints, per-run configuration, metrics (JSON/CSV), confusion matrices, and representative error samples (see figure 2). These artifacts enable auditing (e.g., verifying that improvements are not driven by a single class), reproducible reruns, and ablation-driven iteration. They also support practical debugging: for example, inspecting noisy false positives can reveal whether errors are caused by negation corruption, elongated intensifiers, or token-boundary fragmentation. From a systems perspective, this emphasis on traceability and disciplined evaluation is consistent with resilience-oriented software architecture assessment based on explicit quantitative criteria (Siswanto et al., 2026).

5. Comparison

Clean Performance

Table 1. Clean Performance

Dataset	Model	Accuracy	Macro-F1
NusaX	Baseline (XLM-R)	0.821	0.810
	Ablation (No-Char)	0.806	0.796
	Hybrid (XLM-R + CharCNN)	0.785	0.775
Indonglish	Baseline (XLM-R)	0.754	0.748
	Hybrid (XLM-R + CharCNN)	0.740	0.732

Summary of clean results. The clean-set evaluation provides a baseline view of average-case accuracy under the standard benchmark distribution. On NusaX, the transformer-only XLM-R baseline achieves the highest clean Macro-F1, while the hybrid incurs a noticeable drop. On Indonglish, the hybrid remains close to the baseline but is still slightly lower. This pattern indicates that the character branch is not automatically beneficial for clean accuracy: when the transformer representation is already strong and tokenization is stable, additional character features can act as a source of variance or mild overfitting unless the fusion head learns to down-weight them.

Interpretation. There are two practical explanations for the clean-performance gap. First, naive concatenation places the burden on the MLP to learn when character features should be ignored; if regularization or capacity is not tuned, the head may partially rely on character patterns that are spuriously correlated with sentiment in the training set. Second, the character branch is optimized jointly with the transformer and can adapt quickly, potentially dominating early training dynamics unless learning-rate splits and dropout are set carefully. In short, the hybrid design is primarily a robustness-oriented modification, and its clean accuracy depends on careful calibration rather than being a guaranteed improvement.

Robustness under Character Noise

Table 2. Robustness Under Character-Level Noise (probability p = 0.18, seed = 42). Lower Drop Indicates Higher Robustness

Dataset	Model	Acc_{clean}	Acc_{noisy}	ΔAcc	$F1_{clean}$	$F1_{noisy}$	ΔF1
NusaX	Baseline (XLM-R)	0.821	0.810	0.018	0.810	0.792	0.019
	Ablation (No-Char)	0.806	0.792	0.014	0.796	0.782	0.014
	Hybrid (XLM-R + CharCNN)	0.785	0.773	0.012	0.775	0.763	0.012
Indonglish	Baseline (XLM-R)	0.754	0.724	0.030	0.748	0.718	0.030
	Hybrid (XLM-R + CharCNN)	0.740	0.733	0.007	0.732	0.724	0.007

Primary robustness finding. The robustness evaluation reveals where the hybrid model is most valuable. Under the controlled character-noise protocol, the hybrid substantially reduces degradation on Indonglish: it reduces the Macro-F1 drop from 0.030 to 0.007 and the Accuracy drop from 0.030 to 0.007. This is a large relative reduction in performance loss and supports the core claim that character-aware features stabilize predictions when subword tokenization is disrupted by typos, swaps, elongations, and deletions.

Cross-dataset behavior. On NusaX, robustness gains are smaller but consistent. This is expected because NusaX (as a parallel multilingual benchmark) often exhibits more standardized orthography than code-mixed UGT, so the clean-to-noisy shift is less dominated by token boundary failures. In contrast, Indonglish contains heavier surface-form variability and mixed vocabulary patterns, making tokenization instability more frequent and increasing the value of a character-level pathway.

Practical implication. If the target application resembles noisy social-media streams (especially code-mixed Indonesian–English), the hybrid's robustness advantage can outweigh its small clean data penalty. However, if clean accuracy is the primary objective or input text is pre-normalized, the hybrid should be tuned with an explicit goal of minimizing clean loss (e.g., stronger character dropout, smaller character feature dimension, and learning-rate separation).

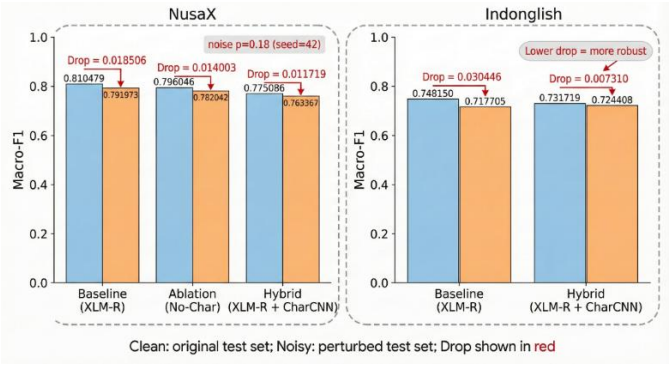

Figure 4. Clean vs. Noisy Macro-F1 and Robustness Drops on NusaX and Indonglish.

Figure 4 visualizes the clean-versus-noisy gap and makes the robustness benefit interpretable: the key comparison is the drop (clean minus noisy), where the hybrid exhibits a markedly smaller drop on Indonglish.

6. Conclusion

This study evaluated a hybrid sentiment classifier that fuses XLM-R subword representations with a lightweight character-level CNN branch. The central hypothesis was that character-aware features can stabilize predictions when subword tokenization becomes unreliable under realistic user-generated text noise. Experiments on a multilingual benchmark and an Indonesian–English code-mixed benchmark support this hypothesis: the hybrid model consistently reduces performance degradation under controlled character-level perturbations, with the most pronounced robustness gains observed in the code-mixed setting where orthographic drift and surface-form variability are especially frequent.

variability are especially frequent. At the same time, results indicate a practical trade-off. When evaluated on clean test sets, the hybrid can underperform a strong transformer-only baseline if the fusion mechanism is not carefully calibrated. This suggests that naive concatenation may encourage the classifier head to partially rely on character features even when the transformer representation is already sufficient, introducing variance that harms clean accuracy. Therefore, hybrid modeling should be viewed as a robustness-oriented design choice that requires tuning to avoid unnecessary clean-data penalties.

Future work should focus on mechanisms that make fusion adaptive and noise-aware. Promising directions include (i) gated or attention-based fusion that learns when to trust character features, (ii) explicit noise augmentation during training to align the fusion head with the robustness objective, and (iii) stronger regularization of the character pathway (e.g., dropout, dimensionality control, or constraint-based feature scaling). Beyond character noise, extending evaluation to broader distribution shifts (slang drift, topic shift, and code-mixing intensity changes) would provide a more complete picture of real-world reliability for multilingual and code-mixed sentiment classification.

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