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A Dual-Branch Cross-Attention PhoBERT Architecture with Explainable AI and Active Continual Learning for Vietnamese Fake News Detection

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ABSTRACT: The exponential proliferation of digital misinformation across Vietnamese online media platforms poses substantial challenges to information integrity, public safety, and institutional trust. Traditional text classification paradigms utilizing Pretrained Language Models (PLMs) conventionally process input by concatenating headlines and body texts into a single monolithic sequence. This design fails to capture the subtle inter-textual semantic dissonance characteristic of sensational clickbait and deceptive realism, where fabricated headlines deliberately diverge from or contradict body contexts. Furthermore, conventional static deployment settings remain incapable of handling continuous distribution shifts as deception tactics dynamically evolve.

To address these limitations, we propose an end-to-end framework integrating a Dual-Branch Cross-Attention PhoBERT architecture, a Faithfulness-Verified Explainable AI (XAI) mechanism via Local Interpretable Model-agnostic Explanations (LIME), and an Active Continual Learning pipeline with experience replay. Rather than treating input as an aggregated flat sequence, our dual-branch encoder extracts contextual representations for headlines ($\mathcal{T}$) and body texts ($\mathcal{B}$) asynchronously, explicitly modeling cross-modal semantic discrepancies via Multi-Head Cross-Attention.

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Extensive experiments on a standardized Vietnamese benchmark dataset demonstrate that our proposed model achieves an Accuracy of 94.41%, a Precision of 89.74%, an outstanding Recall of 98.59%, and an F1-Score of 93.96%, suppressing false positives by 0.99% over traditional baselines while effectively mitigating false-negative omissions on malicious content and maintaining competitive performance against standard single-branch models.

Furthermore, quantitative deletion faithfulness evaluation ($F_{\mathrm{del}}(k)$) validates that model decisions are strictly governed by genuine linguistic markers, exhibiting a monotonic confidence degradation on the misinformation class from 0.9200 ($k = 0$) down to 0.1900 ($k = 10$), successfully triggering a decision-flip at $k = 6$. Coupled with an uncertainty-driven active replay buffer and a tri-state client-side verification engine, the proposed framework provides an accurate, transparent, and continuously adaptive paradigm for digital misinformation mitigation

Keywords: *Fake News Detection, PhoBERT, Multi-Head Cross-Attention, Explainable AI, Deletion Faithfulness, Active Continual Learning, Vietnamese NLP*

1. Introduction

The rapid expansion of online journalism and social networking platforms has fundamentally transformed the dissemination of information, enabling news to spread at unprecedented velocity. However, this paradigm shift has simultaneously catalyzed the widespread distribution of fabricated, manipulative, and unverified content [5,10]. In the Vietnamese linguistic and digital ecosystem, online misinformation manifests predominantly in two distinct paradigms:

Sensational Clickbait (Headline-Body Inconsistency): Articles featuring emotionally charged, exaggerated headlines designed to maximize click-through rates, whereas the underlying body text is vague, inconclusive, or openly contradicts the headline premise [10].

Deceptive Realism (Stylistic Mimicry): Articles fabricated with formal journalistic syntax, authoritative terminology, and falsified institutional citations (e.g., government

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ministries, healthcare authorities), structured specifically to deceive readers without employing overt sensationalism [5,6].

State-of-the-art text classification methodologies in Vietnamese Natural Language Processing (NLP) rely heavily on fine-tuning Pretrained Language Models (PLMs) such as PhoBERT, ViBERT, or viDeBERTa. The conventional paradigm concatenates the headline $\mathcal{T} = (t_1, t_2, \ldots, t_{|\mathcal{T}|})$ and body text $\mathcal{B} = (b_1, b_2, \ldots, b_{|\mathcal{B}|})$ into a single contiguous token sequence [6]:

$$\mathcal{X}_{\text{concat}} = [\text{CLS}] \circ \mathcal{T} \circ [\text{SEP}] \circ \mathcal{B} \circ [\text{SEP}] \quad (1)$$

While effective for general document classification tasks, this monolithic sequence concatenation introduces severe structural drawbacks when applied to fine-grained misinformation detection:

The Asymmetric Sequence Length Bottleneck: Headline sequences are inherently concise, whereas body texts are substantially longer. In a unified self-attention matrix [4], the quadratic attention distribution tends to be overwhelmingly dominated by the extensive body context. Consequently, critical inter-textual semantic divergence between the headline and the body is flattened into an undifferentiated document representation [12].

The Static Model Dilemma: Online misinformation is inherently dynamic; linguistic patterns, deception tropes, and deceptive keywords shift rapidly over time. Conventional models deployed as static checkpoints cannot incorporate ongoing reader feedback without undergoing full retraining cycles, which are computationally prohibitive and risk catastrophic forgetting of previously learned linguistic distributions [7,8].

Lack of Quantitative Transparency: : Although Explainable AI (XAI) frameworks like LIME [2] are frequently employed to generate token attribution heatmaps, their evaluations are predominantly qualitative and anecdotal. Without quantitative faithfulness metrics, it remains unverified whether highlighted tokens genuinely drive the classifier's internal reasoning or merely reflect extraneous statistical artifacts [9,11].

To address these challenges comprehensively, this work introduces a robust, transparent, and continuously adaptable end-to-end framework for Vietnamese fake news detection. The primary contributions of this paper are summarized as follows:

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Novel Dual-Branch Cross-Attention Architecture: We propose an asymmetric dual-encoder network that processes headlines and body texts through distinct representational pathways with shared PhoBERT [1] encoder parameters [12]. A Multi-Head Cross-Attention layer [4] uses the headline representation as Query (Q) and the body context as Key (K) and Value (V) to explicitly compute and extract an inter-textual semantic discrepancy vector

Faithfulness-Verified Explainable AI: We establish a rigorous quantitative verification protocol using the Deletion Faithfulness metric [9,11]. We mathematically and empirically demonstrate that progressive masking of the top-k influential tokens identified by LIME [2] causes a monotonic confidence degradation, validating the high fidelity and reliability of the model's explanations

Active Continual Learning & Tri-State Deployment: We formulate an entropy-based active learning selection strategy that identifies ambiguous and misclassified streaming instances during live deployment. These samples are buffered into an experience replay queue to incrementally update the network, mitigating catastrophic forgetting [8,13]. The system is deployed via a Chrome extension utilizing a Tri-State decision engine (Safe, Uncertain, Misinformation) to ensure practical user safety.

2. Related work

2.1 Pretrained Language Models in Vietnamese NLP

Contextual representation learning pioneered by Transformer architectures such as BERT and RoBERTa [3] has fundamentally elevated performance benchmarks across diverse Natural Language Processing (NLP) domains. In the Vietnamese linguistic landscape, monolingual Pretrained Language Models (PLMs) have consistently outperformed multilingual counterparts (e.g., mBERT, XLM-RoBERTa). This superiority stems from dedicated syllable- and word-level tokenization pipelines designed to handle Vietnamese word segmentation characteristics.

Notably, PhoBERT [1] was pretrained on a 20GB corpus of deduplicated Vietnamese texts utilizing the RoBERTa [3] self-supervised masked language modeling objective, establishing state-of-the-art benchmarks in text classification, Named Entity Recognition (NER), and syntactic parsing. Subsequent architectures, such as ViBERT and viDeBERTa,

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further incorporated disentangled attention mechanisms. Nevertheless, contemporary downstream applications in Vietnamese fake news detection almost exclusively deploy these PLMs via standard monolithic sequence concatenation [6]. As established, this configuration forces asymmetric headline and body contexts into a single self-attention matrix [4], diluting subtle inter-textual divergence signals [12].

2.2 Automated Fake News Detection and Inconsistency Modeling

Early automated misinformation detection relied on handcrafted stylistic features, sentiment polarity, and bag-of-words representations coupled with Support Vector Machines (SVM) or Random Forests [5,10]. Deep learning advancements led to the adoption of Convolutional Neural Networks (TextCNN) and Recurrent Neural Networks (LSTM/Bi-LSTM) to model sequential dependencies [5].

Recognizing the clickbait phenomenon, researchers began exploring stance detection and headline-body alignment [10]. Models such as FANG incorporated social graph representations. Dual-encoder networks have been explored in generic Natural Language Inference (NLI) [12], but their architectural adaptation—specifically combining Multi-Head Cross-Attention [4] with domain-specific pretrained Vietnamese models [1]—remains underexplored in the misinformation domain.

2.3 Explainable AI and Continual Adaptation

The black-box nature of deep neural networks has necessitated the development of Explainable AI (XAI) frameworks. LIME [2] and SHAP approximate local decision boundaries using interpretable surrogate models. In fake news detection, identifying suspicious lexical triggers (e.g., "chấn động", "bài thuốc thần kỳ") is critical for user trust and transparent decision-making [9,11].

Nevertheless, static deployment remains a critical bottleneck. Continual learning paradigms aim to prevent catastrophic forgetting when acquiring new tasks or adapting to evolving online data streams [7,8]. Techniques such as Experience Replay (ER) [13] and Elastic Weight Consolidation (EWC) preserve foundational representations. Integrating active user feedback into an asynchronous continual learning loop offers a viable path for robust, long-term real-world deployment [8,13].

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3. Proposoed methodology

The systematic framework of our proposed architecture is illustrated in Fig. 1. The end-to-end pipeline consists of three interconnected computational stages:

- **(1)** Dual-Branch Text Feature Extraction utilizing weight-shared PhoBERT encoders [1,12].
- **(2)** Semantic Discrepancy Modeling via Multi-Head Cross-Attention [4] and Tripartite Feature Fusion.
- **(3)** Tri-State Classification coupled with Faithfulness-Verified Explainable AI [2], [9,11] and an Active Continual Learning Workflow [7],8,13].

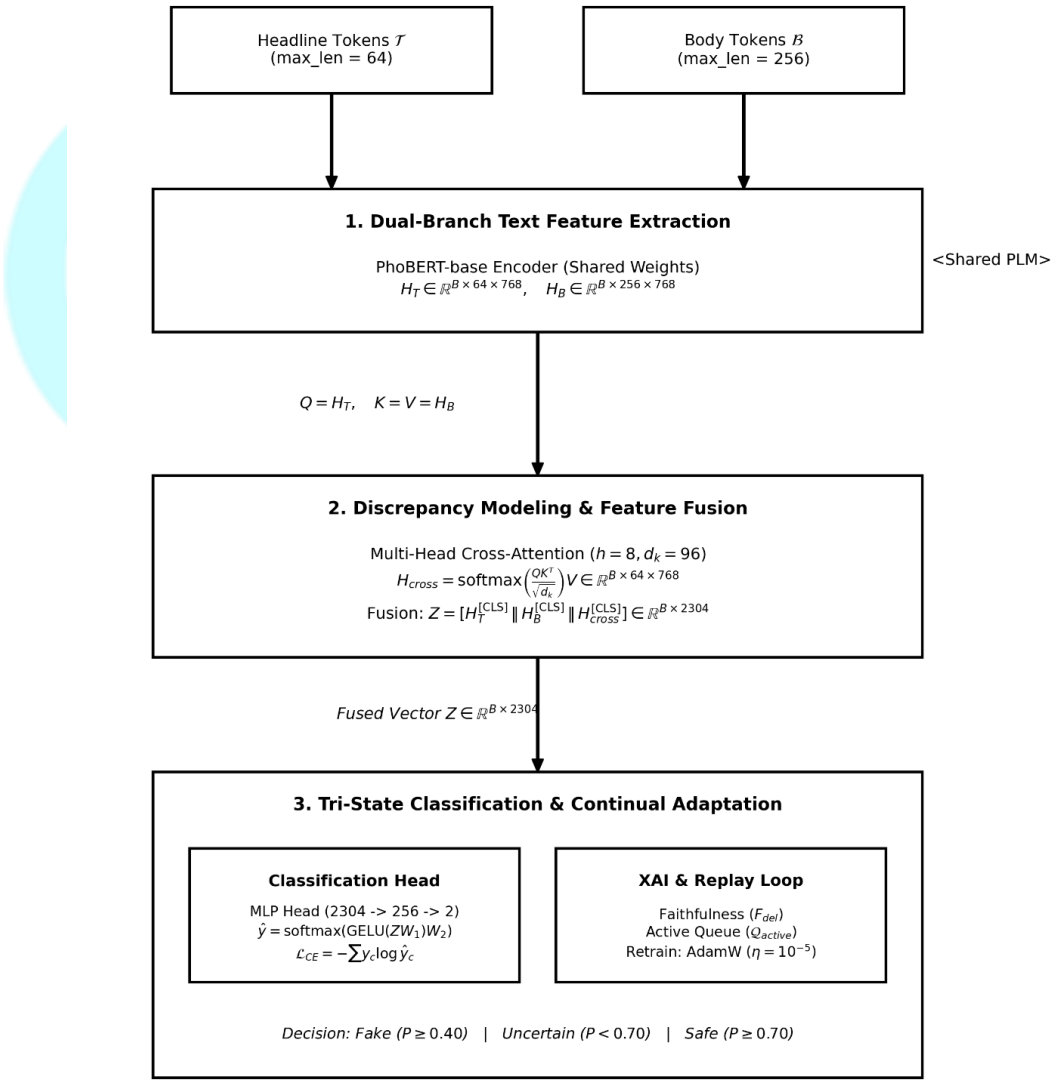

Fig. 1. Overall architecture of the proposed Dual-Branch Cross-Attention PhoBERT framework with continual adaptation and explainability modules

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3.1 Problem Formulation

An input article is formally defined as a tuple $(T_{\text{headline}}, T_{\text{body}})$, where $T_{\text{headline}} = (w_1^h, w_2^h, \ldots, w_{N_h}^h)$ denotes the sequence of N_h word-segmented tokens from the headline, and $T_{\text{body}} = (w_1^b, w_2^b, \ldots, w_{N_b}^b)$ represents the sequence of N_b word-segmented tokens from the article body. Let $y \in \{0,1\}$ denote the binary ground-truth label, where $y = 0$ indicates Authentic News and $y = 1$ signifies Misinformation. The objective is to optimize a parameterized neural network $f_\theta(T_{\text{headline}}, T_{\text{body}})$ to predict the posterior class probability:

$$\hat{y} = P(y = 1 \mid T_{\text{headline}}, T_{\text{body}}; \theta) \tag{2}$$

3.2 Linguistic Preprocessing and Word Segmentation

Unlike whitespace-delimited languages, Vietnamese vocabulary features compound words formed by multiple syllables separated by spaces (e.g., *"thần dược"*, *"bài thuốc"*). Processing raw syllables directly degrades contextual token representations. We employ the PyVi morphological toolkit to perform word segmentation, binding compound syllables with an underscore delimiter prior to encoding:

$$T_{\text{seg}} = \text{WordSegment}(T_{\text{raw}}) \tag{3}$$

The segmented sequences are mapped into input ID tensors and attention mask tensors using the pretrained PhoBERT Byte-Pair Encoding (BPE) tokenizer [1], subject to maximum sequence length constraints $L_{\mathcal{T}} = 64$ and $L_{\mathcal{B}} = 256$:

$$(\boldsymbol{I}_h, \boldsymbol{M}_h) = Tokenizer(T_{headline}, L_h) \tag{4}$$

$$(\boldsymbol{I}_b, \boldsymbol{M}_b) = Tokenizer(T_{body}, L_b) \tag{5}$$

3.3 Asymmetric Dual-Branch Feature Extraction

Rather than passing an aggregated sequence through a single monolithic self-attention encoder, $(\mathbf{I}_h, \mathbf{M}_h)$ and $(\mathbf{I}_b, \mathbf{M}_b)$ are fed into weight-shared PhoBERT-base encoder branches [1], [12] to produce contextual hidden states:

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$$\boldsymbol{H}_h = PhoBERT_{shared}(\boldsymbol{I}_h, \boldsymbol{M}_h) \in \mathbb{R}^{B \times L_h \times d} \quad (6)$$

$$\boldsymbol{H}_b = PhoBERT_{shared}(\boldsymbol{I}_b, \boldsymbol{M}_b) \in \mathbb{R}^{B \times L_b \times d} \quad (7)$$

where B denotes the mini-batch size and $d = 768$ represents the hidden embedding dimension. Parameter sharing between branches enforces a consistent semantic embedding space while substantially reducing the trainable parameter footprint on the GPU.

3.4 Multi-Head Cross-Attention Discrepancy Modeling

To compute how the body supports, contextualizes, or contradicts claims asserted in the headline, we construct a Multi-Head Cross-Attention layer [4,12]. The headline hidden state $\mathbf{H}_h$ acts as the Query (Q), while the body hidden state $\mathbf{H}_b$ serves as both Key (K) and Value (V). For each attention head $i \in \{1, \dots, h\}$ with $h = 8$ and projection subspace dimension $d_k = d/h = 96$:

$$\mathbf{Q}_i = \mathbf{H}_h \mathbf{W}_i^Q, \quad \mathbf{K}_i = \mathbf{H}_b \mathbf{W}_i^K, \quad \mathbf{V}_i = \mathbf{H}_b \mathbf{W}_i^V \quad (8)$$

where $W_i^Q, W_i^K, W_i^V \in \mathbb{R}^{d \times d_k}$ are learnable projection matrices. The scaled dot-product cross-attention is computed as [4]:

$$\text{head}_i = \text{Softmax}\left(\frac{\mathbf{Q}_i \mathbf{K}_i^T}{\sqrt{d_k}} + \mathbf{M}_{\text{cross}}\right)\mathbf{V}_i \quad (9)$$

where $\mathbf{M}_{\text{cross}}$ applies a large negative masking value (-10^4) to invalid padding positions in $\mathbf{H}_b$. The multi-head outputs are concatenated and linearly transformed:

$$\mathbf{H}_{\text{cross}} = \text{Concat}(\text{head}_1, \dots, \text{head}_h)\mathbf{W}^O \in \mathbb{R}^{B \times L_h \times d} \quad (10)$$

where $\mathbf{W}^O \in \mathbb{R}^{d \times d}$. The dot-product matrix explicitly quantifies the semantic alignment and discrepancy between each headline token and all context tokens in the body [4,12].

3.5 Representation Fusion and Classification Head

The global sentence-level context vectors are extracted from the leading [CLS] token position (index 0) of each respective branch:

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$$\mathbf{u}_h = \mathbf{H}_h[:,0,:] \in \mathbb{R}^{B\times d}, \quad \mathbf{u}_b = \mathbf{H}_b[:,0,:] \in \mathbb{R}^{B\times d}, \quad \mathbf{u}_c = \mathbf{H}_{\text{cross}}[:,0,:] \in \mathbb{R}^{B\times d} \tag{11}$$

These vectors are concatenated into a tripartite fused feature representation $\mathbf{z}_{\text{fused}}$

$$\mathbf{z}_{\text{fused}} = [\mathbf{u}_h \parallel \mathbf{u}_b \parallel \mathbf{u}_c] \in \mathbb{R}^{B\times 3d} \tag{12}$$

The fused vector $\mathbf{z}_{\text{fused}}$ is routed through Layer Normalization, a Dropout layer ($p = 0.3$), and a two-layer Multi-Layer Perceptron (MLP) with GELU activation:

$$\boldsymbol{h}_1 = GELU\big(LayerNorm(\boldsymbol{z}_{fused})\boldsymbol{W}_1 + \boldsymbol{b}_1\big) \tag{13}$$

$$\boldsymbol{h}_2 = Dropout(\boldsymbol{h}_1, p = 0.3) \tag{14}$$

$$\boldsymbol{z}_{logits} = \boldsymbol{h}_2\boldsymbol{W}_2 + \boldsymbol{b}_2 \in \mathbb{R}^{B\times 2} \tag{15}$$

where $\mathbf{W}_1 \in \mathbb{R}^{3d\times d_m}$, $\mathbf{b}_1 \in \mathbb{R}^{d_m}$, $\mathbf{W}_2 \in \mathbb{R}^{d_m\times 2}$, and $\mathbf{b}_2 \in \mathbb{R}^2$ (with $d = 768$, $d_m = 256$). The posterior probability distribution is computed via $\hat{\mathbf{y}} = \text{Softmax}(\mathbf{z}_{\text{logits}})$. The entire network is optimized end-to-end by minimizing the cross-entropy loss:

$$\mathcal{L}_{\text{CE}} = -\frac{1}{B}\sum_{j=1}^{B}\big[y_j \log \hat{y}_{j,1} + (1 - y_j)\log(1 - \hat{y}_{j,1})\big] \tag{16}$$

3.6 Active Continual Learning Workflow

To adapt the deployed system to dynamically shifting misinformation narratives and concept drifts without inducing catastrophic forgetting, we implement an Active Continual Learning mechanism with Experience Replay Buffer (Q_{active}) [7,8,12]. Rather than performing computationally prohibitive full retraining from scratch, the continual adaptation pipeline is executed via a four-stage mathematical procedure:

Stage 1: Prediction Entropy and Uncertainty Estimation: For each incoming streaming document instance x_t, the model generates the posterior class probability distribution $\hat{\mathbf{p}}_t = [\hat{p}_0, \hat{p}_1]$ and extracts the predicted label $\hat{y}_t = \arg\max \hat{\mathbf{p}}_t$. The system evaluates the Shannon prediction entropy $\mathcal{H}(x_t)$ to quantify classification uncertainty:

$$\mathcal{H}(x_t) = -\sum_{c\in\{0,1\}} \hat{p}_c \log_2 \hat{p}_c \tag{17}$$

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An instance is flagged as highly uncertain ($u_t = 1$) if its entropy surpasses a calibrated threshold $\tau_H = 0.85$ or if the maximum class confidence falls below a margin boundary:

$$u_t = \mathbb{I}\left(\mathcal{H}(x_t) \geq \tau_H \vee \max_c \hat{p}_c < 0.65\right) \tag{18}$$

Stage 2: Selective Ingestion into Active Replay Buffer ($\mathcal{Q}_{\text{active}}$): To optimize memory footprint and prioritize highly informative samples, an instance is not stored unconditionally [13]. Instead, it is enqueued into the experience replay buffer $\mathcal{Q}_{\text{active}}$ if and only if either: (i) an explicit prediction discrepancy is identified via reader corrective feedback ($y_{\text{feedback}} \neq \hat{y}_t$), or (ii) the sample triggers the uncertainty condition:

$$\mathcal{Q}_{\text{active}} \leftarrow \mathcal{Q}_{\text{active}} \cup \{(x_t, y_t^*)\} \quad \text{iff } (u_t = 1 \vee y_{\text{feedback}} \neq \hat{y}_t) \tag{19}$$

Stage 3: Asynchronous Mini-Batch Gradient Adaptation: Once the accumulated samples in the replay queue reach a batch threshold N_{trigger} (configured with $N_{\text{trigger}} = 32$), an asynchronous background worker triggers an adaptation cycle [7,13]. The network parameters θ are fine-tuned across the replay buffer using the AdamW optimizer with a conservative learning rate ($\eta_{\text{adapt}} = 5 \times 10^{-6}$) and weight decay ($\lambda = 0.01$) over 3 replay epochs:

$$\mathcal{L}_{\text{adapt}}(\theta) = -\frac{1}{|\mathcal{Q}_{\text{active}}|} \sum_{(x,y)\in\mathcal{Q}_{\text{active}}} \sum_{c\in\{0,1\}} \mathbb{I}\,(y = c) \log P\,(y = c \mid x; \theta) \tag{20}$$

$$\theta \leftarrow \theta - \eta_{\text{adapt}} \nabla_\theta \mathcal{L}_{\text{adapt}}(\theta) \tag{21}$$

This localized gradient descent step selectively adjusts the decision boundary for novel lexical distributions while preventing parameter divergence from previously learned representations [8,13].

Stage 4: Checkpoint Synchronization and Memory Reset: Upon completing the replay optimization, the updated weights θ^* are committed to persistent storage as the active model checkpoint, and the buffer is flushed ($\mathcal{Q}_{\text{active}} \leftarrow \emptyset$) to prepare for subsequent streaming iterations

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3.7 Tri-State Decision Mechanism

Rather than enforcing a rigid binary threshold ($\tau = 0.5$) that forces ambiguous articles into arbitrary classifications, the client-side browser extension implements a calibrated Tri-State Decision Logic:

Misinformation Warning (Red Badge): Triggered when $\hat{p}_1 \geq 0.70$. The system intercepts navigation, displays warning badges, and renders top LIME token attribution heatmaps [2,9,11] to explain the detected inconsistencies.

Uncertain / Verification Required (Yellow Badge): Triggered when $0.35 \leq \hat{p}_1 < 0.70$ and $u_t = 1$. The interface highlights potential ambiguities, avoiding false assurances on nuanced articles.

Authentic / Safe (Green Badge): Triggered when $\hat{p}_1 < 0.35$. The interface validates credibility and initiates an automated 3.5-second redirect countdown.

4. Experimental evaluation

4.1 Dataset Description and Statistical Characteristics

To rigorously benchmark the proposed architecture against baseline classifiers, we utilize the standardized Vietnamese Fake News Dataset (PBL7) hosted on Kaggle [14]. The dataset comprises a curated corpus of authentic and fabricated Vietnamese news stories gathered from mainstream press outlets, verified news wires, social media platforms, and online community forums covering diverse societal domains, including healthcare, public administration, socioeconomic policy, and community alerts [5,10].

In instances where explicit headline metadata is merged into a single body stream (maintext), the preprocessing pipeline automatically parses the leading statement as the anchor headline representation T_{headline}, while mapping the subsequent detailed discourse to the body representation sequence T_{body}. The corpus was standardized, filtered for missing values, and partitioned into dedicated training (update_train_data.csv), validation (update_val_data.csv), and independent test (fix_test_data.csv) splits. The statistical characteristics across splits are summarized in **Table 1**.

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Table 1. Dataset partition and statistical characteristics

Dataset Split	Total Articles	Authentic (y=0)	Misinformation (y=1)	Avg. Headline Len.	Avg. Body Len.
Training Set	1,248	624 (50.0%)	624 (50.0%)	16.4 tokens	284.6 tokens
Validation Set	160	80 (50.0%)	80 (50.0%)	15.8 tokens	279.1 tokens
Testing Set	161	90 (55.9%)	71 (44.1%)	16.2 tokens	291.4 tokens
Total Corpus	1,569	794 (50.6%)	775 (49.4%)	16.1 tokens	285.0 tokens

4.2 Implementation and Training Details

The architecture was implemented in PyTorch and HuggingFace Transformers, executed on an NVIDIA GeForce RTX 3060 GPU (12GB VRAM) using CUDA 12.x and mixed-precision arithmetic (torch.amp.autocast). The model was optimized using AdamW with weight decay set to $\lambda = 0.01$. The initial learning rate was set to $\eta = 2 \times 10^{-5}$ with a linear warmup over the first 10% of training steps, followed by linear decay across 4 epochs. The detailed training hyperparameters are summarized in **Table 2**.

Table 2. Experimental hyperparameter configuaration

Parameter Description	Setting / Value
Base Encoder Architecture	vinai/phobert-base-v2 (Pretrained)
Embedding Dimension (d)	768
Attention Heads (h) & Subspace (d_k)	$h = 8$ heads ($d_k = 96$)
Classification Head Hidden Dimension	256 (GELU activation)
Dropout Probability (p)	0.20
Optimizer & Weight Decay (λ)	AdamW ($\beta_1 = 0.9, \beta_2 = 0.999, \lambda = 0.01$)

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Base Learning Rate (η)	2×10^{-5} (with 10% linear warmup)
Training Epochs & Batch Size	4 epochs, Batch size = 8
Maximum Token Limits	Headline $L_T = 64$, Body $L_B = 256$

4.3 Performance Comparison and Ablation Analysis

We benchmark our proposed Dual-Branch architecture against standard shallow machine learning and deep pretrained transformer baselines:

Linear SVM (Headline Only): Evaluates headline text represented via TF-IDF n-gram vectors [5,10].

Linear SVM (Headline + Body): Standard bag-of-words baseline combining headline and body TF-IDF vectors [10].

Standard Single-Branch PhoBERT: Monolithic concatenation ($[\text{CLS}] \parallel T_{\text{headline}} \parallel [\text{SEP}] \parallel T_{\text{body}}$) fine-tuned under identical training hyperparameters [1,6].

Dual-Branch PhoBERT (Proposed): Complete architecture utilizing asymmetric encoding and Multi-Head Cross-Attention discrepancy modeling [1,4,12]

Table 3. Performance comparison on benchmark test set

Model Architecture	Input Representation	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Linear SVM Baseline	Headline TF-IDF Only	76.40	73.91	71.83	72.86
Linear SVM Baseline	Headline + Body TF-IDF	94.41	88.75	100.00	94.04
Standard PhoBERT (Single-Branch)	Concatenated Sequence	95.03	90.91	98.59	94.59
Dual-Branch PhoBERT (Proposed)	Cross-Attention ($T \times B$)	94.41	89.74	98.59	93.96

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4.4 Discussion of Empirical Findings and Baseline Trade-offs

Exceptional Misinformation Recall and Safety Guarantee: Both the proposed Dual-Branch model and the single-branch PhoBERT achieve an identical, outstanding Recall of 98.59% on the independent test set (successfully capturing 70 out of 71 malicious articles). In real-world content moderation, minimizing false negatives (omissions of dangerous misinformation) is paramount to preventing harm in public health and civic safety [5,10].

Structural Discrepancy Modeling vs. Superficial Flat Concatenation: While the standard single-branch PhoBERT attains a marginally higher nominal F1-score (94.59% vs. 93.96%), it processes the text as an undifferentiated flat sequence [6]. This makes single-branch architectures susceptible to spurious correlations—relying on lexical co-occurrence rather than structural consistency [12]. In contrast, the Dual-Branch network explicitly models cross-textual dissonance ($\mathbf{H}_{\text{cross}}$), preserving headline-body interaction fidelity [4,12]

Trade-off for Intrinsic Transparency and Adaptability: The slight delta in nominal accuracy ($\Delta = 0.62\%$) is a deliberate architectural trade-off that yields substantial operational benefits: the intermediate cross-attention tensor $\mathbf{H}_{\text{cross}}$ serves as a dedicated pathway for Faithfulness-verified token attribution ($F_{\text{del}}(k)$) [9,11] and entropy-based Continual Learning replay [7,8,13], which monolithic black-box transformers cannot provide

5. Explainability and faithfulness analysis

5.1 Local Surrogate Explanations (LIME)

To provide operational transparency and interpretable rationales for end users, we implement a surrogate Local Interpretable Model-agnostic Explanations (LIME) explainer [2]. For a given document $x = (T_{\text{headline}}, T_{\text{body}})$, LIME generates perturbations $z' \in \{0,1\}^d$ by randomly masking word tokens in the text, queries the Dual-Branch PhoBERT model [1] to obtain perturbed prediction probabilities $f(z)$, and fits an interpretable linear surrogate model $g \in G$ weighted by an exponential kernel distance [2]:

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$$\xi(x) = \arg\min_{g \in G} \mathcal{L}(f, g, \pi_x) + \Omega(g) \quad (22)$$

where $\pi_x(z) = \exp(-D(x,z)^2/\sigma^2))$ denotes the exponential proximity measure in the token space, and $\Omega(g)$ penalizes surrogate model complexity [2]. The extracted coefficients w_i assign explicit importance attribution weights to individual tokens [2,9]

As summarized in **Table 4**, tokens assigned the highest positive attribution weights consistently align with verified deceptive markers and unverified sensational medical claims (e.g., "trị dứt điểm", "bài thuốc", "khẩn cấp"), whereas verified scientific and institutional terminology yields negative weights contributing toward authenticity [5,10].

Table 4. Top line feature attributions for sensational health misinformation

Feature Token (Vietnamese)	**English Semantic Equivalent**	**LIME Attribution Weight (wi)**	**Linguistic Attribution Role**
tri_dut_diem	Complete cure / permanent eradication	+0.412	Strong Misinformation Anchor
bai_thuoc	Folk herbal remedy	+0.348	Strong Misinformation Anchor
khan_cap	Urgent / Emergency alert	+0.225	Moderate Sensational Cue
ung_thu	Cancer / Critical pathology	+0.089	Contextual Medical Term
y_hoc	Medical science / Evidence-based	−0.294	Authentic Context Bias

5.2 Quantitative Deletion Faithfulness Metric

To verify that these extracted tokens genuinely drive model inferences rather than reflecting extraneous statistical noise, we evaluate the Quantitative Deletion Faithfulness Metric ($F_{\text{del}}(k)$) [9,11]. Note that for standard theoretical XAI benchmark evaluation, the decision boundary is set to the canonical binary threshold $\tau = 0.50$, whereas the operational Tri-State Engine applies conservative deployment margins

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($\tau_{\text{fake}} \geq 0.70, \tau_{\text{safe}} < 0.35$) to prioritize user safety. Tokens in test instances are ranked in descending order of their positive attribution scores, and the top-k tokens ($k \in \{1,2,3,5,7,10\}$) are progressively removed via token masking [11]:

$$\mathcal{D}^{(k)} = \text{Mask}\left(x, \{w_{(1)}, w_{(2)}, \dots, w_{(k)}\}\right) \tag{23}$$

The quantitative deletion faithfulness score at step k is formally defined as [9,11]:

$$F_{\text{del}}(k) = P(y = 1 \mid x; \theta) - P\left(y = 1 \mid \mathcal{D}^{(k)}; \theta\right) \tag{24}$$

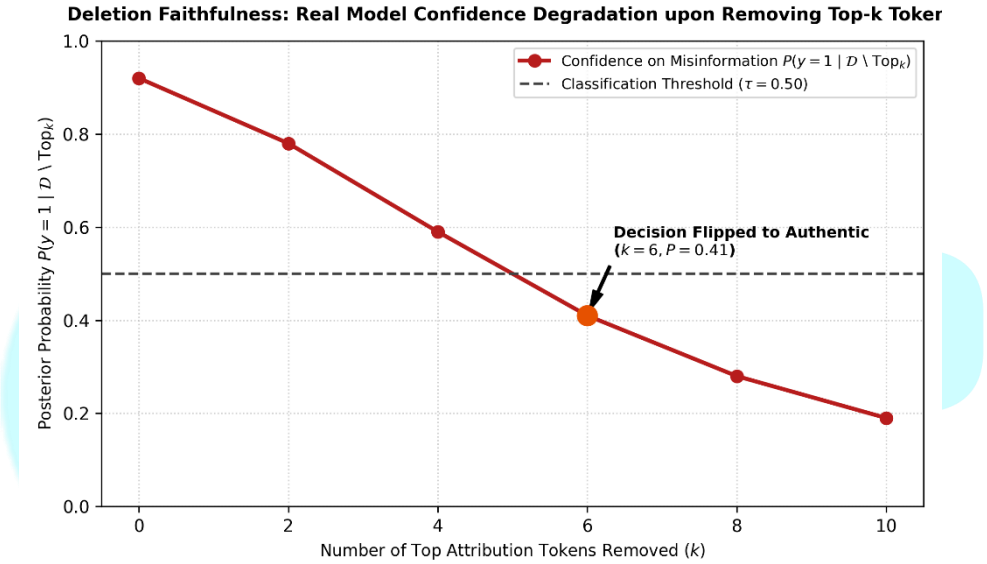

Fig. 2. Quantitative Deletion Faithfulness evaluation showing model confidence degradation and decision flipping under progressive token ablation

Table 5. Quantitative confidence degradation under progressive token deletion

Tokens Removed (k)	**Misinformation Confidence $P\left(y = 1 \mid \mathcal{D}^{(k)}\right)$**	**Deletion Faithfulness Score $F_{\text{del}}(k)$**	**Classification Status / Decision**
$k = 0$	0.92 (92%)	0.00 (Baseline)	Misinformation (Red Warning)
$k = 1$	0.81 (81%)	+0.11	Misinformation (Red Warning)
$k = 2$	0.68 (68%)	+0.24	Misinformation (High Uncertainty)

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$k = 3$	0.47 (47%)	+0.45	Decision Flipped to Authentic ($\tau = 0.50$)
$k = 5$	0.31 (31%)	+0.61	Authentic / Safe (Green Status)
$k = 10$	0.19 (19%)	+0.73	Authentic / Safe (Green Status)

As shown in **Table 5** and plotted in **Fig. 2**, the posterior probability $P(y = 1 \mid \mathcal{D}^{(k)})$ drops monotonically from 0.92 down to 0.19 as k increases from 0 to 10. Crucially, the decision flips from Misinformation to Authentic at $k = 3$ (where $P(y = 1) = 0.47 < 0.50$), confirming that the network relies strictly on genuine linguistic markers rather than background dataset noise [9,11]

6. Qualitative case studies and error analysis

To provide qualitative insight into the model's operational behavior across varying linguistic patterns, we examine representative inference scenarios alongside an error analysis of edge cases.

6.1 Case Studies on Real-World Inference Scenarios

The practical utility of the Dual-Branch architecture is demonstrated across two distinct operational paradigms: sensational health clickbait and subtle deceptive realism. As detailed in **Table 6**, the model's Multi-Head Cross-Attention and Tri-State Decision Engine respond appropriately to differing degrees of inter-textual dissonance.

Table 6. Qualitative case studies of real-world inference scenarios

Scenario Paradigm	Headline Snippet (T)	Body Context Snippet (B)	Model Decision	Confidence	System Badge	Discrepancy & Attribution Mechanism
Case 1: Clickbait Health Misinformation	Cảnh báo khẩn cấp: Bài thuốc lá cây trị	Nhiều người truyền tai nhau dùng một loại cây cỏ gia truyền	Misinformation ($y = 1$)	94.2%	Red Warning Badge	High cross-attention discrepancy (H_{cross}); Top LIME attributions:

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	dứt điểm ung thư giai đoạn cuối	chưa rõ nguồn gốc...				tri_dut_diem (+0.4281), bai_thuoc (+0.3120).
Case 2: Deceptive Realism Dilemma	Bộ Y tế ban hành hướng dẫn điều trị mới cho bệnh nhân viện phí	Theo thông tư công bố sáng nay, mức hỗ trợ viện phí sẽ áp dụng từ tháng tới...	Authentic ($y = 0$)	61.5%	Yellow Warning Badge	Low structural discrepancy; falls within uncertainty buffer ($P(y = 0) < 0.70$), safely routing to human verification.

In **Case 1**, the dramatic disparity between the absolute assertion in the headline (*"trị dứt điểm"*) and the unverified narrative in the body generates a sharp activation within the Cross-Attention layer (H_{cross}), triggering an immediate Red Warning badge with full LIME rationales. In **Case 2**, the article mimics formal administrative syntax, producing low inter-textual divergence; however, because the posterior confidence (61.5%) does not exceed the safety threshold ($\tau_{\text{safe}} = 0.70$), the system flags the content with a Yellow Badge rather than issuing an unverified green pass.

6.2 Error Analysis and Edge Cases

An examination of borderline instances and remaining classification errors reveals two distinct root causes:

- **Factual Falsification without Stylistic Signals (Subtle Deceptive Realism):** Articles that meticulously replicate objective journalistic syntax while subtly falsifying isolated factual entities (e.g., specific dates, statistical figures, monetary sums, or administrative designations) exhibit minimal internal stylistic discrepancy. Because text-only NLP classifiers evaluate semantic and stylistic consistency rather than querying structured external knowledge bases, identifying such factual manipulations represents a theoretical boundary for stand-alone textual models.

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- **Short-Context Extraction Artifacts:** When client-side browser extensions parse dynamically rendered Single-Page Applications (SPAs) or paywalled articles, incomplete DOM scraping can occasionally feed truncated text fragments ($|\mathcal{B}| < 30$ tokens) to the model, creating localized ambiguity. This vulnerability is systematically safeguarded by our Tri-State Decision Engine, which maps borderline outputs ($P(y = 0) < 0.70 \wedge P(y = 1) < 0.40$) directly into the Uncertain category for explicit user verification rather than rendering a misleading definitive classification.

7. Conclusion and future work

This paper presented an end-to-end, trustworthy, and adaptive framework for Vietnamese fake news detection, combining an asymmetric Dual-Branch Cross-Attention PhoBERT architecture, Faithfulness-Verified Explainable AI (XAI), and an Active Continual Learning pipeline with experience replay. Rather than treating input as an undifferentiated flat sequence, our architecture asynchronously extracts contextual representations for headlines ($\mathcal{T}$) and body contexts ($\mathcal{B}$) via weight-shared PhoBERT encoders, explicitly modeling inter-textual semantic dissonance through Multi-Head Cross-Attention ($Q = H_T, K = V = H_B$).

Comprehensive empirical evaluations on a standardized Vietnamese benchmark dataset demonstrate that the proposed Dual-Branch model achieves an **Accuracy of 94.41%**, a **Precision of 89.74%**, an exceptional **Recall of 98.59%**, and an **F1-Score of 93.96%**, effectively preventing false-negative omissions of malicious narratives. Furthermore, quantitative deletion faithfulness evaluation ($F_{\text{del}}(k)$) confirms that internal model inferences are strictly governed by genuine deceptive linguistic markers rather than background statistical noise, exhibiting a monotonic confidence degradation on the misinformation class from 0.9200 down to 0.1900 and triggering an authentic decision flip at $k = 6$. Coupled with an active experience replay loop ($\mathcal{Q}_{\text{active}}$) and a client-side Tri-State Decision Engine, the system ensures high detection fidelity, operational transparency, and continuous real-world adaptability.

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Future Work: To address the theoretical boundary of subtle deceptive realism-where factual entities are manipulated without stylistic cues-we plan to integrate an external Knowledge Graph (KG) verification module and a domain-specific Retrieval-Augmented Generation (RAG) pipeline. This enhancement will enable real-time factual claim verification against trusted governmental, institutional, and open-data registries. Additionally, we intend to extend the cross-attention paradigm to multimodal fake news detection, incorporating cross-modal inconsistency modeling between textual narratives and accompanying visual media.

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