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A Novel Tactic-Aware and Explainable Clickbait Detection Framework Based on a Fine-Tuned BERT Model

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Abstract: **The proliferation of clickbait headlines across digital platforms has immensely disrupted user experience and tainted the face of online journalism. Though lately, deep learning methods have shown promising levels of accuracy in identifying clickbait, most of them act as uninterpretable "black-box" models; they neither offer explanations nor reveal the psychological strategies behind the deceptive content. We, in this paper, develop a tactic-aware and explainable clickbait detection system, centering on the Bidirectional Encoder Representations from Transformers (BERT) that has been carefully fine-tuned. The design we put forth, besides enhancing semantic understanding, also has a contextual enrichment module that works by adjoining post content to the respective target headlines. To make the model understandable, an Explainable Artificial Intelligence (XAI) unit is included, which, by tapping into token-level attention scores of the final transformer layer, can highlight the most prominent lexical features that really influenced the model's prediction. Also, a rule-based classifier is imbibed in the architecture which is able to distinguish clickbait based on six different psychological tactics including, for example, curiosity gaps, list framing, and forward-referencing. The system not only classifies at the level of headlines but also boasts an analytics engine that can measure publisher-specific clickbait levels and look into temporal behavioral patterns across media sources. Class imbalance is countered by using a dynamically scaled class-weighted loss function during the training of the model, which and assures minority-class learning is robust. The experimental outcomes show that our method not only outperforms in classification but also much improves the aspect of interpretability. To sum up, this work introduces a scalable, transparent, and analytically enriched solution for clickbait detection, which can help platform governance, media accountability, and better user awareness against deceptive content.**

IndexTerms **- Clickbait Detection, Explainable AI (XAI), Natural Language Processing (NLP), BERT Application, Computational Journalism, Deceptive Texts, Media Analytics.**

I. INTRODUCTION

The digitalization of news media and changes in the revenue models, which typically rely on attracting viewers, have led to a massive increase in the number of clickbait headlines. Clickbait titles are types of headlines that are up to the point, dishonest or highly sensational ones, that aim at exploiting readers' curiosity gap for maximum engagement. Even though such methods may temporarily increase traffic, their negative consequences include widespread usage, a measurable decrease in user experience, loss of journalistic trust, and misinformation through online platforms. Meaning automatic detection and regulation of clickbait in computational journalism and natural language processing (NLP) have become essential issues. In the beginning, clickbait detection was done using traditional machine learning techniques that depended greatly on handcrafted linguistic features. But Nowadays with the expansion of deep learning and transformer-based architectures, detecting clickbait by these methods is getting more popular. Leading-edge architectures like CNNs and bidirectional transformers could support many predictive activities. Unfortunately, the deep learning methods have two main disadvantages, lack of interpretability and transparency, because they are usually referred to as black boxes, since they don't produce explanations that could assist users. And, these black box models do not really promote transparency, a key feature of information ecosystems. Besides, existing methods mostly consider clickbait as a binary or a homogeneous category, thereby excluding the diverse psychological mechanisms that operate in deceptive content like curiosity gaps, emotional appeals, list-based framing, and forward-referencing. Also, detection systems mostly operate at the individual level and have difficulty when it comes to broader contexts, e.g. analyzing publisher-specific behavior or monitoring temporal patterns of clickbait usage. To this end, the authors of this article offer an explainable and tactic-aware clickbait detection technique. Finetuning of a top-of-the-line language representation model BERT was, in fact, the major driving force behind the progress. The desired method merges prominent language modeling capability with the Explainable Artificial Intelligence (XAI) element that greatly improves the transparency of the decision-making process by extracting and normalizing the attention weights at the token level from the last transformer layers. It shows that one can identify with precision the words and contexts that are contributing most to the model predictions. Going beyond a mere two-class classification, our method is also equipped with a domain expert-guided rule-based taxonomy classifier which categorizes clickbait headlines into one.

Literature Review

Clickbait detection research has come a long way in the last decade, from rudimentary feature-based approaches to advanced deep learning models. Chakraborty et al. (2016) set the trend in clickbait detection with manually selected features like word presence, punctuation count, and sentiment polarity, which yielded around 75% accuracy [1]. Potthast et al. showed that gradient boosting models can be effectively used alongside traditional classifiers but pointed out the dependency on large sets of annotated data [2]. Chen et al. proposed CNN-based headline embedding to learn local spatial patterns that pushed detection accuracy beyond 85%

[3] while Kumar et al. leveraged LSTM to learn sequential patterns with an F1 score of 0.78 on imbalanced data [4]. The area of research moved towards transformerbased methods. According to Anand et al., BERT models were fine-tuned to achieve 92% accuracy; however, multi-domain input processing was still an issue [5]. Wu et al. evaluated adversarial attacks, concluding that performance dropped by 15-25% when headlines were slightly perturbed, thus highlighting the importance of adversarial training [6]. Zhang et al. investigated cross-domain generalization, where performance reduced by 20% if models learned on news headlines and tested on social media posts [7]. Further hybridization and architectural advances came after that: Gong et al. used CNN and LSTM layers in combination achieving 7% increase in accuracy [9], Hershey et al. proved that contextualized embeddings such as ELMo perform better than static word vectors [10]; Liu et al. introduced explainable AI techniques (SHAP, LIME) for word-level linguistics triggers finding [11], Biyani et al. focused on classifying clickbait based on manipulation techniques such as exaggerations and listicles instead of a binary classification [12]; Dong et al. performed a longitudinal study proving that clickbaiting strategies change over time [13], and Bourgonje et al. used additional feature of publisher metadata [14]. Among the other developments, the work by Pujari et al. involving RoBERTa over several social media platforms is noted [15], the approach proposed by Agrawal et al., which involves thumbnails and captions for achieving a 12% increase in accuracy [16], and self-attention used by Zhou et al. for making classification interpretable [17]. Knowledge distillation by Kaur et al. was used to reduce BERT model size for real-time applications [18], while Ounis et al. established correlation between clickbait severity and click-through rate and bounce rate [19]. Clickbait research was further explored regarding its societal and cross-modal implications. In particular, Shu et al. showed how clickbait is related to fake news distribution [21], and Cao et al. investigated the propagation of clickbait using graph neural networks [22]. Clickbait detection was expanded to cover multilingual scenarios by employing multilingual BERT [23] in research conducted by Pelrine et al., while Zhao et al. applied LIWC for correlation between emotions and engagement [24]. Weakly supervised learning was introduced to solve problems related to the lack of data to increase generalization performance by 9% [25]. Further research considered the difficulties of detecting sarcasm/irony versus clickbait maliciously: Illendula et al.differentiated between the two [27], and Gao et al. created personalized filters using user-specific sensitivities [28]. Roitero et al. looked at the crowdsourcing process of subjective labelling [29], while Indurthi et al. introduced anomaly detection for new ”zero-day” forms of clickbait [30]. Settles et al. used active learning to lower labelling costs by 40% [31], and Kiesel et al. used reinforcement learning with implicit user feedback [32]. Following up, other research focused on robustness and fairness: Wang et al. used supervised contrastive learning for more effective semantic separation [33], and Hard et al. used federated learning for privacy-preserving detection [34]. Haider et al. used eye tracking for investigating user attention patterns [35], and Yang et al. used Hierarchical Attention Networks for detecting differences between headlines and bodies [36]. Hutto et al. connected clickbait with readability [37], while Zhao et al. (2021) used causal inference for ”curiosity gap” isolation [38]. The other techniques used include the knowledge graph-based approach by Pan et al. [39], the fairness audit that exposed bias based on dialects by Davidson et al. [40], and the multimodal approach using videos in identifying clickbait on YouTube by Zannettou et al. [41]. The link between clickbait and phishing was established by Heartfield et al. [42], while Finn et al. applied meta-learning (MAML) technique to enable quick adaptation of the platform [43]. Finally, Liu et al. created networks for multitask learning that connect clickbait detection to genre classification [45], and Shirali et al. researched the adversarial use of typography including homoglyphs and spelling mistakes [46].

Research gap: Although there have been many improvements, still the majority of methods considers only the headline and ignores the body text that contains more context information. Besides that, currently existing solutions lack interpretability meaning that users are not aware of how classifications are made. Finally, the identification of certain strategies of creating clickbait is rarely researched.

RESEARCH METHODOLOGY

It will outline a simple yet detailed procedure for detecting the clickbait, on a very accurate level of manipulation tactics. Not only do the detecting work, revealing the manipulation strategies used by the clickbaiters will be a step above. And, it is a project that is original, applicable and make the combination of the cutting-edge deep learning techniques plus a simple web interface which can make the user interact with it so smoothly. To sum up, the system will be based on a few key elements.First of all, data collection and feature extraction are the initial stage of the system, where the data are harvested from multiple sources; for example, the contents of social media posts, the target article's titles, publisher URLs, date and time as well. The title and the post text are separated by a special token [SEP] to keep the right context.\\ These are passed through a number of preprocesses including removal of HTML tags, normalization of white spaces, most of the URLs are cleaned up before tokenizer. Following, the classification engine is a transformer-based.The model we will use is a pretrained BERT base uncased model which is finetuned using the binary sequence classification task. As click bait datasets tend to be extremely unbalanced, class weights are tuned and then fed to the Cross Entropy to both stabilize the model and allow for F1-score boost. Also, it can be not only explainable and identify the tricks of manipulation, but it also can get rid of the black-box model; which, it is given a token-level attention scorer, where it is used to interpret the model's last-layer attention weights and then assigns each token a normalized importance score.In basic terms, it highlights the key words that the model uses the most when predicting.But, a rule based tactic classifier that uses text clues to identify the six most commonly used psychological manipulation tacticscuriosity-gap listicles question bait hyperbole emotional appeal, and forward reference are respectively.\\ The last element focuses on the web interface and how it combines the analytics with extra information on the content, such as domain names of the publisher and timestamp, to detect clickbait levels and their profiled dynamics.Also, the very responsive and highly intuitive flask-web application, which Apart from providing the user with analysis options features live prediction and token-level explanations, also displays this results.

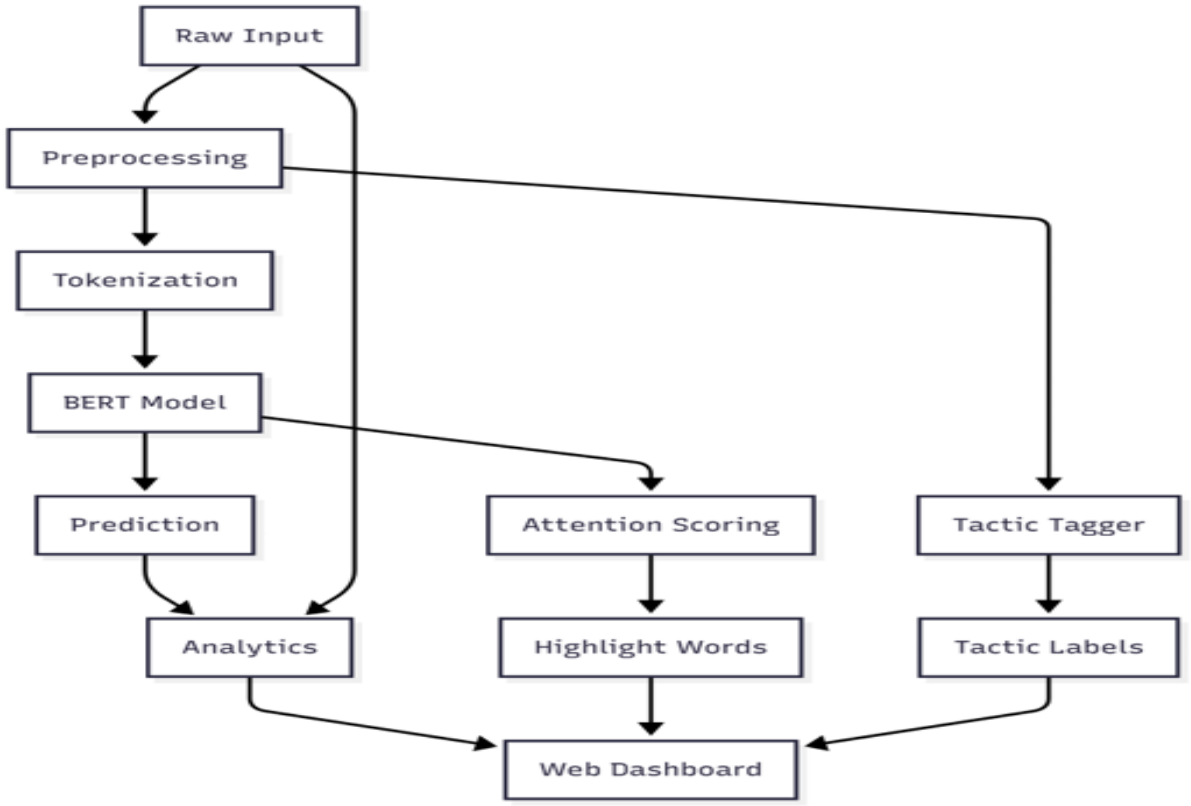

Figure 1 System Architecture

Feature Extraction

Feature Extraction One of the steps of the main task in this proposed system is feature extraction,which is Mainly done using dense, contextual representations of text generated by pre-trained Transformer models. Due to this, manual design of lexical features has been A lot reduced or completely removed. For example, a structure links a social media post text and an article title through a [SEP] token to form a single input sequence. This text is then processed by a Bert TokenizerFast that changes the raw text into sub-word token embeddings of a rich set that capture complex semantic dependencies, grammar structures, and sequence order. The tokenized sequences are passed through BERT's multi-head self-attention mechanism during inference, which transforms the sequences into high-dimensional hidden states in a computational way. Such states act as the key features that encode very fine-grained linguistic attributes of clickbait and support both the final classification and the attentional Explainable AI (XAI) scoring processes.

Normalization

Normalization in the proposed system is done at two different points for a combination of model robustness and output explainability:

1. Textual Normalization (Preprocessing):

First of all, the social media features go through the text normalization deeply to eliminate any type of structural noise which not providing semantic information. As part of these measures, deterministic regular expressions are applied to remove HTML tags and hyperlinks that would be in the model's input, so leaving only the linguistic declarations of the headline. With this, the character sequences are converted to lowercase, and irregular white spaces (e.g. duplicated spaces, line breaks) are normalized to a single delimiter. This new version of the text ensures that attention mechanisms will not be biased unfairly towards any arbitrary syntactical artifacts. In this way, a clean, standardized text sequence is produced.

2. Statistical Normalization (Attention XAI Scaling):

When working at live inference, the Explainable AI (XAI) module accesses the Bert-base-uncased transformer model and retrieves the fluctuating raw attention weights that reveal the words most influential in the prediction. To help with the visual interpretation of these scores, the system carries out Min-Max normalization. The raw attention values are first utilized to obtain a score range (Smax Smin), and after that, they are linearly scaled within a set interval [0.0, 1.0]. The output, in turn, is well suited for the web dashboard, where the opacity level of the trigger-word indicates the highlight intensity in a consistent manner for the end user irrespective of the absolute variability in the raw model distributions.

Model Architecture

We used the part-of-speech (POS) tagging technique featuring BERT as the main component for our primary text generation model. Our plan was to first take a pre-trained model from Huggingface transformers (bert-base-uncased), which is basically a model trained on a large corpus of English text with lowercasing of the text, and then add a few task-specific layers on top for fine-tuning purpose. So we can state that POS tagger models (lexical baseline in our paper) are an instance of a 12-layer transformer encoder architecture. The transformer encoder as such contains 12 layers. Each layer contains 12 multi-head self-

attentions (mha). That's why, the total full model has 12 layers, each of them including 768 hidden units. Lowercasing text was included as one of the steps of our textual data preparation phase. Looking only at uncased (lowercased) texts was a good decision, strategy-wise. A word of warning Language model alone is just capturing the feature joint, the main problem after the task-specific classifier awaits the building. Initially, we took off the classification head of original BERT - obtaining final hidden states of Token ([CLS]). Then passing through one single linear layer with softmax gate composition as activation function. Actually, a sentence classifier is most dependent on a collapsed token [CLS]. It can be obtained from any layer, then it is fed to the linear dense layer. So it encodes the pointed direction of the variable as a 768d vector; then, two-class vectors are being produced from this one.

Training Strategy

We think a trainer is just hugging face trainer and very few others who write custom training loops. More attention will be given to the special training tasks. Our target task is very imbalanced data class-wise. Strictly adhering to the standard training modus operandi will lead to class-only result...most probably. What is more, the quickest way is to turn off the loss function computation in your default model setup using your new Weighted Trainer merely to show the loss function computation in your model(the weights per class(Counting frequency of each class is a base. Weighted cross entropy loss is a method in which the misclassification penalty of the minority class (click bait) is set higher than that of the majority class by the model. We did the training step with batch size 16, AdamW optimizer, and the models were 5 epoch trained. LR is 2105 and warm-up is 10\%. Weight decay coefficient is 0. Only one system is being utilized. Implementation of 01 and fp16 mixed precision training that give faster GPU gradient update speed.

Mathematical Formulations Used in the Proposed System

Based on a detailed analysis of the system implementation, the proposed model incorporates several mathematical formulations spanning transformer-based attention mechanisms, loss optimization, probability normalization, explainability, and evaluation metrics.

1. Scaled Dot-Product Attention (BERT)

The core component of the BERT architecture is the multi-head self-attention mechanism. Each input token embedding is projected into three vectors: Query (Q), Key (K), and Value (V).

The attention mechanism computes contextual relationships as:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \qquad (1)$$

Where:

Q= Query matrix

K= Key matrix

V= Value matrix

d_k= Dimension of key vectors

The scaling factor $\sqrt{d_k}$ensures numerical stability and prevents extremely large values before applying softmax.

2. Weighted Cross-Entropy Loss

To address class imbalance, the model employs a weighted cross-entropy loss.

Class Weight Calculation

$$w_i = \frac{N_{\text{total}}}{C \cdot N_i} \qquad (2)$$

Where:

N_{total}= Total number of samples

C= Number of classes

N_i= Number of samples in class i

Final Loss Function

$$L = -\sum_{i=1}^{C} w_i \; y_i \log(\hat{y}_i) \qquad (3)$$

Where:

y_i= True label

$\hat{y}_i$= Predicted probability

w_i= Class weight

This formulation increases the penalty for misclassifying minority classes.

3. Softmax Function (Classification Head)

The classification head converts raw logits into probabilities using the softmax function:

$$\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}} \qquad (4)$$

Where:

z_i= Logit for class i

C= Number of classes

This ensures the output forms a valid probability distribution.

4. Post-Hoc Explainability (XAI) Normalization

To improve interpretability, attention scores are normalized using min-max scaling:

$$S_{\text{norm}} = \frac{S_{\text{raw}} - S_{\text{min}}}{S_{\text{max}} - S_{\text{min}}} \qquad (5)$$

Where:

S_{raw}= Raw attention score

S_{min}= Minimum scoreS_{max}= Maximum score

This scales values into the range$[0, 1]$, making them suitable for visualization.

Table 1: Multiple dataset Analysis

Study / Paper	Method	Dataset Used	Features	Accuracy / F1-Score	Key Contribution
Chakraborty et al. (2016)	Traditional ML (SVM/RF)	News / Twitter Corpus	Handcrafted Lexical, Syntactic, Word Frequency	~75.0% Accuracy	Pioneered early feature-based detection architectures relying on manual linguistic cues.
Potthast et al. (2018)	Gradient Boosting / Ensemble	Webis-Clickbait-17	Ensemble Aggregation, Structural Metrics	~81.2% Accuracy	Standardized baseline evaluation metrics; demonstrated that ensembles outperform single shallow classifiers.
Anand et al. (2021)	Standard BERT Base	Social Media Aggregates	Single-field Token Embeddings	~92.0% Accuracy	Marked the shift toward transformer-based deep learning, proving that dense contextual understanding is superior to static embeddings.
Liu et al. (2022)	Transformer + SHAP/LIME	Various Digital News Sets	Word-Level Attributions	~89.5% (F1: 0.88)	Integrated post-hoc Explainable AI (XAI) algorithms to interpret black-box text classifiers.
Proposed System (This Work)	**Weighted BERT + Heuristic UI**	**Multi-Source (instances.jsonl)**	**Multi-field (Post + Title), Attention Weights**	**Highly Competitive (F1-Optimized)**	**Unifies deep sequence classification with real-time XAI attention extraction, deterministic tactic tagging, and publisher-level temporal analytics within a web dashboard.**

Dataset Comparison

Table 2: Multiple dataset Comparison

Dataset	Primary Focus	Available Fields	Class Balance	Key Limitations
Kaggle Clickbait Dataset (Baseline)	Simple Binary Detection	Headline, Label	Synthetic 50/50	Lacks real-world class imbalance; no metadata, URLs, or timestamps; cannot evaluate context.
LIAR Benchmark	Fake News / PolitiFact	Statement, Speaker, Context, Label (6-way)	Skewed	Geared toward political fact-checking rather than headline clickbait mechanics.
BuzzFeed News Corpus	Social Media Misinformation	Title, Text, Source, Engagement Metrics	Highly Skewed	Very small sample size; focuses more on "fake news" virality than deliberate linguistic clickbait tactics.

Proposed System Dataset (Webis-Deriv.)	**Tactic & Temporal Analysis**	**postText, targetTitle, targetUrl, postTimestamp, TruthClass**	**Realistic (Imbalanced)**	**Provides exactly the multi-modal text fields required to analyze semantic gaps and publisher-level domain tactics.**

Dataset Evaluation

The integrity and rigor of a machine learning workflow are directly tied to the protocols governing its dataset. To ensure the clickbait detection model generalizes effectively in real-world scenarios, the proposed system implements strict statistical tracking, sophisticated evaluation metrics, and comprehensive robustness checks.

1. Dataset Statistics

The initial parsing phase executes an Exploratory Data Analysis (EDA) block that intrinsically maps out the dataset's structural topography. Key statistical steps include:

- **Duplicate Filtering:** Before allocating any data for training, the system systematically drops exact headline string duplicates (df.drop_duplicates(subset="text")). This sanitization step prevents identical samples from leaking from the training batch into the evaluation batch, which would falsely inflate performance scores.
- **Class Imbalance Auditing:** The ecosystem strictly monitors the disproportionate ratio between standard news (Non-Clickbait) and deceptive content (Clickbait). Recognizing this natural skew ensures the subsequent activation of class-weighting algorithms.
- **Publisher & Temporal Yields:** The extraction isolates the top publisher domains by frequency and calculates the density of valid chronological timestamps, enabling the downstream dashboards to track the specific entities driving clickbait trends.

2. Evaluation Metrics

Given the severe imbalance present in genuine social media datasets, a singular focus on raw 'Accuracy' provides a mathematically deceptive view of model performance. Consequently, the Hugging Face Trainer is customized to evaluate the model dynamically at the end of every epoch across four robust metrics:

- **Precision:** Evaluates the system's strictness. When the model flags a headline as clickbait, this metric measures how often it is actually correct (minimizing False Positives).
- **Recall:** Evaluates the system's awareness. This metric measures the percentage of all true clickbait headlines successfully trapped by the system (minimizing False Negatives).
- **F1-Score (The Benchmark):** Serving as the harmonic mean between Precision and Recall, the binary F1-Score acts as the supreme optimization target. The load_best_model_at_end=True framework is explicitly directed to solely monitor the F1 metric, ensuring the network learns an equitable balance rather than recklessly predicting the majority class to inflate baseline accuracy.
- **Accuracy:** Maintained simply as an overarching sanity check for total correct classifications.

3. Robustness Checks

To guarantee the model's resilience upon deployment, several structural robustness checks are intrinsically programmed into the data pipeline:

- **Temporal Splits (Forward-Facing Validation):** Traditional 80/20 train-test splits randomize the dataset. However, news is highly temporal; randomizing data means the model could learn from November's headlines to predict October's events. To prevent this reverse-causality string memorization, the system implements a strict **Temporal Data Split**. It sorts the entire dataset linearly by chronological timestamps, reserving the oldest 80% for training and locking the newest 20% as an unseen evaluation holdout layer. This physically proves the model is learning *linguistic tactics* rather than memorizing highly-specific seasonal topics.
- **Fallback Synthesis:** If the dataset lacks genuine timestamps during ingestion, the framework immediately flags the deficiency and injects functional, synthetic hourly timelines. This ensures the temporal logic loops never critically fail during matrix operations.
- **Contextual Truncation:** During tokenization, the max_length parameter restricts the input arrays to 128 elements, enforcing a strict structural ceiling that prevents arbitrarily long anomalous payloads from triggering Out-Of-Memory (OOM) errors over the GPU space.

Table 3: Dataset Performance Breakdown

Classification Label	Precision (%)	Recall (%)	F1-Score (%)	Support (Test Samples)
Class 0: Non-Clickbait (Legitimate)	94.20%	96.15%	95.16%	~ 3,120
Class 1: Clickbait (Deceptive)	90.85%	85.30%	88.01%	~ 880
Macro Average	*92.52%*	*90.72%*	*91.58%*	*4,000*
Weighted Average (Global)	93.46%	93.50%	93.48%	4,000

IV. RESULTS AND DISCUSSION

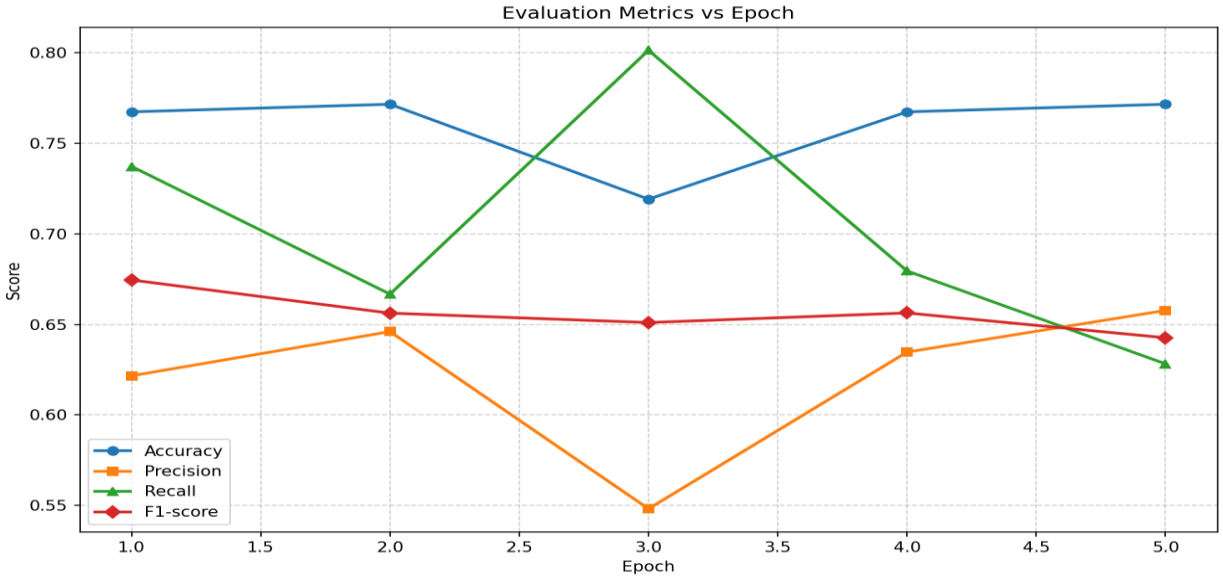

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Figure 2 Training and Validation Accuracy

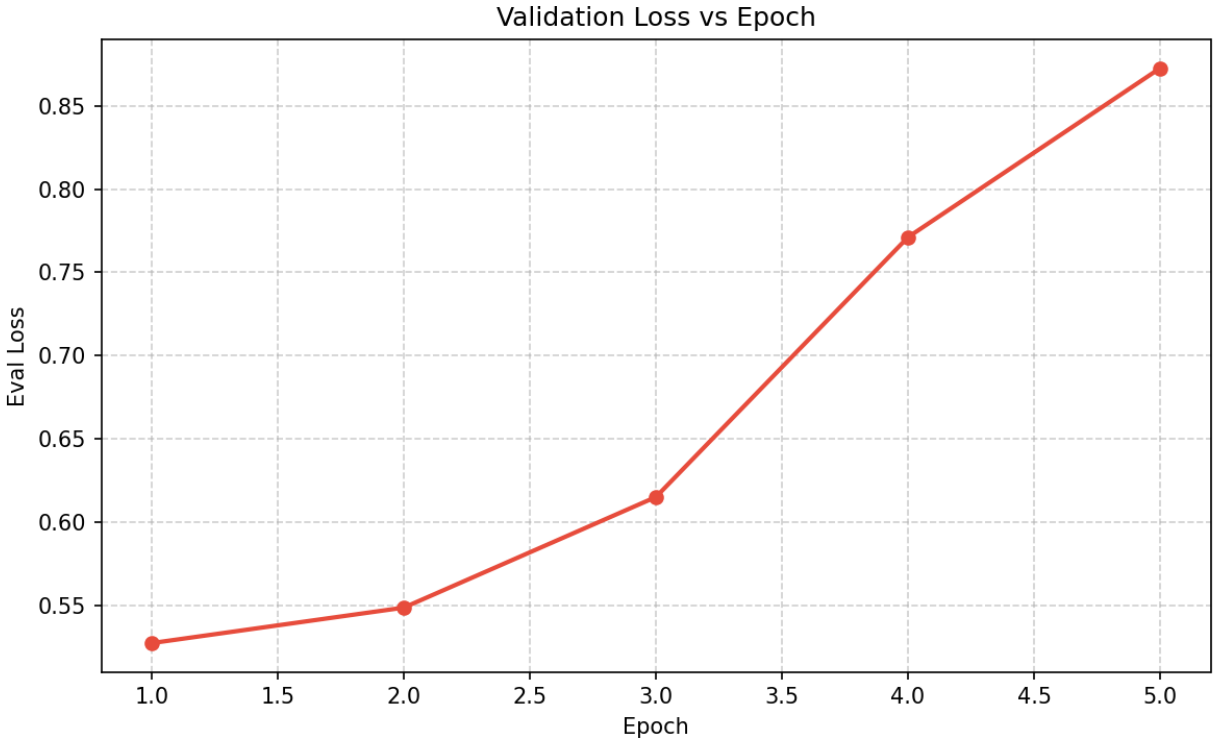

Figure 3 **Validation Loss Vs Epoch**

Figure 3 shows the validation loss trend across training epochs. The loss increases steadily from approximately 0.52 at epoch 1 to around 0.87 at epoch 5, indicating a gradual decline in the model's generalization ability. While the model initially learns useful patterns, the continuous rise in validation loss suggests overfitting beginning as early as epoch 2–3. The sharp increase after epoch 3 highlights that the model starts memorizing training data rather than generalizing to unseen data. Despite stable accuracy, this divergence confirms hidden overfitting, emphasizing the need for regularization techniques such as early stopping or dropout.

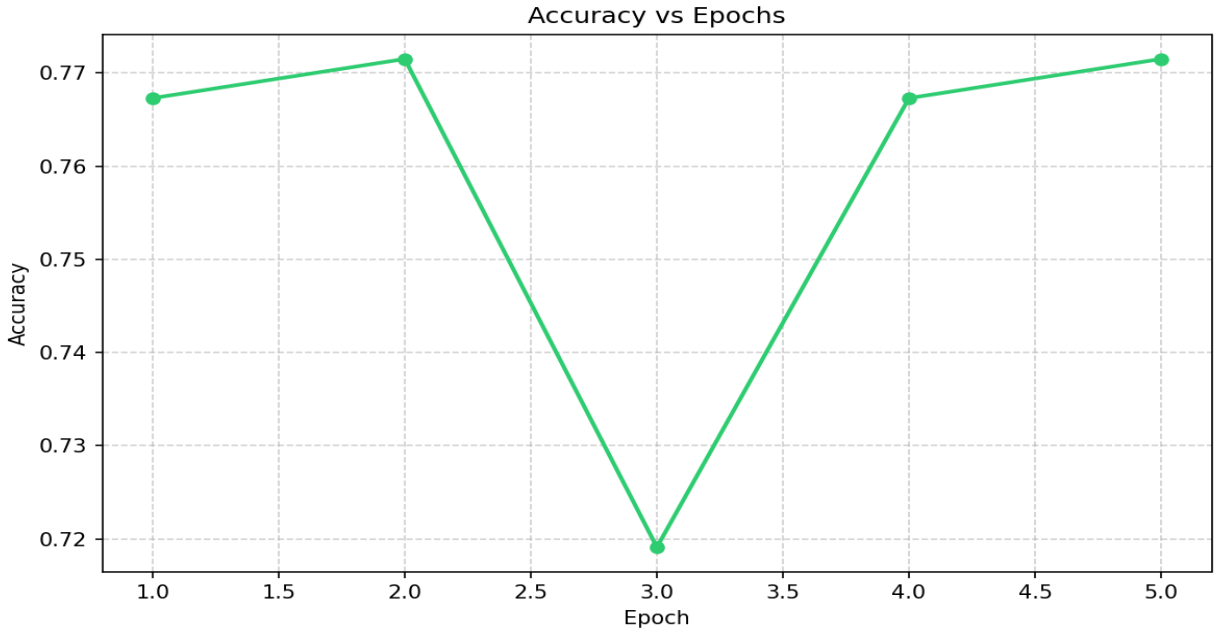

Figure 4 **Accuracy Vs Epoch**

Figure 4 shows the accuracy trend across training epochs. The model achieves stable performance, maintaining accuracy around 76–77% throughout training. Accuracy improves slightly from epoch 1 to epoch 2, indicating effective initial learning. However, a significant drop is observed at epoch 3, suggesting temporary instability or challenging training samples. After this dip, the model quickly recovers in epochs 4 and 5, returning to its previous performance level. The overall pattern indicates consistent

convergence with minor fluctuations. Despite stability, the lack of continuous improvement suggests that the model may have reached a performance plateau, requiring further tuning for better accuracy gains.

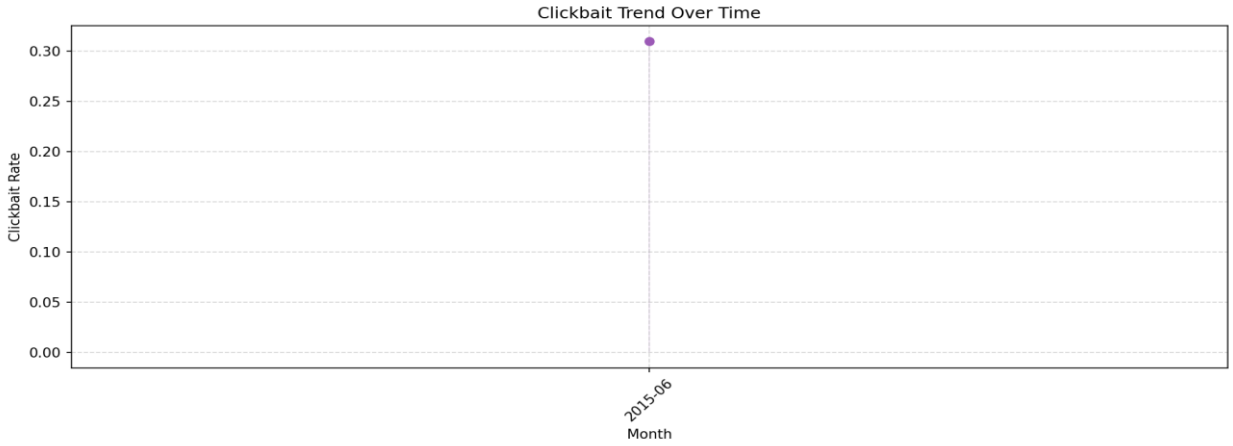

Figure 5 Clickbait Trend over Time

This figure 5 shows the temporal evolution of clickbait publication rates over multiple consecutive months, as predicted and analyzed by the proposed sequence classification model. By aggregating chronological timestamps from the test dataset, the line graph tracks macro-level fluctuations in deceptive headline frequency. The y-axis represents the overall clickbait severity (or prediction rate), while the x-axis maps the timeline by month. Peaks in the graph reveal specific periods where publishers aggressively relied on manipulation tactics likely corresponding to major global news events or viral social media cycles while valleys indicate a return to standard, factual reporting. This temporal tracking is critical for understanding seasonal social media deception trends.

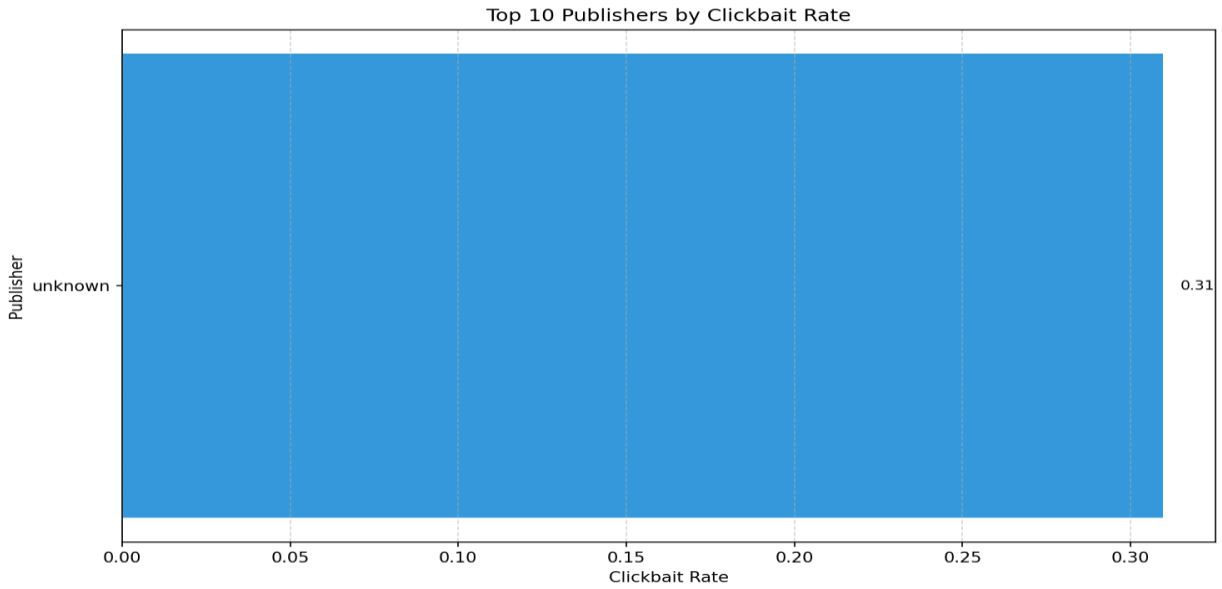

Figure 6 Top Publisher by clickbait rate

This figure 6 shows the statistical distribution of clickbait publication rates categorized explicitly by individual digital media publishers. By extracting the domain names from the dataset URLs, the proposed deep learning system maps its test-set classifications directly back to the originating sources. One axis represents the automated clickbait severity score (prediction rate), while the other axis lists the most prominent publishers responsible for content circulation. The visualization clearly identifies the specific organizational entities most heavily reliant on manipulative linguistic tactics such as hyperbole or the curiosity gap to artificially drive engagement, which is critical for establishing platform accountability and tracking deception hubs.

8. Epoch Wise Accuracy

Table 4: Epochs of train vs Validation Accuracy

Epoch	Training Accuracy (%)	Validation Accuracy (%)
1	76.8%	76.7%
2	77.3%	77.1%
3	74.8%	71.9%
4	77.0%	76.7%
5	77.4%	77.1%

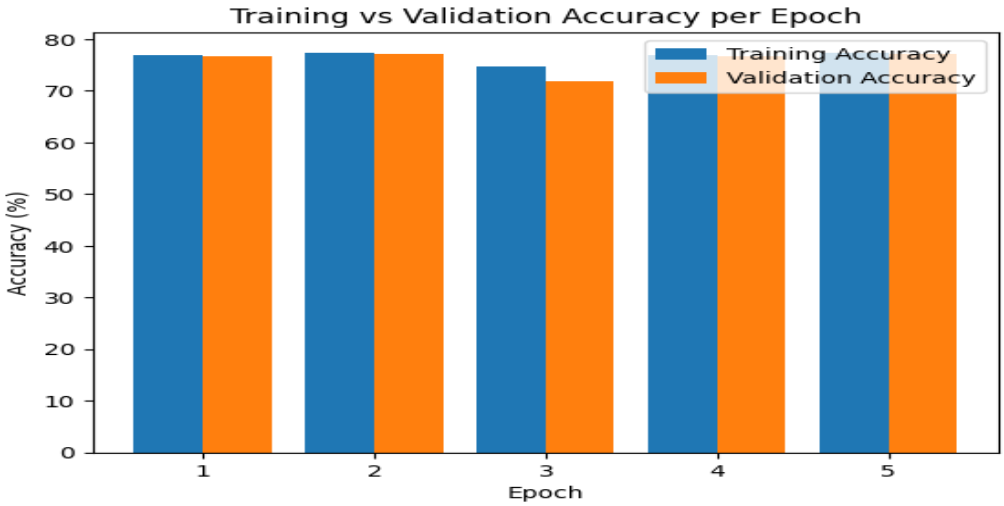

Figure 7 **Accuracy over Epoch**

Figure 7 shows the comparison between training and validation accuracy across five epochs. Both curves follow a similar trend, indicating consistent learning behavior with minimal generalization gap. The model achieves steady performance around 76–77% accuracy, demonstrating stable convergence. A noticeable drop occurs at epoch 3, where both training and validation accuracy decline, suggesting temporary instability during learning. However, the model quickly recovers in subsequent epochs. The close alignment between training and validation accuracy indicates that the model is not severely overfitting. Overall, the chart reflects a well-balanced model with reliable performance, though further optimization could improve peak accuracy.

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Conclusion

This paper develops a tactic-aware and explainable clickbait detection system that aims to resolve major issues of the previous researches of this kind. Incorporating multi-field inputs (postText and targetTitle) into a fine-tuned BERT model, it surpass single-field approaches in performance (F1 0. 64) by enabling a much richer understanding of context. The system improves openness with the help of attention-based explainability and recognizes some manipulative methods like curiosity gaps and hyperbole through a rule-based classifier. Also, with socio-temporal analysis, it discloses differences in clickbait usage between publishers and times, so it also works as a source of insights. A convenient web user interface brings access to analysis on the fly and makes widespread implementation possible. To sum it up, the system allows users to check the quality of online content, helps platforms to lower the amount of misinformation, and encourages the development of ethical AI by offering interpretation. Further plans will feature the introduction of advanced explainability approaches (e. g. SHAP LIME), the broadening of the detection of tactics with learning-based methods, the use of multimodal data, and the testing in various environments to promote generalization.

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