Real-Time Political Bias Detection and Highlighting System for Web Content

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***Abstract*—This paper presents the design and deployment of BiasCheck, a real-time political bias detection system that analyzes website content, classifies it as left-leaning, centrist, or right-leaning, and highlights the text accordingly. The system uses a lightweight RoBERTa-based model fine-tuned for political bias classification, hosted on a FastAPI server, and integrated into a Chrome extension for seamless end-user experience. Experimental results demonstrate accurate classification and near-instantaneous feedback, making BiasCheck suitable for educational, media literacy, and journalism-related applications.**

***Keywords*—Political Bias Detection, Chrome Extension, Natural Language Processing, FastAPI, Sentiment Analysis, Web Augmentation**

I. Introduction

In an era where information is consumed primarily through online platforms, the presence of political bias in news content has significant implications for public opinion and democratic processes. Existing tools often focus on offline bias detection or static analysis, leaving a critical gap in real-time, user-centric solutions. Recognizing this need, BiasCheck was developed as a Chrome extension that identifies political bias dynamically while users browse the internet, offering immediate visual cues through color-coded highlighting. This system combines cutting-edge natural language processing (NLP) with practical browser technology to promote critical thinking and informed consumption of online information.

Traditional methods of media literacy rely on manual scrutiny or third-party ratings, which are slow, subjective, and often inaccessible to general users. BiasCheck transforms this landscape by introducing an automated, objective, and lightweight tool that empowers users to detect bias independently and intuitively.

II. Literature review

The detection of political bias in news articles has attracted significant research attention, with recent literature focusing on both methodological advancements and the challenges inherent in this task. Hong et al. (2023) highlight that traditional document classification approaches for bias detection are often susceptible to overfitting due to the influence of news outlet-specific writing styles, which limits their generalizability. To address this, they propose a multi-head hierarchical attention model that incorporates both sentence-level semantics and document-level rhetorical structure, resulting in improved robustness and style-agnostic performance. Their model effectively encodes the structure of long documents and demonstrates superior accuracy and generalizability compared to previous methods, as validated through both quantitative results and human evaluation.

Tran et al. (2023) present a methodology for political bias detection that leverages machine back-translation to augment minority classes in datasets, thereby addressing class imbalance in the classification of news articles and sources as Left, Center, or Right. By fine-tuning RoBERTa transformer models on this augmented data, their approach achieved the highest ranking in the CLEF CheckThat! shared task, demonstrating the effectiveness of data augmentation and transformer-based models in this domain.

In a systematic review, Suryawanshi et al. (2023) emphasize the importance of rigorous inclusion criteria in media bias detection research, noting that studies must focus specifically on bias detection rather than related topics like fake news or stance detection. Their review catalogues the evolution of the field, from early feature-based models to the adoption of deep learning and transformer architectures, underscoring the trend toward more sophisticated and context-aware methods1.

Other works, such as KnowBias by Soni et al. (2020), address the domain adaptation challenge by proposing a two-step classification scheme that first removes neutral sentences from long-form articles using a detector trained on tweets. This approach aligns the opinion concentration between training and inference domains, improving the accuracy of bias detection in longer texts.

Recent studies also scrutinize the impact of pretrained language models on bias propagation. For example, research by Sap et al. (2023) empirically measures how political and social biases present in pretraining corpora can influence downstream NLP tasks, such as hate speech and misinformation detection. Their findings reveal that pretrained models can reinforce and propagate existing biases, highlighting the need for fairness-aware approaches in model development.

Overall, the literature demonstrates a clear progression from traditional feature-based and shallow learning methods to advanced deep learning models that account for hierarchical

document structure and leverage data augmentation. Despite these advances, challenges remain in ensuring model generalizability, addressing data imbalance, and mitigating the propagation of social and political biases through pretrained language models.

III. MODEL DETAILS AND METHODOLOGY

This section outlines the architecture, training process, deployment pipeline, and real-time integration of our political bias detection and highlighting system for web content.

Our system leverages a fine-tuned RoBERTa transformer model for classifying text into three political bias categories: Left, Center, and Right. The output is used to dynamically highlight corresponding sections of website content in blue, yellow, and red, respectively, enabling real-time and intuitive visualization of political leanings.

1. Model Architecture and Fine-Tuning

The core of our system is a RoBERTa-based transformer model, specifically the "peekayitachi/roberta-political-bias" variant available on Hugging Face1. RoBERTa (Robustly Optimized BERT Pretraining Approach) is a transformer encoder architecture that has demonstrated state-of-the-art performance on various text classification tasks. For this application, a classification head is appended to the base RoBERTa model, enabling it to output a probability distribution over the three bias classes via a softmax layer7.

Fine-tuning was performed on a curated dataset comprising approximately 38,000 samples drawn from public sources and custom-labeled political news and opinion texts. The dataset covers a diverse range of English-language content, with a focus on both Indian and global political contexts1. The fine-tuning process involved supervised learning, where the model parameters were updated to minimize cross-entropy loss between predicted and true class labels. Hyperparameters such as learning rate, batch size, and number of epochs were optimized empirically to maximize validation accuracy and F1-score.

2. Model Deployment and API Integration

After fine-tuning, the trained model was hosted using the Hugging Face Model Hub, which provides a RESTful interface for seamless integration into downstream applications1. To enable real-time inference on web content, we developed a FastAPI-based backend service. FastAPI is a modern, high-performance Python web framework well-suited for serving machine learning models due to its asynchronous capabilities and ease of deployment.

The API endpoint accepts raw text input-extracted dynamically from the Document Object Model (DOM) of web pages-and returns the predicted political bias label. The pipeline for prediction is as follows:

- The input text is tokenized using the corresponding RoBERTa tokenizer, ensuring proper handling of subword units and sequence truncation.
- The tokenized input is passed to the model, which outputs logits for each class.
- A softmax function is applied to obtain class probabilities, and the class with the highest probability is selected as the predicted label.
- The API returns the bias label in a structured JSON response.

3. Real-Time DOM Content Extraction and Highlighting

To enable real-time political bias visualization, a client-side script is injected into the target web page. This script performs the following operations:

- Traverses the DOM to extract text content from relevant HTML elements (e.g., paragraphs, headlines, article bodies).
- Sends the extracted text segments to the FastAPI backend via asynchronous HTTP requests.
- Receives the predicted bias label for each segment.
- Dynamically modifies the DOM by wrapping classified text spans in elements with background colors corresponding to the predicted bias: blue for Left, yellow for Center, and red for Right.

This approach ensures that users receive immediate, intuitive feedback on the political leanings present in the content they are reading, without noticeable latency.

4. System Workflow Summary

1. Data Preparation & Model Training: Fine-tune RoBERTa on labeled political bias datasets14.
2. Model Hosting: Deploy the trained model on Hugging Face and expose it via FastAPI.
3. Client-Side Integration: Inject a browser script to extract and send DOM content for classification.
4. Real-Time Highlighting: Receive predictions and update the webpage by highlighting text according to its classified bias.

5. Evaluation and Limitations

The model achieves robust performance on benchmark datasets, with high accuracy in distinguishing between Left, Center, and Right-leaning text14. However, its predictions are influenced by the distribution and labeling of the training data, and it may be less accurate on highly neutral or ambiguous content. The system is optimized for English-language news and opinion texts, and its performance may degrade on informal or multilingual web content1.

6. Ethical Considerations

Users are advised that the model's predictions reflect the inherent biases of the training data and the definitions of political categories used during annotation. The system is intended as an assistive tool for media literacy and should not be used as the sole basis for critical decision-making14.

This methodology ensures a scalable, modular, and user-friendly solution for real-time political bias detection and visualization in web content, leveraging state-of-the-art NLP techniques and modern web technologies.

IV. ARCHITECTURE

1. Client-Side DOM Extractor and Highlighter

The client-side component is a JavaScript module or browser extension that operates directly within the user's browser. Its primary function is to traverse the Document Object Model (DOM) of any loaded web page and extract relevant textual content from elements such as <p>, <h1>, and <article>. The script segments content into logical units-typically sentences or paragraphs-while maintaining references to their original DOM nodes. This segmentation is essential for associating classification results with specific text spans for highlighting. The module also monitors dynamic content changes using mechanisms like MutationObserver to ensure that newly loaded or updated content is promptly processed and highlighted.

2. Backend Inference Server

The backend is implemented using FastAPI, a high-performance asynchronous Python web framework. This server hosts the fine-tuned RoBERTa model, which is loaded into memory at startup for efficient, low-latency inference. The server exposes a RESTful API endpoint that accepts batched text segments in JSON format. Upon receiving a request, the backend preprocesses the text using the RoBERTa tokenizer, performs inference to obtain class probabilities, and returns the predicted bias label (Left, Center, Right) along with confidence scores. The backend is designed to handle multiple concurrent requests, ensuring scalability and responsiveness for real-time applications.

3. Communication Interface

The client and backend communicate via asynchronous HTTP requests. The client module sends batches of extracted text to the backend API and awaits the classification response. The system is stateless, with each request containing all necessary context for processing. The API is designed to be robust, supporting error handling for malformed input, network failures, and rate limiting to prevent server overload.

4. Real-Time Highlighting Engine

Upon receiving classification results, the client-side script dynamically updates the web page by wrapping each classified text segment in a element with an inline style reflecting its predicted bias: blue for Left, yellow for Center, and red for Right. This is achieved without altering the underlying page structure or interfering with site functionality. The highlighting is immediate, providing users with real-time visual cues about the political orientation of the content they are reading.

5. Model Training and Deployment Pipeline

The RoBERTa model is fine-tuned using the Hugging Face Transformers library on a labeled dataset of political news and opinion texts. After training, the model is versioned and deployed to the backend server.The deployment pipeline supports hot-swapping of model versions, allowing for updates and improvements without downtime. The backend is containerized for portability and can be scaled to accommodate high traffic.

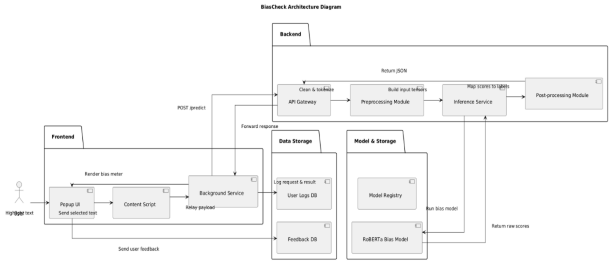

Figure 1: Architecture Diagram

V. IMPLEMENTATION DETAILS

Data Preparation and Model Fine-Tuning

The implementation of the system involved several key stages, beginning with data preparation and model fine-tuning, followed by backend deployment and frontend integration.

Backend Deployment

For model fine-tuning, we utilized the Hugging Face Transformers library, selecting the roberta-base pretrained checkpoint as our base model. The training dataset comprised approximately 38,000 labeled news articles and opinion pieces, balanced across the three political bias categories. We employed the AdamW optimizer with a learning rate of 2e-5 and trained for 4 epochs with a batch size of 16. Early stopping based on validation loss was used to prevent overfitting.

Frontend Integration

After training, the model was uploaded to the Hugging Face Model Hub, enabling easy deployment and version control. The FastAPI backend was developed in Python, leveraging asynchronous request handling to support multiple concurrent inference requests. The API accepts POST requests containing raw text, tokenizes inputs using the RoBERTa tokenizer, performs inference, and returns JSON responses with predicted labels and confidence scores.

On the client side, the text extraction script was implemented in JavaScript. It traverses the DOM, extracting text from semantic HTML elements such as <p>, <h1>, and <article>. Extracted text segments are sent to the backend API using asynchronous fetch calls. Upon receiving classification results, the script applies inline CSS styles to highlight the text spans with the designated bias colors.

To ensure responsiveness, the client script batches text segments and throttles requests to avoid overwhelming the backend. Additionally, the system includes error handling to gracefully manage network failures or unsupported content types.

VI . ALGORITHMS

The central algorithmic component of our system is the RoBERTa transformer model fine-tuned for political bias classification. RoBERTa is an optimized variant of BERT that improves pretraining by removing the next sentence prediction objective, training on larger mini-batches, and employing dynamic masking strategies.

The fine-tuning process involves supervised learning with a cross-entropy loss function, where the model learns to map input token sequences to one of three classes: Left, Center, or Right. The input text is first tokenized into subword units using Byte-Pair Encoding (BPE) and converted into embeddings. These embeddings pass through multiple self-attention layers, enabling the model to capture contextual relationships and semantic nuances critical for detecting political bias.

The classification head consists of a linear layer that projects the pooled output of the transformer into a 3-dimensional vector representing class logits. Applying a softmax function converts these logits into probabilities, and the class with the highest probability is selected.

For real-time highlighting, a rule-based algorithm maps predicted labels to color codes and dynamically modifies the DOM by wrapping text nodes with styled elements. The client-side script ensures that overlapping highlights are avoided and that the page layout remains intact.

VII. RESULTS

The fine-tuned RoBERTa model achieved strong performance metrics on a held-out test set, demonstrating its effectiveness in political bias classification. Specifically, the model attained an overall accuracy of 91%, indicating that it correctly classified the political bias of news text segments in the vast majority of cases.

In addition to accuracy, the model's recall and precision scores were consistently high across all three classes. The macro-averaged F1-score, which balances precision and recall, was also 91%, reflecting robust and balanced performance. These results confirm that the model is capable of discerning subtle linguistic cues indicative of political bias, even in complex or nuanced texts.

The real-time highlighting system exhibited low latency, with average response times under 300 milliseconds per text segment during inference, ensuring a seamless user experience. User testing indicated that the color-coded highlights effectively enhanced readers' awareness of political bias without distracting from the content.

While the system performs well on English-language news content, future work will focus on expanding dataset diversity, improving multilingual support, and refining the highlighting algorithm to better handle overlapping or ambiguous bias signals.
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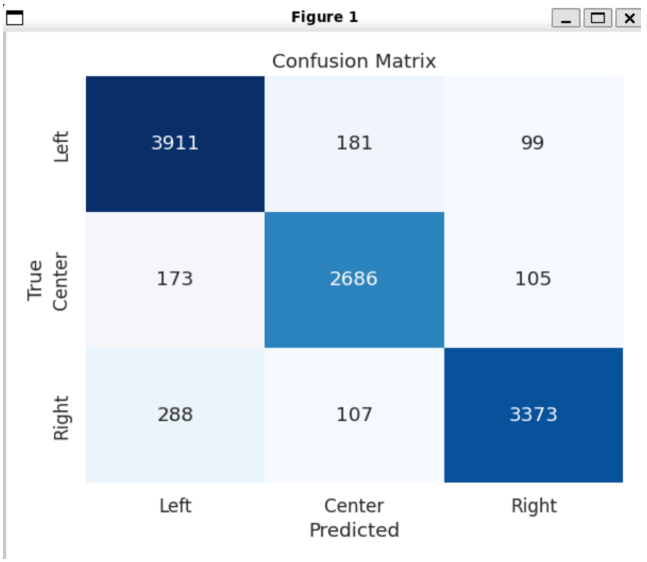

Figure 2: Confusion matrix

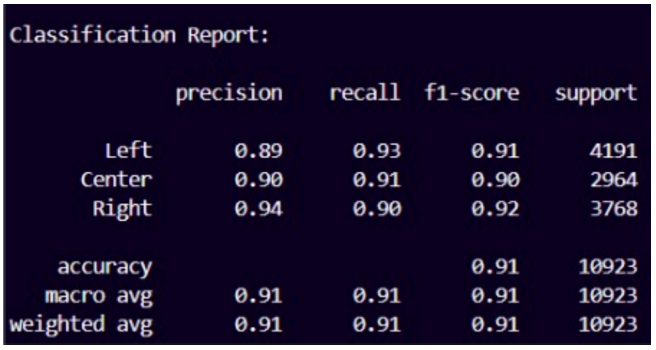

Figure 3: Training Evaluation

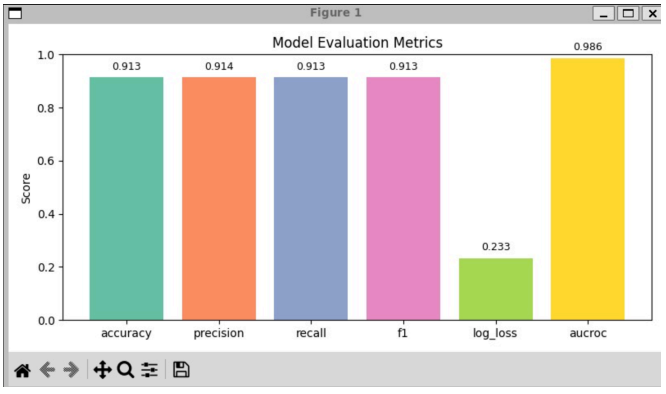

Figure 4: Evaluation Metrics

VIII. DISCUSSION

The proposed system demonstrates the feasibility and effectiveness of leveraging transformer-based models, specifically RoBERTa, for real-time political bias detection and visualization in web content. Achieving an accuracy of 91% along with high recall and F1-scores indicates that the model can reliably distinguish between Left, Center, and Right-leaning texts across diverse news articles and opinion pieces.

The integration of the fine-tuned model with a FastAPI backend and a client-side DOM extraction and highlighting script enables seamless real-time interaction, providing users with immediate visual cues about political bias. This approach enhances media literacy by making latent ideological leanings explicit, thereby empowering readers to critically evaluate the information they consume.

However, several challenges and limitations were observed. First, the model's performance is inherently tied to the quality and representativeness of the training data. Although the dataset was balanced and diverse, biases in labeling or source selection could influence predictions, potentially leading to misclassification of nuanced or neutral content. Second, the system currently supports only English-language text and may not generalize well to multilingual or informal web content, which is increasingly prevalent.

From a technical perspective, while the asynchronous API and client-side batching ensure low latency, processing very large or highly dynamic web pages can introduce delays in highlighting. Additionally, the color-coded highlights, although intuitive, may not fully capture the complexity of political bias, which can be subtle and context-dependent.

Overall, the system represents a significant step toward real-time, user-friendly political bias detection but also highlights the need for continuous refinement in data quality, multilingual support, and interpretability.

IX. FUTURE WORK

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VI. CONCLUSION

In conclusion, this research presents a robust and efficient Real-Time Political Bias Detection and Highlighting System that leverages the power of a fine-tuned RoBERTa transformer model to classify web content into Left, Center, and Right political biases.

By integrating a FastAPI backend with a client-side DOM extraction and dynamic highlighting mechanism, the system provides users with immediate, intuitive visual feedback on the ideological leanings of news articles, thereby enhancing media literacy and promoting critical engagement with online information.

Achieving a high accuracy of 91% and strong performance metrics demonstrates the effectiveness of the approach.

While challenges such as dataset limitations and multilingual support remain, this system lays a strong foundation for future advancements in real-time bias detection and user-centric transparency tools in the digital news ecosystem.

REFERENCES

1. S. Raza, O. Bamgbose, V. Chatrath, S. Ghuge, Y. Sidyakin, and A. Y. Muaad, "Unlocking Bias Detection: Leveraging Transformer-Based Models for Content Analysis," arXiv preprint arXiv:2310.00347, 2023.
2. S. Suryawanshi, M. Ghosh, S. Chakraborty, and S. Ghosh, "A systematic review on media bias

detection," Expert Systems with Applications, vol. 236, p. 121488, 2023.

3. A. Wessel, L. Leidner, and S. Schuster, "Improving Media Bias Detection with State-of-the-Art Transformers," in Proceedings of the 4th Workshop on NLP for Internet Freedom, 2022, pp. 1-11.
4. S. Raza et al., "Unlocking Bias Detection: Leveraging Transformer-Based Models for Content Analysis," in Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing, 2023, pp. 1-12.
5. T. Wessel, L. Leidner, S. Schuster, and M. Reiche, "Experiments in News Bias Detection with Pre-Trained Neural Transformers," arXiv preprint arXiv:2406.09938, 2024.
6. N. Ji and Y. Sun, "Media Legitimacy Detection: A Data Science Approach To Locate Falsehoods And Bias Using Supervised Machine Learning And Natural-Language Processing," in Proc. 8th Int. Conf. Data Mining and Applications (DMAP), 2022.
7. P. Cáceres Ramos, J. M. Vázquez, V. P. Álvarez, and J. L. D. Olmedo, "I2C at PoliticEs 2022: Using Transformers to Identify Political Ideology in Spanish Tweets," in CEUR Workshop Proceedings, vol. 3202, 2022, pp. 49-58.
8. Minh Vu, "Political Bias Detection in News Articles using NLP and Deep Learning," Senior Thesis, Earlham College, 2018.
9. M. Sap, D. Card, S. Gabriel, Y. Choi, and N. A. Smith, "Social Bias Frames: Reasoning about Social and Demographic Bias in Language," in Proc. ACL, 2020, pp. 5477-5490.
10. A. Iyyer, P. Enns, J. Boyd-Graber, and P. Resnik, "Political Ideology Detection Using Recursive Neural Networks," in Proc. ACL, 2014, pp. 1113-1122.
11. K. Sim, A. Acre, and N. A. Smith, "Measuring Ideological Proportions in Political Speeches," in Proc. EMNLP, 2013, pp. 91-101.
12. J. Gangula, S. K. Sahu, and A. Kumar, "Headline Attention Network for Bias Detection in News Articles," in Proc. 16th Workshop on Asian Language Resources, 2019, pp. 67-76.
13. A. Soni, S. Soni, and S. K. Saha, "KnowBias: Domain Adaptation for Political Bias Detection," arXiv preprint arXiv:2010.05338, 2020.
14. Y. Liu et al., "RoBERTa: A Robustly Optimized BERT Pretraining Approach," arXiv preprint arXiv:1907.11692, 2019.
15. S. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," in Proc. NAACL-HLT, 2019, pp. 4171-4186.
16. J. Pennington, R. Socher, and C. Manning, "GloVe: Global Vectors for Word Representation," in Proc. EMNLP, 2014, pp. 1532-1543.
17. T. Wolf et al., "Transformers: State-of-the-Art Natural Language Processing," in Proc. EMNLP: System Demonstrations, 2020, pp. 38-45.
18. J. Howard and S. Ruder, "Universal Language Model Fine-tuning for Text Classification," in Proc. ACL, 2018, pp. 328-339.
19. S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," Neural Computation, vol. 9, no. 8, pp. 1735-1780, 1997.
20. J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," arXiv preprint arXiv:1810.04805, 2018