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Article

A Comprehensive Survey of News Bias Detection Datasets

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Abstract: News is one of the leading sources of knowledge that provides insight into what kind of perception shapes public beliefs, affects decisions, and also facilitates democratic systems. Today, digital journalism, along with extensive use of news portals on the web and social media, has considerably increased the speed and frequency in terms of its production and circulation. Digitisation of info is continuous, as it can alter content that is not natural and that contains a particular agenda that would challenge how someone interprets this content and understand exactly why it had been generated. Auto News Bias Detection research has become a major discipline utilizing various machine learning and natural language processing techniques in order to automatically assess different categories of media bias. The performance of this model mainly depends on the quality of benchmark data, which enables objective annotation, diversity and relevance of training/testing data. So, the quality, relevance, and annotation guidelines of the data have a key influence on the accuracy and effectiveness of models that could perform automatic bias detection.
Keywords: News Bias, Media Bias, Framing Bias, dataset

1. Introduction

News is some information about an event or occurrence that the public knows for a decision to be made. Previously, the news used to be reported by reporters; later, it circulated in the press (newspapers), on the airwaves (radio and television), now, news spreads quickly through the internet, websites, and media on social networks. However, compared to conventional media, this digital media has to face problems, including, misformation, overload information, news with sensational headlines, and credibility/accuracy.

News bias analysis is an important topic of study in current media research, as news reports often have implicit or explicit biases that might influence the perception of the public. News bias can be expressed by selective reporting, by using loaded words, or by focusing on some views while ignoring others. Such methods can manipulate information and shape people's perceptions of how events and circumstances unfold, ultimately affecting their actions and decisions.

Studying Media Bias exposes concealed tilts so that press members and news organizations will remain responsible for fair coverage [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11] . It encourages critical analysis and media literacies in users, thus encouraging them to evaluate their consumption and source information. Also, it provides a framework that researchers can utilize to challenge fake news and promote media diversity [12],[13]. It's important for sustaining the credibility and reinforcing the values of a democratic nation. It assists individuals, organizations, fact checkers, and political bodies that strive for objective coverage and truth within the news and media ecosystem news Bias.

News Bias is comprised of several types, and in effect is a phenomenon comprised of a variety of dimensions: Framing Bias [1],[6] (emphasizing specific elements of the narrative), Word Bias [14] (selecting terminology that influences the target's perception), Omission Bias (unintentionally leaving certain parts out of the report) and Selection Bias (favoring only specific sources or opinions). Each layer is examined together with other levels to give researchers and policy analysts a comprehensive picture of how bias works in modern-day media.

News articles have a great impact on public opinion, but they are often subject to different kinds of biases (e.g. political, gender, racial) [3], [6], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29]. Traditional bias detection is usually limited to a few biases and is not comprehensive for multi-bias detection. The goal of this study is to propose a study for the detection of multiple types of biases (e.g., lexical, informational, language) in news articles and headlines [1], [32], [33], [34], [35] . For this kind of analysis, the major aspect is selection of an exact dataset for analysis. As given in the abstract, after reviewing some papers, the following information is extracted related to datasets available and its usage.

1.1 News Bias

News Bias refers to news coverage that presents information from multiple angles, perspectives, and contexts rather than a single viewpoint. It integrates political, social, economic, cultural, and technological dimensions of an event, helping readers understand not just the what, but also the why and how. The types of biases are as shown in Fig. 1.

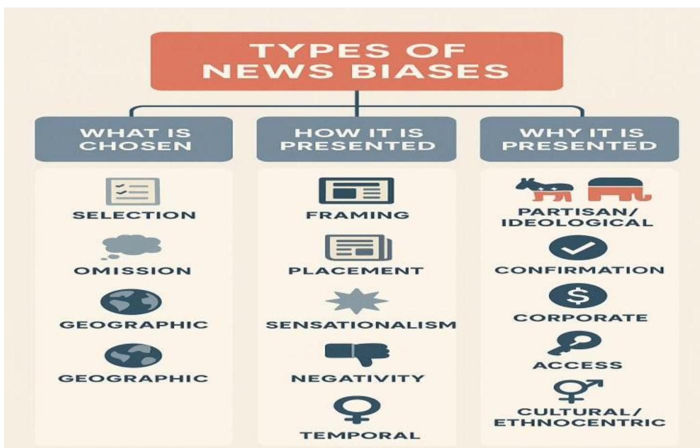

Fig. 1 Types of NEWS Biases

1.2 News Bias Detection

News bias detection is a method used to detect, analyze, and measure biased content in news articles such as words, statements or structures. The goal is to assess whether a news story is presented objectively or whether there are signs that support a specific political, ideological or social standpoint and the extent to which news consumers can rely on the story. Fig. 2 shows the taxonomy of News bias detection by various levels.

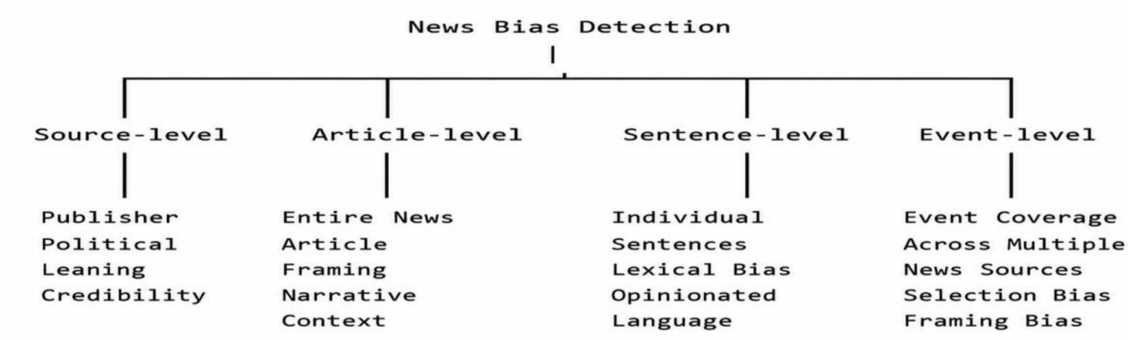

Fig. 2 Taxonomy of News Bias Detection

Source-level Bias: This research focuses on the reputation and systematic orientation of news organizations. Approaches include calculating a "Bias Short-term Impact Score" for outlets based on social media reach, using "media-level representations" like follower bios to predict outlet leaning, and evaluating model performance across different ideological media groups[8],[16],[26],[31].

Article-level Bias: Research at this level assesses the overall slant, framing, or spin of an entire piece. Papers in this category use techniques such as "headline attention"[27],[25], "second-order bias distributions" (aggregating sentence-level data to predict article bias), and manual article-level ideology classification [30].

Sentence-level Bias: This is the most common focus, with researchers identifying biased words, phrases, or specific sentiment polarities in individual sentences. Notable work includes the detection of "bias-inducing words"[14] ,[36], identifying "sentence-level bias" in specialized datasets like BABE, and analyzing the veracity of individual political statements[6], [19].

Event-level Bias: This level involves comparing how different outlets cover the same occurrence. Research includes "linking events across datasets" to identify selection bias, using datasets like BASIL, which group articles by event, and reconstructing event narratives across liberal, conservative, and neutral outlets [11],[25],[31]

The datasets used for each type are given in Table 1, News bias detection by levels.

Table 1: News bias detection by levels

Level	**Description**	**Datasets**
Source-level Bias	Bias associated with the overall political orientation or credibility of a news organization.[1], [3], [4], [6], [15], [16], [17], [18], [19], [20], [21], [22], [23], [26], [27], [28]	AllSides, MBFC[1], [3], [16], [17], [21], [22], [26], [27]
Article-level Bias	Bias present throughout an entire news article due to framing, omission, or narrative choices.[6], [30]	BASIL [1], [7], [14], [15], [18], [22], [24], [25], [34], [36]
Sentence-level Bias	Bias occurring in individual sentences through subjective	BABE [1], [35], [36]

	wording, sentiment, or loaded language.[23], [27], [33]	
Event-level Bias	Bias arising from differences in how multiple media outlets report the same event, including selection and framing. [6], [8], [11], [25], [30], [31]	GDELT, Multi-source event datasets [8]

1.3 Approaches used in Bias Detection:

News bias detection using machine learning has evolved considerably from the conventional methods utilizing machine learning algorithms to the recent state-of-the-art large language models (LLMs) [25]. Conventional machine learning techniques employ traditional algorithms like Support Vector Machines (SVM) [27], Naïve Bayes (NB) [35], and Random Forest (RF) [35], and manual crafted features like TF-IDF [27], n-grams and linguistic features for news bias classification. Deep learning models including CNNs and LSTMs can capture meaningful semantics from news articles automatically and hence improve classification for intricate bias patterns. With the introduction of the Transformer based architecture like BERT, RoBERTa and DeBERTa that can encode the long-range and long-distance relations in sequences through its self-attention mechanism and gain a deeper understanding of language semantics, the performance is increased. LLMs such as GPT, Llama and Gemma have lately displayed impressive capabilities for detecting news bias, realizing zero-shot, few-shot and instruction-based bias classification by eliminating the need of feature extraction on task specific feature datasets and supervised information extraction approach. As given in the following Table 2. Approaches in Bias Detection.

Table 2: Approaches in Bias Detection**.**

Approach	**Characteristics**	**Common Algorithms/Models**
Traditional Machine Learning	Relies on handcrafted linguistic features such as TF-IDF, n-grams, sentiment scores, and POS tags.	Naïve Bayes (NB), Support Vector Machine (SVM), Random Forest (RF), Logistic Regression (LR)
Deep Learning	Automatically learns feature representations from text using neural networks.	CNN, RNN, LSTM, BiLSTM, GRU
Transformers	Uses self-attention to capture contextual semantics and long-range dependencies.	BERT, RoBERTa, DeBERTa, XLNet, ELECTRA
Large Language Models (LLMs)	Employs large-scale pretrained generative models for zero-shot, few-shot, and instruction-based news bias detection.	GPT-3/4, Llama, Mistral, Gemma, Claude

2. News Bias Detection Datasets

News bias detection is of great importance for building machine learning and deep learning models with large news news and their labels for bias to train and validate models for determining, quantifying, and removing bias. As shown in Fig. 3 Taxonomy of News and Media Bias Related datasets 6 types are identified and described as follows.

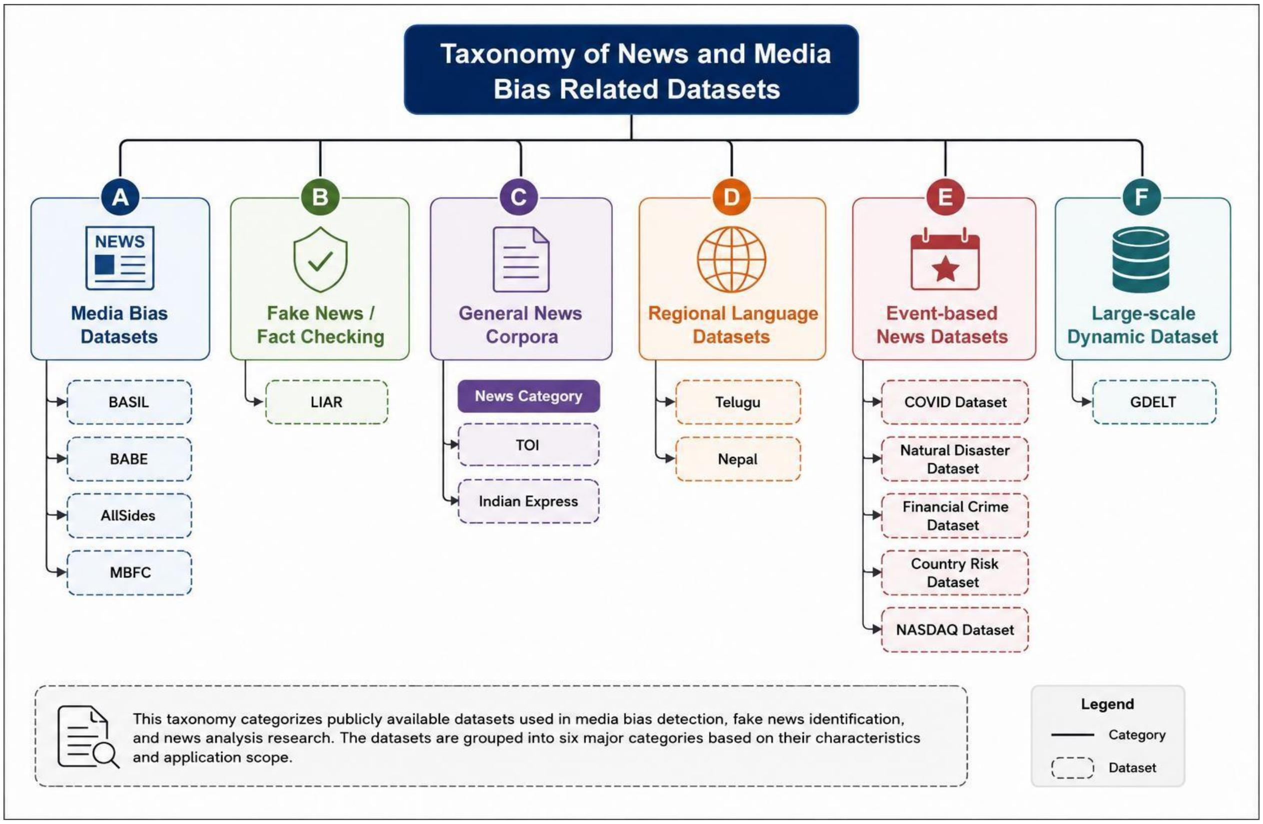

Fig. 3 Taxonomy of News and Media Bias Related datasets

Media Bias Datasets

These datasets are specifically designed to identify and analyze different forms of media bias, such as political orientation, framing, and subjective language, in news articles and media sources.

Fake News / Fact-Checking

These datasets contain verified true and false claims or news articles and are primarily used for fake news detection, misinformation analysis, and automated fact-checking.

General News Corpora

General news corpora consist of large collections of news articles from multiple domains and publishers. They are widely used for text classification, topic modeling, sentiment analysis, and other natural language processing tasks.

Regional Language Datasets

Local language datasets of news content in regional and local languages, which may be low-resource ones. It facilitates multilingual studies as well as aids language-specific news analytics and bias detectors.

Event-based News Datasets

These datasets compile news articles related to specific events, such as pandemics, natural disasters, financial crimes, or economic risks. They are useful for studying event-specific reporting, media framing, and temporal news analysis.

Large-scale Dynamic Datasets

Large-scale dynamic datasets continuously collect and update news from multiple global sources. They enable real-time monitoring of news events, trend analysis, media bias detection, and geopolitical studies at scale.

3. Comparative Analysis of Existing Datasets

It is important to identify what information other news bias datasets have and can provide by conducting comparative studies. Researchers are able to assess the quality of a data set in regards to size, accuracy, and coverage of news outlets by comparing a number of them, so that it becomes possible to then find the best-quality, richest-in-information datasets to produce your models and fill any knowledge gap that is existing by building new data sets that may represent well News bias phenomena. It is given in Table 3 Comparative Analysis of Existing Datasets.

Table 3: Comparative Analysis of Existing Datasets

Comparison Criterion	**Media Bias Datasets (BASIL, BABE, AllSides, MBFC)**	**Fake News / Fact-Checking (LIAR)**	**General News Corpora (News Category, TOI, Indian Express)**	**Regional Language Datasets (Telugu, Nepal)**	**Event-based Datasets**	**Large-scale Dynamic Dataset (GDELT)**
Dataset Size	Small to Medium	Medium	Medium to Large	Small to Medium	Medium	Very Large (Millions of records)
Dynamic vs. Static	Static	Static	Mostly Static	Static	Mostly Static	Dynamic (Continuously Updated)
Manual vs. Automatic Annotation	Mostly Manual	Manual	Generally Unannotated	Manual/Semi-automatic	Semi-automatic	Automatic
Multilingual Support	Limited	English Only	Limited	Yes (Regional Languages)	Limited	High (100+ Languages)
Bias Categories	Political, Framing, Lexical, Source Bias	Truthfulness, Misinformation	Topic Classification (Limited Bias Labels)	Language-specific Bias	Event Framing, Reporting Bias	Source, Geographic, Event, Sentiment Bias
Domain Coverage	Politics, Society	Politics, Public Claims	Multiple News Domains	Regional News	Specific Events	Global Multi-domain News
Temporal Coverage	Fixed Time Period	Fixed Time Period	Fixed Archives	Fixed Archives	Event Duration	Continuous Real-time Coverage
Explainability	High (Sentence/Article-level Labels)	High (Claim Verification Labels)	Low	Moderate	Moderate	Low to Moderate

Computationa l Requirements	Low to Moderate	Low	Moderate	Moderate	Moderate	High (Big Data Processing)

Summary of Datasets:

Media Bias datasets provide detailed annotations and are best suited for bias detection but are relatively small and static.

LIAR is effective for fake news and fact-checking research but is limited to English and political claims.

General News Corpora have a wide range of domains, but without clearly biased information. Regional Language Datasets cover multilingual and low-resource languages, but often are very small and are unavailable.

Event-based Datasets focus on report styles related to specific events, but are very limited in their temporal scope.

GDELT is the most exhaustive dataset; it contains real-time coverage from around the globe. It is multilingual, but it is also extremely large and automatically generated, and so needs large

computational resources and more preprocessing steps in order for us to perform detailed bias analysis. The observation is as shown in Table 4

Table 4: Observations

Criterion	**Observation**
Dataset Size	GDELT is the largest, while BASIL and BABE are relatively small but highly annotated.
Dynamic vs Static	GDELT, AllSides, and MBFC are dynamic and regularly updated; most research datasets are static.
Manual vs Automatic Annotation	BASIL, BABE, LIAR, and MBFC rely heavily on manual annotation, whereas GDELT and News Category datasets use automated methods.
Multilingual Support	GDELT offers extensive multilingual coverage (100+ languages). Most other datasets are English-only.
Bias Categories	BASIL and BABE provide annotations of fine-grained bias, and AllSides and MBFC target source-level political bias. Bias annotations are often missing in many general news datasets.
Domain Coverage	BASIL, BABE, and LIAR mainly cover politics. GDELT spans multiple domains globally, while News Category datasets include business, sports, entertainment, technology, etc.
Temporal Coverage	Dynamic datasets support continuous monitoring; static datasets cover only a fixed time period.
Explainability	BASIL and BABE provide the best explainability due to sentence-level annotations. GDELT has limited explainability because of automated extraction.
Computational Requirements	GDELT requires significant storage and computational resources, whereas BASIL, BABE, and LIAR can be processed on standard research hardware.

4. Challenges in Existing Datasets

Existing datasets exhibit several limitations:

- The majority are focused on the English language with a narrow scope on multiculturalism & native languages.
- The sentence-level fine-grained bias annotations only exist for small datasets (BASIL, BABE).
- Large-scale datasets like GDELT focus on event information rather than bias labelling explicitly.
- Few datasets simultaneously support multiple bias levels (source, article, sentence, and event).
- Dynamic datasets often lack detailed explainability, while explainable datasets are relatively small.
- There is a need for a large-scale, multilingual, dynamically updated, explainable bias detection dataset that integrates multiple bias categories and supports modern AI-based bias detection models.

5. Conclusion

Existing media and news bias datasets have driven significant progress in various research areas including bias detection, fake news detection, and computational journalism by supplying much-needed benchmark data for machine learning and natural language processing. These efforts span from biased corpus-based studies to human annotations of bias in political content or specific domains using datasets like BASIL, BABE, AllSides, MBFC, LIAR, corpora of various regional languages, event-specific corpora, and news aggregators like GDELT, which support bias analysis at different levels of granularity and application fields. Nevertheless, existing corpora are still hindered by their relatively static characteristics, English preference, non-uniformity in guidelines, limited support for other languages besides English and their restricted scope, often limited to political biases, rather than being comprehensive and capturing a wide array of societal biases. Such limitations affect the scalability, explainability, and comparison of current models.

This research can further advance toward the design of large-scale dynamic multilingual and multimodal benchmark datasets tracking media biases through news evolution and multiple modalities. The unified annotation schemes from source, article, sentence, and event levels integrated with the interpretable bias labels must be employed for data consistency and model interpretability. LLM, agent based AI, with the integration of humans-in-the-loop will achieve the semi-automated large-scale high-quality annotations.

Besides, expanded data sources including text, images, and social media in multiple languages and different domains will facilitate a flexible, accurate, and interpretable detection of multiple biases for real digital journalism and computational media analysis.

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