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Lexicon–Sentiment-Based Model for Detecting Fake News

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Abstract: The spread of misinformation poses a challenge to social media platforms, which requires elaborate detection systems. Most existing approaches to detecting misinformation skip using multiple features and are therefore bound to specific topic domain. This study presents a new model, Lexicon–Sentiment-Based Model (LSBM), which combines lexical and sentiment features and applies them alongside unigrams to improve the chances of detecting fake news from any domain. We applied our model to three heterogeneous datasets: Fake and Authentic News Articles (44K samples), Combined Corpus Dataset1 (80K samples), and Merged FA-KES and CoAID datasets (70K samples)—which cover politics, health, economics, and entertainment. The proposed approach applies feature selection to discriminate evaluating linguistic and emotional constructs, such as punctuation, sentiment value, and Term Frequency–Inverse Document Frequency weighted unigrams. These features were then evaluated against six classifiers: logistic regression, decision tree, random forest, support vector machine, K-nearest neighbors, and Naive Bayes. The results demonstrated that the inclusion of lexicon–sentiment features with unigrams substantially enhanced detection accuracy: SVM achieved 97% accuracy in the Combined Corpus Datasets, while RF achieved 88% accuracy in cross-domain data. Regarding cross-domain robustness, LSBM overcomes dataset constraints by exploiting domain-neutral features such as emotional tone and lexical diversity. Regarding feature fusion, the combination of sentiment, lexical, and unigram features performs better than single-feature approaches; it increases accuracy more than 6% over models using only unigrams. Regarding interpretability, feature importance analysis shows marks, ALL CAPS, and sentiment scores as primary indicators of falsity. This research improves fake news detection through a tested framework adaptable to different subjects and large-scale datasets. Further work includes model expansion to multilingual scenarios and applying deep learning techniques for better analysis of semantics.

Keywords: sentiment feature, lexical feature, unigram

1. Introduction

The term "fake news" is often described in the literature as "misinformation," "disinformation," "hoax," or "rumor," which are different variations of false information. Misinformation is used to refer to the spreading of false information, disregarding the true intent. False information can be the result of false label (e.g., of persons in a photo) or poor fact-checking and can easily spread among users who do not care much about the authenticity of what they are reading or sharing. From an etymological point of view, the term combines the prefix "mis," which means "wrong" or "mistaken" with information [1].

Disinformation implies an intent to mislead the target of information. It refers to false information that is disseminated tactically to bias and manipulate facts. It is usually coined with the term "propaganda." The prefix "dis" is used to indicate a reversal or negative instance of information.

Rumors and hoaxes are interchangeably used to refer to false information that is deliberately constructed to seem true. The facts that they report are either inaccurate or false, although they are presented as genuine [1].

There has been considerable academic interest in the automated detection of fake news [1]. With the exponential growth in social media usage, these manual verification processes are no longer sufficient to truly combat this issue [2]. As a result, various kinds of automated methodologies have been studied to identify fake news with machine learning, deep learning, hybrid model, and natural language processing (NLP) [3, 4].

Though there are many existing studies on fake news detection, they have mostly focused on specific types of news, often centered around political topics [5, 6]. This narrow focus lead to datasets bias, where the models become specialized in detecting fake news related to those specific topics but may not perform well when applied to news from different domains [7]. The lack of generalizability across topics can hinder the effectiveness of the detection system in real-world scenarios where fake news spans across various subjects [8]. Therefore, our research highlighted an important aspect of the issue.

To overcome this limitation, we propose a new approach that aims to detect fake news from different topic domains by identifying the inherent lexical and sentiment features of fake news. By considering

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linguistic and emotional characteristics, our model seeks to capture more universal indicators of fake news that can be applicable across various domains.

Existing comparative studies on fake news detection have explored only a limited number of features and have not extensively investigated lexicon–sentiment features [9]. This might have hindered the ability to fully leverage the potential of these linguistic and emotional cues in detecting fake news. Thus, our study aims to more comprehensively explore the lexicon–sentiment features in order to construct more robust and effective models for fake news detection across different topic domains.

The significance of our work lies in its broader scope, which takes into account various topic domains and leverages lexical and sentiment features. Our approach seeks to develop a more generalized and accurate fake news detection model that can be applied to a wider range of news articles, mitigating the impact of datasets bias and potentially improving the overall performance of fake news detection systems.

This work presents a lexicon–sentiment-based model (LSBM), wherein lexical features are used in the analysis of textual aspects including punctuation frequency and capitalization pattern used by fake news spreaders along with the use of tokenization and emoji to comprehend a text in order to help humans in differentiating between real and fake news. Sentiment features are referred to in the assessment of the emotional impetus of the content, thus extracting intimacy or biased news [10]. To further improve the model's inclusion, the lexical and sentiment features are complemented by the unigram units—descriptive single-word sequences in a context.

Important contributions of this model are cross-domain robustness, where LSBM overcomes dataset constraints by exploiting domain-neutral features such as emotional tone and lexical diversity; feature fusion, where the combination of sentiment, lexical, and unigram features performs better than single-feature approaches (e.g., it increases accuracy more than 6% over models using only unigrams); and interpretability, in which feature importance analysis shows important features such as ALL CAPS and sentiment scores as primary indicators of falsity.

This research addressed the challenge of false information detection in the news field, particularly for English content, and applied the analysis for its text patterns and emotional tone features (lexical and sentiment). This study implemented six types of machine learning methods including logistic regression (LR), decision tree (DT), random forest (RF), support vector machine (SVM), K-nearest neighbors (KNN), and Naive Bayes (NB). To measure performance, four metrics were employed: accuracy, precision, recall, and F1-score. Three datasets were used to perform the experiments. The study was purposely limited to more simplistic machine learning methods to evaluate the features and did not include deep learning or hybrid models.

The article is structured as follows: Section 2 discusses related work, Section 3 presents our proposed fake news detection approach in detail, Section 4 presents discussion of experimental results, and finally Section 5 concludes with future research directions.

2. Literature Review

The academic review highlights the growing importance of sentiment analysis in uncovering fake news. This approach is based on the hypothesized relationship between the optimism of an article (in terms of conveyed emotion) and its quality [11]. Rashkin et al. [10] introduced a pioneering approach with a word-centric analytical framework that incorporated a linguistic perspective through providing distributions of grammatical categories and sentiment orientation classifications. This study aimed to find linguistic patterns that are good detectors of fake news and use the LIAR dataset. We hypothesized that these detected linguistic cues might provide important insights for differentiating between true and false news in order to develop more complex misinformation detection algorithms.

Rubin et al. [12] investigated fake news detection using richer features and more embedded linguistic elements; this process involved the determination of vocabularies (total word count, character-to-word proportion), analysis frequency, words and polysyllabic terms as well as phrasal occurrences recognition using parts of speech (POS). Through synthesizing these linguistic features with sentiment analysis, we conceptualized that carrying out the aforementioned functions would attempt to increase the feasibility of any existing detection algorithms for data falsification while employing this as a main corpus in fake and real datasets [8].

This review, as well as its precedents, mainly focused on political discourse using datasets built around news of the world. However, there were salient questions about external validity and the generalizability of models produced from these methods when focusing on so narrow a phenomenon as relationship dynamics. The possibility of limitations when using these models for other subjects or across domains beyond the political realm are interesting and should be explored by further research into their generalizability.

The study presented in Indu and Thampi [13] adopted a feature space consisting of textual metrics (characters and word count), sentiment analysis (+ve/−ve/neutral emotions), and structural features like the presence of URL, hashtags, or mentions with respect to disaster-related keywords. This holistic approach was intended to encompass linguistic and structural properties that might distinguish genuine news from fake news.

In a parallel work, Alrubaian et al. [14] attempted an identical approach but without sentiment scores included in their features. Each such study, though methodologically rigorous, suffers from the inherent limitation of a dialing algorithm trained on only one category or another. Though the features they selected were relevant and informative, this limited set of feature results have cast doubts that these sets could account for more complex types of misinformation.

This limitation highlights the difficulty in building models that can generalize well for such a broad and diverse form of fake news across domains [14]. In this proposed practical model, greater diversity and granularity of feature sets would enhance both how well actual fake news will be caught and for features to generalize across a more considerable part of future false news cases.

For detecting misinformation in news content, Khan et al. [8] and Elhadad et al. [15] have studied different feature sets and showed that using a variety of n-gram models (unigrams, bigrams, trigrams, longer n-grams) as features constructed very strong false news detection systems. Nevertheless, the datasets were minor problems relating to particular domains and consequently performance of n-gram features can vary between different subjects.

In a corresponding study, Khan et al. [8] carried out an intermediate-scale examination that considered lexical frequency, average word length, and overall article size as well as the incidence of numeric per textual field (between headline-baseline-sub-caption-footnote sections), POS distribution, question marks, and exclamations marks. They also included sentiment measures, Term Frequency–Inverse Document Frequency (TF-IDF)-weighted unigram, and bigram models as well as Empath. Although their evaluation mainly focused on datasets of political content, the integration of lexical and sentiment-based features showed no significant improvements in model performance.

Koloski et al. [16] expanded the scope of word-level analysis and found a variety of features that are useful for detecting fake news. This feature set included grammatical categories, min-max word lengths per document, average and standard deviation of the word length, frequency of digits letters spaces, punctuation marks, hashtags, and one sound-based vowel chunks. These features were tried on several datasets, like the Fake Newsnet: FNID and Profiling Fake New Spreaders dataset and COVID-19 misinformation, and replicated this experiment using the Mirti dataset around in LIAR dataset.

Similarly, Varshney and Vishwakarma [17] and Catelli et al. [18] also studied different features for fake news detection including the quantity of question marks, proportion of lying-related words used in statements provided by fact-checking services (e.g., POLITIFACT), and POS tags-based properties. During these investigations, they set state-of-the-art performance on numerous natural language processing and text classification tasks. Nonetheless, these studies centered on a specific thematic domain and used illustrative features.

Mimura and Ishimaru [19] investigated the identification of misinformation using three different datasets: Fake and Real Datasets (Politics), TI-CNN Dataset Politics, and Fake News Sample Dataset (Politics +Health). The features used were sentence length, vocabulary diversity (lexical richness), grammatical diversity, and mean word length. Although their approach seems to be effective in discerning fake news for politics and health, the focus on a single set of features involving specific topics may hinder its performance when tackling other problems beyond this scope.

Sepúlveda-Torres et al. [20] introduced a different solution to improve generalization ability in detecting misleading headlines: similarity-based metrics (cosine similarity and soft cosine similarity), sentiment-based indicators (sentiment polarity), and used ANOVA feature selection processions.

In a subsequent work, Jing et al. [21] developed a multimodal approach for fake news detection through progressive fusion networks. Datasets from microblogging sites Twitter and Weibo were used, which were relevant to their issues such as API limits and restrictions, respectively. Semantic features were extracted based on textual and visual content using pretrained bidirectional encoder representations from transformers (BERT) models.

Concurrently with Islam et al. [22], another research was presented by Bhardwaj et al. [23] titled "Fake social media news and distorted campaign detection framework using sentiment analysis & machine learning." Their investigation was limited to a single domain health articles and used only sentiment-based features.

The current study can complement the deficiencies of prior studies by adopting a wide range of intrinsic lexical, sentiment and unigram features in order to capture the nuances of various forms of misinformation from different contexts. Table 1 presents an overview of the reviewed literature.

3. Research Methodology

This section clearly states the proposed method, how it works, and how it effectively solves the problem.

3.1. Architecture of proposed method

Here we use an LSBM to detect fake news using its unigram, word-level features in lexicon and sentiment at different topic domains. To address this issue, we proposed another method to recognize the bias of data set by discovering common lexical and sentiment features in different topic categories.

3.2. The proposed lexicon–sentiment model working principle and its efficiency in tackling the problem

This section describes how LSBM works as shown in Figure 1.

3.2.1. Identify news dataset

1) Dataset selection matters: A good fake news datasets must be diverse, well-annotated, large, and sufficiently balanced between real and fake news.
2) Common datasets: A combined fake/authentic news datasets of 44K articles, a large corpus from an original collection of 80k, and one merged with other collections to cover broader topics
3) Identifying datasets: This involves an extensive review of literature to evaluate datasets based on passing criteria and then extract the exact datasets (and cite them appropriately).
4) Datasets characteristics: Good datasets come from a wide range of topics (politics, economy, health sciences, sports, etc.) and various sources and provide an equal distribution between real and fake news articles.
5) Research integration: The next phase after finding the appropriate datasets and obtaining them is research integration, which consists of data pre-processing.

3.2.2. Pre-processing of data

1) Tokenization: The process of breaking down text into individual words, or tokens.
2) Lemmatization/stemming: To obtain the same output for a word in any form.

3.2.3. Determine lexical and sentiment features

1) Literature review: The literature was reviewed to collect all conceivable academic papers and articles relevant for fake news detection by using key words such as fake news lexicon and sentiment feature and then filtering out those studies that discussed text analysis/feature of classification.
2) Lexical features extraction: Core lexical features from the literature included counts for POS, words, and characters as well as TF-IDF variant feature sets (word/phrases frequencies), additional related attributes (ALL CAPS), words with URLs, and punctuation used in the descriptions.
3) Sentiment features extraction: Sentiments of features were aggregated from sentiment polarity, intensity, and emotion detection within the feature that also acts as specialized indicators for differentiating between fake and real news.
4) Considerations in additional features: This step includes consideration of features not common to literature such as numeric presence, exclamation point, and symbolic word lengths.
5) Compilation and standardization: Finally, an all-encompassing list of the chosen lexical/sentiment features was made along with their definitions standardized such that each feature could be best represented in fake news detection models.

3.2.4. Extract lexical and sentiment features through natural language processing techniques

1) Feature extraction process: The proposed approach (LSBM) shows a detailed process of extracting features from text data for identifying fake news.

Table 1
Summary of the literature review

Researchers	Features	Dataset	Constraints
Sepúlveda-Torres et al. [20]	Parts-of-speech (POS) frequency and sentiment Categories	LIAR datasets	They used one topic domain
Rubin [12]	Total words, characters per word, frequencies of large words, frequencies of phrases, POS	Fake and Real datasets	They used one topic domain
Alrubaian et al. [14]	Number of characters, words, sentiment analysis of the text (positive, negative, neutral), message with URL, hashtag, and ampersand	LIAR dataset	They have not investigated other lexical and sentiment features. They assessed the efficacy of their models using a single corpus of data.
Indu and Thampi [13]	A message with URL and hashtag, number of hashtags	LIAR dataset	They evaluated the model only on one datasets and did not investigate other lexical and sentiment feature
Elhadad et al. [15]	Unigram (TF-IDF), trigram, and N-gram	CoAID dataset	They evaluated the model only on one datasets
Khan et al. [8]	Total words, mean word size, overall text length, frequency of numerical characters, grammatical categories, presence of exclamation mark, emotional tone assessment, single-word occurrences, and two-word phrase occurrences	LIAR dataset, Fake and Real datasets and combined corpus dataset	They used limited features
Koloski et al. [16]	Word length, tallies of numerical characters, alphabet character count, punctuation-mark occurrences, and number of hashtags	COVID-19 fake news, LIAR dataset, Pants on Fire, FNID: FakeNews-Net	They used limited features, and their approach depended only on one topic (politics or health).
Varshney and Vishwakarma [17]	Frequency of question mark, total word tally, grammatical category distribution, and emotional tone indicators	A datasets from the CONSTRAINT 2021 competition, containing 5,600 authentic entries and 5,100 fabricated entries	They used limited features, and their approach depended only on one topic (politics or health).
Catelli et al. [18]	Sentiment polarity	Datasets consists of vaccine related tweets published in Italy from (https://www.ailc.it/en/)	They used limited features.
Maimura et al. [19]	Number of words per sentence, range of unique terms used, average word length, typical sentence size, variation in sentence length, average paragraph length, variation in paragraph length, total text length, and measure of textual similarity	Fake and Real dataset, TI-CNN dataset and fake news, sample dataset	They used limited features, and their model focused on one topic domain (politics)
Sepúlveda-Torres et al. [20]	Sentiment polarity	Fake News Challenge (FNC-1) dataset	They used limited features and focused on one topic (politics)
Jing et al. [21]	Semantic features	Twitter and Weibo datasets (microblogging datasets)	They used limited features
Islam et al. [22]	Sentiment feature	Twitter dataset known as sentiment140	They used limited features
Bhardwaj et al. [23]	Sentiment feature	Health and Medical Articles on Thai Websites	They used limited features, and their model focused on one topic domain (health)

2) Term frequency analysis: The frequency of words present in the document was counted and normalized to prevent bias in longer documents, using equation (1):

$$\mathrm{TF(LF)} = \frac{\text{Number of times lexical feature (LF) is present}}{\text{Total number of lexical features (LF) in the document}} \tag{1}$$

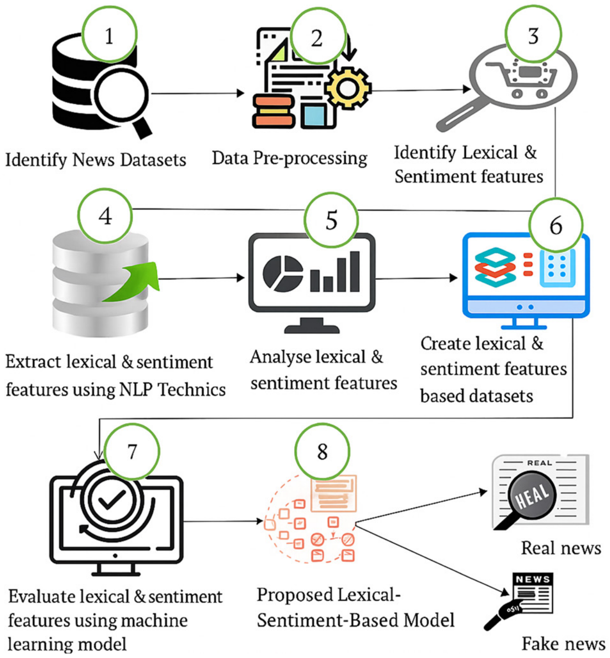
3) Lexical feature extraction: Various text features, including sentiment scores, capitalization, punctuation marks, and statistical measures based on word and character, were evaluated.

4) Sentiment analysis: The polarity and intensity of the overall sentiment were determined to identify different emotions. The analysis extracted the sentiment from the document.

5) Term Frequency-Inverse Document Frequency (TF-IDF) is used to emphasize the importance of specific words on the whole document (corpus), using equation (2):

$$\mathrm{TF(t,\ d)} = \frac{\text{(Number of times term t appear in document d)}}{\text{(Total number of terms in document d)}} \tag{2}$$

Figure 1
Architecture of proposed lexicon–sentiment-based model (LSBM)



6) Inclusion of more features: Additional features from existing literature approach were integrated such as POS frequency and empath features.
7) Feature normalization and compilation: All the features for each document were part of one vector that was normalized, to ensure during comparison that all have similar chances on influence in the output analysis.

3.2.5. Analyze lexical and sentiment features

This subsection shows how lexical and sentiment features have been analyzed for fake news detection using two feature selection methods: RF and Chi-square test.

1) Feature selection process: Features were selected based on three items such as taking all important variables using a supervised classification method and top k variables, weight tags, and exclusion of tendency.
2) RF feature selection: This approach recognized important features like question marks, capitalization, sentiment scores, and multiple punctuation counts.
3) Chi-square feature selection: Selected similar features as the RF feature selection but few add-ons like contractions words and quotation marks.
4) Benefits of RF: The advantages of using RF for feature importance analysis are as follows:
   a. Ensemble architecture that pervades stability and dependability
   b. Risk of overfitting mitigation
   c. Implicit feature selection during the training process
5) The general approach: Driven by a focus on the statistical properties of data, this analysis works to identify statistically significant lexical and sentiment features to provide reasonable discriminative power for detecting fake news in different feature spaces.

3.2.6. Create lexical and sentiment features based on datasets

1) Dataset construction: A new dataset was created using specific lexical and sentiment features.
2) Metrics: For the components of this dataset, features that had nonzero score during previous partial least square analysis were used.
3) Anchoring step: This pipeline was dependent on the results of a previous stage, in particular "Stage 5: Analyze lexical and sentiment features."
4) Purpose: To generate and purify datasets focusing only on those features that are most central in driving fake news detection, with their top nonzero scores from the last analysis.

This approach guarantees that the data is succinct and captures only relevant features that may improve performance and efficiency of future models for fake news detection.

3.2.7. Evaluate the lexical and sentiment features using machine learning models

1) Model selection: Different models were selected: LR, SVM, RF, KNN, DT, and NB.
2) Train model: The dataset was split into training and testing portions, which were inputted in the k-fold cross-validation to keep the model robust, not overfitted.
3) Model evaluation: Different performance metrics like accuracy, precision, recall, and F1-score were used to check the efficiency of each model.
4) Hyperparameter tuning: Optimization for hyperparameters of each model using grid search and random search.
5) Selection of the best model: Based on the evaluation metrics, the top performing model was selected.
6) Conclusion and analysis: The significance of various lexical and sentiment features was analyzed, and conclusions from the model behavior were drawn.
7) Report results: Both the findings of a project, performance metrics, and feature importance should be well documented through visualizations for better interpretation.

Here, we adopted this systematic method to carefully compare the performances of lexical and sentiment features on detecting fake news with several different types of machine learning models.

3.2.8. Proposed lexicon–sentiment-based model

1) Model architecture: This model has a well-layered architecture in all aspects where we have bare minimum for feature extraction, pre-processing, and machine learning. Diagrams and flowcharts may also be used to visually represent the model architecture.
2) Performance metrics: This last section shows how the final model performed in terms of accuracy, precision, recall and F1-score in comparison to baseline models or results from related works.

The approach proposed focused on presenting an in-depth view of the model itself, showing its definition and indicating how good it performs with numbers supporting this claim along comparisons. Instead, the proposed model has further discussed on training requires lexical relevant and attitude-related features compared to individual datasets.

3.3. Datasets description

3.3.1. Overview of selected datasets

We used three datasets with different topic domains: the Fake and Authentic News Articles, Combined Corpus Dataset1, and Combined Corpus Dataset2 (Table 2).

3.3.2. Fake and authentic news articles

The datasets were sourced from Kaggle and focused on articles about the 2016 US election that contain known misinformation. In contrast, the authentic news component comes from respected media

Table 2
Description of datasets

S/N	Dataset	Size
1	Fake and Authentic News Articles [1]	44,898 news
2	Combined Corpus 1 [1]	80k news
3	Merged Corpus 2 (FA-KES [24] & CoAID [25])	70k news

outlets like the New York Times, Wall Street Journal, Bloomberg, NPR, and The Guardian, featuring articles from 2015 or 2016. Overall, the datasets consisted of approximately 44,000 news articles, which were evenly split between fake and real news examples [8].

3.3.3. Combined Corpus Dataset1

In total, a large dataset of 80k articles was assembled to identify fake news with topics ranging from domestic and international politics to economics, investigative reporting, healthcare, sports and entertainment. With this large scope, the model could recognize general features related to fake news across diverse contexts [8].

3.3.4. Merged Corpus Dataset2

The datasets were expanded by incorporating two additional collections: the FA-KES datasets, previously utilized by Shu et al. [24], and the CoAID datasets, which was employed by Abu Salem et al. [25]. These datasets were added to the main corpus to broaden the range of subjects covered. As a result, the combined datasets encompassed a wide variety of topics, including domestic and international political affairs, economic issues, investigative journalism, healthcare matters, sports coverage, and entertainment news.

3.4. Data pre-processing in fake news detection

Pre-processing is an important stage in detecting fake news. Redundant things are removed from the data and make text fit for analysis [26]. The major steps of text processing are noise removal, tokenization, and stop word removal and stemming [26, 27].

3.4.1. Feature extraction method

Various lexical features were extracted from the datasets using term frequency (TF), which measures how often a term appears in a document or corpus. It was calculated by dividing the number of times a lexical features (LF) appeared by the total lexical features count in the document. This normalization prevents bias toward longer documents. The feature vector is represented as in equation (3):

$$\mathrm{TF(LF) = number\ of\ LF\ present/}\\ \mathrm{total\ number\ of\ LF\ in\ the\ document} \tag{3}$$

Using this method, the features were extracted: sentiment scores, capitalization, numbers, punctuation marks, URLs, ellipses, negation and contraction words, hashtags, and various symbols.

For sentiment analysis, the emotional tone of each article (positive or negative) was determined, which can help identify potential bias or deception in news content.

The unigram feature was weighted using TF-IDF as represented in equation (4):

$$\mathrm{tf - idf(t, d) = tf(t, d)*idf(t)} \tag{4}$$

where tf(t,d) is the TF in a document and idf(t) is the inverse document frequency across all documents. The higher the TF-IDF, the more significant the words are in the document.

Other features were extracted from the literature: POS frequencies, word and character counts, word lengths/standard deviation/max/min, presence of URLs/hashtags/numbers, capitalization patterns, and punctuation/n-gram. These features aim to capture various aspects of the text that may help distinguish between genuine and fake news articles.

3.4.2. Feature selection method

The largest part of this step is the feature selection technique. Features are essential information because they aim to exclude irrelevant set of features and keep the most important ones for any classifier on both supervised learning phase or unsupervised surrogate filtering method like that by Zhang et al. [27].

The above set of explanations was followed by how we performed feature selection based on these extracted features using the respective techniques described. In this study, we used two algorithms, RF and Chi-square tests, to identify the most relevant and informative features from our extracted feature set.

RF detects readers of informative features with the Combined-Corpus Dataset (those above a score of zero) as positive and performs in all other two sets. This includes 48 features such as count-Question Mark, caps and sentiment score, Count-Single Quote, Count-Parenthesis, Count-Full Stop, and Count-Braces.

Chi-square test identifies and selects all prominent features on the Combined-Corpus Dataset (and subsequently applies the same function to the remaining two datasets). These features include Count-Question-Mark, ALL CAPS, sentiment score, Count-Single Quote, Count-Parenthesis, Count-Full Stop, Count-Braces, Count-Exclamation Mark, Count-Astrisk, Count-Comma, Count-Colon, Count-HashTag, Count-Hyphen, Count-Negation Words, Count-Contraction Words, CountQoutation Mark, Count-Ampersand, and Count-Percentage.

3.4.3. Feature integration

We propose a novel method to combine lexical and sentiment features and unigram feature into an integrated text representation methodology for fake news detection. Because it is a combined model, it can handle the content and linguistic information such as emotions and word orders in texts. Thus, by combining all these types of features, the proposed model can identify fake news across varied domains.

3.5. Machine learning models

The datasets were divided into two parts: 80% for training and 20% for testing. The training data was then processed using various classification algorithms available in Python's Scikit-learn machine learning library. Lexical, sentiment, and unigram features were trained using six different machine learning algorithms: LR, DT, RF, SVM, KNN, and NB. The above machine learning algorithms were used to evaluate the feature sets:

1) Unigram: Models that evaluate unigram features.
2) Lexical and sentiment features: Models that evaluate lexical features integrated with sentiment features.
3) Lexical and sentiment features + unigram: Models that combine lexical/sentiment/unigrams.

In this study, multiple models were adopted to evaluate how well the extracted and integrated features perform from a classifier-agnostic standpoint.

4. Analysis of Findings and Interpretation

In this section, some results based on LSBM for fake news detection coded in Jupyter Notebook using Python libraries like Numpy Pandas, Matplotlib, and Scikit-Learn are discussed.

4.1. Lexical and sentiment feature analysis

The performance levels of lexical and sentiment features in detecting fake information were explored. Two feature selection methods were used to identify the most important features. To further demonstrate the effectiveness and utility of these features, these methods were applied on different datasets using several machine learning algorithms.

4.1.1. Feature extraction and selection

The lexical and sentiment features were processed using natural language processing techniques combined with Sklearn library. This was followed by feature selection using the RF feature selection and Chi-square test-based methods. Results of all these feature selection methods on three different datasets are shown in Figure 2, Figure 3, and Figure 4.

Figures 2-4 show a heterogeneous distribution of features, with both positive and zero scores in the experimental results. Features with zero score were found to have negative impact on the model. Thus, to improve training and testing of the model, only nonzero scoring features were selected.

4.1.2. Comparative analysis of random forest and Chi-square test (with nonzero lexical + sentiment features)

We experimented with the lexical and sentiment features that yielded a nonzero score from Figures 2-4 on three different datasets using RF and Chi-square test and divided the data into 80% training data and 20% testing data. Machine learning models such as LR, DT, RF, SVM, KNN, and NB were used to test the models. The evaluation metric included accuracy (A), precision (P), recall (R), and F1-score (F1). It can be interpreted from the outcomes in Table 3 that when

Figure 2
(a) Random forest-based importance analysis and (b) Chi-square analysis for distinguishing between genuine and false news content

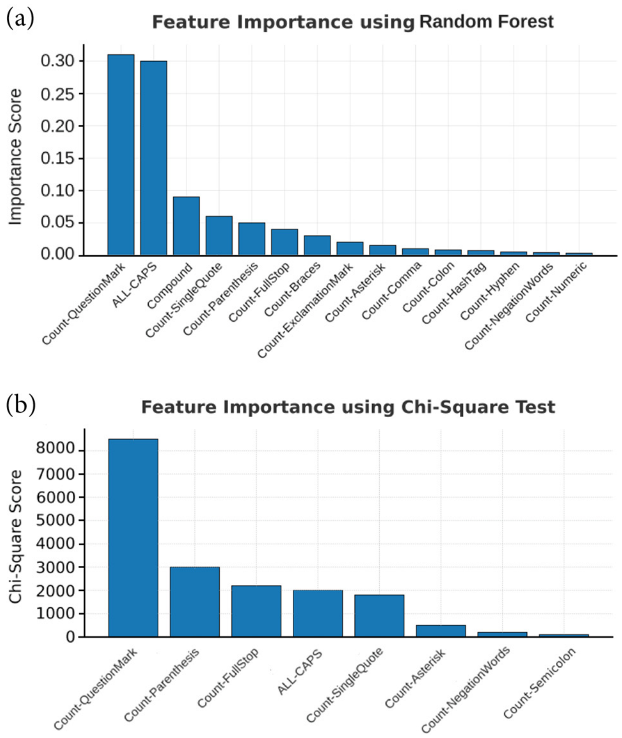


Figure 3
(a) Random forest and (b) Chi-Square test feature selection on Combined Corpus Datasets

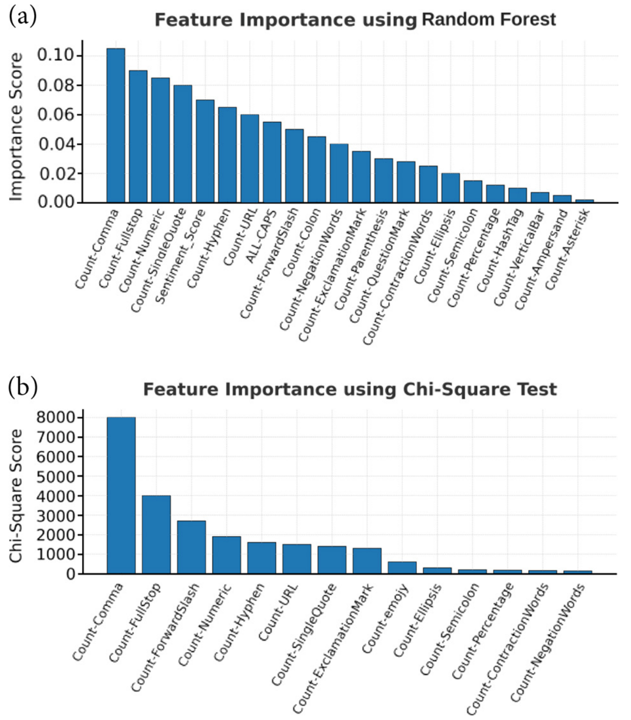


Figure 4
(a) Random forest and (b) Chi-square test feature selection on combined FA-KES and CoAID datasets

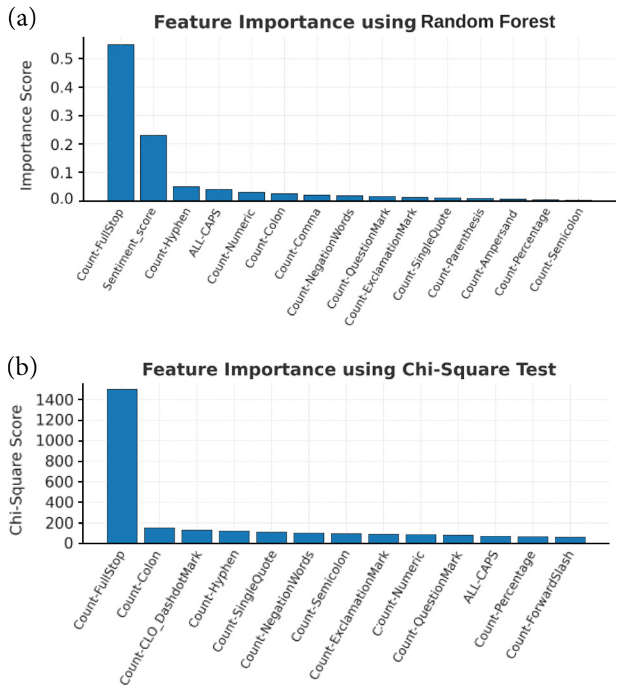


Table 3
Result of two feature selection methods with nonzero scores lexical and sentiment features on Fake and Authentic News Articles datasets

Algorithms	Random Forest				Chi-Square Test			
	A	P	R	F1	A	P	R	F1
LR	0.91	0.92	0.91	0.91	0.90	0.90	0.90	0.90
DT	0.89	0.89	0.89	0.89	0.91	0.91	0.90	0.90
RF	0.90	0.90	89	0.90	0.90	0.91	0.90	0.90
SVM	0.91	0.91	0.90	0.90	0.90	0.90	0.90	0.90
Naive Bayes	0.88	0.89	0.88	0.88	0.84	0.87	0.83	0.83
KNN	0.90	0.90	0.90	0.90	0.88	0.90	0.88	0.88

combining with RF, LR and SVM potentially yielded a maximum accuracy of up to 91%. In simple terms, the Chi-square method for feature selection can detected 91% correct results on the DT model, implying that RF could well improve the performance of LR and SVM because only nonzero lexical/semantic feature were selected.

Table 4 indicates that feature selection via RF achieved an accuracy score up to over 87%, on either datasets combined. RF worked well because it was efficient in locating the most helpful nonzero lexical and sentiment factors for fake news detection. As shown in Table 5, both RF and KNN models achieved the same level with an accuracy rate of 87%, but they outperformed for other scenarios.

Table 4
Result of two feature selection methods with lexical and sentiment features on Combined Corpus Datasets

	Random Forest				Chi-Square Test			
Algorithms	A	P	R	F1	A	P	R	F1
LR	0.79	0.80	0.79	0.79	0.76	0.76	0.76	0.76
DT	0.79	0.79	0.79	0.79	0.78	0.78	0.78	0.78
RF	0.87	0.87	0.87	0.87	0.85	0.85	0.85	0.85
SVM	0.80	0.81	0.80	0.79	0.77	0.78	0.77	0.77
NB	0.75	0.75	0.75	0.75	0.74	0.74	0.74	0.74
KNN	0.79	0.79	0.79	0.79	0.78	0.78	0.78	0.78

Table 5
Result of two feature selection methods with lexical and sentiment features on combined FAKES and CoAID datasets

	Random Forest				Chi-Square Test			
Algorithms	A	P	R	F1	A	P	R	F1
LR	0.86	0.85	0.86	0.85	0.85	0.85	0.85	0.85
DT	0.85	0.85	0.85	0.85	0.86	0.86	0.86	0.85
RF	0.87	0.87	0.87	0.87	0.86	0.87	0.86	0.86
SVM	0.86	0.86	0.86	0.86	0.85	0.85	0.85	0.85
NB	0.87	0.87	0.87	0.86	0.86	0.86	0.86	0.86
KNN	0.87	0.87	0.87	0.87	0.85	0.85	0.85	0.85

4.2. Comparative analysis of lexical and sentiment features

This study was aimed to compare and determine which lexical and sentiment features could work more efficiently in fake news detection. This model uses the best features in Tables 3-5, which were shortlisted using RF attribute selection techniques. The exact same datasets and the same machine learning models were used to evaluate how they perform. Finally, in Tables 6 and 7, the results of our comparative study using different fake news datasets show that on all datasets, the lexical and sentiment features achieved better accuracy than either class alone. When this method was used to train a classifier, the SVM model performed best (97% accuracy). As shown in Table 8, merging lexical and sentiment attributes along with unigram have better result compared to using the feature sets separately (comparing them

Table 6
The role of lexical and sentiment features in detecting fake news within a fake and real news article datasets

Algorithms	Features	A	P	R	F1
LR	Unigram	0.93	0.93	0.94	0.93
LR	Lexical and sentiment features	0.91	0.92	0.91	0.91
LR	Lexical and sentiment features combined with unigram	0.95	0.95	0.95	0.95
DT	Unigram	0.89	0.89	0.89	0.89
DT	Lexical and sentiment features	0.89	0.89	0.88	0.89
DT	Lexical and sentiment features combined with unigram	0.94	0.94	0.94	0.94
RF	Unigram	0.93	0.94	0.93	0.93
RF	Lexical and sentiment features	0.90	0.90	0.89	0.90
RF	**Lexical and sentiment features combined with unigram**	**0.97**	**0.97**	**0.97**	**0.97**
SVM	Unigram	0.93	0.94	0.94	0.93
SVM	Lexical and sentiment features	0.91	0.91	0.90	0.90
SVM	**Lexical and sentiment features combined with unigram**	**0.97**	**0.97**	**0.97**	**0.97**
NB	Unigram	0.81	0.83	0.81	0.81
NB	Lexical and sentiment features	0.88	0.89	0.88	0.88
NB	Lexical and sentiment features combined with unigram	0.92	0.92	0.92	0.92
KNN	Unigram	0.91	0.92	0.91	0.91
KNN	Lexical and sentiment features	0.90	0.90	0.90	0.90
KNN	Lexical and sentiment features combined with unigram	0.94	0.94	0.93	0.94

Table 7
The role of lexical and sentiment features in detecting fake news within Combined Dataset1

Algorithms	Features	A	P	R	F1
LR	Unigram	0.93	0.93	0.93	0.93
LR	Lexical and sentiment features	0.79	0.80	0.79	0.79
LR	Lexical and sentiment features combined with unigram	0.85	0.85	0.85	0.85
DT	Unigram	0.84	0.84	0.84	0.84
DT	Lexical and sentiment features	0.79	0.80	0.79	0.79
DT	Lexical and sentiment features combined with unigram	0.86	0.87	0.86	0.87
RF	Unigram	0.94	0.94	0.94	0.94
RF	Lexical and sentiment features	0.87	0.87	0.87	0.87
RF	**Lexical and sentiment features combined with unigram**	0.95	0.95	0.95	0.95
SVM	Unigram	0.96	0.96	0.96	0.96
SVM	Lexical and sentiment features	0.87	0.87	0.87	0.87
SVM	**Lexical and sentiment features combined with unigram**	**0.97**	**0.97**	**0.97**	**0.97**
NB	Unigram	0.84	0.87	0.84	0.84
NB	Lexical and sentiment features	0.75	0.75	0.75	0.75
NB	Lexical and sentiment features combined with unigram	0.88	0.87	0.87	0.87
KNN	Unigram	0.82	0.83	0.82	0.82
KNN	Lexical and sentiment features	0.79	0.79	0.79	0.79
KNN	Lexical and sentiment features combined with unigram	0.78	0.78	0.78	0.78

Table 8
The role of lexical and sentiment features in detecting fake news within combined FAKES and CoAID datasets (Combined Dataset2)

Algorithms	Features	A	P	R	F1
LR	Unigram	0.80	0.80	0.80	0.78
LR	Lexical and sentiment features	0.86	0.85	0.86	0.85
LR	Lexical and sentiment features combined with unigram	0.87	0.87	0.87	0.86
DT	Unigram	0.77	0.76	0.77	0.76
DT	Lexical and sentiment features	0.85	0.85	0.85	0.85
DT	Lexical and sentiment features combined with unigram	0.86	0.86	0.86	0.86
RF	Unigram	0.79	0.79	0.79	0.79
RF	Lexical and sentiment features	0.87	0.87	0.87	0.87
RF	**Lexical and sentiment features combined with unigram**	**0.88**	**0.88**	**0.88**	**0.88**
SVM	Unigram	0.82	0.81	0.82	0.81
SVM	Lexical and sentiment features	0.86	0.86	0.86	0.86
SVM	Lexical and sentiment features combined with unigram	0.87	0.87	0.87	0.87
NB	Unigram	0.82	0.83	0.82	0.80
NB	Lexical and sentiment features	0.87	0.87	0.87	0.86
NB	Lexical and sentiment features combined with unigram	0.87	0.87	0.87	0.87
KNN	Unigram	0.77	0.76	0.77	0.75
KNN	Lexical and sentiment features	0.79	0.79	0.79	0.79
KNN	Lexical and sentiment features combined with unigram	0.87	0.87	0.87	0.87

to each other) for both fake news datasets. This combination approach garnered 88% accuracy with the RF model.

4.2.1. Hyperparameter tuning

Hyperparameter tuning is the process of selecting the optimal values for a machine learning model's hyperparameters. These are typically set before the actual training process begins and control aspects of the learning process itself. They influence the model's performance its complexity and how fast it learns.

RandomizedSearchCV was used with Combined Dataset1, and the result is shown in Table 9. The SVM model (A linear kernel and c value 0.05) accuracy was slightly higher at 97%, whereas KNN failed to reach even near the optimized rate, with only 78%. The RF, LR, and DT models achieved 95%, 85%, and 93%, respectively.

Hyperparameter tuning can significantly boost performance, as illustrated when using RandomizedSearchCV with our Combined Corpus Dataset. This provides valuable feedback on a set of representations, models, and hyperparameters that need to be modified for any work in the future with respect to fake news detection (as one possible avenue).

Bagging in RF model was 1% better than just unigram features, and it achieve a more accurate score when combined lexical and sentiment features were used with the best hyperparameters. This accuracy corresponds with the results in Table 7, and by inspecting it, we can observe that RF model, which was trained on combined feature set (i.e., lexical features tokenized + sentiment word list+ unigram TF-IDF), did very well in fake news detection for this datasets.

Interestingly, this topic-independent phenomenon demonstrates that despite the different datasets, there are some common lexical and sentiment features, thereby confirming the usefulness of these factors

Table 9
Cross-validation results for lexical and sentiment features in fake news detection on a Combined Corpus Dataset (Randomized-SearchCV)

Mod-el	Best Parameters	Best accuracy
LR	C: 0.1	0.85
DT	'splitter':'best','max_depth':'None', 'criterion':'entropy'	0.86
RF	'n_estimators': 800, 'min_samples_split': 14, 'min_samples_leaf': 4, 'max_features': 'auto', 'max_depth': 1000, 'criterion': 'gini'	0.95
KNN	'n_ neighbours:3,'algorithm':'ball-tree'	0.78
SVM	'kernel':'linear','gama':0.1,'C':0.05	0.97

on a broader level of fake news detection and generalization among other applications.

4.3. Analysis and discussion in detail

4.3.1. Performance of models with combinations of features

The experiments showed that the combination of lexical and sentiment features significantly improved data performance and generalizability in fake news detection.

1) RF model: The RF model achieved 88% accuracy when using both lexical and sentiment features on merged FA-KES–CoAID dataset. This showcases that the model has been successful in making use of more input data coming from sentiment features, which are very helpful since they coarsely capture emotional tone of text.
2) SVM model: For Combined Corpus, it results in the maximum accuracy among all descriptors, at 97%, which proved its ability to handle well various sources from the dataset. The sentiment features have greatly improved the model's performance by better discriminating between true and fake news.
3) RF versus SVM: On the fake and genuine datasets, both RF and SVM accomplished a 98% accuracy. This excellent performance is another example of how feature creation aids in accuracy boosting. By combining the reinforcement signals of lexical and sentiment features, these models were able to more accurately perceive the nuances and subtleties embedded withing data.

4.3.2. Analysis of tables 6, 7, and 8

The most critical result presented in Tables 6-8 demonstrates the usefulness of the lexical and sentiment features in effectively escalating the performance obtained for fake news detection models. This is consistent with our claim that sentiment analysis comes along valuable context information for lexical features, in which fake and true news can be discriminated.

1) Table 6: Performance of different models on Fake and Real News Article (Test set). The results reveal that the inclusion of sentiment features complementing the lexical ones improves generalization. Thus, the critical insights that would have helped in better classification are characterized by sentiment analysis.
2) Table 7: Performance summary on Combined Dataset1. As shown in Table 6, models with combined features achieved better results than all other baseline. The strength of the proposed feature combination approach generalizes well, as indicated by consistent results across six different datasets.
3) Table 8: Combined datasets with properties. These results confirm the effectiveness of our proposed combination and thus support for extracting both lexical features with sentiment provides highest accuracy on multiple datasets. Therefore, this additionally proves the proposed method to be successful in correcting datasets bias.

4.3.3. Summary of prior work

Khan et al. [8] reported the following results about NB with n-gram features for Combined Corpus Datasets, with 93% accuracy. Comparing our results, even though Khan et al. [8] concluded that sentiment features did not improve performance, such difference is likely owed to the manners in which feature engineering and model architectures are implemented.

1) NB with n-gram features: As per Khan et al. [8], NB has the highest accuracy when using n-gram features, and additional sentiment features added no value. The model explains this, specifically its implementation of feature extraction having an influence on how though effective sentiment features were.
2) Performance of SVM and LR models: SVM and LR models performed better with the inclusion of sentiment features, contrary to the findings of [7]. This aligns with previous research by Amer et al. [9], Sepúlveda-Torres et al. [20], Islam et al. [22], and Altunbey et al. [28], which suggested that these models are particularly effective for fake news detection when equipped with rich feature sets.

4.3.4. Conclusion and future work

The spread of fake news in different areas especially calls for more universal and sophisticated detection system. This study put forth a proposal for LSBM, which uses lexical features and sentiment analysis alongside unigrams to enhance fake news detection in various domains. The testing done on three diverse datasets—Fake and Authentic News Articles (44K samples), Combined Corpus Dataset 1 (80K samples), and Merged FA-KES & CoAID Dataset (70K samples)—revealed that using multiple features significantly improves accuracy compared to single-feature approaches.

1) Noteworthy conclusions:

Cross-domain coverage: LSBM identified fake news in politics, health, economics, and entertainment, thus making it class-robust by using nonspecific domain features like emotional tone, punctuation frequency, and lexical diversity. Detection of LSBM is cross cut on numerous domains.

Best results obtained with supplementing features: Performance was enhanced by over 6% with lexicon–sentiment features and unigrams combined, compared to detectors with unigrams only. SVM achieved 97% accuracy on Combined Corpus Datasets, and RF achieved 88% accuracy in cross-domain evaluation.

Feature importance: Punctuation features such as question marks and exclamation points, ALL-CAPS sentiment, and sentiment polarity scores are strong indicators of fake news.

Datasets bias: LSBM mitigates dataset bias through analysis of the same linguistic and emotional features that are common across topics, thereby broadening applicability. Still, some of the shortcomings pertain to datasets being in English, as well as using classical machine learning models and not deep learning methods.

2) Important contributions:

   a. Cross-domain robustness: LSBM overcomes datasets constraints by exploiting domain-neutral features such as emotional tone and lexical diversity.
   b. Feature fusion: The combination of sentiment, lexical, and unigram features performs better than single-feature approaches.

For example, it increases accuracy more than 6% over models using only unigrams.

c. Interpretability: Feature importance analysis shows importance features such as question marks, ALL CAPS, and sentiment scores and many more were the primary indicators of falsity.

3) Future directions:
   a. Adapting LSBM for multilingual fake news detection.
   b. Leveraging deep learning such as BERT and transformers for sentiment analysis.
   c. Developing the datasets to incorporate multimodal (text + image/video) misinformation.

In this study, we developed a framework for fake news detection that was adjustable to different domains, was easy to interpret, and explains instances. This serves as a basis for further development relevant to fake news detection.

4.3.5. Implications

The present study has a number of important impaction for future research on fake news detection as best practices move forward from large-scale passive experimentation to development and deployment at the industrial scale.

The proposed model distinguished itself from existing methods by discovering common lexical–sentiment features across different topic domain (Section 4.1.1). Those features were evaluated to assess the model's efficiency in fake news detection across different topic domain (Section 4.1.2). The proposed model demonstrated that the combination of the lexical and sentiment features improved fake news detection across different topic domain (Section 4.2).

1) Feature engineering: This research encourage further research to investigate innovative feature engineering, in particular the combination of lexical features with sentiment analysis. Our findings suggest that such combinational auxiliary techniques can bring in non-trivial improvements in the performance of models.
2) Model selection: This is the most crucial part to interpret and detect fake news. RF and SVM models were the top-performing in this analysis; however, other additional advanced techniques might just benefit from fine-tuning of hyperparameters and feature engineering.
3) Datasets diversity: The experiments underscore the necessity of both using multiple datasets and their diversity, which could guarantee that they could generalize their results. Many of the proposed approaches should be validated on a variety of datasets in future studies to investigate its general performance across domains.
4) Dealing datasets bias: The proposed model avoids dataset bias by demonstrating increased efficiency over multiple datasets repeatedly. This indicates that by using a set of lexical and sentiment-based features, the specific effects based on datasets itself can be reduced, which results in better robustness during real-time detection.

Figures 2-4 illustrate that simple words with broad utilization can be found through datasets representing common lexical/sentiment features even when spanning across different topic domains. Additionally, Tables 3-5 proved the ability of these features in detecting fake news. Our experiments (Tables 6-8) have demonstrated that the proposed model, LSBM, have the highest accuracy among other models in different datasets, therefore highlighting the potential of effectual feature engineering and model selection in fake news detection models across different subjects. These provide valuable insights for further research as well as any actual applications.

5. Findings and Future Directions

This study evaluated the impact of combining lexical and sentiment features with unigrams. Our results consistently showed that improvement in the accuracy of all models compared to when using only either lexical and sentiment features, or unigram separately. This emphasizes that lexical and sentiment features are important for detecting fake news and enhance the performance of the model with the addition of textual representation (i.e., unigram).

Some of the features in this study were considered important via feature selection methods like RF and Chi-square tests since they have nonzero score. On the other hand, zero score features were eliminated as insignificant in fake news detection.

The findings in this study also implied that lexical and sentiment features could be important for identifying fake news because they can separate true information from false ones. Addressing the dataset bias by ordering common and robust lexical and sentiment features spanning a much wider variety of topic domains is also an important step toward creating fake news detection models more immune to domain shifts.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in Lexical_Sentiment_Based_Model_Datasets at https://github.com/asbichi362/Lexical_Sentiment_Based_Model_Datasets.

Author Contribution Statement

Abdulkadir Shehu Bichi: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Funding acquisition. **Ibrahim Said Ahmad:** Conceptualization, Methodology, Validation, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Amina Imam Abubakar:** Methodology, Writing – review

& editing. **Fa'iz Ibrahim Jibiya:** Writing – review & editing. **Aisha Mustapha Ahmad:** Writing – review & editing. **Nur Bala Rabiu:** Writing – review & editing.

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