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A Hybrid Linguistic and Knowledge-Based Analysis Approach for Fake News Detection on Social Media

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ABSTRACT The rapid development of different social media and content-sharing platforms has been largely exploited to spread misinformation and fake news that make people believing in harmful stories, which allow to influence public opinion, and could cause panic and chaos among population. Thus, fake news detection has become an important research topic, aiming at flagging a specific content as fake or legitimate. The fake news detection solutions can be divided into three main categories: content-based, social context-based, and knowledge-based approaches. In this paper, we propose a novel hybrid fake news detection system that combines linguistic and knowledge-based approaches and inherits their advantages, by employing two different sets of features: (1) linguistic features (i.e., title, number of words, reading ease, lexical diversity,and sentiment), and (2) a novel set of knowledge-based features, called *fact-verification* features that comprise three types of information namely, (i) *reputation of the website* where the news is published, (ii) *coverage*, i.e., number of sources that published the news, and (iii) *fact-check*, i.e., opinion of well-known fact-checking websites about the news, i.e., true or false. The proposed system only employs eight features, which is less than most of the state-of-the-art approaches. Also, the evaluation results on a fake news dataset show that the proposed system employing both types of features can reach an accuracy of 94.4%, which is better compared to that obtained from separately employing linguistic features (i.e., accuracy=89.4%) and fact-verification features (i.e., accuracy=81.2%).

INDEX TERMS Social media, fake news detection, linguistic analysis, knowledge analysis, fact-checking website.

I. INTRODUCTION

Social media are taking an increasing part in our professional and personal lives [21]. More and more people tend to search and consume news via social media rather than traditional media outlets. It has become common that important news are first broadcasted on social networks before being released by traditional media such as television or radio. Due to the massive propagation of news on social networks, users rarely check the accuracy of the information they share. It is therefore common to see false and manipulated information that are circulating on social media such as hoaxes, rumors [10], urban legends, and fake news [5], [5], [23], [41], [42], [82]. Moreover, it is difficult to stop the spreading of fake news when it is already shared many times and at large-scale [48]. This massive dissemination of false information [47], [61] could cause a serious negative impact on individuals and society. First, fake news could negatively influence the public opinion. Second, fake news change the way people interpret and react to real news. For example, some fake news

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could make people suspicious, and affect their ability to discern real news from fake news. In the literature, many approaches have been proposed for fake news detection. Early approaches were mainly based on linguistic-based techniques, which rely on language usage and its analysis to predict deception [3], [57], [60], [76]. The goal of these approaches is to look for instances of leakage found in the content of a text at different levels (i.e., words, sentences, characters, and documents levels). These approaches implement different methods such as: data representation, deep syntax, sentiment, and semantic analyses [17], [72]. In data representation methods, each word is considered as a single unit, and individual words are aggregated and analyzed to reveal linguistic cues of deception. In deep syntax methods, the sentences are converted into a set of rewritten rules (i.e., parse tree) in order to describe the syntax structure [12]. The semantic analysis determines the truthfulness of authors, which describes the degree of compatibility of personal experience compared to the content derived from a collection of analogous data. Finally, the sentiment analysis focuses on the extraction of opinion, which involves examining written texts about people's attitudes, sentiments, and evaluations using analytical techniques. Recent research has shown that linguistic-based techniques alone are not sufficient to reach a high detection accuracy, which generally does not exceed 80% [36], [37], [55], [57].

The knowledge-based approach is the most straightforward way to detect fake news, which allows to check the truthfulness of the statements claimed in news content [64]. Knowledge-based approaches [54] use external sources to verify if the news is fake or real and identify it before it spreads. This approach is divided into two distinct techniques [20] manual fact-checking, and automated fact-checking.

The manual fact-checking can be further divided into (a) crowd-sourced fact-checking, which is based on a large population of regular individuals acting as fact-checkers (i.e., collective intelligence), and (b) expert-based fact-checking, which is based on experts' judgments in the field (i.e., fact-checkers) to verify the content of the given news item [86]. Expert-based fact-checking is often performed by a small group of highly credible fact-checkers, which could lead to very accurate results. However, they require continuous and manual updates, and cannot perform automatic learning.

Through consultations and extraction of data from different sources, automated fact-checking aims at automatically verifying claims. Then, a classification based on the stance and strength of reputable sources regarding the claim is assigned [16]. Despite this technique is still in progress, it is very promising.

The major challenges that hinder the efficiency of the existing fake news detection solutions are related to the highly versatile nature of deceptive information. Indeed, it is very difficult to obtain a generalized dataset for fake news detection. Thus, it is very difficult to extract relevant features that can well represent and allow to detect fake news in various domains. In addition, it is also very challenging to detect fake news of a newly emerged event due to the limited information and knowledge regarding this event. For this reason, the use of one single technique for detecting fake content in news media will not able to reach the required level of efficiency.

In this paper, we propose a hybrid fake news detection system that takes advantage of both linguistic-based and knowledge-based approaches. The proposed system uses five different linguistic features, which are the title of the news, the number of words composing the news, its reading ease, its lexical diversity, and the dominant sentiment about the news. The system also employs three different knowledge-based features namely reputation, fact-check, and coverage. The system also implements four (04) different machine learning algorithms namely Random Forest (RF), Logistic Regression (LR), Additional Trees Discriminant (ATD), and XG-Boost. The earlier mentioned learning algorithms are trained and tested using different combinations of the aforementioned features, and the most performing classifier is selected. To the best of our knowledge, our work is the first that proposes this hybridization in the context of fake news detection. Specifically, the main contributions of the paper are the following:

- We propose a hybrid linguistic and knowledge-based fake news detection system that combines (1) linguistic features (i.e., title, number of words, reading ease, lexical diversity and sentiment), and (2) a novel set of knowledge-based features, called *fact-verification* features.
- The proposed fact-verification features allow to determine the truthfulness of a news trough the assessment of the reputation of the source (i.e., the website from which the information is obtained), and credibility to check if other fact-checking websites have already given their opinion about the news whether it is true or false.
- The proposed system only employs eight features, which is less than most of the state-of-the-art approaches.
- The evaluation results show that the proposed combination of features records more than 94% accuracy for fake news detection, and allows an increase of more than 7% compared to linguistic-based features.

The rest of the paper is organized as follows: Section II presents related work on fake news detection. In section III, we describe our proposed fake news detection system. Section IV describes the implementation of the proposed system. The evaluation results are presented in Section V, and discussed in Section VI. Finally, Section VII concludes the paper and highlights its key perspectives.

II. RELATED WORK

In this section, we provide a literature review of existing fake news detection solutions. As shown in Figure 1, fake news detection approaches can be divided into three categories namely, linguistic-based, social context-based, and knowledge-based. In the figure, some selected approaches from the literature are shown under each category, considered to be the most relevant ones in the last fifteen (15) years.

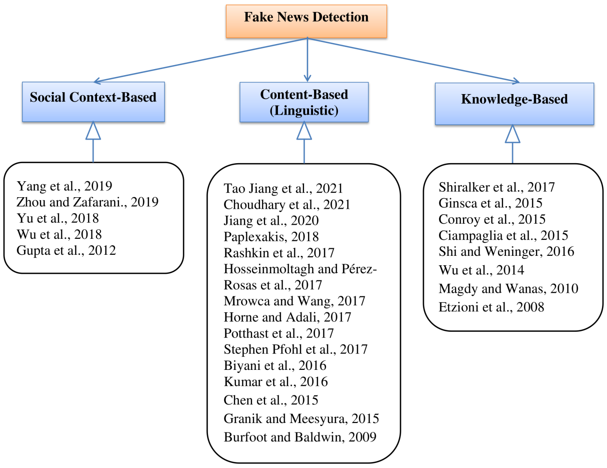


FIGURE 1. Taxonomy of fake news detection approaches.

A. LINGUISTIC-BASED ANALYSIS

Linguistic analysis refers to the typical and the accurate examination of natural language. This approach [1], [19], [26], [83], [84] extracts valuable data from the news content, and examines the associated language patterns, meanings and structures of the news. As explained in [59], linguistic analysis mainly aims to identify the language competence of the news creator by the cognition of language formats and finding out the writing patterns. Data representation, deep syntax, semantic analysis and sentiment analysis are the main used techniques in linguistic analysis [17].

Many studies were conducted to examine the unique linguistic styles in clickbait articles such as in Biyani *et al.* [6]. Chen *et al.* [13] examined potential methods for the automatic detection of clickbait, which aim to find out both textual and non textual clickbait hints among images and users' behaviors.

Kumar *et al.* [43] proposed an approach for the identification of hoax documents in Wikipedia. Similar work [7], [62] detected different types of fake news based on the stance of headlines and by considering their corresponding article bodies. This approach could be applied on clickbait detection scenarios, and could be generalized to fake news detection.

Granik and Meesyura [28] introduced a simple and straightforward method for fake news detection based on machine learning techniques. The proposed approach used naive Bayes classifier and achieved good results considering the simplicity of their model.

Burfoot and Baldwin [9] proposed an approach for the automatic detection of satirical news. The proposed approach relies on Support Vector Machine (SVM) classifier, which is trained on lexical and semantic features (i.e., Headline, Profanity, Slang and validity). By applying Bi-normal separation feature scaling (BSN), a precision of 0.958 is achieved.

Rashkin *et al.* [58] studied and compared the language used by real news and that used by satire, hoax, and propaganda. They aimed to find linguistic features characterizing fake content.

Hosseinmoltagh and Paplexakis [37] investigated the problem of identifying the different types of fake news with high accuracy. To this end, they proposed a tensor model that captures the relations between the articles and terms, as well as the spatial relations among terms. In order to build high-coherent fake news clusters (i.e, clusters of similar types of fake news), the authors further proposed an ensemble method that combines the results of of multiple tensor decompositions.

To build a fake news detection model, Pérez-Rosas *et al.* [55] combined morphological, syntactic, understandability, psychological, and n-grams patterns. The authors observed that authentic news in newspaper and entertainment magazines are likely to begin with the first-person pronouns, besides containing positive feeling words. However, fake contents commonly utilize the second-person pronouns and negative feeling words, and focus on the present actions.

Mrowca *et al.* [52] applied different deep neural network models on the Fake News Challenge (FNC)[1] dataset to solve the stance detection problem. The goal was to determine if there is any relationship between the headline and the news article. The results show that Word Embeddings Conditioned Bidirectional Long Short-Term Memory (LSTM) achieves the best classification accuracy.

To distinguish between satire, fake, and original news articles, Horne and Adali [36] and Potthast *et al.* [57] proposed models that consider complexity, stylistic and psychological aspects. In [36], the results show that fake news are similar to satire news with respect to content. On the other hand, it is very easy to distinguish between real news and fake news. Potthast *et al.* [57] constructed two categorizations models for the purpose of distinguishing between satire, fake, mainstream, and hypopartisan news articles. The first model is called topic-based and the second one is known as style-based. The two categorization models are proved to be efficient at differentiating between hyperpartisan news and mainstream news.

Pfohl [56] addressed the stance detection problem, which aims at identifying the relationship between the headline and the body text of the news article. They applied four neural models namely, Bag of Words (BoW), LSTM, LSTM with attention, and conditional encoding LSTM with attention on Fake News Challenge dataset. The results show that the attention models achieve better results than BoW and LSTM with respect to F1 Score.

Jiang *et al.* [38] proposed a fake news detection system, which applied BiLSTM and text embedding Glove on linguistic-based features. The proposed approach was able to achieve an accuracy of 99.82%. In a more recent work [39],the same authors introduced a new stacking method for fake news detection that consists of training nine (09) different machine learning and deep learning algorithms on a set of linguistic features that were extracted using Term

[1] Available at : http://www.fakenewschallenge.org/

Frequency- Inverse Document Frequency (TF-IDF) feature extraction.

Choudhary and Arora [14] introduced a fake news detection system based on linguistic features. The authors extracted four different linguistic features, namely, syntactic, grammatical, sentimental, and readability features. In order to classify news into either fake or real, the authors used a sequential neural network (SNN), which was trained on different combinations of features, and thus building various linguistic-features-based SNN models. Experimental results showed that the classification model, which was trained on combined features, achieved the highest performances with 86% of accuracy using a dataset composed of 250 news.

Some metaheuristics algorithms have been proposed to deal with the fake news detection issue. In [53], two metaheuristic algorithms, i.e, salp swarm optimization (SSO) and grey wolf optimization (GWO) were proposed. In [65], the authors proposed a linguistic-based fake news detection system that applies the Extreme Gradient Boosting Tree (xgbTree) algorithm, which is optimized by the Whale Optimization Algorithm (WOA). Al-Ahmad *et al.* [2] proposed an approach that aims at reducing the number of symmetrical features that exist in news, and particularly in COVID-19 pandemic news. To do so, they implemented different evolutionary classifications such as Salp swarm algorithm (SSA), particle swarm optimization (PSO), and genetic algorithm (GA). Zivkovic *et al.* [87] also focused on detecting misinformation related to COVID- 19 pandemic. They proposed an arithmetic optimization algorithm (AOA) as a a wrapper feature selection to reduce the number of features, and combined it with KNN classifier.

Despite the fact that linguistic-based solutions can effectively detect fake news, some research works [17], [44] have shown that relying only on linguistic analysis, is not suitable for designing robust fake news detection systems. We also agree with this opinion, knowing that the effectiveness of a linguistic-based solution is closely tied to data veracity, which is difficult to ensure.

B. KNOWLEDGE-BASED ANALYSIS

Knowledge-based analysis aims to complement the content–based approaches such as the linguistic ones, by checking the existing body of human knowledge to estimate the likelihood of new statements to be false. The method [17] allows to collect and compare a large number of common and connected statements from different networks like metatags and social network behavior to compute the probability that the content is fake. According to [68], [74], knowledge–based analysis and particularly fact checking, aims at using external sources to check the truthfulness of claims in news contents.

Magdy and Wanas [46] measured the support for each fact of the document using web search. The measured supports are accumulated to compute the support of the document. According to Ginsca *et al.* [27], the technique in [46] has to take into consideration the different aspects of web information credibility such as: quality, expertise, trustworthiness, and reliability. Etzioni *et al.* [24] proposed an approach for fake news detection based on knowledge analysis, which consists of matching the claims extracted from the web with the analyzed news story.

Some existing solutions rely on ontologies in order to model fake news domain knowledge, which can be then used to distinguish fake from real news content. For instance, in [29], ontology reasoning and natural language processing (NLP) have been combined in order to detect deceptive information about COVID-19. The major challenge that faces this specific category of news, is the lack of scientific knowledge related to the disease. For this purpose, the proposed approach applies Description Logics semantic reasoning and NLP in order to identify inconsistencies between trusted and non-trusted medical sources. For instance, the study demonstrated that trusted news are written in a formal language, unlike non-trusted ones, which are written in a less formal way. Similarly, Mazepa *et al.* [51] suggested an ontology for fake news detection on social networks, and Hamilton [31] focused on identifying propaganda techniques in news articles.

Wu *et al.* [79] proposed a fact-checking framework, which applies different perturbations on the claims and checking the corresponding results.

Shi and Weninger [66] formulated the fact checking problem as a link-prediction algorithm in a knowledge graph, Ciampaglia *et al.* [15] used the shortest path between concepts in a knowledge graph. The approaches in [15], [66] are inappropriate for new claims due to the lack of corresponding entries in knowledge bases.

Ciampaglia *et al.* [15] addressed fact-checking as a network problem, through the use of Wikipedia infoboxes to draw out truths in an organized manner. They suggested a measurement to evaluate the truthfulness of a statement by studying path lengths between concepts and the specificity of the terms of the claim in the Wikipedia knowledge graph.

Shiralker *et al.* [67] proposed a fact-checking algorithm called Relational Knowledge Linker, which converts the knowledge network to a smooth–continuous network and examines a claim on the single shortest and semantically connected path in the knowledge graph.

Although knowledge-based approaches can achieve good results, they are inappropriate for new claims without corresponding entries in a knowledge base. Thus, relying only on knowledge-based analysis to build a fake news detection system is not recommended.

C. SOCIAL CONTEXT ANALYSIS

The social context-based approaches [30], [45], [78], [80], [85] typically analyze the spreading patterns and the diffusion on social networks to distinguish misleading substance. Yang *et al.* [80] proposed an unsupervised approach for fake news detection on social media. The authors investigated the veracity of news and credibility of users, and utilized a probabilistic graphical model to capture the complete generative spectrum. They evaluated the model on two different datasets (i.e., LIAR and BuzzFeedNews), and obtained an accuracy of 75.9% and 67.9% respectively.

Zhou and Zafarani [85] proposed a network-based pattern-driven approach for fake news detection in social networks. The main idea behind this work is to focus on the credibility of the news source, covering both the sources that create and publish the news, as well as the sources that spread the news. The method was evaluated on PolitiFact and BuzzFeed datasets showing good performance compared to the state of the art, with an accuracy of 93.30%.

Wu and Liu [78] proposed an approach for social media news classifying using diffusion traces in social networks. They first inferred embeddings of social media users with social network structures to classify news items. To this end, they utilized a new Long Short-Term Memory networks (LSTM-RNN) model to represent and classify the propagation pathways of a message. They evaluated the proposed model on real-world datasets, and the experimental results demonstrated its effectiveness on the task of fake news detection and categorization.

Liu and Wu [45] used a combination of recurrent and convolutional neural networks to model news diffusion pathways as multivariate time series, where each tuple of a news story is a numerical vector representing characteristics of a user who engaged in spreading the news. The method was evaluated on three real-world datasets and experimental results showed that the proposed model was able to effectively identify fake news content with an accuracy of 92.3%.

Gupta *et al.* [30] proposed a PageRank-like credibility propagation algorithm on a multi-typed network by encoding users' credibility and tweets' implications. Further, they enhanced the basic trust analysis by updating event credibility scores and exploited event graph-based optimization to assign similar scores to similar events. They evaluated the model on two tweet feed datasets, and the proposed approach achieved an accuracy of 86%.

In general, context-based approaches achieve better performance compared to both linguistic and knowledge-based ones. However, they work only a posteriori, disregarding the actual news content and requiring large amounts of data.

D. COMPARISON WITH RELATED WORK

As previously discussed, the existing fake news detection solutions are either linguistic-based, knowledge-based, or social context-based. Considering the limitations of the aforementioned categories, it would be a good idea to investigate combining two different categories in order to overcome their respective limitations. In the literature, there are only few hybrid approaches, that only considered combining linguistic and social context analyses [10], [63], [69], [75]. To the best of our knowledge, there is no hybrid approach that considers both linguistic and knowledge-based features. Differently from related work, we propose in our work a hybrid approach, which combines linguistic-based and knowledge-based analyses to build a more robust and accurate fake news detection system.

III. PROPOSED FAKE NEWS DETECTION SYSTEM

The proposed fake news detection system consists of two phases, namely training and testing. Both phases include a preprocessing task, which consists of cleaning and preparing the training and testing datsets of real and fake news. In the training phase, the feature extracting task extracts a set of relevant features from the training dataset, which are then fed to several machine learning algorithms to build a fake news detection model. In the testing phase, the detection model is applied on test data to decide whether the provided news articles are real or fake. Figure 2 presents the overall architecture of the proposed fake news detection system.

A. PRE-PROCESSING

Before extracting the various features and analyzing the news content, we need to conduct a pre-processing task. In this work, we apply the following text processing methods:

- Tokenization: It consists of splitting a news content into a set of individual words.
- Stopwords removal: It consists of removing the most commonly used words (e.g., the, and, is), which have no effect on the classification.
- Stemming: It consists of reducing a word either to its base form by removing suffixes and prefixes or to its root form, also known as a lemma.
- Cleaning: It consists of removing URLs, punctuation,.etc.

B. FEATURE EXTRACTION

In machine learning, features are usually numerical, but structural features such as strings and graphs can also be used. In the context of our work, features represent different properties of the news article, such as its title, the number of words, sentiment, etc.

In our work, we use a set of linguistic features, which have been considered by [33], [36], [55], [70] as the most relevant ones for distinguishing between real and fake news. These features are: title, number of words, reading ease, lexical diversity, and sentiment.

In addition to the linguistic features, we propose our own set of features, called fact-verification, which are: Fact Check (FC), Reputation (Rep), and Coverage (CV).

By combining linguistic and fact-verification features, we expect to obtain a better detection accuracy, since we leverage the benefits of both categories of features. Table 1 defines the set of feature, which are used by the proposed detection system.

1) FACT-VERIFICATION FEATURES

We list the used fact-verification features and their corresponding extraction methods:

- **Fact check:** It is extracted using fact-checking websites (Snopes[2] and Google Fact Check Explorer[3]).

[2]Available at : https://www.snopes.com/

[3]Available at: https://toolbox.google.com/factcheck/explorer

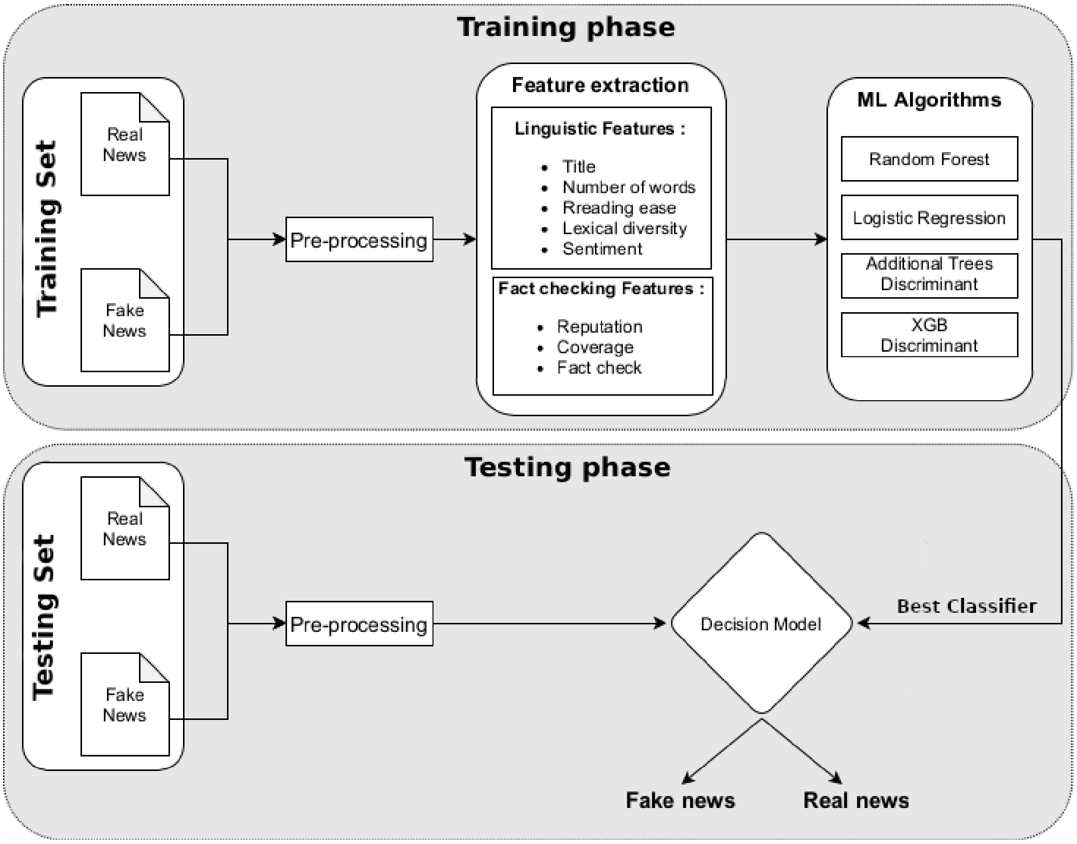


FIGURE 2. Architecture of the proposed fake news detection system.

TABLE 1. List of Linguistic and fact-verification features used by the proposed detection system.

Features	Type	Description
Title	Linguistic	The title of the news article
Reputation	Fact-verification	It allows to rate the website that published the article. A website can have good, bad, or no reputation if it is not known.
N of word	Linguistic	It represents the number of words
Reading ease	Linguistic	It represents the reading difficulty of each article, as shown in Equation 1. The higher the score, the easier the article is to read.
Lexical diversity	Linguistic	It is an aspect of 'lexical richness' and refers to the relationship between different types of words and the total number of words.
Sentiment	Linguistic	It indicates the dominant sentiment that is present in the article. It can be either positive, negative or neutral.
Fact check	Fact-verification	It is used to check if other fact checking sites have already given their opinion about the article, i.e., whether it is true or false.
Coverage	Fact-verification	This feature answers the question: How many credible sources published the same information ?

- **Reputation:** It is obtained using two different tools: Decodex of the French newspaper Le Monde[4] and Media Bias Fact Check,[5] a famous American fact checking site.
- **Coverage:** It is extracted using the google search engine.[6]

2) LINGUISTIC FEATURES

We list the following linguistic features and their corresponding extraction tools:

- **Title:** It is obtained using two web-based software: Zyte[7] and BuzzStream.[8]
- **N of words:** It is obtained using different tools such as WordCounter.[9]
- **Reading ease:** It computes the reading ease of a text using the Readability Formulas tool, which provides the Flesch Reading Ease score, as shown in Equation 1.

$$RE = 206.835 - (1.015 \times ASL) - (84.6 \times ASW) \quad (1)$$

[4]Available at: https://www.lemonde.fr/verification
[5]Available at: https://mediabiasfactcheck.com/
[6]Available at: https://www.google.com/
[7]Available at : https://www.zyte.com/data-extraction/
[8]Available at: http://tools.buzzstream.com/meta-tag-extractor
[9]Available at: https://wordcounter.net/

where :
- *RE* : Readability Ease.
- *ASL* : Average Sentence Length (i.e., the number of words divided by the number of sentences).
- *ASW* : Average number of syllables per word (i.e., the number of syllables divided by the number of words).
The Flesch Reading Ease Formula provides a score between 1 and 100, and 100 represents the best readability score. According to its reading ease score, a text is classified as follows:

  - **90-100 :** Very easy.
  - **80-89 :** Easy.
  - **70-79 :** Fairly easy.
  - **60-69 :** Standard.
  - **50-59 :** Fairly difficult.
  - **30-49 :** Difficult.
  - **0-29 :** Very confusing.

- **Lexical diversity:** It can be computed using a variety of measures by considering the following variables:
  - V: is the number of types of tokens.
  - N: is the total number of tokens.
  - $f_v(i, N)$: is the numbers of types occurring i times in a sample of length N.

  The lexical diversity measures are the following:

  - *Type-Token Ratio* [35] (Equation 2), denoted by:
$$TTR = \frac{V}{N} \tag{2}$$
  - *Log Type-Token Ratio* (or *Herdan's C*) [73] (Equation 3), denoted by:
$$C = \frac{\log V}{\log N} \tag{3}$$
  - *Guiraud's Root TTR* [73] (Equation 4), denoted by:
$$R = \frac{V}{\sqrt{N}} \tag{4}$$
  - *Carroll's Corrected TTR* [49] (Equation 5), denoted by:
$$CTTR = \frac{V}{\sqrt{2N}} \tag{5}$$
  - *Dugast's Uber Index* [73] (Equation 6), denoted by:
$$U = \frac{(\log N)^2}{\log N - \log V} \tag{6}$$
  - *Summer's index* [49] (Equation 7), denoted by:
$$S = \frac{\log(\log V)}{\log(\log N)} \tag{7}$$
  - *Yule's K* [81] (Equation 8), denoted by:
$$K = 10^4 \times [-\frac{1}{N} + \sum_{i=1}^{v} f_v(i, N)(\frac{i}{N})^2] \tag{8}$$
  - *Yule's I* [81] (Equation 9), denoted by:
$$I = \frac{V^2}{M_2 - V}$$
where
$$M_2 = \sum_{i=1}^{v} i^2 \times f_v(i, N) \tag{9}$$
  - *Simpson's D* [71] (Equation 10), denoted by:
$$D = \sum_{i=1}^{v} f_v(i, N)\frac{i}{N}\frac{i-1}{N-1} \tag{10}$$
  - *Herdan's V_m* [34] (Equation 11), denoted by:
$$V_m = \sqrt{\sum_{i=1}^{v} f_v(i, N)(i/N)^2 - \frac{i}{V}} \tag{11}$$
  - *Maas' indices* [50] (Equation 12), denoted by:
$$Maas = (a, \log V_0, \log_e V_0)$$
where
$$a^2 = \frac{\log N - \log V}{\log N^2}$$
and
$$logV_0 = \frac{\log V}{\sqrt{1 - \frac{\log V^2}{\log N}}} \tag{12}$$
  - *Moving-Average Type-Token Ratio* [18], denoted by *MATTR*. It is computed by moving a fixed size window through the text, compute the *TTR* of every window, and average the obtained *TTRs*.
  - *Mean Segmental Type-Token Ratio* [40], denoted by *MSTTR*. It is computed by dividing the text into segments, compute the *TTR* of each segment, and average the obtained *TTRs*.

  The above equations are computed using Quanteda tool [4], as shown in Figure 3. In our case, we define our lexical diversity as the sum of all values obtained from Equations 2 to 12, *MATTR*, and *MSTTR*.

- **Sentiment:** We used the SEO Scout's analysis tool[10] to get this feature, as it can effectively and rapidity estimate the dominant sentiment in the news.

```
textstat_lexdiv(
  x,
  measure = c("TTR", "C", "R", "CTTR", "U", "S", "K", "I", "D", "Vm", "Maas", "MATTR",
    "MSTTR", "all"),
  remove_numbers = TRUE,
  remove_punct = TRUE,
  remove_symbols = TRUE,
  remove_hyphens = FALSE,
  log.base = 10,
  MATTR_window = 100L,
  MSTTR_segment = 100L,
  ...
)
```

FIGURE 3. Lexical diversity measures in quanteda tool.

[10]Available at: https://seoscout.com

C. TRAINING PHASE

In the training phase, we leverage AutoAI experiment of IBM Watson Studio[11] to select the best learning algorithm among a set of candidate ones. The best algorithm is the one that offers the best match for training data. To this end, we employ four candidate classification algorithms namely, Random Forest (RF), Logistic Regression (LR), Additional Trees Discriminant (ATD), and eXtreme Gradient Boosting (XGBoost). The best model, which is selected by AutoAI experiment is Random Forest. To select the best model, AutoAI initially applies the candidate algorithms on small subsets of the dataset, and ranks them. Then, it repetitively increases the size of subsets and executes the candidate algorithms until the best algorithm is found.

AutoAI performs hyper-parameter optimization of the best selected algorithm by applying an optimization algorithm that allows fast convergence to a good solution, and generating the best model. Note that AutoAI automatically selects the hyper-parameters of each machine learning algorithm. Thus, we did not apply any parameter tuning.

1) RANDOM FOREST CLASSIFIER (RF)

Random forest [8] is a supervised classification algorithm that consists of a set decision trees, which are merged together for better performance in terms of accuracy. Each tree in the random forest produces a class prediction, and the class with the majority of predictions becomes the model's prediction. The RF algorithm, introduced by Dietterich [22], describes the steps of constructing the decision tress as follows :

1) Take L instances of M attributes from the training set.
2) $m < M$, is the number of parameters in the training set that determines the next selected attribute at each node.
3) For each training sample, a tree is constructed with replacement.
4) Arbitrarily select m attributes for each node of the tree.
5) Compute the best split using m training set's attributes.
6) Grow each tree without pruning.

2) LOGISTIC REGRESSION (LR)

Logistic regression [77] is a linear algorithm used for binary classification problems. Linear and logistic regressions are very similar, but the main difference is that linear regression generates a continuous output, and logistic regression generates a discrete one. This algorithm allows the description of the data and the level of strength in the relationship between a dependant binary variable and the associated independent variables. In other words, Logistic Regression predicts a categorical dependent variable representing the target class based a given set of independent variables representing the features' set.

3) ADDITIONAL TREES DISCRIMINANT (ATD)

Decision Trees are supervised machine learning algorithms where data is segmented according to a specific parameter. The objective of this algorithm is to build a training model that is used to predict the class of the target variable, which is used by the decision tree to solve the classification problem. Discriminant analysis creates a predictive model that determines to which group the class belongs. The model is composed of a discriminant function based on linear combinations of the variables used as predictors, i.e., offering the best discrimination between the groups.

4) XGBOOST (EXTREME GRADIENT BOOSTING)

XGBoost [11] is a decision-tree-based ensemble machine learning algorithm that implements the Gradient Boosting method. Gradient boosting is a supervised learning algorithm aims at providing accurate prediction of a target variable by combining the estimates from other models. XGBoost offers parallel construction of trees, as well as an optimization step for each attached tree (i.e., boosting). Moreover, XGBoost employs regularization that helps avoiding overfitting when training the model. All these characteristics make XGBoost one of the widely used machine learning algorithms that allows solving various regression and classification problems in a fast and an accurate manner.

D. TESTING PHASE

In the testing phase, each news is pre-processed. Then, the extracted features are fed to the decision model, which is selected in the training phase. The decision model decides whether the news is real or fake.

IV. IMPLEMENTATION

In this section, we present the software and hardware tools, which are used to implement our system.

A. IMPLEMENTATION ENVIRONMENT

To implement our learning models, we use IBM Watson Machine Learning software.[12] This software can generate analysis models, which are trained on our dataset.

Watson Machine Learning offers a full range of tools and services to generate, train, and deploy machine learning models.

The following tools are available with the Watson Machine Learning service:

- The AutoAI experimentation generator, which automatically processes structured data to generate model pipelines. The best performing pipelines can be saved as machine learning models and deployed for evaluation and the best algorithm is determined by the model selection and optimization during AutoAI training.

[11] Available at: https://dataplatform.cloud.ibm.com/docs/content/wsj/analyze-data/autoai-overview.html

[12] Available at : https://eu-gb.dataplatform.cloud.ibm.com/login?context=cpdaas

TABLE 2. Experimental environment of the proposed detection system.

Component	Settings
Hardware Settings	
CPU	Intel(R) Core(TM) i5-4200U CPU @ 1.60 GHz 2.30 GHz
RAM	8 GB
Software Settings	
OS	Windows 10(32-bit)
Watson Machine Learning Service instance	Machine Learning-3e
Notebook	2 Executors: 1 vCPU and 4 GB RAM, Driver: 1 vCPU and 4 GB RAM
Programming Language	Python 3.7 with Spark

- Notebooks that provide an interactive programming environment for working with data, testing models, and obtaining rapid prototyping.
- Deep learning experiments, which automate the execution of hundreds of training runs while tracking and storing results.
- Tools to view and manage model deployments.

The hardware and software settings, which are used to implement our system, are depicted in Table 2.

B. DATASET

In our experiments, we use the Buzzfeed Political News data set[13] that have been proposed by Horne and Adali [36]. This dataset contains two categories of news, namely, fake and real, and it has been gathered from a Buzzfeed's 2016 article[14] on fake news election that have been spread on Facebook.

V. EVALUATION

In this section, we present the evaluation methodology, the evaluation metrics, and the performance results of our system in terms of accuracy, recall, and F1-score.

A. EVALUATION METHODOLOGY

Our experimental process consists of training and testing our system using only linguistic features, then using only fact-verification features. Finally, we train and test the proposed system using various combinations of linguistic and fact-verification features. In order to assess the effectiveness of the proposed fake news detection system, we used the holdout cross-validation technique, which consists in dividing the dataset into two subsets: training and testing. In our case, we choose to use 85% of the data for training, and 15% of the data for testing.

B. EVALUATION METRICS

To evaluate the performance of our system, we used several evaluation metrics, which are: Accuracy (ACC), Recall (REC), and F1-score ($F1$) [32].

[13]Available at: https://github.com/rpitrust/fakenewsdata1
[14]Available at: https://www.buzzfeednews.com/article/craigsilverman/viral-fake-election-news-outperformed-real-news-on-facebook

1) ACCURACY (ACC)

It is a measure of the proportion of correct predictions of the model, and is defined as the number of true predictions divided by the total number of analyzed items. Formally:

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \tag{13}$$

2) RECALL (REC)

It corresponds to the ratio of the number of correctly classified positive items to the number of actual positive items. Formally:

$$REC = \frac{TP}{TP + FN} \tag{14}$$

3) F1-SCORE ($F1$)

It relates precision (PRE) and recall (REC) metrics to obtain a quality measure that balances the relative importance of these two metrics. Formally:

$$F1 = \frac{2 \times (PRE \times REC)}{PRE + REC} \tag{15}$$

where:

$$PRE = \frac{TP}{TP + FP} \tag{16}$$

- TP : It is the number of accurately classified fake news (true positives).
- FP : It is the number of incorrectly classified real news (false positives).
- TN : It is the number of accurately classified real news (true negatives).
- FN : It is the number of inaccurately classified fake news (false negatives).

C. EVALUATION RESULTS

Table 3 presents the performance results of our system. We can observe that the linguistic-based features give an accuracy of 89.4% under ATD and XGBoost algorithms. On the other hand, fact-verification features gives an accuracy of 81.2% under ATD and RF algorithms. We can observe that the combination of the linguistic features and fact-verification features considerably increases the accuracy, especially when the eight (08) features (i.e., title, number of words, reading ease, lexical diversity, sentiment, Fact check, Coverage, and Rep) are employed together. Indeed, we obtain the highest accuracy, i.e., 94.40%, which represents an improvement of respectively, 5%, and 13% compared to the highest accuracy obtained when linguistic features, and fact-verification features are employed separately.

D. COMPARISON WITH OTHER APPROACHES

Actually, a fair comparison with previous approaches is not possible due to many reasons including the use of different methods (i.e., machine learning, deep learning, neural Networks, …etc), as well as different datasets. However, we can only compare our work (Accuracy=94.40%) with

TABLE 3. Experimental results of the proposed detection system under different sets of features.

Features	Learning Algorithm	F1 (%)	REC(%)	ACC (%)
Fact check	LR	69.40	54.40	75.30
	ATD	69.40	54.40	75.30
	XGBoost	70.40	54.40	76.50
	RF	70.40	54.40	76.50
Linguistic	LR	79.60	84.10	77.60
	ATD	89.60	88.90	89.40
	XGBoost	90.00	91.10	89.40
	RF	88.30	93.20	87.00
Linguistic + Fact check	LR	84.30	91.10	82.30
	ATD	88.90	84.30	89.50
	XGBoost	88.40	86.30	88.20
	RF	91.20	93.30	90.60
Fact-verification (Fact check + Coverage + Rep)	LR	76.7	63.70	80.00
	ATD	77.80	63.70	81.20
	XGBoost	75.10	61.40	78.80
	RF	77.80	63.70	81.20
Linguistic + Fact-verification (Fact check + Coverage + Rep)	LR	84.30	91.10	85.10
	ATD	89.10	84.10	88.40
	XGBoost	87.10	84.10	90.50
	RF	**94.90**	**97.90**	**94.40**

Horne and Adali [36] (Accuracy=77%), as the same data set, i.e., Buzzfeed Political News Data, is used.

In Table 4 and Figure 4, we present the performances of our system and those of machine learning-based state-of-the-art approaches with respect to accuracy and the number of features. Zhou and Zafarani [85] employed linguistic and social features, and achieved a detection accuracy of 93.30%. Gupta *et al.* [30] and Yang *et al.* [80], which only used social-context features, obtained an accuracy of 86% and 75.90% respectively. Shu *et al.* [69] and Castillo *et al.* [10] achieved an accuracy of 87.80% and 89% respectively. Almeida [19], Potthast *et al.* [57], Horne and Adali [36], Pérez-Rosas *et al.* [55], and Fairbanks *et al.* [25], which only used linguistic-based features, obtained an accuracy of 74.30%, 75%, 77%, 78%, and 88% respectively. Shakeel and Jai [64] that applied only knowledge-based features, reached an accuracy of 86%.

The efficiency of the detection approach, with respect to detection time, mainly depends on the used number of features. From Table 4, we can observe that our work only employs eight features, which is less compared to most of the state-of-the-art approaches. For instance, 10, 15, 17, 20, 26, 68, and 69 features are used by [10], [55], [57], [69], [80], [85], and [19] respectively. On the other hand, Horne and Adali [36], which uses the same dataset as our work, employs the lowest number of features (4 features). However, it records poor effectiveness (i.e., ACC=77%). Therefore, our system offers a good tradeoff between effectiveness and number of features.

VI. DISCUSSION

The evaluation results from Table 3 and Table 4 consolidate the claim that combining linguistic-based and knowledge-based features is an effective approach for fake news detection. Indeed, by employing linguistic features, our system reached an accuracy between 77.6% and 89.46%. The approaches that only employed linguistic-based features [19], [25], [36], [55], [57] recorded an accuracy between 74.3% and 88%. Specifically, Almeida [19], Potthast *et al.* [57], Horne and Adali [36], Pérez-Rosas *et al.* [55], and Fairbanks *et al.* [25], which used linguistic-based features, obtained an accuracy of 74.30%, 75%, 77%, 78%, and 88% respectively. This shows that linguistic-based features are not sufficient for fake news detection and they provide poor accuracy performance.

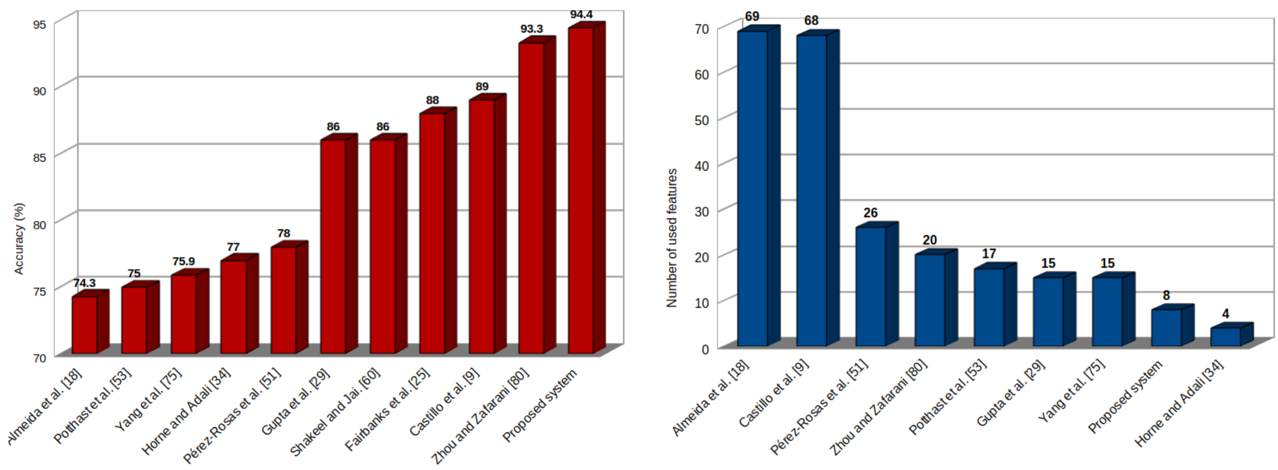
On the other hand, we tested our system on two types of knowledge-based features. The first type only considers the Fact check feature, which contributed in reaching an accuracy between 75.3% and 76.5%. The second type considers the fact-verification features (i.e., Fact check, Coverage, and Reputation), which improved the accuracy to reach values between 78.8% and 81.2%. Shakeel and Jai [64], which only employed knowledge-based features, recorded an accuracy of 86%. The approaches that only employed social context features such as Yang *et al.* [80] and Gupta *et al.* [30] only recorded an accuracy of 75.96% and 86% respectively. These results indicate that knowledge-based features and the social-context features alone still cannot be a good choice for fake news detection.

By combining different types of features, a better detection accuracy can be obtained. For instance, Shu *et al.* [69], Castillo *et al.* [10], and Zhou and Zafarani [85], which combined between linguistic-based features and social-context features, reached an accuracy of 87.7%, 89%, and 93.3% respectively.

As for the combination between linguistic-based and knowledge-based features, we tested our system under two combinations. The first combination considers the

TABLE 4. Comparison with related work tested under different datasets.

Work	Decision method	Dataset	Features	Number of Features	ACC
Pérez-Rosas et al. [55]	Support Vector Machine	Celebrity	Linguistic	26	78%
Fairbanks et al. [25]	Random Forest,Logistic Regression, Loopy Belief Propagation	Private	Linguistic	N/A	88%
Gupta et al. [30]	Support Vector Machine, Naive Bayes, Decision Trees	Twitter	Social Context	15	86%
Shu et al. [69]	Support Vector Machine	Fakenewsnet	Linguistic+Social Context	10	87.80%
Yang et al. [80]	Support Vector Machine, Naive Bayes	LIAR	Social Context	15	75.90%
Potthast et al. [57]	Random Forest	BuzzFeed-Webis	Linguistic	17	75%
Shakeel and Jai [64]	Support Vector Machine,Logistic Regression	DBpedia	Knowledge	N/A	86%
Zhou and Zafarani [85]	Random Forest, Support Vector Machine, Naive Bayes , Decision Trees	Fakenewsnet	Linguistic + Social Context	20	93.30%
Almeida et al. [19]	k-Nearest Neighbor, Support Vector Machine, Naive Bayes, Random Forest	Fakenewsnet	Linguistic	69	74.30%
Horne and Adali [36]	Support Vector Machine	BuzzFeedNews	Linguistic	4	77%
Castillo et al. [10]	Decision Tree	Twitter	Linguistic+Social Context	68	89%
Proposed system	**Random Forest**,Logistic Regression, Additional Trees Discriminant, XGBoost	BuzzFeedNews	Linguistic+fact-verification	8	**94.40%**



(a) Accuracy

(b) Number of features

FIGURE 4. Performance of fake news detection approaches.

linguistic-based features and Fact check feature. This allowed to record an accuracy between 82.3% and 90.6%. The second combination considers the linguistic and the fact-verification features, i.e., after trying various combinations of these features, we find that the combination of all the eight features i.e., title, number of words, reading ease, lexical diversity, sentiment, Fact check, Coverage, and Reputation produces the best performance results. Indeed, this combination allows to reach an accuracy of 94.40% with RF algorithm. This represents a considerable leap in the effectiveness of the proposed system, since the obtained accuracy is 5% higher than that obtained using only linguistic features, and 13% higher than that obtained using fact verification ones.

VII. CONCLUSION

In this paper, we have proposed a novel hybrid fake news detection system that employs two types of features: linguistic and fact-verification features.

The proposed detection system employs only eight features, which less compared to the stat-of-the-art approaches. It operates in two phases: training and testing. In the training phase, the detection system runs four machine learning algorithms, i.e., Logistic Regression (LR), Random Forest (RF), Additional Trees Discriminant, and XGBoost, in order to select the best classifier for the testing phase.

Evaluation results on the Buzzfeed Political News data set show that the proposed detection system achieves an accuracy of 94.4% under Random Forest. These results are better compared to those obtained from employing linguistic features, (i.e., Accuracy=89.4% under ATD and XGBoost), and fact-verification features (i.e., Accuracy=81.2% under ATD and Random Forest). The proposed system also employs eight features, which is less than most of the state-of-the-art approaches.

As future work, we aim at improving the accuracy of our detection system by investigating other discriminating features such as visual-based and style-based features. Moreover, we plan to further detect other types of false information such as biased/inaccurate news and misleading/ambiguous news.

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