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# Analysis and Classification of Fake News using Sequential Pattern Mining

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**Abstract:** Disinformation, often known as fake news, is a major issue that has received a lot of attention lately. Many researchers have proposed effective means of detecting and addressing it. Current machine and deep learning-based methodologies for classification/detection of fake news are content-based, network (propagation)-based, or multimodal methods that combine both textual and visual information. We introduce here a framework, called FNACSPM, based on SPM (sequential pattern mining), for fake news analysis and classification. In this framework, six publicly available datasets, containing a diverse range of fake and real news, and their combination, are first transformed into a proper format. Then, algorithms for SPM are applied to the transformed datasets to extract frequent patterns (and rules) of words, phrases, or linguistic features. The obtained patterns capture distinctive characteristics associated with fake or real news content, providing valuable insights into the underlying structures and commonalities of misinformation. Subsequently, the discovered frequent patterns are used as features for fake news classification. This framework is evaluated with eight classifiers, and their performance is assessed with various metrics. Extensive experiments were performed and obtained results show that FNACSPM outperformed other state-of-the-art approaches for fake news classification, and that it expedites the classification task with high accuracy.

**Key words:** Disinformation, Fake news, SPM, Frequent patterns, Classification

## 1 Introduction

People can now quickly receive news and information through various online sources. However, easy and cheap access to information has made disinformation (fake news)[1–3] not only widespread but also a great threat to our society and everyday life. Unlike conventional news outlets like television and newspapers, users can now easily use online social networking (OSN) platforms and messaging services to create, publish content, and spread it quickly[4–6]. According to the report published in November 2023, at least half of American adults received most of their news from OSN platforms as compared to television, radio, and paper publications*. Analysis and identification of fake news are critical for many reasons, such as: (1) Individuals or organizations create and spread fake news for personal, financial, or political gains. (2) Fake news can mislead the general public and make them adopt false beliefs. (3) Fake news has the power to change the way the public responds to true news and can undermine the credibility of the whole

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*pewresearch.org/journalism/fact-sheet/social-media-and-news-fact-sheet/

news ecosystem[7–9]. Thus, it is important to analyze and detect fake news on OSN and other platforms.

Many manual tools and websites for fact-checking (e.g. PolitiFact†, FactCheck‡, Snopes§ and Fiskkit¶) are currently available for the analysis, evaluation and recognition of fake news. However, the problem of fake news analysis and detection is far from being solved. Now it is not possible to manually assess and verify every news or information due to the enormous amount of online data generated every minute, particularly on OSN platforms[1]. Moreover, determining the credibility of online news articles is difficult as fake news frequently contains wrong or false information mixed with certain facts[10]. In the last decade, computational approaches for fake news classification/detection have drawn a lot of interest. Fake news classification/detection methods, based on machine learning (ML) and deep learning (DL), can be broadly classified into two main groups: (1) content-based methods and (2) propagation-based methods[11–14]. Content-based methods detect fake news by analyzing the news content or information present in articles by either relying on a *knowledge-based system*[15,16] or finding latent[13,17] and non-latent (hand-crafted) features[16,18] in the content.

Knowledge-based fake news detection methods can only detect false news but not fake news[1,11]. Non-latent features are style-based and self-defined at various language levels, and various embedding and encoding techniques are used for these features. Latent features are features that are automatically generated by using matrix or tensor factorization, or DL techniques (for more details about non-latent and latent features, see Section 2). Selecting features or extracting non-latent features requires expertise, and some discovered linguistic clues might not be applicable to news or information. Latent features perform well, but they are difficult to comprehend. Moreover, content-based methods often face problems of computational efficiency, interpretability, scalability, and generalization because they are tested on limited datasets. As far as we are aware, no study has been published yet for fake news classification or detection based on pattern mining that focuses on a diverse set of datasets.

†politifact.com/
‡factcheck.org/
§snopes.com/
¶fiskkit.com/

This study's two primary objectives are to: (1) examine the application of SPM (sequential pattern mining)[19] for the reliable and accurate classification and detection of fake news from datasets in textual format, and (2) evaluate the SPM-based fake news classification approach on multiple datasets, and their combination, to get insights into its effectiveness and generalization ability across different data sources and characteristics. In the past, SPM is used extensively in various applications such as tourist movements analysis[20], bioinformatics[21,22], market basket[23], text analysis[24], energy reduction in smarthomes[25], malware analysis[26], proof sequence analysis[27] and webpage click-stream analysis[28]. However, no one has explored its applicability for fake news analysis and classification yet. Based on the analysis of online news and information contents, we present a new content-based framework, called FNACSPM (Fake News Analysis and Classification using Sequential Pattern Mining) that provides:

- One approach based on SPM to analyze news contents. Using this approach, the datasets are first transformed into an appropriate learning format. Second, SPM techniques are employed to find frequent sequential patterns in the transformed datasets. Additionally, frequent sequential rules among fake and real news are identified.
- One fake news detection approach that uses frequent patterns, discovered by using SPM algorithms. These patterns are then utilized in the fake news classification process. For classification, eight classifiers are utilized and comprehensive experiments are conducted by using various evaluation metrics to evaluate the effectiveness of the detection approach.

The proposed framework is evaluated on six datasets, and their combination for both binary and multi-class fake news classification. Obtained results indicate that using the FNACSPM to identify frequent sequential patterns in news and using these patterns yields improved classification results as compared to using all the news. It is also observed that logistic Regression (LR) performed well, overall, for both types of classification. Using all the news in the classification process provided less accurate results and took more time. FNACSPM also outperformed state-of-the-art approaches for fake news classification/detection. By utilizing frequent patterns, this study offers valuable insights into the linguistic and semantic structures present in fake news. This aids in a deeper and better understanding of the characteristics and commonalities of misinformation, potentially assisting in the development of more fast and reliable strategies and models for detection.

The rest of the paper contains five sections. Section 2 examines the previous research on the analysis and classification of fake news by using ML and DL. Section 3 provides the details for the six datasets that are used in this study. FNACSPM is presented in Section 4 which offers approaches for fake news analysis and classification. The experimental results and comparison of FNACSPM with recent fake news classification/detection approaches is presented in Section 5. Finally, the paper is concluded with some remarks in Section 6.

## 2 Related Work

The two main categories of fake news detection techniques are content-based and propagation (or social context)-based. Content-based approaches for fake news detection evaluate online news/information by examining textual information, visual information, or both. Content-based approaches use three common textual representations to analyze news: *knowledge*, *style* information (non-latent or general), and *latent* information[13,15–18]. Propagation or network-based methods analyze and identify fake news by investigating how news/information spreads over social networks. As the second category of propagation-based techniques is not relevant to this work, those are not discussed further.

The first representation, Knowledge, is an SPO (Subject, Predicate, Object) tuples set that is obtained from the text of online news. To identify fake news, knowledge-based methods assess the news authenticity by evaluating the knowledge discovered in news content that needs verification. One way to identify true knowledge is by comparing the obtained SPO from a news article with a Knowledge Graph (KG)[15,16]. Generally, knowledge-based systems access the credibility of a given news, but they also face challenges related to the authenticity of the source(s) from which the KG is constructed. For fact-checking online news, it is necessary to identify not only parts of the news that are worth checking but also to have or create a KG that has all the possible “valuable” information and facts[1].

Style-based approaches for fake news detection, as opposed to knowledge-based systems, examine the news contents. To differentiate fake news from the truth, these methods use various general self-defined (non-latent) features that represent the writing style of online news. Non-latent features describe the style of the news (or content) at four language levels: (1) lexicon[11,16,17], (2) syntax[11,29], (3) discourse[30,31] and (4) semantic[18]. At the lexicon level, these approaches compute the lexicon frequency statistics with models such as bag-of-words (BOW)[11]. Part-of-speech (POS) taggers are used for shallow syntax tasks at the syntax level to compute the frequencies of POS[11,29,32]. Moreover, probabilistic context-free grammar (PCFG) can be used in style-based methods to examine and compute the rewrite rules frequencies[18,29]. The rhetorical structure theory (RST) and tools for rhetorical parsing are used at the discourse level to compute the frequencies of rhetorical relations among sentences as features[30,31]. In the fourth language level (semantic), phrases or lexicons that fit into each category of psycho-linguistic (like those that are described in LIWC (linguistic inquiry and word count)[18]) or that fit into each self-described psycho-linguistic feature are assigned frequencies. Experience and associated deception theories can be used to learn such features. Style-based approaches can also use TF-IDF (term frequency–inverse document frequency) and n-grams at various language levels to capture features of sequences of words (POS tagging, rewrite rules, etc.)

Latent textual features are generally used to create embeddings of the news content. These features can be extracted at the word, sentence, or document level. Embeddings are vectors that can be fed to classifiers within a traditional ML framework for fake news detection. In a DL framework, such embeddings can also be incorporated into neural networks and transformers[1,11]. In theory, a latent representation can also be generated automatically by processes such as matrix or tensor factorization. The selection or extraction of general (non-latent) features is heavily influenced by experience and is weakly supported by fundamental theories from other disciplines. Latent features are difficult to comprehend and thus make it difficult to educate the public about fake/real news. Content-based approaches do not take into account auxiliary information that plays a role in news propagation, such as news spreaders. Moreover, these approaches are sensitive to news content. A malicious entity can also manipulate the detection results by disguising their writing styles[14].

Next, we review style-based fake news detection studies published in the last seven years, based on traditional ML and DL.

The semi-supervised learning method[5] to detect breaking news rumors combined unsupervised and supervised learning objectives. Sitaula et al.[10] assessed the veracity of fake news, and they found that the total authors and the link for the creator of a news article with false information play important roles in identifying fake news. The theory-driven method[11] represented news articles with various manual features that captured content structure and writing style. A multi-modal approach was used in SAFE[13] to identify fake news that relied on similarities between news text and visual information. Reis et al.[33] used various supervised classifiers for fake news classification on some features from the literature and also on a new set of features. Some studies[34, 35] have compared various ML classifiers on different datasets for fake news detection. Ahmad et al.[36] investigated various textual properties of news and used an ensemble approach to detect fake news. TF-IDF and 23 classifiers were used in[37] to detect fake news in three datasets. Shu et al.[38] examined fake news datasets from various contexts to understand their characteristics and used various standard ML classifiers and social article fusion models for classification.

A hybrid framework, named BerConvoNet[12], combined BERT embeddings and CNN to detect fake news. Two-level CNN with User Response Generator (TCNN-URG) framework[39] for fake news detection represented online articles at sentence and word levels for extraction of semantic information. The BERT model was applied in another study[40] to examine how the news title and the text (body) relate to fake news. Shu et al.[41] proposed dEFEND, an explainable fake news detection method that was based on RNN and co-attention-based techniques. Another study[42] proposed a co-attention sub-network explainable detection model based on sentence-comment. Sastrawan et al.[43] combined CNN and RNN to identify fake news. Similarly, the approach[44] examined news headlines using BERT and an LSTM network. To classify fake news on OSN, the FakeBERT[45] approach combined CNN with BERT. An ensemble learning model based on BERT and text sentiment analysis was employed in[46] for improved detection of harmful news. A study[47] used various word vector representation techniques with FNN and LSTM for fake news identification. FNDNet[48] is a deep CNN for fake news identification. Until now, the majority of the literature has focused on fake and real news identification as a binary classification problem. Some studies[49–59] worked on multi-class fake news identification. Recently, DL and neural network-based techniques have been proposed and developed for fake news detection that incorporated multi-modal data such as social context[60], text, and image[13, 17, 61–65] and text with users behavior and profiles[66].

## 3 Datasets

This study uses six publicly available datasets to analyze and validate the effectiveness of the proposed framework. Fact-checking experts provided the ground truth labels of true (real) or false (fake) for news articles in each of these six datasets. The George McIntire Dataset[67] is the first dataset, referred to as Dataset-1 (DS-1), containing 2,291 fake news and 2,285 real news. The second and third datasets are from FakeNewsNet Repository[38]. The websites (GossipCop and PolitiFact) for fact-checking are used to get both fake and true news. The GossipCop dataset, referred to as Dataset-2 (DS-2), contains 5,335 (16,819) fake (real) news. The PolitiFact dataset, referred to as Dataset-3 (DS-3), contains 474 (798) fake (real) news stories.

The next three datasets are originally sourced from the Kaggle data science community. The BuzzFeed dataset[68], called Dataset-4 (DS-4), comprises both 91 real and fake news articles. Another dataset known as Fake News Classification[69], referred to as Dataset-5 (DS-5), contains 23,503 (21,418) fake (real) news articles. The last dataset used in this study is known as Fake and Real news classification[70] and is here called Dataset-6 (DS-6). It contains 34,980 (35,208) fake (real) news articles. The authors of this dataset integrated four famous datasets (i.e., McIntire, Kaggle, BuzzFeed, Political, and Reuters).

Statistical details about the six datasets are given in Table 1. Furthermore, the data present in the aforementioned six datasets are combined into one large dataset which is called the whole dataset (WDataset). In each of the six datasets, the articles vary in nature. WDataset goal is to access and evaluate the classifiers

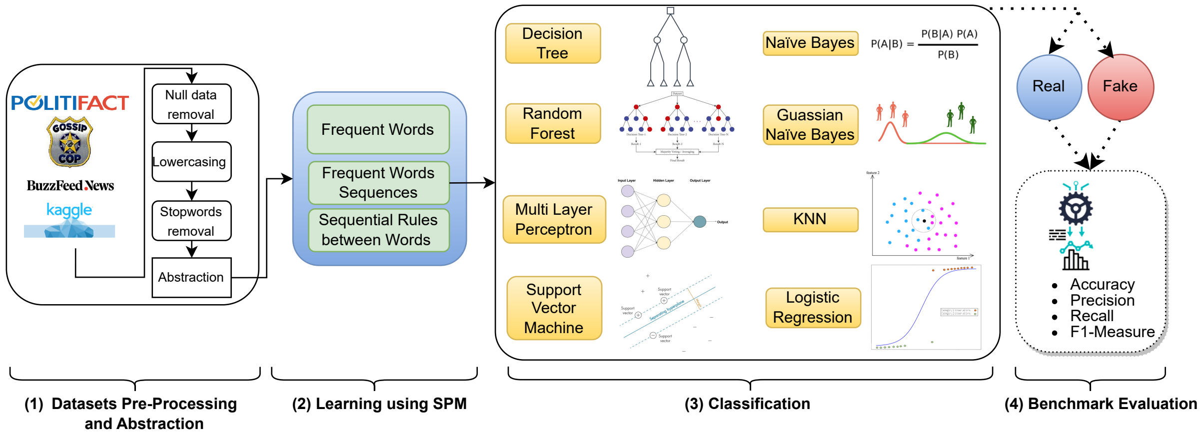


**Fig. 1** FNACSPM framework, for fake news analysis and classification, consists of four main steps: (1) Datasets pre-processing and abstraction, (2) Learning using SPM, (3) Classification via discovered frequent sequential patterns of words in the datasets by training various classifiers, and (4) Evaluation of the framework by performing extensive experiments.

on a whole dataset that includes news and information from a wide range of diverse domains.

**Table 1** Datasets statistics

| Dataset | Fake News | True News | Features | MiL | MaL | MeL |
|---|---|---|---|---|---|---|
| **DS-1** | 2,291 | 2,285 | T, B | 23 | 32,674 | 4,379.5 |
| **DS-2** | 5,335 | 16,819 | NURL, T, TID | 10 | 204 | 69.5 |
| **DS-3** | 474 | 798 | NURL, T, TID | 10 | 340 | 60.7 |
| **DS-4** | 91 | 91 | T, B, URL * | 62 | 32,641 | 3,257.3 |
| **DS-5** | 23,503 | 21,418 | T, B, Subject | 30 | 32,888 | 2553.49 |
| **DS-6** | 34,980 | 35,208 | T, B | 15 | 33,026 | 3,138.40 |

T: Title, B: Body, NURL: News URL, TID: Tweet ID, MiL: Minimum Length, MaL: Maximum Length, MeL: Mean Length, *: top_img, authors, source, publish_date, movies, images, canonical_link, meta_data

These datasets contain various attributes such as title, body, subject, video, and image. To prepare the data for analysis, we combined only text-based data (i.e., title and body) into a single attribute called "Text". For the datasets with only a title attribute, we simply used the title as the text. For the datasets with both title and body attributes, we concatenated the two attributes with a separator (e.g., a space or newline character) to form the text. For the datasets with additional attributes (such as subject, timestamps, video, and image links), we ignored them. This process of combining the attributes into a single "Text" attribute enabled us to easily feed the data into pattern mining tools for analysis and, consequently, our ML models for classification. It also helped to standardize the input format across all datasets and to make the modeling process less complex.

## 4 Methodology

The proposed FNACSPM framework (Figure 1) for the analysis and detection/classification of fake news consists of four main parts:

(1) *Datasets pre-processing and abstraction*: First step is to pre-process the datasets to put them into a suitable format for SPM. This is carried out by converting each sequence into a discrete sequence, where each distinct word is transformed into a distinct positive integer.

(2) *Learning via SPM*: Second step entails applying various algorithms for SPM on the abstracted datasets to find frequent words, their frequent patterns, and the sequential relationships among discovered frequent patterns.

(3) *Classification via frequent patterns*: Third step is to use frequent patterns, discovered in Step 2, for the classification/detection of fake news. Various classifiers are utilized, and their performance is evaluated with various evaluation measures.

(4) Evaluation: Comprehensive experiments are carried out to access FNACSPM's performance and compare it with recent approaches for fake news detection.

In the next subsections, the first three parts of FNACSPM are explained in greater detail.

### 4.1 Datasets Pre-processing and Abstraction

The first step is data pre-processing, where cleaning operations such as lemmatization and stemming, and eliminating special characters, punctuation, and stop words are performed to prepare the data for further analysis. After the pre-processing, the sequences of words in the datasets are represented in an appropriate format. Table 2 provides the statistical details of six datasets after pre-processing. After pre-processing, the datasets are reduced, approximately, as follows: DS-1 (29%), DS-2 (24%), DS-3 (23%), DS-4 (35%), DS-5 (32%), and DS-6 (31%). For example, DS-1 (29%) indicates that the size of DS-1 is reduced to 29% of its original size as a result of the cleaning operations performed in pre-processing.

**Table 2** Datasets statistics (after pre-processing)

| | MiL | MaL | MeL |
|---|---|---|---|
| **DS-1** | 17 | 21,875 | 3,144 |
| **DS-2** | 4 | 174 | 53.1 |
| **DS-3** | 10 | 279 | 47.1 |
| **DS-4** | 39 | 20,203 | 2,124.3 |
| **DS-5** | 22 | 3,279 | 1,759.5 |
| **DS-6** | 9 | 22,831 | 2,189.1 |

Let $W = \{w_1, w_2, ..., w_m\}$ represents the set of words in a dataset. A *Words set* $WS$ is a set of words such that $WS \subseteq W$. Set cardinality is represented by $|WS|$. A Words set $WS$ has a length of $n$ (known as *n-WS*) if it contains $n$ words, i.e., $|WS| = n$. For instance, take $W$ = {*trump, image, people, featured, via, even*}. Then, the set {*trump*, *people*, *via*, *even*} is a $WS$ containing four words. A total order relation on words is defined, indicated by the $\prec$, to aid in the identification of patterns. In the framework's implementation, this lexicographical order is employed as the processing order for pattern searching.

A sequence of words is basically a list of words set $S = \langle WS_1, WS_2, ..., WS_n \rangle$, such that $WS_i \subseteq WS$ ($1 \leq i \leq n$). A *Words corpus* dataset, $WCD = \langle S_1, S_2, ..., S_n \rangle$, is a list of words sequences. In $WCD$, a sequence is associated with an ID. Table 3 shows a $WCD$ containing four word sequences. According to the first sequence, the word *trump* is followed by *featured*, then *via*, and *show*.

**Table 3** A sample of $WCD$

| ID | Sequences |
|---|---|
| 1 | ⟨{*trump*},{*featured*},{*via*},{*show*}⟩ |
| 2 | ⟨{*image*},{*getty*}, {*image*},{*image*}, {*said*},{*president*}⟩ |
| 3 | ⟨{*one*},{*donald*},{*image*},{*said*},{*reuters*},{*release*},{*image*},{*american*}⟩ |
| 4 | ⟨{*republican*},{*american*},{*horror*},{*image*},{*one*},{*republican*},{*ring*},{*american*},{*getty*}⟩ |
| **Representation of words sequences as integer sequences** | |
| **ID** | **Sequences** |
| 1 | 1 -1 3 -1 4 -1 5 -1 -2 |
| 2 | 6 -1 12 -1 6 -1 6 -1 32 -1 23 -1 -2 |
| 3 | 7 -1 11 -1 6 -1 32 -1 15 -1 18 -1 6 -1 22 -1 -2 |
| 4 | 19 -1 22 -1 14 -1 6 -1 19 -1 22 -1 31 -1 22 -1 12 -1 -2 |

The word sequences are transformed into integer sequences. This is done to prepare the datasets in a format that SPM algorithms can process more easily. Each line in the final transformed datasets denotes a word sequence for a fake/real news. In sequences, a unique positive integer is used to replace each unique word type. For instance, the words *trump* and *featured* are changed to 1 and 3, respectively. A single space and the negative number -1 are used to separate the words in sequences from one another. News (sequence) ends when a negative number (-2) appears at the end of a line. Table 3 also provides the conversion of four word sequences into integer sequences.

### 4.2 Learning via SPM

$WCD$ is analyzed, in the second step, to discover frequent patterns. Suppose $S_a = \langle a_1, a_2, ..., a_n \rangle$ and $S_b = \langle b_1, b_2, ..., b_m \rangle$ are two sequences of words. $S_b$ contains $S_a$ ($S_a \sqsubseteq S_b$) iff there exist integer $1 \leq k_1 < k_2 < ... < k_n \leq m$, s.t. $a_1 \subseteq b_{k1}, a_2 \subseteq b_{k2}, ..., a_n \subseteq b_{km}$. $S_a$ is considered to be $S_b$'s *subsequence* if $S_b$ contains $S_a$. The importance and interestingness of a subsequence in SPM can be found via various measures, in which the *support* measure is mostly used. In a $WCD$, the support of $S_a$ is the total number of sequences ($S$) that contain $S_a$, which is denoted by the symbol $sup(S_a)$:

$$sup(S_a) = |\{S | S_a \sqsubseteq S \wedge S \in WCD\}| \quad (1)$$

In a sequential dataset, such as $WCD$, SPM deals with the enumeration problem to find all the *frequent subsequences*. If support of a sequence $S$ is equal to or greater than a user-provided threshold of minimum support ($sup(S) \geq minsup$), then $S$ is said to be a *frequent sequences*. Sequences can have upto $2^n - 1$ distinct subsequences, where $n$ represents the total number of items. For most datasets, finding the support of all potential subsequences using the naive method is not possible[71]. However, over the past two decades, various effective algorithms have been developed that can discover all sequential patterns without having to search through all the potential subsequences.

SPM algorithms use the *s-extensions* and *i-extensions* operations to move through the search space of sequential patterns. For an item $y$, $S_b$ is an *s-extension* of $S_x$, if $S_b = \langle x_1, x_2, ..., x_n, \{y\} \rangle$. On the other hand, $S_c$ is an *i-extension* of $S_x$ if $S_c = \langle x_1, x_2, ..., x_n \cup \{y\} \rangle$. In general, SPM algorithms use a depth-first or breadth-first search with various optimizations and data structures.

Frequent itemset mining (FIM), a special case of SPM, deals with analyzing records where the sequential ordering among items is not considered. The first and best-known FIM method, called Apriori[72], can discover frequent itemsets (like word sets) in large databases. Apriori first discovers items (e.g. words) in databases that occur frequently. Then, discovered items are expanded to discover larger itemsets that often appear adequately. Besides finding itemsets, Apriori can also finds relationships (association rules) among items. Multiple memory efficient and fast algorithms can be used for FIM, which find the same patterns. These new algorithms use different types of data structures, optimization techniques, and search strategies.

One SPM algorithm used in this work is TKS (Top-k Sequential)[73], which can find the top-*k* most common sequential patterns in a database (or dataset), where a user sets the parameter $k$. TKS finds the desired $k$ patterns by applying the SPAM's candidate generation procedure and a vertical database representation (VDR). The VRD facilitates the counting of patterns without expensive database scans. Thus, SPM algorithms based on VDR generally work more effectively on dense or long sequences. Other strategies for search space reduction are also used in TKS, along with the data structure of the Precedence Map (PMAP). These methods allow TKS to lower the number of costly operations like bit vector intersections. Another SPM algorithm used in this work is CM-SPAM[74]. It scans the search space of a dataset or database to find frequent sequential patterns. CM-SPAM uses the data structure of Co-occurrence MAP (CMAP) that stores items co-occurrence information. CM-SPAM uses a generic mechanism to prune the search space via the VDR. The reader may refer to two studies[73,74] for more details about the two aforementioned algorithms for SPM.

The aforementioned algorithms have the main drawback that they may discover too many sequential patterns, most of which are not interesting or important for users. Sequential patterns appearing frequently in a database with low confidence are of no value in tasks of prediction or decision-making. Due to this, there is another pattern type known as sequential rules. A pattern as a sequential rule considers both the confidence (conditional probability) that some events (words in this work) will follow or be followed by others in addition to the support of events. A sequential rule $X \rightarrow Y$ in this work represents a relationship between two $WS$s $X, Y \subseteq W$ s.t. $X, Y \neq \emptyset$ and $X \cap Y = \emptyset$. According to the rule $r : X \rightarrow Y$, if words from $X$ appear in a series, then words from $Y$ will follow in the same sequence. $S_x$ contains $X$ iff $X \subseteq \bigcup_{i=1}^{n} x_i$. Similarly, $S_x$ contains the rule $r$ if an integer $k$ exists s.t $1 \leq k < n$, $X \subseteq \bigcup_{i=1}^{k} x_i$ and $Y \subseteq \cup_{i=k+1}^{n} x_i$. In a dataset ($WCD$), the confidence of a rule $r$ is:

$$conf_{WCD}(r) = \frac{|\{S|r \sqsubseteq S \wedge S \in WCD\}|}{|\{S|X \sqsubseteq S \wedge S \in WCD\}|} \quad (2)$$

Similarly, in $WCD$, the support of a rule $r$ is:

$$sup_{WCD}(r) = \frac{|\{S|r \sqsubseteq S \wedge S \in WCD\}|}{|WCD|} \quad (3)$$

For a $WCD$ and a user-specified minimum support threshold ($minsup$), a rule $r$ is considered a *frequent sequential rule* iff $sup_{WCD}(r) \geq minsup$. Similarly, for a user-specified minimum confidence threshold ($minconf$), a rule $r$ is considered a *valid sequential rule* if (1) it is frequent and (2) $conf_{WCD}(r) \geq minconf$. Enumerating all the valid sequential rules in a dataset is the goal of sequential rule mining. In this work, the ERMiner algorithm[75] is used to discover frequent sequential rules in fake news datasets. A VDR is employed by ERMiner. The rules search space is investigated by the use of equivalency classes of rules with identical antecedent and consequent. Moreover, the search space of sequential rules is investigated by using two procedures (called left and right merges). ERMiner is more effective than earlier algorithms for mining sequential rules because it uses the Sparse Count Matrix (SCM) approach for search space pruning. In summary, SPM algorithms are different from each other on the basis of (1) the use of a depth-first or breadth-first search, (2) the use of a VDR or horizontal representations and of particular data structures, and (3) how the support measure is calculated to find those frequent patterns that satisfy *minsup* constraint.

### 4.3 Classification

The third step of the framework involves the fake news classification using the sequential frequent patterns discovered with SPM. The lengths of news articles are generally long, for example, see Tables 1 and 2. A close inspection of the $WCD$ reveals that the majority of the sequences (both real and fake) contain the same words repeated multiple times. This word repetition in online news can be avoided during the classification process by treating contiguous identical words as a single word.

More precisely, FNACSPM uses the sequential frequent patterns, found with the SPM algorithms, to classify fake and real news in datasets. For classification, two methods (binary and multi-class (MC)) are employed. Two types of binary classification are considered for training a classifier so that it classifies each fake or real news.

**Type 1**: Each dataset is considered separately in the first type. For a separate dataset, binary classification assigns "fake" or "real" labels to each sequence (news) corresponding to that class.

**Type 2:** In this type, all datasets are combined together to create one dataset, that is used in training a model for the classification of news (sequence) type. This classification type labels "1" to sequence(s) that originally belonged to that dataset type and labels "Others" (or 0) to all other sequences.

**Definition 1** Assume that $NT$ denotes the set of all news types (classes). A sequence $S$ is labeled with regard to $c$ for a chosen class $c \in NT$:

$$S_c = \begin{cases} 1, & \text{if } s \in c, \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

The news class labels, according to Equation 1, are labeled to 1 for those that belong to $c$, while others are labeled as 0 (or "Others"). A simple example is provided to illustrate this process. For instance, if the news type of interest in DS-1 is *Fake*, then Equation 1 assigns 1 to all the DS-1 sequences belonging to the *Fake* type and 0 to all other sequences in DS-1 and other sequences in the whole dataset.

A second way to train and test classifiers for fake news classification/detection is to use MC classification. In the context of this work, each sequence in the whole dataset (DS-7 or WDS), which combines all six datasets, is labeled with its respective class name. There are 12 classes in total (as shown in Table 4). In MC classification, a classifier is trained to correctly label sequences according to those classes.

For classification, seven standard ML algorithms and one DL algorithm are used, which are: (1) BNB (Bernoulli Naive Bayes), (2) GNB (Gaussian Naive Bayes), (3) DT (Decision Tree), (4) RF (Random Forest), (5) SVM (Support Vector Machine), (6) kNN (k-Nearest Neighbors), (7) LR (Logistic Regression) and (8) MLP (Multilayer Perceptron). We chose these eight classifiers for this work because most previous studies on fake news analysis and detection also used them.

**Table 4** MC labeling of sequences from the whole dataset

| Dataset | Class | MC Class |
|---|---|---|
| DS-1 | Fake | DS1-F |
| | Real | DS1-R |
| DS-2 | Fake | DS2-F |
| | Real | DS2-R |
| DS-3 | Fake | DS3-F |
| | Real | DS3-R |
| DS-4 | Fake | DS4-F |
| | Real | DS4-R |
| DS-5 | Fake | DS5-F |
| | Real | DS5-R |
| DS-6 | Fake | DS6-F |
| | Real | DS6-R |

The performance of classifiers is assessed using the following seven metrics: accuracy, precision, F1 score, recall, MCC (Matthews correlation coefficient), AUC (Area Under the Receiver Operating Characteristic Curve) and AUPRC (Area Under the Precision-Recall Curve). The seven measures are defined as follows:

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

$$Precision(P) = \frac{TP}{TP + FP} \tag{6}$$

$$Recall(R) = \frac{TP}{TP + FN} \tag{7}$$

$$F1 = 2 \times \frac{P \times R}{P + R} \tag{8}$$

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{9}$$

$$\text{AUC} = \int_0^1 \text{TPR}(d\text{FPR}) \tag{10}$$

$$AUPRC = \sum_{i=1}^{n} \frac{(R_i - R_{i-1}) \times (P_i + P_{i-1})}{2} \tag{11}$$

*TP* = true positive, *TN* = true negative, *FP* = false positive and *FN* = false negative. In equation 10, *TPR* represents the recall (*R*) and *dFPR* is the derivative of the false positive rate (*FPR*), that is equal to $\frac{FP}{FP+TN}$. $P_i$ and $R_i$ in equation 11 represent the values for precision and recall, respectively, at the $i$-th decision threshold.

## 5 Results

A computer equipped with 16 GB RAM and an 11th-generation Core i5 processor was utilized for carrying out experiments. A JAVA-based open-source library, called SPMF[76], was used to examine and find patterns in the datasets. Implementations of over 250 data and pattern mining algorithms are available in this library. For classification purposes, Python is used, where a variety of libraries are utilized, including scikit-learn[77] for ML algorithms, NumPy for numerical computations, and Pandas for data manipulation. In the text pre-processing phase, the TF-IDF was used, utilizing the "TfidfVectorizer" module from the scikit-learn library. To ensure reliable model evaluation, the dataset(s) is split into training and testing sets (80% training and 20% testing) by using the *train_test_split* function from the scikit-learn. This function facilitated the random partitioning of the data, allocating a specified proportion for training the models and the remaining portion for evaluating their performance. Next, we discuss the obtained results by using the SPM algorithms on the abstracted datasets.

(a) Fake

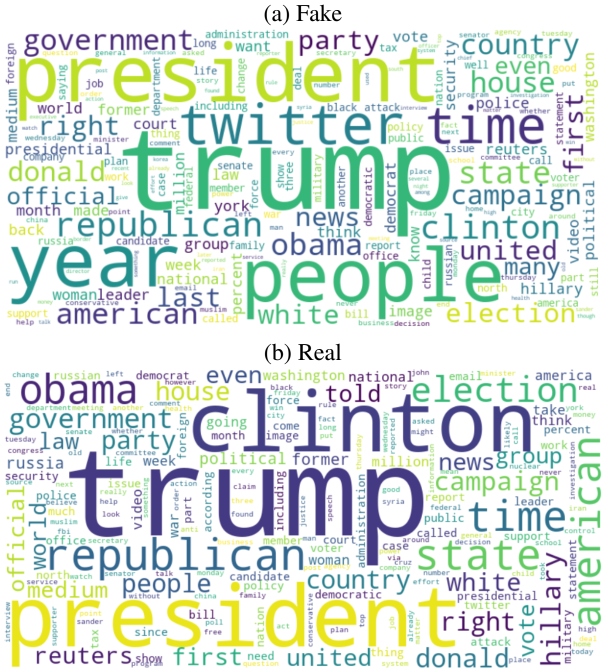


**Fig. 2** Frequent words discovered in the whole dataset

### 5.1 Discovered Patterns and Rules

The Apriori is first applied to the transformed datasets to find frequent words. Both fake and real news contain many similar words (Figure 2). We found that in the first 3,000 frequent words discovered by Apriori in fake and real news, approximately 93% are similar to each other. However, frequent sets of words are unordered. Besides, Apriori does not guarantee that words from a word set ($WS$) occur in a sequence consecutively. As a result, Apriori's long patterns are not interesting or important and offer no helpful information. Apriori is unable to identify sequential patterns because it ignores the relationships between words in order. Next, we present the outcomes for SPM algorithms that improve upon Apriori.

More important and meaningful patterns can be discovered in data using SPM algorithms like TKS, CM-SPAM, and ERMiner. The top-k sequential patterns of words in the datasets are discovered using the TKS algorithm. CM-SPAM algorithm needs the $minsup$ threshold to be set, unlike TKS. Table 5 lists some frequent sequential patterns of words that are found in six datasets with TKS and CM-SPAM. From discovered patterns, one can find useful and interesting details about the frequent occurrences of words in fake and real news. The bold patterns represent fake ones while others represent real ones. We find that some fake and real patterns are similar to each other and there is some difference among the patterns found in the six datasets. Overall, it was observed that using pattern mining on news was quite fast. However, for datasets that contain long news sequences, we need to fine-tune some parameters of both algorithms to find frequent sequential patterns.

Table 6 shows the relationships between frequent words that are identified in each dataset via the ERMiner algorithm. It was observed that different dataset requires different parameter settings (*minsup* and *minconf*) before they start giving sequential rules. For example, for DS-1, *minconf* = 15%. This indicates that rules should therefore have a minimum of 15% confidence. The third rule in DS-1 indicates that the word *campaign* is followed by the word *clinton*. Similarly, the last rule indicates that the words *new* and *people* are followed by *hillary* and *state* respectively. ERMiner offered some useful dependencies and relationships that are present among frequent words. On six datasets, the three SPM algorithms performed effectively. The obtained results showed a clear association between the total number of words in news sequences and the effectiveness of algorithms for sequential patterns.

**Table 5** Frequent sequential patterns in six datasets

| | **DS-1** | **DS-2** | **DS-3** |
|---|---|---|---|
| TKS | new york | **image via image** | tax |
| | cruz kasich | **would featured via** | obama |
| | **trump vote** | cut tie jazz jennings | debate |
| | **america news** | khloe kardashian baby | **breaking** |
| | trump delegate | **trump one getty image** | transcript |
| | general election | selena gomez justin bieber | **michelle obama** |
| | **fbi investigation** | **getty donald trump president** | **president trump** |
| | **onion finest news source** | shannon open relationship beador | **news latest video** |
| | **DS-4** | **DS-5** | **DS-6** |
| | **get life** | reuters said said | **york new one** |
| | **like one** | said republican said | state said would |
| | **people one** | york state house said | **trump said make** |
| | new get time one | **donald twitter image** | president year said |
| | donald trump said | washington reuters said | president new said |
| | hillary clinton said | **donald trump one said** | **state hillary clinton** |
| | trump continued trump | **president donald trump image** | donald trump image |
| | **story campaign donald trump** | **twitter one trump featured image** | **american people trump** |
| | **DS-1** | **DS-2** | **DS-3** |
| CM-SPAM | **fbi email** | tv scoop award | tax |
| | clinton win | **kim kanye west** | obama |
| | donald trump | **brad angelina jolie** | debate |
| | hiliray clinton | **kim kardashian west** | **breaking** |
| | **onion america** | **prince harry meghan** | transcript |
| | general election | blake shelton stefani | **michelle obama** |
| | **trump woman problem** | linkin park bennington | **president trump** |
| | **america finest news source** | jennifer aniston justin theroux | **news latest video** |
| | **DS-4** | **DS-5** | **DS-6** |
| | **get life** | **trump said trump** | state said one |
| | **like one** | **donald twitter image** | **one would said** |
| | **people one** | said republican would | donald trump year |
| | hillary clinton said | washington u said house | featured image said |
| | donald trump story | president washington said | news president said |
| | also one trump donald | **president donald trump like** | **american make trump** |
| | **like one hillary clinton** | **donald trump image feature** | reuters said washington |
| | trump continued trump | **trump one trump featured image** | **republican hillary clinton** |

**Table 6** Extracted sequential rules by using the ERMiner algorithm

| **DS-1** | **DS-2** | **DS-3** |
|---|---|---|
| donald→republican | **brad → pitt** | week → transcript |
| state → hillary, clinton | **miley, cyrus → liam** | news, latest → video |
| **campaign → clinton** | kim → kardashian | office → news, breaking |
| **state → time, year** | selena, gomez → justin, bieber | **donald → paid** |
| party, campaign → president, said, state | **beyonce → jay, z** | senate, call, vote → congress |
| trump, donald → said, clinton, hillary, campaign | wedding, prince, harry → meghan, markle | **trump, executive → order** |
| **clinton, state → people** | **jennifer, leaving → biggest, mistake** | **queen → say, elizabeth** |
| **new, people → hillary, state** | brad, pitt → angelina, jolie | **kim, jong → trump, north** |
| **DS-4** | **DS-5** | **DS-6** |
| **new → president** | reuters → president | **X** |
| **get, life → people** | washington → persident, trump | video → trump |
| **thing, get → short, life** | official, house → state, year | **X** |
| hillary → trump | **featured → image** | president, donald → trump |
| hillary, clinton → donald, trump | government, last, president → new, republican | donald → image, trump |
| hillary → said, clinton, trump | **trump → people, president** | **X** |
| donald, continued → trump | **obama, president → time, image** | trump → image, featured |
| **thing, know → get, trial** | **twitter, pic, country → white, house** | **X** |

### 5.2 Results for Classification

The experimental results for both binary and MC classification on six datasets are presented in this section. The eight classifiers were used for two cases:

**Case 1**: All the words, after prepossessing, in news sequences are used in the classification process.

**Case 2**: The frequent sequential patterns, found with two SPM algorithms are used in the classification process.

TKS and CM-SPAM algorithms are used in Case 2 to find frequent 100, 200, 400, and 600 patterns of words in each dataset. Four different numbers of patterns were considered to investigate whether or not the number of patterns affects how well classification models perform. After discovery, the frequent patterns are further pre-processed to ensure that in each pattern there are at least 3 distinct frequent words. For the classification in both cases, the default hyperparameters for algorithms were as follows: BNB with an alpha value of 1.0, GNB with no significant hyperparameters to tune, DT with a criterion of 'gini', a splitter of 'best', no maximum depth limit, a minimum samples split, and leaf of 2 and 1 respectively. RF with 100 estimators, 'gini' criterion, no maximum depth limit, minimum samples split of 2, and minimum samples leaf of 1, MLP with a hidden layer size of 600, 'tanh' activation function, 'adam' solver, an alpha value of 0.0001, *invscaling* learning rate, and learning rate initialization of 0.001. SVM with a C value of 1.0, an 'rbf' kernel, a degree of 3, and a 'scale' gamma value. kNN with 2 neighbors, 'uniform' weight scheme, 'auto' algorithm, leaf size of 30, Euclidean distance metric (p=2) and LR with a C value of 1.0, 'lbfgs' solver, and a maximum iteration limit of 100.

**Table 7** Classifiers accuracy for binary classification (Case 1).

| Dataset | BNB | GNB | DT | RF | MLP | SVM | kNN | LR |
|---|---|---|---|---|---|---|---|---|
| DS-1 | 0.84 | 0.81 | 0.82 | 0.90 | 0.93 | **0.93** | 0.84 | 0.92 |
| | 9.5 | 17.8 | 55.8 | 28.8 | 3402.4 | 2845.6 | 3.5 | 8.4 |
| DS-2 | 0.84 | 0.65 | 0.80 | 0.84 | 0.77 | – | 0.81 | **0.85** |
| | 17.4 | 23.4 | 1677.8 | 943.4 | 6390.5 | – | 26.7 | 10.9 |
| DS-3 | 0.75 | 0.75 | 0.76 | 0.75 | 0.79 | 0.81 | **0.86** | 0.81 |
| | 0.1 | 0.1 | 0.9 | 1.8 | 34.9 | 4.9 | 0.3 | 0.07 |
| DS-4 | 0.62 | 0.59 | 0.76 | **0.80** | 0.65 | 0.70 | 0.73 | 0.69 |
| | 0.2 | 0.1 | 0.5 | 0.7 | 27.7 | 0.7 | 0.4 | 0.08 |
| DS-5 | 0.85 | 0.90 | **0.99** | **0.99** | – | – | 0.66 | 0.98 |
| | 28.2 | 58.1 | 60.6 | 72.6 | – | – | 8.6 | 19.4 |
| DS-6 | 0.84 | 0.75 | 0.91 | 0.90 | 0.92 | – | 0.86 | **0.91** |
| | 62.9 | 329.2 | 329.2 | 118.3 | 3749.1 | – | 15.1 | 30.7 |
| WDS | 0.58 | 0.57 | 0.57 | 0.61 | – | – | 0.62 | **0.65** |
| | 83.6 | 167.7 | 217.7 | 212.5 | – | – | 12.9 | 43.1 |
| Ave. | 0.76 | 0.71 | 0.80 | 0.82 | – | – | 0.76 | **0.83** |
| | 28.8 | 85.2 | 334.6 | 196.8 | – | – | **9.64** | 16.1 |

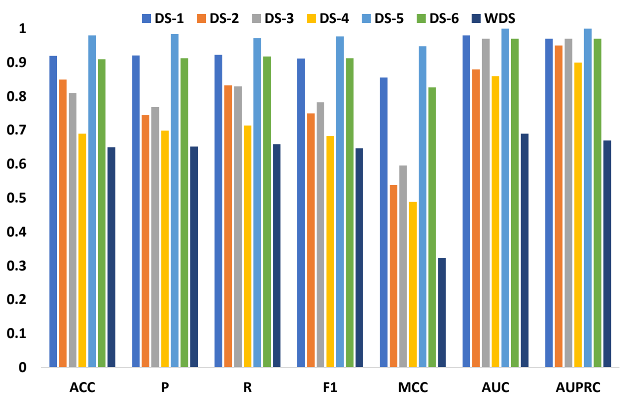


**Fig. 3** Binary classification results for LR (Case 1)

### 5.2.1 Binary Classification Results

Table 7 provides the results of binary classification for Case 1 (all words are used for classification). The format $\frac{Acc}{Time(Sec.)}$ is used for classifiers. For example, the entry $\frac{0.84}{9.5}$ represents that BNB achieved an accuracy of 84% on DS-1 and took 9.5 seconds to terminate. For Case 1, 10,000 random and fake news articles were used in DS-5 and DS-6 in the classification. For the whole dataset (WDS), proportionate sampling was used to deal with data imbalance. It involves selecting a subset of data from each dataset in a way that maintains the original class distribution. This helps to ensure that each class is represented proportionally in the 10,000 randomly selected articles. LR achieved the highest accuracy of 83% on average, on all datasets. On DS-5, DT and RF achieved the highest accuracy of 99%, followed by LR (98%). The ranking of classifiers based on average accuracy is in the order LR > RF > DT > kNN > BNB > GNB. SVM and MLP are not included in the ranking as they were unable to produce results within 5 hours on various datasets.

kNN performed best in terms of computational time, followed by LR. The ranking of classifiers based on time is kNN > LR > BNB > GNB > RF > DT. RF and LR performed better overall but RF was slow compared to LR. The accuracy of classifiers, except RF, was low on DS-4 compared to the other five datasets. This is because DS-4 contained few fake and real news. For the whole dataset, the results for all the classifiers decreased significantly. In Case 1, interestingly we find that classifiers achieved the highest accuracy, except kNN, on the Fake News Classification dataset (DS-5). In previous studies[10–14, 35–38, 41, 42, 44, 60, 63] that used multiple datasets, classifiers performed better on the PolitoFact dataset (DS-3). Figure 3 shows the overall results for LR, which performed best for Case 1.

Classifiers in Case 2 performed significantly better than classifiers in Case 1 (Table 8). Overall for varying pattern lengths, it is observed that classifiers achieved better results on patterns found with TKS as compared to CM-SPAM. Moreover, classification models achieved the highest accuracy with 400 patterns, followed by 600, 200, and 100 respectively. The ranking of classifiers based on accuracy on patterns found by using TKS (CM-SPAM) is in the order LR (LR) ≈(>) SVM (MLP) >(>) MLP (BNB) >(>) RF (SVM) >(>) DT (kNN) >(>) BNB (RF) >(>) kNN (DT) >(>) GNB (GNB). Table 9 lists the overall

**Table 8** Classifiers accuracy for binary classification on frequent sequential patterns discovered by TKS (CM-SPAM)

| Name | FP | BNB | GNB | DT | RF | MLP | SVM | kNN | LR |
|---|---|---|---|---|---|---|---|---|---|
| DS-1 | 100 | 0.78(0.80) | 0.80(0.88) | **0.90**(0.88) | 0.80(0.85) | 0.85(0.82) | 0.88(0.82) | 0.80(0.80) | 0.88(0.80) |
| | | 0.2(0.2) | 0.01(0.01) | 0.07(0.07) | 0.3(0.2) | 0.7(0.7) | 0.02(0.02) | 0.2(0.4) | 0.02(0.02) |
| | 200 | 0.85(0.82) | 0.82(0.81) | **0.96**(0.85) | 0.85(0.75) | 0.89(0.81) | 0.90(0.82) | 0.85(0.81) | 0.91(0.85) |
| | | 0.2(0.3) | 0.01(0.01) | 0.07(0.07) | 0.4(0.3) | 2.2(2.6) | 0.05(0.06) | 0.2(0.3) | 0.01(0.01) |
| | 400 | 0.89(0.86) | 0.90(0.92) | 0.89(0.84) | 0.89(0.85) | 0.92(0.91) | **0.94**(0.88) | 0.82(0.78) | 0.94(0.88) |
| | | 0.4(0.2) | 0.02(0.01) | 0.09(0.08) | 0.5(0.4) | 4.4(4.03) | 0.2(0.1) | 0.3(0.2) | 0.03(0.02) |
| | 600 | 0.95(0.92) | **0.96**(0.92) | 0.88(0.86) | 0.93(0.92) | 0.93(0.95) | 0.94(0.93) | 0.85(0.84) | 0.95(0.94) |
| | | 0.2(0.3) | 0.02(0.03) | 0.08(0.09) | 0.6(0.5) | 5.9(9.1) | 0.2(0.8) | 0.2(0.2) | 0.02(0.03) |
| DS-2 | 100 | **1**(0.80) | **1**(0.80) | 0.95(0.68) | **1**(0.72) | **1**(0.70) | **1**(0.68) | **1**(0.65) | **1**(0.70) |
| | | 0.3(0.2) | 0.01(0.01) | 0.07(0.08) | 0.2(0.3) | 0.7(0.8) | 0.01(0.02) | 0.3(0.2) | 0.01(0.02) |
| | 200 | 0.94(0.90) | 0.94(0.89) | **1**(0.88) | **1**(0.88) | 0.94(0.90) | **1**(0.94) | **1**(0.78) | **1**(0.94) |
| | | 0.2(0.3) | 0.01(0.02) | 0.07(0.08) | 0.2(0.3) | 0.7(2.7) | 0.02(0.05) | 0.2(0.3) | 0.01(0.02) |
| | 400 | 0.99(0.94) | 0.99(0.94) | **1**(0.91) | **1**(0.92) | 0.99(0.94) | **1**(0.94) | **1**(0.92) | **1**(0.94) |
| | | 0.2(0.3) | 0.01(0.02) | 0.07(0.08) | 0.3(0.4) | 1.8(4.1) | 0.08(0.3) | 0.3(0.2) | 0.02(0.02) |
| | 600 | 0.99(0.95) | 0.99(0.96) | **1**(0.93) | **1**(0.95) | 0.99(0.95) | **1**(0.97) | **1**(0.91) | **1**(0.96) |
| | | 0.2(0.3) | 0.01(0.02) | 0.07(0.08) | 0.3(0.4) | 1.8(4.7) | 0.1(0.5) | 0.4(0.3) | 0.04(0.03) |
| DS-3 | 100 | **1**(0.89) | 0.48(0.55) | **1**(0.82) | **1**(0.91) | **1**(0.91) | **1**(0.86) | **1**(0.89) | **1**(0.89) |
| | | 0.2(0.3) | 0.01(0.01) | 0.07(0.07) | 0.4(0.3) | 0.8(0.9) | 0.01(0.02) | 0.3(0.2) | 0.01(0.02) |
| | 200 | **1**(0.92) | 0.68(0.54) | **1**(0.56) | **1**(0.57) | **1**(0.91) | **1**(0.92) | **1**(0.92) | **1**(0.92) |
| | | 0.2(0.3) | 0.01(0.02) | 0.09(0.08) | 0.3(0.4) | 0.8(3.3) | 0.02(0.05) | 0.2(0.4) | 0.01(0.02) |
| | 400 | **0.98**(0.84) | 0.69(0.61) | **0.98**(0.57) | **0.98**(0.56) | **0.98**(0.83) | **0.98**(0.62) | 0.96(0.82) | **0.98**(0.84) |
| | | 0.2(0.3) | 0.01(0.02) | 0.07(0.1) | 0.3(0.7) | 1.5(12.5) | 0.06(0.3) | 0.2(0.3) | 0.02(0.03) |
| | 600 | 0.98(0.80) | 0.76(0.52) | 0.96(0.50) | 0.98(0.51) | 0.98(0.78) | **0.99**(0.79) | 0.90(0.79) | 0.97(0.81) |
| | | 0.2(0.3) | 0.01(0.04) | 0.07(0.3) | 0.3(1.1) | 1.7(21.5) | 0.1(1.1) | 0.3(0.2) | 0.02(0.04) |
| DS-4 | 100 | **0.98**(0.92) | **0.98**(0.95) | 0.95(0.95) | 0.95(0.95) | 0.95(0.95) | 0.95(0.95) | 0.92(0.95) | 0.95(0.95) |
| | | 0.2(0.2) | 0.01(0.01) | 0.07(0.06) | 0.2(0.2) | 0.8(0.7) | 0.02(0.01) | 0.3(0.2) | 0.01(0.02) |
| | 200 | 0.96(**0.98**) | 0.94(0.91) | 0.94(0.96) | 0.95(0.96) | 0.96(0.96) | 0.96(90.6) | 0.94(0.96) | 0.96(0.96) |
| | | 0.3(0.2) | 0.01(0.02) | 0.09(0.07) | 0.3(0.4) | 1.6(1.9) | 0.03(0.02) | 0.4(0.2) | 0.02(0.01) |
| | 400 | **0.98**(0.97) | 0.96(0.93) | 0.96(0.96) | **0.98**(0.96) | **0.98**(**0.98**) | **0.98**(**0.98**) | 0.96(0.95) | **0.98**(**0.98**) |
| | | 0.3(0.2) | 0.02(0.01) | 0.2(0.07) | 0.4(0.3) | 2.5(2.6) | 0.2(0.04) | 0.3(0.2) | 0.03(0.02) |
| | 600 | **0.96**(**0.96**) | 0.95(0.93) | 0.95(0.93) | **0.96**(0.95) | 0.95(**0.96**) | 0.95(0.95) | 0.95(0.94) | 0.95(**0.96**) |
| | | 0.2(0.3) | 0.01(0.02) | 0.08(0.07) | 0.4(0.3) | 3.2(2.8) | 0.2(0.07) | 0.2(0.3) | 0.02(0.03) |
| DS-5 | 100 | 0.92(**0.95**) | 0.82(0.90) | 0.88(**0.95**) | 0.89(**0.95**) | 0.90(**0.95**) | 0.90(**0.95**) | 0.85(**0.95**) | 0.90(**0.95**) |
| | | 0.1(0.2) | 0.02(0.01) | 0.1(0.07) | 0.4(0.3) | 1.2(0.6) | 0.03(0.01) | 0.3(0.2) | 0.03(0.01) |
| | 200 | 0.88(**0.98**) | 0.81(0.91) | 0.90(0.96) | 0.91(0.96) | 0.84(0.96) | 0.89(0.96) | 0.88(0.96) | 0.79(0.96) |
| | | 0.1(0.2) | 0.02(0.01) | 0.09(0.06) | 0.4(0.2) | 1.2(1.1) | 0.07(0.02) | 0.3(0.2) | 0.02(0.01) |
| | 400 | 0.88(0.92) | 0.77(0.62) | 0.87(0.91) | 0.88(0.91) | 0.88(**0.95**) | 0.87(0.94) | 0.88(0.93) | 0.89(**0.95**) |
| | | 0.3(0.2) | 0.03(0.01) | 0.09(0.07) | 0.4(0.3) | 2.4(1.6) | 0.1(0.2) | 0.2(0.3) | 0.02(0.02) |
| | 600 | 0.87(0.92) | 0.71(0.67) | 0.86(0.91) | 0.89(0.90) | 0.90(0.94) | 0.92(**0.95**) | 0.89(0.93) | 0.92(0.94) |
| | | 0.2(0.3) | 0.02(0.01) | 0.1(0.09) | 0.5(0.6) | 2.5(2.4) | 0.2(0.1) | 0.2(0.2) | 0.03(0.02) |
| DS-6 | 100 | 0.90(**0.98**) | 0.57(0.62) | 0.90(0.88) | 0.88(0.95) | 0.95(**0.98**) | 0.92(0.95) | 0.90(0.90) | 0.95(**0.98**) |
| | | 0.3(0.2) | 0.01(0.009) | 0.07(0.07) | 0.2(0.3) | 0.7(0.5) | 0.02(0.01) | 0.2(0.3) | 0.01(0.02) |
| | 200 | **0.96**(0.91) | 0.71(0.68) | **0.96**(0.85) | **0.96**(0.84) | 0.91(0.89) | 0.91(0.85) | 0.92(0.82) | 0.92(0.88) |
| | | 0.3(0.2) | 0.01(0.01) | 0.08(0.07) | 0.4(0.3) | 1.5(1.8) | 0.02(0.03) | 0.3(0.2) | 0.03(0.02) |
| | 400 | **0.91**(0.88) | 0.67(0.71) | 0.89(0.84) | 0.89(0.85) | **0.91**(0.86) | 0.89(0.86) | 0.88(0.83) | 0.90(0.86) |
| | | 0.2(0.3) | 0.02(0.01) | 0.07(0.08) | 0.4(0.3) | 2.8(4.1) | 0.08(0.09) | 0.2(0.5) | 0.02(0.02) |
| | 600 | 0.90(**0.91**) | 0.75(0.76) | 0.88(0.86) | 0.88(0.87) | 0.90(0.89) | 0.89(0.90) | 0.87(0.87) | 0.89(0.90) |
| | | 0.3(0.2) | 0.02(0.01) | 0.08(0.07) | 0.5(0.4) | 5.01(5.6) | 0.2(0.2) | 0.3(0.2) | 0.03(0.02) |
| WDS | 100 | 0.78(0.82) | 0.72(0.75) | 0.76(0.82) | 0.78(**0.83**) | **0.83**(0.82) | 0.77(**0.83**) | 0.70(0.78) | **0.83**(0.82) |
| | | 0.7(0.7) | 0.03(0.03) | 0.1(0.1) | 0.7(0.7) | 11.3(11.1) | 1.4(0.8) | 0.2(0.2) | 0.03(0.06) |
| | 200 | 0.72(0.85) | 0.66(0.71) | 0.76(0.76) | 0.77(0.78) | 0.78(**0.88**) | 0.78(**0.88**) | 0.65(0.80) | 0.79(0.87) |
| | | 0.9(0.7) | 0.07(0.08) | 0.2(0.2) | 1.5(1.3) | 23.8(17.1) | 3.2(2.9) | 0.2(0.2) | 0.08(0.09) |
| | 400 | 0.85(0.84) | 0.81(0.75) | 0.87(0.80) | 0.89(0.82) | **0.91**(0.86) | 0.90(0.86) | 0.80(0.79) | 0.88(0.86) |
| | | 0.8(0.7) | 0.2(0.2) | 0.9(0.7) | 3.4(3.6) | 59.8(30.5) | 13.5(14.8) | 0.2(0.2) | 0.2(0.2) |
| | 600 | 0.79(0.87) | 0.64(0.75) | 0.80(0.87) | 0.83(0.84) | 0.84(0.87) | 0.86(**0.89**) | 0.70(0.81) | 0.84(0.88) |
| | | 1.5(1.6) | 0.5(0.8) | 2.3(2.8) | 8.3(8.1) | 78.6(71.8) | 55.2(52.6) | 0.3(0.3) | 0.5(0.6) |
| Ave. | 100 | 0.891(88) | 0.767(0.778) | 0.905(0.854) | 0.90(0.879) | 0.925(0.875) | 0.916(0.862) | 0.88(0.845) | **0.929**(0.869) |
| | | 0.28(0.24) | 0.015(0.017) | 0.086(0.088) | 0.39(0.43) | 3.1(4.8) | 0.26(0.2) | 0.2(0.2) | 0.01(0.02) |
| | 200 | 0.90(0.90) | 0.79(0.77) | **0.931**(0.831) | 0.92(0.817) | 0.911(0.901) | 0.919(0.904) | 0.89(0.864) | 0.91(0.911) |
| | | 0.31(0.3) | 0.02(0.03) | 0.09(0.08) | 0.5(0.4) | 4.5(4.3) | 0.04(0.04) | 0.2(0.2) | 0.02(0.02) |
| | 400 | 0.925(0.892) | 0.827(0.782) | 0.922(0.832) | 0.929(0.838) | **0.938**(0.903) | 0.936(0.873) | 0.899(0.859) | **0.938**(0.901) |
| | | 0.3(0.3) | 0.04(0.04) | 0.09(0.08) | 0.4(0.5) | 10.6(8.4) | 2.03(2.2) | 0.2(0.3) | 0.03(0.02) |
| | 600 | 0.919(0.904) | 0.822(0.786) | 0.903(0.836) | 0.924(0.848) | 0.925(0.905) | **0.935**(0.911) | 0.88(0.87) | 0.928(0.912) |
| | | 0.3(0.3) | 0.02(0.03) | 0.3(0.5) | 1.5(1.5) | 14.05(16.7) | 7.9(7.8) | 0.3(0.2) | 0.03(0.03) |
| Ave. | | 0.908(0.894) | 0.802(0.781) | 0.915(0.838) | 0.918(0.845) | 0.924(0.896) | **0.926**(0.887) | 0.887(0.859) | **0.926**(0.898) |
| | | 0.3(0.3) | 0.02(0.02) | 0.1(0.2) | 0.6(0.7) | 8.06(8.5) | 2.5(2.5) | 0.2(0.2) | 0.02(0.023) |

results for LR, which performed best on patterns discovered using TKS. LR performed best on DS-2 (GossipCop), followed by DS-3 (PolitiFact). Obtained results so far clearly indicate that using all the words not only provides less accurate results, compared to using frequent patterns, but also takes much time and memory.

**Table 9** LR binary classification results on TKS's patterns

| Name | FP | ACC | R | P | F1 | MCC | AUC | AUPRC |
|---|---|---|---|---|---|---|---|---|
| DS-1 | 100 | 0.88 | 0.869 | 0.804 | 0.878 | 0.765 | 0.94 | 0.93 |
| | 200 | 0.91 | 0.925 | 0.908 | 0.897 | 0.84 | 0.96 | 0.96 |
| | 400 | 0.94 | 0.919 | 0.973 | 0.94 | 0.879 | 0.97 | 0.97 |
| | 600 | 0.95 | 0.949 | 0.950 | 0.948 | 0.899 | 0.97 | 0.98 |
| DS-2 | 100 | 0.95 | 0.949 | 0.954 | 0.949 | 0.899 | 0.97 | 0.97 |
| | 200 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 400 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 600 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| DS-3 | 100 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 200 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 400 | 0.98 | 0.969 | 0.973 | 0.972 | 0.969 | 1 | 1 |
| | 600 | 0.99 | 0.991 | 0.983 | 0.987 | 0.975 | 1 | 1 |
| DS-4 | 100 | 0.95 | 0.938 | 0.968 | 0.932 | 0.832 | 0.96 | 0.97 |
| | 200 | 0.96 | 0.988 | 0.933 | 0.954 | 0.912 | 0.98 | 0.97 |
| | 400 | 0.98 | 0.967 | 0.993 | 0.977 | 0.950 | 1 | 1 |
| | 600 | 0.95 | 0.947 | 0.949 | 0.954 | 0.901 | 0.98 | 0.97 |
| DS-5 | 100 | 0.90 | 0.918 | 0.89 | 0.898 | 0.824 | 0.95 | 0.96 |
| | 200 | 0.79 | 0.788 | 0.813 | 0.793 | 0.635 | 0.88 | 0.92 |
| | 400 | 0.89 | 0.908 | 0.892 | 0.888 | 0.781 | 0.97 | 0.97 |
| | 600 | 0.92 | 0.919 | 0.918 | 0.915 | 0.846 | 0.98 | 0.98 |
| DS-6 | 100 | 0.95 | 0.94 | 0.955 | 0.949 | 0.89 | 0.97 | 0.97 |
| | 200 | 0.92 | 0.917 | 0.919 | 0.911 | 0.855 | 0.98 | 0.98 |
| | 400 | 0.90 | 0.896 | 0.902 | 0.901 | 0.793 | 0.92 | 0.98 |
| | 600 | 0.89 | 0.888 | 0.908 | 0.893 | 0.778 | 0.92 | 0.96 |

### 5.2.2 MC Classification Results

Table 10 provides the obtained MC classification results for both cases. For Case 1, LR and SVM performed better accuracy (77%) compared to others. The ranking of classifiers based on accuracy is in the order LR $\approx$ SVM $>$ RF $>$ MLP $>$ DT $\approx$ BNB $>$ GNB. Interestingly, the classifiers achieved high accuracy for MC as compared to binary classification for Case 1. Computation-wise, kNN performed better, followed by BNB, while SVM performed worst, followed by MLP.

For Case 2, LR performed better (average accuracy 76.7%) compared to others. For Case 2, the ranking of classifiers based on average accuracy is in the order LR $\approx$ MLP $\approx$ SVM $>$ BNB $>$ RF $>$ DT $>$ kNN $>$ GNB. When compared to TKS, all classifiers performed generally better on patterns found with CM-SPAM. Moreover, classifiers achieved high accuracy on 600 patterns, followed by 400, 200, and 100 respectively. Again, the time taken by classifiers reduced significantly in Case 2 as compared to Case 1. For Case 2, GNB performed worst.

Interestingly, the majority of the classifiers, except BNB, GNB and MLP, performed better in Case 1 as compared to the results obtained by using TKS's 100 and 200 frequent patterns. Conversely, all classifiers performed better with 600 patterns obtained by CM-SPAM. Moreover, the classifiers in Case 1 performed better in some cases than Case 2. Figure 4 provides the overall results of LR for Case 1 and Case 2.

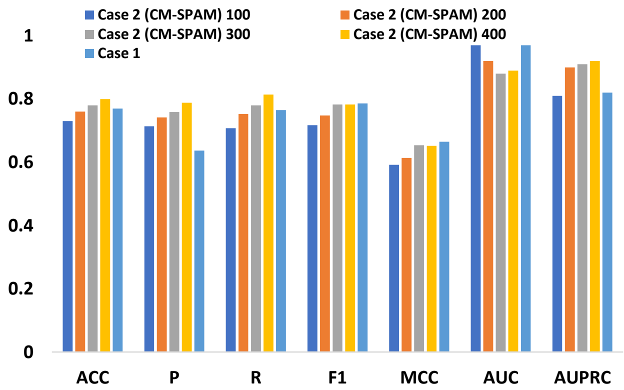


**Fig. 4** MC classification results for LR

In summary, the obtained results show that frequent patterns discovered in news can be used efficiently to classify and detect fake news instead of providing the whole news sequences. Using all the words (or the entire news) not only provides less accurate results, compared to using frequent patterns but also takes much more time. From Table 1 and Table 2, it is evident that news articles typically consist of thousands of words. However, the sequential patterns discovered by the TKS algorithm contain 74 words at most. For binary classification, it was observed that classification models performed better, overall, on TKS's patterns as compared to CM-SPAM's patterns. The opposite was true for MC classification. However, classifiers performed better on TKS's 600 patterns as compared to CM-SPAM's 600 patterns. For binary (MC) classification, classifiers performed better on 400 (600) patterns.

### 5.2.3 Comparison

FNACSPM is compared in this section with state-of-the-art approaches (published in 2017-2023) for fake news classification and detection.

Table 11 provides a comparison for binary and MC classification. For binary classification, the majority of prior studies used multiple datasets. The maximum number of 4 datasets was used in[12, 34, 36, 62]. The bold datasets in column 2 of Table 11 for binary classification are those datasets with which the corresponding learning model achieved the highest results. For example, the study[10] achieved the highest *F1-macro* of 82% on the PolitiFact dataset using Linear SVM. Except[12] no previous study used the MCC metric to

**Table 10** MC classification results

| Case 1 | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Name | | BNB | GNB | DT | RF | MLP | SVM | kNN | LR |
| WDS | | 0.70 | 0.56 | 0.70 | 0.76 | 0.74 | **0.77** | 0.72 | **0.77** |
| | | 32.6 | 129.9 | 181.4 | 197.5 | 1117.2 | 17894.1 | 5.1 | 213.5 |
| **Case 2** | | | | | | | | | |
| Name | FP | BNB | GNB | DT | RF | MLP | SVM | kNN | LR |
| WDS | 100 | 0.68(0.71) | 0.53(0.58) | 0.56(0.69) | 0.62(**0.74**) | 0.68(0.73) | 0.70(0.72) | 0.62(0.72) | 0.67(0.73) |
| | | 0.9(1.3) | 0.1(0.1) | 0.2(0.4) | 0.8(1) | 20.6(23.7) | 0.8(1) | 0.2(0.4) | 0.1(0.2) |
| | 200 | 0.68(0.750) | 0.55(0.56) | 0.68(0.60) | 0.64(0.67) | 0.72(**0.76**) | 0.70(**0.76**) | 0.63(0.66) | 0.71(**0.76**) |
| | | 0.7(0.8) | 0.3(0.4) | 0.2(0.2) | 1.4(1.8) | 49.9(56) | 5.5(4.1) | 0.2(0.2) | 0.5(0.4) |
| | 400 | 0.72(0.75) | 0.62(0.60) | 0.66(0.66) | 0.72(0.70) | 0.74(0.77) | 0.74(0.74) | 0.67(0.66) | 0.72(**0.78**) |
| | | 0.9(0.9) | 1.03(1.5) | 0.8(0.6) | 3.8(4.1) | 69.9(74.7) | 17.9(24.8) | 0.2(0.2) | 1.3(1.3) |
| | 600 | 0.82(0.77) | 0.80(0.62) | 0.84(0.74) | **0.85**(0.78) | **0.85**(0.78) | **0.85**(0.79) | 0.73(0.64) | **0.85**(0.80) |
| | | 0.9(0.9) | 1.9(2.1) | 1.4(1.4) | 7.2(7.8) | 147.5(129.7) | 63.2(75.7) | 0.2(0.3) | 3.4(4.04) |
| Ave. | | 0.725 (0.745) | 0.63 (0.59) | 0.685 (0.672) | 0.707 (0.722) | 0.747 (0.76) | 0.747 (0.757) | 0.662 (0.67) | 0.737 (**0.767**) |
| | | 0.85 (0.97) | 1.1 (1.02) | 0.65 (0.65) | 3.37 (3.67) | 71.9 (71) | 21.85 (26.4) | 0.2 (0.27) | 1.32 (1.48) |

evaluate models.

Interestingly, in studies that used multiple datasets, the highest accuracy was achieved on the PolitiFact dataset which contains few real and fake sequences. Here, the highest accuracy for binary classification is achieved on the GossipCop dataset which is much larger in size than PolitiFact. For binary classification, some studies[36,43,46,58,59] achieved the highest accuracy of 99%, followed by[34,45,48] with an accuracy of 98%. Because LR outperformed other classifiers in both types of classification (binary and MC), we have included LR findings for comparison with other classifiers from the literature. LR outperformed the multimodal approaches[13,17,60–66] for fake news detection. Some studies such as[58,59] used their models for binary classification in the ISOT dataset and MC classification on the LIAR dataset. The proposed framework outperformed all the recent approaches[12,42–45,56–59,61–63] (published in the last three years) for binary and MC fake news detection.

RF results (highlighted in bold) for both binary and MC classification of FNACSPM outperformed other classifiers. For MC classification, the majority of the previous studies used the LIAR dataset that has 6 labels. The whole dataset used in this work for MC classification has 12 labels. Interestingly, MC results that we obtained with classifiers in Case 1, when all the words in the pre-processed data are considered, are better than the approaches listed in Table 11, except for [5] that achieved the highest F1.

We also accessed the proposed framework robustness and scalability on LIAR dataset[49] that contains 12.8K short statements, labeled manually, in various contexts from PolitiFact. From this dataset, we took relevant attributes including "statement", "subject", "speaker", "speaker's job", "state", "party affiliation", and "context (venue)". For the LIAR dataset, BNB achieved the highest accuracy of 49% on patterns discovered by using TKS. This result for the LIAR dataset shows the superior performance of the proposed framework by outperforming other approaches[49,50,52,54–59] that also used the LIAR dataset for MC classification.

## 6 Conclusion

A novel SPM-based framework (called FNACSPM) is presented to analyze and classify fake news. Six diverse datasets, and their combination, were used to investigate the effectiveness and generalization ability of FNACSPM. The datasets were first abstracted and algorithms for SPM were then applied on them to discover frequent words, their frequent sequential patterns, and sequential rules. Discovered frequent patterns were then used in the classification process. Eight classifiers were applied and their performance was accessed and compared by using seven metrics. The results suggest that LR performed better than others for binary and MC classification. It was also observed that (1) using all the words (or news) not only provided less accurate results, compared to using frequent patterns, but also took more time and memory, and (2) Limited (or short) sequences of news that contain only frequent patterns of words can be used for reliable prediction and classification rather than entire news. Moreover, FNACSPM outperformed the previous fake news classification/approaches. The

**Table 11** Comparison of FNACSPM with recent studies for fake news identification

| **Binary** | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Ref.** | **Dataset(s) used** | Best Learning Model | ACC | P | R | F1 | MCC | AUC | AUPRC |
| [5] | PHEME | LSTM-RNN | – | 0.83 | 0.84 | 0.83 | – | – | – |
| [10] | BuzzFeed, **PolitiFact** | Linear SVM | – | – | – | 0.82 | – | – | – |
| [11] | BuzzFeed, **PolitiFact** | RF | 0.89 | 0.87 | 0.90 | 0.89 | – | – | – |
| [12] | George M., **Kaggle**, GossipCop, PolitiFact | BERT+CNN | 0.97 | 0.96 | 0.98 | 0.97 | 0.94 | – | – |
| [13] | BuzzFeed, **PolitiFact** | SAFE (Multimodal) | 0.87 | 0.88 | 0.90 | 0.89 | – | – | – |
| [14] | BuzzFeed, **PolitoFact** | DT | 0.92 | – | – | 0.93 | – | – | – |
| [17] | Twitter, **Weibo** | EANN (Multimodal) | 0.82 | 0.84 | 0.81 | 0.82 | – | – | – |
| [18] | FakeNewsAMT, **Celebirty** | Linear SVM | 0.76 | – | – | – | – | – | – |
| [30] | Combine 5 datasets | HDSF | 0.82 | – | – | – | – | – | – |
| [33] | Buzzfeed | XGB | – | – | – | 0.81 | – | 0.86 | – |
| [34] | LIAR, **George M.,** self made | RoBERTa | 0.98 | 0.98 | 0.98 | 0.98 | – | – | – |
| [35] | BuzzFeed, **PolitiFact** | Linguistic+SVM | 0.84 | – | – | – | – | – | – |
| [36] | **ISOT Fake News**, 2 Kaggle, George M. | LIWC+RF | 0.99 | 0.99 | 1 | 0.99 | – | – | – |
| [37] | BuzzFeed, Random Political News, **ISOT Fake News** | TF-IDF+DT | 0.96 | 0.96 | 0.97 | 0.96 | – | – | – |
| [38] | GossipCop, **PolitiFact** | SAF | 0.69 | 0.63 | 0.78 | 0.70 | – | – | – |
| [39] | Weibo, self made | TCNN-URG | 0.89 | – | – | – | – | – | – |
| [40] | News Headlines from CNN, Daily Mall | BERT+WCE | – | – | – | 0.74 | – | – | – |
| [41] | GossipCop, **PolitiFact** | co-attention network | 0.90 | 0.90 | 0.95 | 0.92 | – | – | – |
| [42] | GossipCop, **PolitiFact** | co-attention network | 0.93 | 0.93 | 0.97 | 0.95 | – | – | – |
| [43] | **ISOT Fake News**, 2 Kaggle | GloVe+BiLSTM | 0.99 | 0.99 | 0.99 | 0.99 | – | – | – |
| [44] | GossipCop, **PolitiFact** | BERT+LSTM | 0.88 | 0.91 | 0.90 | 0.90 | – | – | – |
| [45] | Kaggle | BERT+CNN | 0.98 | – | – | – | – | – | – |
| [46] | Fake and Real News Dataset | BERT-based ensemble | 0.99 | 0.98 | 0.99 | 0.99 | – | – | – |
| [47] | George M., | Word2Vec+LSTM | 0.91 | 0.89 | 0.94 | 0.91 | – | – | – |
| [48] | Kaggle | GloVe+CNN | 0.98 | 0.99 | 0.96 | 0.98 | – | – | – |
| [58] | ISOT Fake News | CNN-ML | 0.99 | – | – | | – | – | – |
| [59] | ISOT Fake News | Static+Capsule neural net | 0.99 | – | – | – | – | – | – |
| [60] | Buzzfeed, **Politifact** | TriFN (MultiModal) | 0.87 | 0.86 | 0.89 | 0.88 | – | – | – |
| [61] | GossipCop, **Weibo** | TRIMOON (MultiModal) | 0.91 | 0.92 | 0.88 | 0.90 | – | – | – |
| [62] | Twitter, Weibo A, Weibo B, **Weibo C** | MCN+CARN (MultiModal) | 0.92 | 0.92- | 0.92 | 0.92 | – | – | – |
| [63] | GossipCop, **PolitiFact** | BERT+CapsNet (MultiModal) | 0.93 | 0.92 | 0.91 | 0.92 | – | – | – |
| [64] | GossipCop, **PolitiFact** | SceneFND (Multimodal) | 0.83 | 0.84 | 0.84 | 0.83 | – | – | – |
| [65] | **Twitter**, Weibo | MPFN (MultiModal) | 0.88 | 0.82 | 0.82 | 0.81 | – | – | – |
| [66] | **Twitter15**, Twitter16 | GCAN (MultiModal) | 0.86 | 0.79 | 0.79 | 0.79 | – | – | – |
| **FNACSPM(LR)** | George M., **GossipCop**, PolitiFact, Buzzeed, Fake News Classification, Fake and Real News classification, all combined | | **1** | **1** | **1** | **1** | **1** | **1** | **1** |
| **MC** | | | | | | | | | |
| [5] | PHEME | LSTM-RNN | – | – | – | 0.79 | – | – | – |
| [49] | LIAR, 6 classes | Hybrid CNN | 0.27 | – | – | – | – | – | – |
| [50] | LIAR, 6 classes | MMDF | 0.34 | – | – | – | – | – | – |
| [51] | PolitiFact, 6 classes | LIWC+LSTM | – | – | – | 0.22 | – | – | – |
| [52] | LIAR, 6 classes | DT | 0.39 | – | – | – | – | – | – |
| [53] | CT-FAN-21, 4 classes | RoBERTa | 0.47 | 0.36 | 0.34 | 0.29 | – | – | – |
| [54] | LIAR, 6 classes | BiLSTM | 0.41 | – | – | – | – | – | – |
| [55] | LIAR, 6 classes | BERT | 0.41 | – | – | – | – | – | – |
| [56] | LIAR, 6 classes | BERT+CNN-BiLSTM | 0.47 | – | – | – | – | – | – |
| [57] | LIAR, 6 classes | AC-BiLSTM | 0.33 | – | – | 0.36 | – | – | – |
| [58] | LIAR, 6 classes | Static CNN-ML | 0.41 | – | – | – | – | – | – |
| [59] | LIAR, 6 classes | non-static+capsule neural net | 0.40 | – | – | – | – | – | – |
| **FNACSPM(LR, Case 1)** | Combination of 6 datasets, 12 classes | | **0.77** | **0.76** | **0.63** | **0.78** | **0.66** | **0.97** | **0.82** |
| **FNACSPM(LR, Case 2)** | Combination of 6 datasets, 12 classes | | **0.80** | **0.81** | **0.78** | **0.78** | **0.65** | **0.89** | **0.92** |
| **FNACSPM(BNB)** | LIAR, 6 classes | | **0.49** | **0.49** | **0.47** | **0.48** | **0.42** | **0.78** | **0.61** |

proposed framework can handle both binary and MC classification tasks, showcasing its versatility and efficacy in distinguishing between fake and genuine news articles across different complexity levels. Additionally, the research has shed light on the linguistic and semantic structures underlying fake news articles through the utilization of frequent patterns.

This study has various limitations: (1) A drawback of using SPM for fake news classification is that it may exclude crucial words that serve as significant differentiators between fake and real news. This occurs when these words have low frequency and are not considered frequent patterns. As a result, this approach may overlook valuable discriminatory features, which may affect the classification accuracy. (2) The credibility of online datasets used for training and testing may not be reliable and bias in information collection may not be completely eliminated. (3) The interpretability of the extracted frequent sequential patterns and their relationship to the classification decisions may be limited. Understanding the underlying reasons behind the classification results and explaining them to users or stakeholders may be challenging. (4) Patterns and rules discovered by SPM algorithms require validation and verification from experts. The study focused on extracting patterns from static and retrospective datasets, which do not capture the dynamic nature of fake news propagation in real-time. Real-time analysis and detection of emerging fake news may require additional considerations and techniques beyond pattern mining. Moreover, emerging or contrast pattern mining[78] can be used on the datasets to find contrasting frequent patterns of words and using these patterns for analysis and classification.

## References


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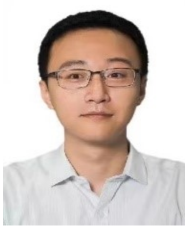

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