TẠP CHÍ KHOA HỌC
TRƯỜNG ĐẠI HỌC QUY NHƠN

# Phát hiện tin giả dựa trên nội dung và ngữ cảnh xã hội sử dụng học máy

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**TÓM TẮT**

Bài báo này trình bày nghiên cứu về phát hiện tin giả dựa trên nội dung tin và ngữ cảnh xã hội sử dụng học máy. Đầu tiên, chúng tôi phân tích các khái niệm liên quan, các phương pháp phát hiện tin giả. Tiếp theo, chúng tôi mô hình hóa nhiệm vụ này như một bài toán phân lớp nhị phân, biểu diễn nội dung tin và ngữ cảnh xã hội dưới dạng véc-tơ đặc trưng. Sau đó, chúng tôi sử dụng một số thuật toán học máy để xây dựng mô hình phân lớp. Kết quả thực nghiệm với ba thuật toán học máy: Support Vector Machine, Naive Bayes và *k*-Nearest Neighbors trên bộ dữ liệu FakeNewsNet cho thấy hiệu quả của phương pháp đề xuất.

**Từ khóa:** *Phát hiện tin giả, nội dung tin, ngữ cảnh xã hội, phân lớp, học máy.*

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# Fake news detection based on news content and social contexts using machine learning

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**ABSTRACT**

This paper presents research on detecting fake news based on news content and social context approach using machine learning. First of all, we analyze related concepts, methods of detecting fake news. Next, we model this task as a binary classification problem, representing news content and social context as feature vectors. Then we use machine learning algorithms to build the classification model. Experimental results with three machine learning algorithms: Support Vector Machine, Naive Bayes and *k*-Nearest Neighbors on the FakeNewsNet dataset show the effectiveness of the proposed method.

**Keywords:** *Fake news detection, news content, social context, classify, machine learning.*

## 1. INTRODUCTION

The development of online social media platforms (e.g. Facebook, Twitter, Instagram, etc.) brought about a significant increase in the accessibility of information on the one hand, and accelerated the propagation of fake news on the other hand. As a result, the influence of fake news is growing and threatening the safety of the community.[1] The scope of fake news was most marked during the 2016 US presidential election campaign. The top 20 election fake news received 8,711,000 shares and comments on Facebook, larger than the total of 7,367,000 shares and comments on top 20 election stories from 19 major media outlets.[2]

Distinguishing true news from fake news is one of the difficult tasks for humans. Psychosocial and media studies show that people's ability to detect deception ranges from 55% –58%.[3]

There have been several expert-based manual fake news detection tools, platforms and websites (e.g. PolitiFact, Snopes) and community-based (e.g. Fiskkit, VAFC) so far. However, manual fake news detection is not suitable for the large amount of information generated, especially on social media.[4] Therefore, the research direction fake news detection [automatic] has become a "hot" topic recently.[5-9] In which, fake news detection can be classified

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into two approaches namely (i) content-based and (ii) propagation-based.[10-13]

Content-based fake news can be detected by analyzing the news content. Meanwhile, propagation-based fake news detection exploits how news spread on social networks. The "life-cycle" of fake news has three basic stages: (1) content creation, (2) publication, and (3) propagation as illustrated in Figure 1. Propagation-based approach using social context information is difficult to apply in predicting fake news before the third stage (before fake news is spread on social media). Therefore, it is necessary to detect fake news early to prevent its spread (i.e., when fake news is at the publication stage and it has not yet spread widely).

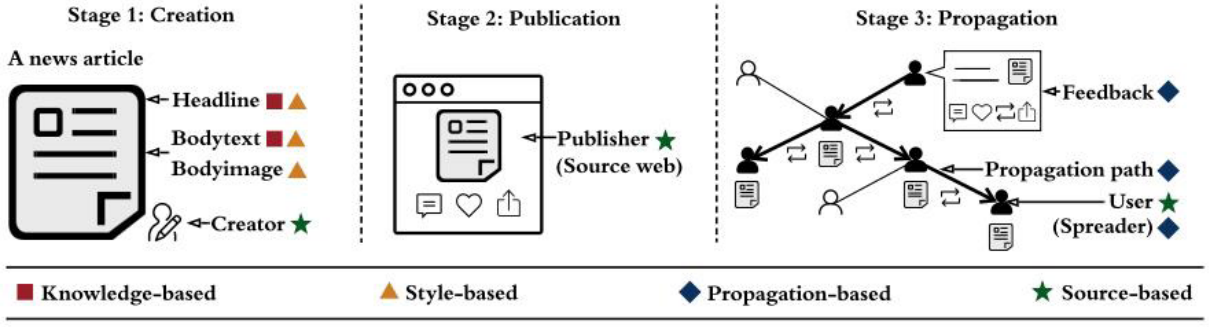


**Figure 1.** Fake news life cycle and detection methods.[2]

In this paper, we present a research on detecting fake news according to content-based and social context approach using machine learning. The main contributions of the paper are:

1) Analysis of related concepts, methods of detecting fake news.

2) Proposal of a method to detect fake news based on news content and social context using machine learning, including: (i) modeling this task as a binary classification problem; (ii) representing content at the lexical and social context level in the form of feature vectors; and (iii) using machine learning algorithms to build classification models.

3) Experiment to evaluate the effectiveness of classification models on the FakeNewsNet dataset.

The rest of the paper is organized as follows: Section 2 presents an overview of fake news and fake news detection. Section 3 then presents news content and social context-based fake news detection method using machine learning followed by Section 4 describing experiments. Section 5 wraps up the article with the conclusion.

## 2. OVERVIEW OF FAKE NEWS AND FAKE NEWS DETECTION

### 2.1. Definition of fake news

Current studies about fake news detection often involves the following concepts: fake news, false news, satire news, disinformation, misinformation, and rumor. These concepts can be distinguished based on three characteristics: (i) authenticity, (ii) intention, and (iii) whether information is news. Table 1 summarizes related concepts based on these characteristics.[1] For example, disinformation has false authenticity [news or not news] with bad intentions.[2]

**Table 1.** Compare related concepts.

| Concepts | Authenticity | Intention | News or not news? |
|---|---|---|---|
| Fake news | False | Bad | News |
| False news | False | - | News |
| Satire news | - | Not bad | News |
| Disinformation | False | Bad | - |
| Misinformation | False | - | - |
| Rumor | - | - | - |

According to Zhou,[2] "*fake news is intentionally false news published by a news outlet"*. Typically, news agencies publish news in the form of articles with the following components: title, content, author (including user's feedback) as illustrated in Figure 1.

### 2.2. Fake news detection methods

#### *2.2.1. Content-based*

Content-based approaches include (i) knowledge-based and (ii) style-based/writing-style. Knowledge-based fake news detection evaluates the veracity of news by comparing knowledge drawn from verified news content with known facts (i.e. true knowledge). Similar to knowledge-based methods, style-based fake news detection also focuses on news content analysis. This process includes two steps called style representation (using language features) and style classification (using machine learning models). While the knowledge-based method mainly evaluates the authenticity of the news, the style-based method can assess the intention of the news.[2,14-15]

#### *2.2.2. Propagation-based*

Propagation-based approach uses social context information to detect fake news, for example, how fake news spreads on social networks, who spreads it, and how spreaders connect with each other.

The news ecosystem on social media provides social contextual information regarding three basic entities: publishers, news [pieces], and users.

Figure 2 and Figure 3 illustrate the spread of news. In Figure 3, $p_1$, $p_2$ and $p_3$ are the publisher of the news $a_1$, ..., $a_4$ and $u_1$, ..., $u_6$ are the users sharing these news. In addition, users tend to form social links with people with similar interests.[16-17]

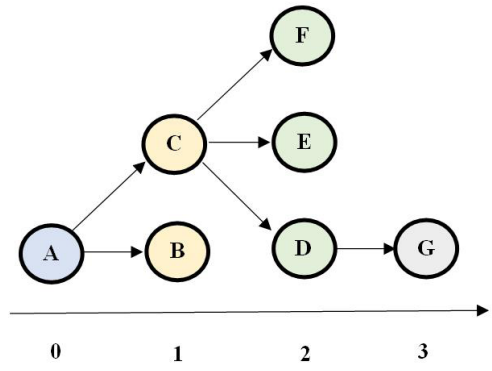


**Figure 2.** Tree structure-based news propagation.

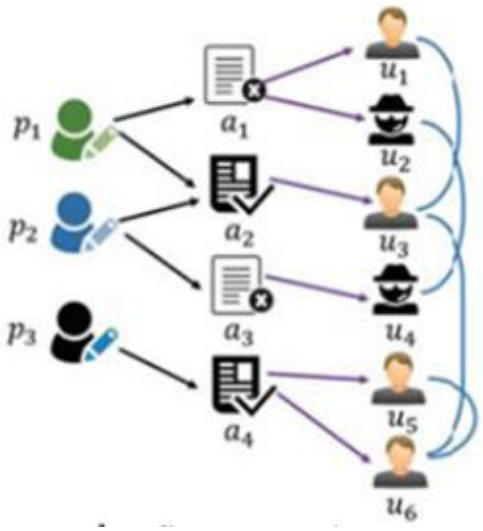


**Figure 3.** The relationship between publisher and user.

In general, the input to a propagation-based method can be (i) news cascades or (ii) self-defined propagation graphs.

A news layer is a tree structure that represents the direct spread of news on social network (example in Figure 2).[2] The root node corresponds to the user who first shared the news (i.e. the initiator); other nodes in the layer correspond to users who then forwarded the post after it was posted by the parent node. In a news propagation network (subgraph of a social network), each network corresponds to news, each node in the network represents a user, and an edge between two nodes represents the relationship of the two users. For example, in Figure 3, edge ($p \rightarrow a$) represents publisher $p$ publishing news $a$, edge ($a \rightarrow u$) represents new $a$ sspread by user $u$ and edge ($u_1 \rightarrow u_2$) is social relationship between $u_1$ and $u_2$.[16]

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Thus, propagation-based fake news detection focuses on categorizing (i) news layers or (ii) self-defined graphs.

## 3. PROPOSED METHODS

In this section, we present a news content and social context-based fake news detection method using machine learning. First, we model this task as a binary classification problem. Next, we represent the news content at the lexical level according to the BoW model (Bag of Words) as a feature vector and connect to the social context vector. Then we use machine learning algorithms to build the classification model.

### 3.1. Problem definition

We consider the problem of detecting fake news based on content (part of text), where A = $\{a_1, a_2,..., a_n\}$ is the set of n news. Suppose the news to be verified $a$ can be represented as a feature vector $v \in R^k$. The task of verifying the content-based is defined a function $f$, such that:

$$f : v \xrightarrow{D} y \quad (1)$$

Where $y \in \{0,1\}$ (0 – true news, 1- fake news) is the predicted label of the news and $D = \{(v_i, y_i) | v_i \in R^k, y_i \in \{0,1\}, i = 1..n\}$ is the training dataset. The training dataset $D$ consists of $n$ news, each news $a_i \in D$ is represented by the feature vector $v_i$ with the label $y_i$.

And news content and social context based fake news detection problem is defined as follows: Let $N = \{n_1, n_2,\ldots, n_{|N|}\}$ is a set of news, each of which is labeled as $y_i\{0,1\}$, $y = 1$ is the fake news and $y_i = 0$ is the true news. The news $n_i$ is represented by the news content (news body) and side information such as (title, source, author, ...). When $n_i$ is posted on a social network, it is usually interacted with by social network users $U = \{u_1, u_2,\ldots, u_{|U|}\}$. Social context includes user interactions such as comments, posts, likes/shares, etc.

$$SC(n_i) = \left((u_1, sc_1, t_1), (u_2, sc_2, t_2), \ldots, (u_{sc}, sc_{sc}, t_{sc})\right) \quad (2)$$

Each tuple $(u, sc, t)$ refer to user $u$'s context $sc$ for news $n_i$ in timet . Here, a user can interact with a post multiple times.

Task of this problem is to find a model M to predict the label $y(n_i) \in \{0,1\}$ for each news based on the news content and social context. Therefore, this task is defined by Equation (3):

$$y(n_i) = M(C(n_i), SC(n_i)) \quad (3)$$

Where $C(n_i)$ is news content and $SC(n_i)$ is the social context of the news. Figure 4 describes the problem of detecting fake news through news content and social context.

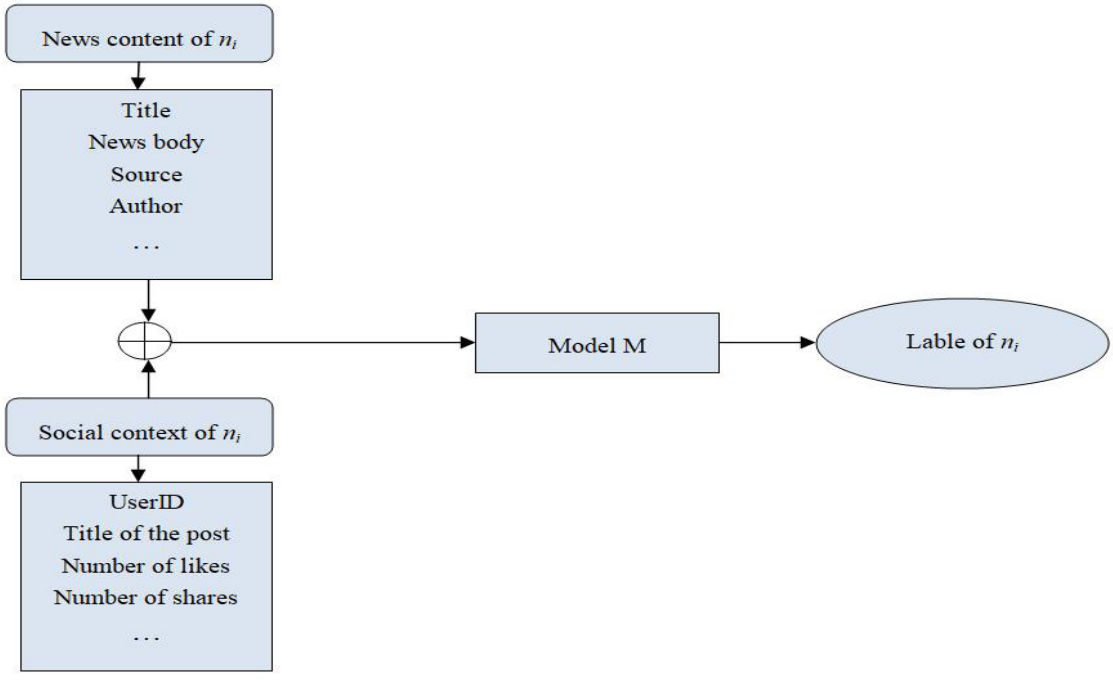


**Figure 4.** Description of problem.

### 3.2. News content and social context

*3.2.1. News content*

News content is the main component that makes up the story/event (news body) and includes the following auxiliary information:

- Source (e.g. https://dantri.com.vn, https://saobiz.vn).
- Headline is the title that describes the main topic of the news. The title is often named so that it attracts the reader's attention.
- Author
- Publication time

*3.2.2. Social context*

The social context of a news can be posts, likes, shares, replies, etc. When the features relevant to the news content are insufficient or unavailable, the social context is useful information for authenticating the news. Ancillary information related to the social context is as follows:

- Social network users (user)
- Title is the title or short caption of the post. This title is closely related to the title of the news.
- Score is the rating for a post given by other users, which determines the acceptance or disapproval of the post by other users.
- Number of comments is the number of comments on a post, this characteristic shows the popularity of the post.
- The upvote/downvote ratio estimates the approval/disapproval of other user's posts.
- User credibility: This is a feature that helps determine if users are prone to spreading fake news. For example, if the user's other posts are not trusted, it is likely that the next post will also be unreliable.

*3.2.3. Representation of news content and social context*

News content description features have four [language] levels: (i) lexicon, (ii) syntax, (iii) discourse and (iv) semantic. In this step, we represent the content at the lexical level according to the BoW model. Suppose the dataset contains $n$ news $N = \{n_1, n_2, ..., n_{|N|}\}$ with a total of t words $W=\{w_1, w_1, \ldots, w_t\}$. Let $x_j^i$ is the number of words $w_j$ appearing in $n_i$. Then, the normalized frequency of $w_j$ for the news $n_i$ is calculated according to Equation (4).

$$w_j = \frac{x_j^i}{\sum_{j=1}^{t} x_j^i} \quad (4)$$

Thus, the new $n_i$ is represented as a feature vector $v_i = \{w_1, w_1, \ldots, w_t\}$.

### 3.3. Classification model

Figure 5 shows an overview of the model that we propose to use.

- First, from the raw dataset (as shown in Figure 6), the data is preprocessed and extracted featuring news content and social context, respectively. The input is news content (identifier of news, publishing source, title of news, main content) and social context features (number of likes, number of shares, user identifier), the output is a vector representation of news content and social context. For each news $n_i \in A$ (set of news), we represent it as a feature vector $v_i \in R^k$. This representation is tailored to each machine learning algorithm. The vector representations are combined to produce a single representation that is passed as input at the next stage. The final output is passed to the classifier.
- Next, we use machine learning algorithms to train the classification model (traditional machine learning algorithms such as Support Vector Machine (SVM), Naive Bayes (NB), $k$-Nearest Neighbor ($k$-NN)).
- Finally, we use the classification model to predict whether the input data is true or fake news. The model's prediction results are compared with actual (labeled) data to evaluate the model's effectiveness.

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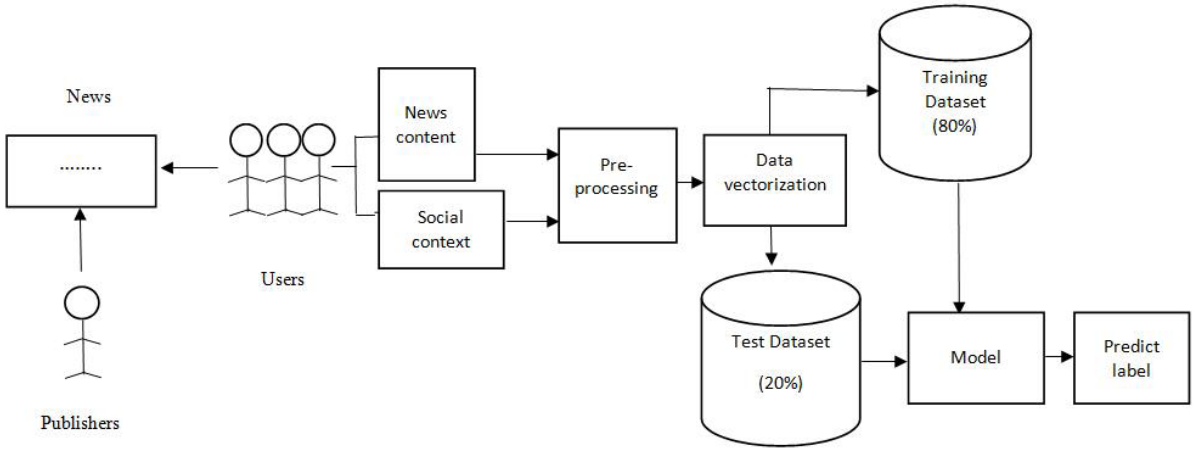


**Figure 5.** Proposed model.

*3.3.1. Naive Bayes*

Naive Bayes algorithm uses conditional probability between attributes and class label to determine the class of a data sample to be classified.[18]

Let $D$ is the training dataset: $D = \{X_1, X_2,\ldots, X_n\}$. Where, each $X_1$ is represented by a vector containing $m$ attributes $X_1 = \{x_{i1}, x_{i2},\ldots, x_{im}\}$. Let $C$ be a set of labels consisting of $p$ classes: $C = \{C_1, C_2, ..., C_p\}$.

Given the data sample $X = \{X_1, X_2,\ldots, X_m\}$, the Naive Bayes classifier will predict $X$ belong to class $C_i$ if: $P(C_i|X) > P(C_j|X)$, $(1 \le i, j \le p, i \ne j)$. The process of classifying data sample $X$ according to Naive Bayes algorithm is described in Algorithm 1.

**Algorithm 1** Naive Bayes classifier algorithm

**Input:** $D$: Training dataset; $C$: Label set; $X$: New data samples.
**Output:** Label of $X$

1: for $i = 1$ to $p$ do
2: $P(C_i) = |X_i|/|D|$ //Calculate the probability of occurrence of the class $C_i$, where $|X_i|$ is the number of data samples belonging to the class $C_i$.
3: $P(C_i|X) = P(x_1|C_i) \times P(x_2|C_i) \times ... \times P(x_n|C_i) \times P(C_i)$ //Calculate the classification probability $C_i$ is the label of the data sample $X$.
4: $label(X) \longleftarrow C_i$ if $P(C_i|X)$ is the biggest.

*3.3.2. Support Vector Machine*

The main idea of the SVM algorithm is that given a training set represented in vector space, where each data sample is a point, this method finds a decision hyperplane $h$ that can best divide the points on this space into separate classes. The quality of this hyperplane is determined by the distance of the nearest data point of each class to this plane. The larger the boundary distance, the better the decision plane, and the more accurate the classification. The purpose of the SVM algorithm is to find the maximum boundary distance to give the best classification result.[19]

Suppose we need to classify a data sample $X$ into one of two classes $C_1$ = -1 and $C_2$ = 1. The SVM classification algorithm is detailed in Algorithm 2.

**Algorithm 2** SVM classifier algorithm

**Input:** $D$: Training dataset; $C$: Label set; $X$: New data samples; $T$: bias coefficient; $W = \{w_1, w_2, ..., w_n\}$: The set of hyperplane coefficients (*vector* weights).
**Output:** Label of $X$

1: for $i = 1$ to $n$ do
2: $f(X) \longleftarrow sign(T + \sum w_i \times x_i)$
3: $z = T + \sum w_i \times x_i$
4: if $(z \geq 0)$ then
5: $sign(z) \longleftarrow 1$
6: else $sign(z) \longleftarrow -1$
7: $label(X) \longleftarrow sign(z)$

The SVM classification algorithm depends on the weight vector parameters $W$ and the bias coefficient $T$. The goal of SVM is to estimate $W$ and $T$ to maximize the margin between the data classes.

*3.3.3. k-Nearest Neighbor*

$k$-NN is one of the simplest supervised learning algorithms. $k$-NN algorithm classifies new data points based on $k$ nearest data points ($k$ - neighbors). The measure used to calculate the distance between two data points can be Euclidean, Manhattan, Minkowski, Cosine.[20] Algorithm 3 describes the steps to classify a data point according to the $k$-NN algorithm.

**Algorithm 3** $k$-NN classifier algorithm

**Input:** $D$: Training dataset; $C$: Label set; $X$: New data samples; $K$: Number of neighbors.

**Output:** Label of $X$

1: for $i = 1$ to $n$ do
2: $d(X_i, X)$ //Calculate the distance between $X$ and the data points in the training set.
3: end for
4: Create a set $I = \{X_i\}$, $|I| = K$ //$I$ contains $K$ data point closest to $X$.
5: for $i = 1$ to $p$ do
6: Count the number of classes $C_i$ that appear in $I$
7: $label(X) \longleftarrow C_i$, if $C_i$ is the most appear class.

## 4. EXPERIMENT

### 4.1. Dataset

A significant challenge for automated fake news detection is the availability and quality of datasets. In the experiment, we use two datasets PolitiFact and GossipCop.[21]

Table 2 describes the news type, size and number of label 1 (fake news) statistics of the datasets. PolitiFact dataset has news of the type of article, and it includes 1,056 news, in which 432 news is fake news.

**Table 2.** Description of experimental data.

| Dataset | Type | Size | Number of label 1 |
|---|---|---|---|
| PolitiFact | article | 1,056 | 432 |
| GossipCop | article | 22,140 | 5,323 |

Figure 6 is a snapshot of the data in the GossipCop dataset. The data includes news content and social context. In which, the content features include id (identifier of news), news_url (publishing source), title (title of news), news_body (main content), count_like (number of likes), count_share (number of shares), user_ids (user identifier, each with 18 numbers). For example, the first data line in Figure 6 has the following features:

| | A | B | C | D | E | F | G | H |
|---|---|---|---|---|---|---|---|---|
| 1 | id | news_url | title | news_body | count_like | count_share | user_ids | label |
| 2 | gossipcop-2493749932 | www.daily | Did Miley Cyr | Congratulations mig | 12096 | 5421 | 2843290759029 | fake |
| 3 | gossipcop-4580247171 | hollywooc | Paris Jackson & Cara Delevingne E | | 746 | 1167 | 9928955082671 | fake |
| 4 | gossipcop-941805037 | variety.co | Celebrities Joi | Elaine L. Chao, a vet | 1269 | 529 | 8533593535328 | fake |
| 5 | gossipcop-2547891536 | www.daily | Cindy Crawfo | In a move that left r | 870 | 577 | 9888219051961 | fake |
| 6 | gossipcop-5476631226 | variety.co | Full List of 201 | Good morning. (Wa | 756 | 921 | 9557927936324 | fake |
| 7 | gossipcop-5189580095 | www.tow | Here's What F | Federal prosecutors | 2932 | 147 | 8902530052993 | fake |
| 8 | gossipcop-9588339534 | www.foxn | Biggest celebr | As he prepared last | 4564 | 125 | 6832263807425 | fake |
| 9 | gossipcop-8753274298 | www.eonl | Caitlyn Jenne | Taiwan scrambled | 4511 | 1000 | 1026891446081 | fake |
| 10 | gossipcop-8105333868 | www.inqu | Taylor Swift R | President Xi Jinping | 1966 | 2476 | 8189285335694 | fake |
| 11 | gossipcop-2803748870 | www.huff | For The Love | First it was the icy sr | 629 | 1185 | 8160302481900 | fake |
| 12 | gossipcop-7312096991 | www.msn | Miley Cyrus, L | Abdul Ali Shamsi ha | 11188 | 917 | 9301835055138 | fake |
| 13 | gossipcop-5328748354 | yournews | Miley Cyrus C | SEOUL, South Korea | 8573 | 93 | 9142087416078 | fake |
| 14 | gossipcop-9878194459 | www.mar | Selena Gome | Photographs recent | 4529 | 1741 | 1016502265060 | fake |
| 15 | gossipcop-9521617242 | www.eonl | Critics' Choice | President Obama de | 538 | 500 | 9386812614086 | fake |

**Figure 6.** Part of the data in the GossipCop dataset.

| news_body | count_like | count_share | user_ids | label |
|---|---|---|---|---|
| Congratulations might be in order for Miley Cyrus and Liam Hemsworth, according to new reports. Insiders told Life & Style magazine the pair secretly web in a 'hippie-style' ceremony at their Malibu, California mansion. 'They've actually done the deed for real this time! Miley and Liam recently had a secret wedding at her Malibu mansion,' the source said. 'Neighbors had no clue it was a wedding. Kids were running around everywhere. It was a hippie-style wedding.' The source continued: 'She wore a white, flowey dress and all her animals were roaming around, it was crazy! The food was vegetarian and organic.' As for their vows, the anonymous informant said: 'They expressed their love, how they're each other's best friend and want to grow old together. 'There wasn't a dry eye in the house.' Life & Style reported that, rather than invite someone to perform at their wedding, Miley did the honors herself. She sang a rendition of godmother Dolly Parton's song, Islands in the Stream. Wayne Coyne of the Flaming Lips also performed a few songs. Miley's mother and father, Billy Ray and Trish Cyrus, were both present along with siblings Noah, Trace, Brandi, Braison and Christopher. Liam's famous family attended as well. According to the report, both Chris and Luke Hemsworth looked on as Miley and Liam said their 'I Dos'. Neither Miley nor Liam have shared photos from their rumoured wedding day, but this won't be their last opportunity. According to the outlet, the couple plan to have another wedding ceremony in Australia so that more of Liam's family can be involved. As for their post wedding plans, the source said Miley and her alleged hubby have their sights set on a baby. 'It's been Miley's dream to have a baby,' they said. Here's what you need to know. | | | | |

**Figure 7.** Main content of the news.

| user_ids | label |
|---|---|
| 2843290759029268 | 4828433274455996825628433541259029708928435991879288012828438538515133235328445638883345203228464487826731827328465655896356454528470539196579430428470539195740160128476242555372339228476608982772121728476976680623576426476976949062041628476977544233779228476977298030182428476977865518694428476977707391795228477191375304294428490294320183705628491893997530316928559226671688499328563542187297996928563551692430131328573132410128793729595453355579392029663963271045939229665127662682521670013715214369996870050164241256038470059945776789094470092521303114137675759898037304524875761401780843724875781020444874342575785545488629350481845487229916364981853220899037184181862238252499763281862364473787187282432805933569229084023792664253644984027798806743040084030555673687244884031264104210432084032038343787724884032137815067033684032544938960076884034679267169894584035911575499981084035914011969945784036645967506227484039688158698291284041337065005056084044084752711680084044429973291008084046255013536563384184926864633856084967804105588736092585119156055654492742672865323008092753101221245747392758887557652889792758887555136307292758912119076044992760651040602931492844201952916275292853261305635225692865342475275878495320193757434265895333640865099366495369219206488473795399944538488832195430767034491699210100397788914524161010184150970654720101018441015727361101019144461775257610102290139089920001010262428670709766101033476770156134410103938091447992321010418444016259072101112776426139648110137235788340142081013723601571340291101372381368566988910160005628931235841016431705132093440103644429634866380810605947074478530581060595446488358912106067950224043622410606833976499527701060708573590773761106072222723731865610608121262002

**Figure 8.** User identifier.

- id: gossipcop-2493749932

- news_url:

www.dailymail.co.uk/tvshowbiz/article-5874213/Did-Miley-CyrusLiam-Hemsworth-secretly-married.html

- title: Did Miley Cyrus and Liam Hemsworth secretly get married?

- news_body: (Figure 7)

- count_like: 12096

- count_share: 5421

- user_ids: (Figure 8)

### 4.2. Experimental setup

We use three machine learning algorithms, including: SVM, NB, and *k*-NN to train classification models on two different datasets. From the input datasets, we preprocess the data by removing stop word and special symbols, then vectorize the data matching each algorithm at the lexical level.

The training data and the test data were split in a ratio of 8:2, using a 5-fold cross-validation method.

To evaluate the classification models, we use the confusion matrix as shown in Table 3, where:

- TP (true positive): Number of news predicted to be fake news and actually fake news;
- FN (false negative): Number of news that are predicted to be fake news when in fact they are true;

● FP (false positive): Number of news that are predicted to be true when they are actually fake;

● TN (true negative): Number of news predicted to be true and in fact true.

**Table 3.** Confusion matrix performance.

| **Actual ↓ Prediction →** | **Fake news** | **True news** |
|---|---|---|
| Fake news | TP | FP |
| True news | FN | TN |

P (Precision), R (Recall) and $F_1$ is calculated as follows:

$$P = \frac{TP}{TP + FP} \quad (5)$$

$$\mathrm{R} = \frac{TP}{TP + FN} \quad (6)$$

$$\mathrm{F_1} = 2 \times \frac{P \times R}{P + R} \quad (7)$$

We implement machine learning algorithms and evaluate classification models based on the open source tool Scikit-learn.[22] We use the following classification models:

● SVM classification model: *SVC (kernel = linear)*

● Naive Bayes classification model: *GaussianNB()*

● *k*-NN classification model: *KNeighborsClassifier()*

### 4.3. Results and discussion

Table 4, Table 5 and Table 6 present the experimental results of the classification models on the datasets that are news content only (PolitiFact (C) and GossipCop (C)) and social context only, respectively (PolitiFact (SC) and GossipCop (SC)), and combine both news content and social context (PolitiFact (C+SC) and GossipCop (C+SC)). Experimental data show that all three classification models (SVM, NB and *k*-NN) achieve the measure of $F_1$ above 75%. It can be seen from the experimental results that when using a dataset combining news content and social context, almost all three models give better classification results. Specifically, when applying the *k*-NN algorithm on the PolitiFact (C+SC), the $F_1$ measure is 7.4% higher when running on the PolitiFact (C) and 7.7% higher when running on the PolitiFact (SC). In another case, when applying the SVM algorithm on the GossipCop (C+SC) dataset, the $F_1$ measure is 2.8% higher when running on the GossipCop (C) dataset and 2.6% higher when running on the GossipCop(SC) dataset.

Figure 9 and Figure 10 show the comparison of the $F_1$ measure between the classifiers on PolitiFact(C), PolitiFact(SC) and PolitiFact(C+SC) datasets; and between classifiers on GossipCop(C), GossipCop(SC) and GossipCop (C+SC) datasets. Experimental results show that most algorithms applied to datasets that combine news content and social context give better results of measuring $F_1$ when applied on datasets with only news content or social only social context.

**Table 4.** Experimental results on datasets with only news content.

| **Dataset→** | **PolitiFact (C)** | | | **GossipCop (C)** | | |
|---|---|---|---|---|---|---|
| **Metric→** | **P** | **R** | **$F_1$** | **P** | **R** | **$F_1$** |
| ***k*-NN** | 0.609 | 0.995 | 0.755 | 0.827 | 0.879 | 0.852 |
| **NB** | 0.821 | 0.862 | 0.841 | 0.87 | 0.655 | 0.751 |
| **SVM** | 0.795 | 0.922 | 0.853 | 0.876 | 0.904 | 0.890 |

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**Table 5.** Experimental results on datasets with only social context.

| Dataset→ | PolitiFact (SC) | | | GossipCop (SC) | | |
|---|---|---|---|---|---|---|
| Metric→ | P | R | $F_1$ | P | R | $F_1$ |
| ***k*-NN** | 0.603 | 1.0 | 0.752 | 0.831 | 0.894 | 0.861 |
| **NB** | 0.831 | 0.817 | 0.824 | 0.875 | 0.645 | 0.743 |
| **SVM** | 0.793 | 0.849 | 0.820 | 0.876 | 0.910 | 0.892 |

**Table 6.** Experimental results on datasets combining news content and social context.

| Dataset→ | PolitiFact (C+SC) | | | GossipCop (C+SC) | | |
|---|---|---|---|---|---|---|
| Metric→ | P | R | $F_1$ | P | R | $F_1$ |
| ***k*-NN** | 0.887 | 0.779 | 0.829 | 0.798 | 0.856 | 0.826 |
| **NB** | 0.874 | 0.832 | 0.852 | 0.831 | 0.868 | 0.849 |
| **SVM** | 0.815 | 0.917 | 0.863 | 0.883 | 0.956 | 0.918 |

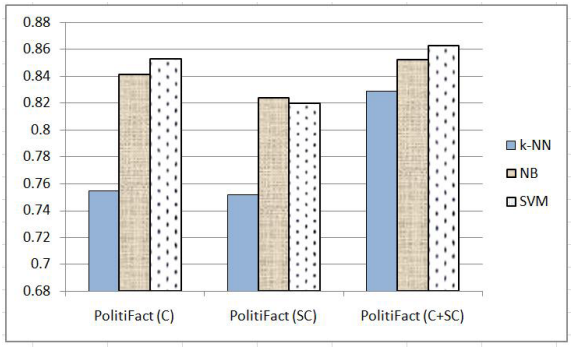


**Figure 9.** Compare the $F_1$ measure on the PolitiFact(C), PolitiFact(SC) and PolitiFact(C+SC) datasets.

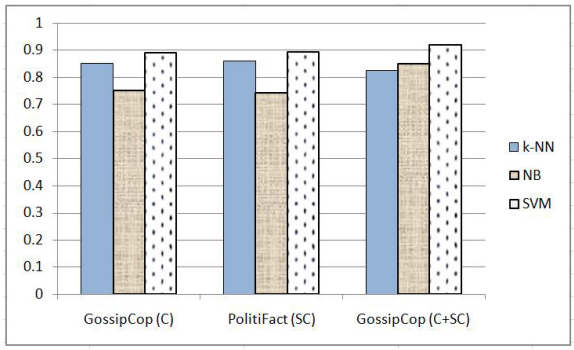


**Figure 10.** Compare the $F_1$ measure on the GossipCop(C), GossipCop(SC) and GossipCop(C+SC) datasets.

## 5. CONCLUSION

In this paper, we have presented a research on detecting fake news based on news content and social context approach using machine learning. We have analyzed related concepts, methods of detecting fake news. We have modeled this task as a binary classification problem, representing content and social contexts as feature vectors. Then we used machine learning algorithms to build the classification model. Experimental results with three machine learning algorithms (SVM, NB and *k*-NN) on two different datasets show the effectiveness of the proposed method.

In the future, we plan to extend this study towards content analysis in terms of natural language processing at the syntactic and semantic levels, and build a Vietnamese dataset for research on fake news detection problem.

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