Detecting Fake News with Tweets' Properties

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***Abstract*—Social media has replaced the traditional media and become one of the main platforms for spreading news [1]. News on social media tends to travel faster and easier than traditional news sources due to the internet accessibility and convenience. However, not all the news published on social media are genuine and/or came from unverified sources. False information can be created and spread easily through social media and this false news can potentially or deliberately mislead or misinform readers. The extensive spread of fake news brings negative impact to not only individual but also society [2]. Consequently, fake news may affect how readers perceive an online news on social media and indirectly mislead the way they respond to real news [2] [11]. Though there are some existing manual fact-checking websites developed to examine if a news is authentic, it does not scale with the volume of the fast spread online information, especially on social media. To overcome this problem, there are automated fact-checking applications were developed to tackle the need for automation and scalability. However, the existing application approaches lack an inclusive dataset with derived multi-dimension information for detecting fake news characteristics to achieve higher accuracy of machine learning classification model performance. To solve this limitation, we derived and transformed social media Twitter's data to identify additional significant attributes that influence the accuracy of machine learning methods to classify if a news is real or fake using data mining approach. In this paper, we present the mechanisms of identifying the significant Tweets' attributes and application architecture to systematically automate the classification of an online news.**

Keywords*—*Fake news, Social media analytics, Data mining, Machine learning, Classification application

I. Introduction

Nowadays, social media has replaced traditional news sources and became the main platform in terms of spreading news. The reasons for this replacement are due to: i) less expensive to get news from social media; and ii) easier to share, comment and discuss with other readers on social media. According to a survey conducted by [1], 62% of U.S. adults consume news on social media while in 2012, only 49% of consumers get news from social media. As there is a significant increase in social media users, news on social media tends to travel faster and easier than traditional news sources. However, not all the news disseminated on social media are accurate and some of them came from the unverified source.

The huge spread of false news brings negative impact to individual and society. Furthermore, fake news can break the genuineness balance of the news ecosystem. For instance, during the U.S. 2016 presidential election, the most popular fake news was widely spread on social media like Facebook and Twitter compared to the most popular authentic news [2]. Also, since fake news is made to influence people's view, it purposely convinces readers to accept false information. Nevertheless, fake news makes readers confused and this will indirectly change the way they respond to real news.

There are some existing manual fact-checking websites, also known as traditional fact-checking websites, to allow users to identify the authenticity of a news. The example of the fact-checking websites are PolitiFact [3], The Washington Post Face Checker [4], FactCheck [5], Snopes [6], TruthOrFiction [7] and HoaxSlayer [8]. These websites provide ground-truth for identifying the authenticity of a news. Although the fact-checking websites are easy to manage and have higher accurate results, they cannot scale with the large volume and they are slow in coping with fast spread of online news that are increased vastly day by day.

To address scalability issue, automated fact-checking have been advanced. There are three core elements of automated fact-checking, which are identification, verification and correction [9]. Automated fact-checking focus on one or more of the three overlapping objectives: to find wrong and questionable claims propagating on online social media; to verify and identify the claims; and to deliver the corrections across social media. With automatic capability, fact-checkers can respond quickly to the misinformation or fake news. Therefore, automated fact-checking are useful to scale with the high volume of news created on social media nowadays.

However, existing approaches for automated fact-checking have their own limitations because they lack an all-inclusive dataset with derived multi-dimension information for detecting fake news characteristics to achieve higher accuracy rate of machine learning classification model in detecting fake news. Though most of the limitations of existing datasets have been addressed in FakeNewsNet dataset [18], we argue that existing dataset attributes can be further derived and transformed for more accurate classification model performance results. To fill this gap, we performed analysis, derivation and transformation on social media Twitter's data to identify additional derived and significant attributes that influence the accuracy of machine learning methods to detect fake news using data mining approach. In this paper, we present the derived additional Tweets' attributes compared to existing dataset and identified the significant attributes. Additionally, we also show the application architecture functional components that systematically automate the classification of an online news.

This paper is structured as follows: section II gives the background knowledge of the related studies; section III explains the setting of our research methodology using data mining process approach; section IV shows the performance measurement and results of our news classification model to detect fake news, together with our discussion based on the results finding; section V concludes our research work discussed in this paper.

II. Literature Review

A. Definitions and Characteristics of Fake News

Fake news such as news, stories, or hoaxes created to mislead or misguide the readers. These news aim to manipulate society's perspectives on certain issues, either economically, socially, or politically. Fake news often raises hesitation, doubt and it creates a rather judgmental society with extreme mind set. Therefore, although the information is false, most of the audiences will still believe the "news" as it seems true [3].

Social media for news consumption is a double-edged sword. Nowadays, social media has become the most popular platform for people to widespread fake news because it is very cheap and easy to access [1]. Therefore, false information can be created and spread easily through social media and this false news will deliberately mislead or misinform readers who consume daily news from social media. Since fake news is made to influence people's views, it will potentially bring negative impacts to not only individual but also society especially during political events. According to [10], there's a huge amount of fake news spread on social media like Facebook and WhatsApp that brought confusion to society and caused political chaos [11].

The main characteristics of online fake news can be categorised into two main streams:

1) Fake News on Tranditional Media: Traditional media refers to newspaper, radio, TV, etc. When someone came across a piece of news, it is rather difficult to determine whether the news is genuine as intrinsically, everyone tends to believe that their perception is always true. Therefore, journalists tend to target this 'first-hand perception' without checking the authenticity of it with the motive to attract the reader's attention. Moreover, correcting mis-perceived information generally takes a longer time than transferring real news from scratch to people [12]. Another trait of fake news in traditional media is social acceptance. Readers mostly believe in what they have perceived to be the truth although they had read news via different sources. In addition, this creates a loop in their mind which allows them to continue accepting and believing all the future incoming information in relation to the piece of news.

2) Fake News on Social Media: Social Media refers to social communication platforms such as Facebook, Twitter, Instagram, and etc. One of the many ways for fake news to be spread across social media is to create a malicious account. It is because creating malicious accounts like social bots and trolls on social media is low cost. Those malicious accounts are created to spread fake news on social media to mislead readers [2] [11]. In addition, social platforms also promote 'Echo Chamber Effect'. This happened when there are naive social media users follow famous public influencers such as well-known celebrities and subsequently get affected by the words and information conveyed by these influencers due to the blind admiration they have for these influencers. For example, users who are not biased receives less attention compared to partisan users [13].

B. Existing Fake News Datasets

As social platforms play a substantial role in spreading fake news, it is extremely important to develop precautious apparatus to detect fake news on social media to inform such fake news to online users. Therefore, it is critical for all social media to develop a large-scale dataset with multi-dimension attributes in the context of social media platforms, which potentially provide information as signals upon detecting fake news and to be used for research purposes. According to prior studies, there are several related datasets created for the purpose as shown in Table I.

TABLE I. EXSITING FAKE NEWS DATASETS

Dataset	**Description**
BuzzFeed News [14]	All-inclusive sample news released on Facebook almost a week near to the United States election in 2016 from 19th September – 23rd September and 26th, 27th September. Journalists from BuzzFeed checked for every linked articles and posts. Overall, it consists of 1,627 articles 836 mainstream, 545 right-wing and 356 left-wing articles.
LIAR [15]	The dataset composed of 12.8k of human label short statements which are gathered from Politifact [3]. All of the brief statements are classified into 6 categories vary from totally false to totally true like pants on fire, false, barely-true, half-true, mostly true and true.
CREDBANK [16]	The large-sized crowd-sourced dataset contains around 60 million of tweets which are linked to over 1000 news events that cover from October 2015.
BuzzFace [17]	The news is collected by extending the dataset from BuzzFeed with opinions related to news articles on Facebook. It consists of 1.7 million comments discussing news content.
FacebookHoax [18]	Contains information that range from scientific news, political news to conspiracy and fan pages. Information collected for the dataset utilizes an API that originates from Facebook (Facebook graph API). This dataset has 15,500 posts from 32 pages with more than 2,300,000 likes.
BS Detector [19]	A browser extension analyzes the reliability and authenticity of news by actively collecting and comparing news from multiple different sources. It searches all the links on a given webpage for references to unreliable sources by cross comparing it against a manually compiled lists of domains.
FakeNewsNet [20]	This dataset contains multi-dimension information from news content, social context and spatiotemporal information which are collected from two domains, i.e. political and entertainment sources.

Comparing with the existing datasets, FakeNewsNet is considered the most suitable dataset to be used as the base for our research work to further enhance the dataset because comparatively FakeNewsNet includes more multi-dimension information from news content, social context and spatiotemporal information. Therefore, we chose FakeNewsNet repository as the base to further enhance the dataset. Our enhanced dataset is then used for our machine learning methods' training dataset as it provides all possible features of interests compared to others as shown in the comparison Table II derived from [18]. News content obtained in FakeNewsNet dataset is collected from two fact-checking websites, i.e. PolitiFact [3] and GossipCop [21]. For the social context, the user engagement related to both fake and real news are collected by using Twitter's Advanced Search API. The spatiotemporal information has spatial and temporal data. In addition, the spatial data is obtained by collecting the location particularly supplied in the user's twitter profiles while the temporal data obtained by recording the timestamps of user engagements. There are several samples dataset files in FakeNewsNet repository in which each of the files contains fake news and real news samples from PolitiFact and GossipCop. Each of the sample files has four attributes which are `id`, `url`, `title` and `tweet_ids` [22]. The attributes of `id`, `url`, `title` and `tweet_ids` represent a tweet's unique id, url given for the news in a tweet property, title of the online news, and a list of Tweet ids of tweets sharing the news respectively.

TABLE II. COMPARISON OF FAKENEWSNET WITH OTHER DATASETS

Features / Datasets	News Content		Social Context				Spatio-temporal Information	
	Linguistic	*Visual*	*User*	*Post*	*Response*	*Network*	*Spatial*	*Temporal*
BuzzFeedNews	√							
LIAR	√							
CREDBANK	√		√	√			√	√
BuzzFace	√			√	√			√
FacebookHoax	√		√	√	√			
BS Detector	√							
FakeNewsNet	√	√	√	√	√	√	√	√

C. Machine Learning Algorithms for Classification

The concept of classification in machine learning is focussed on building a model that separates data into distinct classes, for example, "real" or "fake" news in the context of this paper. Machine learning classification is a form of supervised learning. This model is built by inputting a set of training data for which the classes are pre-categorised (i.e. pre-labelled as "real" or fake" news) in order for the algorithm to learn from. The model is then used by inputting a different dataset (i.e. commonly called validation dataset) for which the classes are withdrawn, letting the model to predict their class value based on what it has learned from the training set.

There are several well-known algorithms for classification machine learning including Decision Tree (DT), Naïve Bayes, Support Vector Machines (SVM) and Logistic Regression (LR) as this type of algorithms require explicit class labelling for training the model for classification. Table III below summarises the methods:

TABLE III. SUMMARY OF ALGORITHMS FOR MACHINE LEARNING CLASSIFICAITON

Classification Methods	Description
Decision tree (DT) [23][24]	A decision tree makes rule-based decision on important attributes for classification. A decision tree consists of three components, root node, branches and leaf nodes. Decision tree builds in the form of a tree structure. It utilizes an if-then rule set which is mutually exclusive and exhaustive for classification. The rules are learned sequentially using the training data one at a time. Each time a rule is learned, the observations/rows of a training dataset covered by the rules are removed. This process is continued on the dataset until meeting a termination condition. The tree is constructed in a top-down recursive divide-and-conquer approach.
Naïve Bayes (NB) [23][24]	Naive Bayes is a probabilistic classifier based on the Bayes theorem under an assumption that the attributes in the dataset are conditionally independent. It classifies binary or multi-class classification problems. To get the posterior probability, Bayes theorem has provided a formula: $P(c\|x)= P(x\|c)P(c)/P(x)$ in which $P(x\|c)$ is the probability of predictor given class, $P(c)$ is the probability of class, $P(x)$ is the probability of predictor.
Support Vector Machines (SVM) [23][24]	It presents organization tasks by building a hyperplane in a multidimensional space that divides cases of distinct class labels.
Logistic Regression (LR) [23][24]	The goal of logistic regression is to find the best fitting model to describe the relationship between the dichotomous characteristic of interest (dependent attribute) and a set of independent attributes as predictors. Additionally, logistic regression is to identify how the probability of an event is affected by dependent attribute(s). The equation is P= 1/ (1+e-Y), Y is the equation of linear regression.
Random Forest (RF) [23][24]	Random forests or random decision forests are an ensemble learning method, that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees depending on the purpose of the prediction.

D. Fake News Checking and Classification Applications

Fact-checking is the process by comparing the claims of news with known facts to analyse whether a news is real or fake. There are two types of fact-checking, manual fact-checking and automatic fact-checking.

1) Manual Fact-Checking: Manual fact-checking is handled by a group of domain experts to verify the news content. Today, many fact-checking websites have been developed for easier management and accessibility of the results. Table IV shows the details of existing fact-checking websites.

TABLE IV. EXISITNG FACT-CHECKING WEBSITES

Website	Topics Covered	Content Analyzed	Assessment Labels
FactCheck [5]	Politics of the United States	TV advertisement, debates, speeches, interviews, and news	True; No evidence; False
PolitiFact [3]	Politics of the United States	Statements	True; Mostly true; Half true; Mostly false; False; Pants on fire
Snopes [6]	Politics and other issues such as social and topical	News articles and videos	True; Mostly true; Mixture; Mostly false; False; Unproven; Outdated; Miscaptioned; Correct attribution; Misattributed; Scam; Legend
TruthOrFiction [7]	Politics, religion, hoaxes, aviation, etc.	Email rumors	Truth; Fiction; etc.
HoaxSlayer [8]	Ambiguity	Articles and messages	Hoaxes, scams, malware, misleading, spams, etc.

The fact-checking websites in Table IV classify the message contents into true or false news. Though fact-checking websites are useful for readers to recognise true news, they do not scale with the high volume of fast spread online information on social media. Therefore, automatic fact-checking techniques are developed to address this scalability problem.

2) *Automated Fact-Checking:* Automated Fact-Checking aims to address three elements – identification, verification, and correction [25]. adjust the template as follows.

a) *Identification:* Monitor all media and political sources and identifying factual statements.

b) *Verification:* Check against existing fact-checks and authoritative sources.

c) *Correction:* Flagging repeated falsehoods, provide contextual data and publish new fact-checks.

Table V shows the existing automated fact-checking that used machine learning approaches and their reported accuracy of classification model performance.

TABLE V. EXISITNG AUTOMATED FACT-CHECKING APPLICATIONS

Application	**Dataset used**	**Machine Learning method(s)**	**Reported Accuracy**
DeFactoNLP [26]	FEVER	RF	F1-score 42.77%
Stance Detection in Fake News [27]	FNC-1	NN	Macro F1 59.60%
FakeNewsNet studies [20]	FakeNews Net	SVM, LR, NB, Social Article fusion (SRF) and Convolutional Neural Network (CNN)	Highest Accuracy: 72.3% using CNN with Politifact dataset; Highest Recall and F1 using SRF GossipCop dataset: 88.2% and 71.7% respectively with
Fake News Identification on Twitter with Hybrid CNN and RNN Models [28]	PHEME dataset of rumors and non-rumors	Recurrent Neural Network (RNN) Convolutional Neural Network (CNN)	Accuracy – 82%
Identifying Fake News and Fake Users on Twitter [29]	Not specified	Naïve Bayes SVM	Not specified

To summarise the exiting automated fact-checking approaches, overall their accuracy performance of classification models reaches 88.2% the highest regardless of datasets used on various classification algorithms accept work in [29] did not specify the model performance measurement and result.

III. RESEARCH METHODOLOGY

We adopted data mining process approach and focussed on the phases of data understanding, data pre-processing/transformation, data modelling and evaluation. For data understanding, we firstly analysed the FakeNewsNet repository that only have 4 attributes which are `id`, `URL`, `title`, and `tweet_ids` (i.e. a list of tweet ids of tweets sharing the news which separated by tabs). All these four attributes can be obtained directed from a Tweet's properties using relevant Twitter API for data crawling. We further crawled more attributes from Twitter as we consider the dataset can be enhanced by extracting more attributes related to the tweet ids and add them into the combined dataset. Some attributes that can be retrieved are a total count of tweet_ids, total favourite (`t_fav`) count of the `tweet_ids`, and total retweet (`t_retweet`) of the tweet_ids. During the pre-processing and transformation process, we developed an enhanced the dataset to capture Tweets' attributes. Table VI lists the enhanced, derived and transformed attributes we developed and used for classification modelling to detect fake news.

TABLE VI. ENHANCED TWEETS' ATTRIBUTES FOR CLASSIFICTION

Attribute	**Description**
`id`	Unique identifier for a tweet that contains the news.
`t_givenids`	This is a derived attribute from the value of attribue `tweet_ids` from a Tweet's properties, which contains total number of the `tweet_ids` of tweets sharing the news.
`p_availids`	This is a derived attribute from the value of attribute `tweet_ids` from a Tweet's properties, which contains percentage of total number of the available tweet_ids of tweets sharing the news.
`t_retweet`	This attribute is obtained from a Tweet's properties, indicates the total number of retweets of the available `tweet_ids` of tweets sharing the news.
`t_fav`	This attribute is obtained from a Tweet's properties, represents the total number of favourite of the available tweet_ids of tweets sharing the news.
`url_protocol`	This is a derived attribute from the value of attribute `url` from a Tweet's properties, denotes the protocol specified in the URL given for the news in a tweet property.
`url_level`	This is a derived attribute from the value of attribute `url` from a Tweet's properties, denotes the number of directories within the URL given for the news in a tweet property.
`url_www`	This is a derived attribute from the value of attribute `url` from a Tweet's properties, denotes if the URL given for the news in a tweet property contains "www".
`title_words`	This is a derived attribute from the value of attribute `title` from a Tweet's properties, represents The number of words in the title of a news.
`status`	Real or fake news labelled adopted from PolitiFact [3] and GossipCop [19].

Figure 1 below diagrammatically depicts the web-based application architecture of our approach to detect fake news using machine learning classification by adopting data mining process approach. The main functional components in the architecture are the fake news detection application functions (contains server main program and frontend user interface), news classifier, data transformer and data crawler. A real-time web application server and a user interface are developed. The user interface is used to capture either the title of the news or the URL in a tweet. The crawler algorithm then goes through Twitter API and gets the properties of the tweet from Twitter.

The enhanced Twitter's attributes are used to train the news classification model and cross validate the model performance. Several classification algorithms and test parameters setting were used for performance comparison. Before training the model, the crawled data from Twitter is passed to the data transformation algorithm (i.e. data transformer) to perform the following data preparation tasks:

- Performs summation to derive total values for `t_givenids` and `p_availids` attributes from the value of attribue `tweet_ids;`

- Performs truncation on `url` attribute to derive the values of `url_protocol`, `url_level` and `url_www`;
- Performs words count on the `title` attribute to derive the value of `title_words`;
- Performs logarithm on `t_givenids`, `p_availids`, `t_retweet` and `t_fav` attributes' values to reduce scaling problem due to high skewness before applying the classification model for predicting if the inputted news is real or fake.

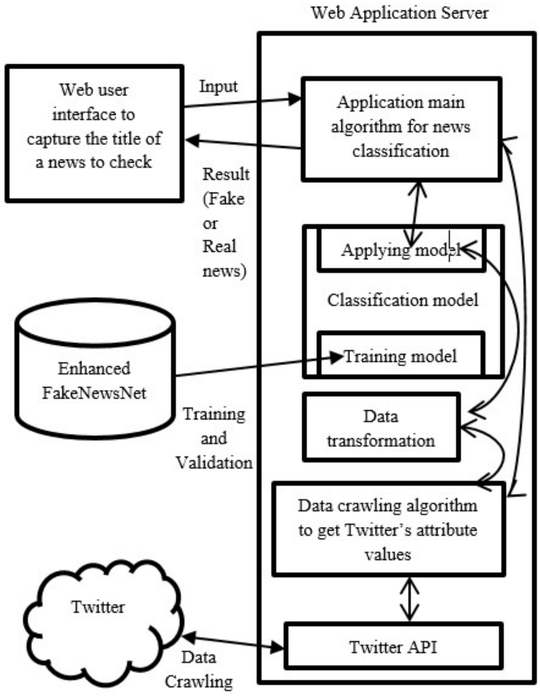

Fig. 1. Architecture of Our News Classification Application

After data preparation, data transformer passed the transformed attributes' values to the classification model for training and cross validation to assess the performance.

For applying the model to classify a news for detecting fake news, the data transformer will perform the data preparation tasks on the input data before sending them for prediction. Finally, the predicted result is sent back to the user interface via the application server main algorithm.

IV. Results and Discussion

By using the enhanced Tweets' attributes as listed in Table VI for training and validating the news classification algorithms, we achieved higher accuracy and recall rates compared to existing automated fact-checking applications presented in Table V. We trained the classification model using various machine learning algorithms including SVM, Naïve Bayes (NB), Logistic Regression, Decision Tree and Random Forest (RF). Additionally, we attempted different parameter settings during the training process. Based on the cross validation results, we found that Naïve Bayes (NB) and Random Forest (RF) methods perform the best among all the methods with stratified data partition ratio of 60:40 on 23,206 on news dataset for training and cross validation respectively.

We observed that a Tweet's property can be categorised into two aspects:

i) Tweet-specific attributes (i.e. `t_givenids`, `p_availids`, `t_retweet` and `t_fav`);

ii) News-specific attributes (i.e. `url_protocol`, `url_level`, `url_www` and `title_words`);

which both of them are contained in a tweet as properties.

Table VII presents the performance measurement and results of the classification models we experimented with different aspects (Tweet-specific, News-specific and both) of attributes. Accuracy denotes a ratio of correctly predicted news types to the total observations while recall is the ratio of correctly predicted observations in all actual Fake news observations. F1 score is an overall measure of a model's accuracy that combines both precision and recall. A good F1 score in this context implies the model correctly identifying fake news and not disturbed by false alarms of real news.

TABLE VII. PEROFRMANCE MEASUREMENT AND RESULTS

Aspect	Accuracy	Recall (Fake news)	F1 score
Tweet-specific attributes (Best method: RF)	84.0%	55.0%	61.6%
News-specific attributes (Best method: DT)	98.3%	94.5%	93.8%
Attributes from both aspects (Best method: RF)	98.6%	95.4%	97.2%

It is found that the model using RF algorithm with all input attributes including both Tweet-specific and news-specific achieve the best performance result, i.e. 98.6% accuracy, 95.4% recall(fake) and 97.2% F1 score. The results based on Loss Reduction Variable Importance showed the following important sequence from highest to lowest: 1) `url_protocol`; 2) `log_t_givenids`; 3) `log_t_fav`; 4) `log_p_availaids`; 5) `news_url_www`; 6) `log_t_reweet`; 7) `url_levels`; and 8) `title_words`.

Due to the complexity of RF algorithm in model interpretation, we choose to use the second highest accuracy model i.e. using Decision Tree (DT) algorithm, which shows merely small variance of 0.3% compared to the RF algorithm, i.e. the DT produces model performance with accuracy 98.3%, recall(fake) 94.51%, and F1 93.82%. The rationale for this choice is on the basis of a modern codification of the wildly known age old principle Occam's razor: the simplest explanation is the most likely one to be true. Therefore, for predicting fake news using the DT algorithm, the least complex and having the highest impurity difference between classes rule is as follow:

```
if url_protocol IS ONE OF: EMPTY, NOTSPECIFY
then
        Tree Node Identifier   = 3
        Number of Observations = 3840
        Predicted: Status=Real = 0.01
        Predicted: Status=Fake = 0.99
```

We attempted to investigate from Tweet-specif and news-specific aspects because news-specific attribute values can potentially be manipulated after referring to our model performance results in this paper by intentionally appending values of `url_protocol` with "`http`" or "`https`" (i.e. to avoid '`EMPTY`' and '`NOTSPECIFY`') as this attribute is found significantly the most important variable for predicting a fake news. Despite this possibility, our proposed enhanced attributes and approach is still performed better than the existing approaches without using the news-specific attributes. In this case, the least complex and having the highest impurity difference between classes rule is as follow:

```
 if Transformed: T_GivenIDs < 2.602 or MISSING
AND Transformed: T_Fav >= 0.34657 then
       Tree Node Identifier   = 10
       Number of Observations = 1487
       Predicted: Status=Real = 0.14
       Predicted: Status=Fake = 0.86
```

Overall, the important attributes as input variables significantly influence the fake news prediction are `url_protocol`, `t_givenids`, `t_fav` and `p_availids`. These attributes are the derived values we identified through our research work explained in section III as our main contribution in detecting online fake news.

V. CONCLUSION

In this paper, we propose the enhanced Tweets' attributes listed in Table VI for training and validating the news classification algorithms. The online news classification model performance results showed that we achieved far higher accuracy compared to existing applications. This paper presents the mechanisms and application architecture for realising online news classification application system. This research has its limitations due to the constraints set by Twitter and it API. At this stage, the crawling time from Twitter requires substantial waiting time and additionally, only tweets that are set as 'public' can be considered and included in this study.

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