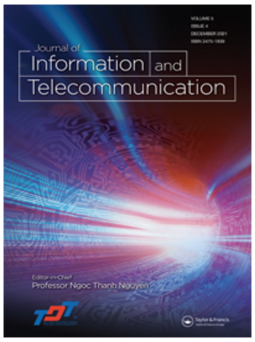

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Content-based fake news classification through modified voting ensemble

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ABSTRACT

Credibility is a crucial element for journalism. As fake news impacts credibility, it affects the general public, policymakers, decision-makers, and the journalistic environment. However, current research on fake news using content-based approaches focuses majorly on one or two dimensions of stylometrics, semantic and linguistic processes, but not on these three simultaneously. Considering that content-based detection of fake news would benefit from a multidimensional approach because of their inherent characteristics, we proposed a method that uses all of these dimensions to improve classification accuracy, using a voting ensemble designed in an ensemble classifier form. The results show that the multidimensional voting classifier has produced more accurate results than its peers while being more sensitive to distinguish between true and false news when using randomized data.

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KEYWORDS

Fake news; classification; style analysis; stylometrics; content-based

1. Introduction

Journalism is the activity to gather, assess and distribute information about key persons and institutions of public interest. As such, the concept of news relates intrinsically to democracy, society values, and individual rights. Moreover, it results in the constant scrutiny of these newsworthy subjects from their societal group.

Consumers of journalistic content have, nowadays, access to instant information anytime, anywhere. People consume news from online and offline sources, such as newspapers, magazines, television, and their online counterparts, including social media and other news outlets. The information consumed spreads across their circles of influence, echoing their beliefs and reinforcing them, objectively impacting the perception of their peers who share similar attitudes, values, and concerns.

From a perspective of newsworthiness, fake news is false information verifiable from other news sources. Furthermore, fake news can be intentionally deceptive (active deception) or not (passive deception). Active deception relies on the quality of deceiving the reader into believing that such information is accurate. In contrast, passive deception relies on interpreting the information from the reader while positively providing linguistic, factual, and visual cues that this given news is false, mainly aimed at entertaining, rather than deceiving, the reader.

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Consequently, searching for solutions to prevent the spread of fake news and its damaging effects on public opinion, democracy, and society is an excellent topic of interest for the general public, policymakers, decision-makers, and democratic institutions.

Fake news has three main distinguishable characteristics: authenticity (or lack of), intention, and if it is newsworthy (Zhou & Zafarani, 2020). Because they try to convince the reader of their content, create engaging stories compelling to trust the news source and manipulate the truth by intentionally falsifying facts or altering their original meaning through misleading factual connections, fake news presents a unique style that can be used for automatic detection.

Finally, the consequences of fake news consumption go beyond the pure informational aspects and reach practical consequences: impacting democratic elections (Rapoza, 2021), the possibility of affecting the stock market through media manipulation (Chambers, 2021), or even the simple differentiation between fiction and fact. Thus, responsible consumption of news through proper provenance of legitimate information is a significant challenge that fake news classification problems aim to resolve.

Style analysis is a content-based method that utilizes specific written text characteristics to determine whether a text belongs to a specific class. As a classification problem, fake news utilizes the style analysis to obtain properties from the text, such as readability scores, n-gram frequency, and polarity, to create a set of features on which a machine learning algorithm can utilize as input for assigning one or more class labels belonging to this text.

The research on classification using style analysis had some progress and limitations– most of the research utilized content-based, context-based, or hybrid approaches for detection. Researchers reported good accuracy results from content-based methods such as word classification model, rhetorical structure theory, and style assessment to detect fake news. Other studies focused on context-based features such as user reach, engagement, and social network spreading patterns. Other authors argue, based on evidence, that content-based methods for fake news detection should be utilized in conjunction with context-based features for an improved detection rate.

Most researchers worked on one or another aspect of the content-based feature classification, such as stylometric, linguistic, or semantic (or a combination of stylometric/semantic, or stylometric/linguistic) approaches. The limitation of the current research on the topic is that, until recently, there was no unified framework for studies of fake news classification problems. A proposed study framework for research (Zhou & Zafarani, 2020) includes a multidisciplinary approach considering other theories in linguistics, sociology, psychology, and other humanistic sciences. Also noteworthy is that it is challenging to quantify certain textual features without considering these former disciplines. Current research on content-based methods rarely takes into consideration the specific writing style of the journalistic text. Their focus on social networks and other sources of information might impair the quality of the data and, by its turn, the accuracy and sensitivity of the detection model.

1.1. Fake and real news examples

To illustrate the differentiating patterns between real and false news, we have selected two samples from our dataset. Note: the author has shortened the article's content.

1.1.1. Fake news example

- Source: shorturl.at/cwWZ6
- Date: 04/01/2020 00:00:00
- Article Title: Michelle Obama Officially Announces Her Candidacy for President
- Author: Bob The Empire News Potato
- Publisher: Empire News
- Article Body: 'PHILADELPHIA, PA – Michelle Obama, the wife of former president Barack Obama, has announced that she will be running for president in the 2020 election. 'I know I'm a lot later than most people, but to be honest, there's no reason to start running 2 years before the election,' said Michelle Obama from the family home in Philadelphia. 'It's much easier to wait until the "little people" drop out, and we can see what's left of the field. At this point, the field is pretty bland, so I'm going to come in and mow it down.' Obama, who was highly involved in education and children's health during her husband's two terms, says that she plans to continue her advocacy for the young people of America. 'Kids are our future, and education and health are the most important things for the next generation,' said Obama. 'I have no stance at all on foreign policy, taxes, abortion, religion, or literally anything else. My platform is the children, and between that and my name, I think I have a great shot of becoming the Democratic nominee, and our next president.'

1.1.2. Real news example

- Source: shorturl.at/qARU5
- Date: 21/05/2020 20:21:00
- Article Title: Michelle Obama is stepping into the 2020 election with a programme to boost voter turnout
- Author: Jada Yuan
- Publisher: The Washington Post
- Article Body: 'As the 2020 presidential campaign heated up this year, and candidates crisscrossed the country in a pre-pandemic world of handshakes and rallies that seems almost unimaginable now, one question loomed: Where were the Obamas in all this? On Thursday, Michelle Obama took her first concrete step toward being a factor in the 2020 election. Her nonpartisan voting initiative, When We All Vote, which she founded months before the 2018 midterms, announced a coalition of 31 mayors across the country who will be brainstorming and sharing lessons and practices about how to increase voter registration and civic engagement. […] When he was asked earlier this year whether he'd ask Michelle Obama to be his vice president, Biden said he'd choose her in a 'heartbeat,' but, 'I don't think she has any desire to live in the White House again.' Jarrett emphatically agreed that Obama will not be running for office. […] When they met in the summer of 1991, Jarrett said, Obama was still practicing law 'and what was clear to me then is that she has a deep passion for public service. And what became clearer to me later is that does not include politics. She loves the service, not the politics.' Civic engagement like these

voting initiatives 'and being a force for good is her life's work,' said Jarrett, and one that will continue long-term. 'But she will not run for political office. Of that I am confident.'

1.2. Differentiating patterns

We understand that content-based detection can be made using three significant dimensions: stylometric, syntactic, and semantic. Some stylometric features are the average number of characters, words, punctuations per sentence, and quantity of sentences, words, and unique words. Syntactic features can be: affect words, cause, certainty, discrepancies in the text, self-references (amount of first persons in the text, both singular and plural), interrogatives, non-fluencies, numbers, past focus, quantifiers, other references (second or third persons, both singular and plural), and the use of tentative language. Semantic features, by its turn, are anger, anxiety, feelings, overall cognitive processes, polarity, and informality (netspeak, swear words). From a content-based perspective, differentiating patterns can be obtained from both the title and the body of the articles. These distinctive patterns can be observed in Table 1.

There are significant differences between real and false news concerning content-based features. At the title of the article, real news utilizes shorter titles, more commas, and numbers – implying more factuality; fake news utilizes emphatic wording, shown by increased usage of exclamation marks, swear words, other references (1st person plural and third-person singular), visual references, slightly more prone to emotional tones and higher polarity (both positive and negative). At the article body, real news utilizes a higher amount of quotation marks and language focus on the past and significantly uses fewer self-references (first person singular) and other references (third-person plural) than fake news. False news, by its turn, utilizes at the body of the article significantly higher amounts of informality, including netspeak, tentative language, higher amount of colons, and interrogation marks. Fake news can be distinguished from real news by its intrinsic writing characteristics and semantic and linguistic properties. Therefore, most methodologies incorporate, to some degree, the usage of one or more dimensions to compute classifications for labelling fake news through a binary classifier.

Current research approaches the problem of content-based classification by using machine learning (notably Support Vector Machines (SVM), Random Forest, Decision Trees, Ensemble of Classifiers), deep learning (Recurrent Neural Networks and Convolutional Neural Networks, or a mixed approach), or other approaches (Rhetorical Structure

Table 1. Patterns of differentiation between the article title and article body for fake news detection.

	Article part	
Dimension	Title	Body
Stylometric	average amount of characters or words per sentence; quantity of commas or exclamation marks or semicolons)	Amount of words, overall punctuation marks, colons, periods, quotation marks, unique words.
Syntactic	Other references (3rd person singular), affect words, certainty, self-reference (1st person plural), numbers	Cause, discrepancies, self-reference (1st person singular), interrogatives, past focus, tentativeness, other references (3rd person plural)
Semantic	Anxiety, overall cognitive processes, feelings, polarity, visual references, informality (swear words)	Informality (netspeak), sadness.

Theory, Vector Space Model, anomaly detection using Factor Analysis of Mixed Data, crowdsourcing, and computational-oriented fact-checking). However, some of these approaches, albeit used successfully, might not present a complete solution for the content-based detection of fake news: they might not address specifically the intrinsic style of news articles, does not differentiate between social network posts and their sources of information, and do not consider the intentions of the news article, if actively deceitful or not.

As such, we proposed a method for detecting fake news utilizing an ensemble of classifiers, with engineered features obtained from stylometric, syntactic, and semantic information, and training the model by using a dataset crafted with only journalistic texts, both from true and false news sources, annotated with their intentions (fake news, real news, satirical text, or fact check). The idea behind this process is that, for an improved detection rate, it was imperative to train the model with actual examples of false and accurate news, from which we could extract relevant content-based features, produce a model and then utilize it within our ensemble of classifiers to detect actual or false news from a variety of datasets, including our own.

1.3. Structure of the paper

We explain the main processes and ideas supporting this research (Section 2) by briefly revising the theories behind fake news detection using style analysis (Section 2.1) and describing the resulting research problem (Section 2.3). Further, we detail the methodology (Section 2.3) consisting of how did we prepare the fake news dataset (Section 2.3.1), the model design (Section 2.3.2) and the process utilized to produce the results (Section 2.3.3). Finally, we present our results (Section 3), giving a brief discussion about the key findings (Section 4) and present our conclusions (Section 5).

2. Materials and methods

2.1. Literature summary

Considering that fake news is not a new topic, several studies propose structured approaches for their study, including frameworks, methodologies, and datasets (Bondielli & Marcelloni, 2019; Zhou & Zafarani, 2020). However, with the specifics of content-based strategies for their detection and classification (mainly considered a classical method, previously utilized for spam detection in e-mail and webpages), not so many articles have been published, with specific regards to stylometric, semantic, and syntactic features.

Potthast et al. (2018) analyses the writing style of hyperpartisan news and verifies its connections to fake news. Their study utilizes style analysis to assess whether certain news is true or false; they obtained data from BuzzFeed, building a corpus of news from nine publishers, and utilized it to predict the veracity and satire of the content. Though they successfully distinguished satire from other news sources, they did not claim to have successfully resolved fake news using the content-based method.

Nguyen et al. (2019) performs a similar strategy as Potthast et al. (2018) but utilizes n-grams of words, n-grams of parts of speech, and n-grams of characters as their methodology for content-based analysis.

Yang et al. (2017) utilizes style analysis to differentiate between satirical and authentic news. The authors proposed a 4-level hierarchical model containing the character, word, paragraph, and document attributes to compute linguistic, stylistic, structural features, and readability scores, using SVM for classification. The authors found that satirical news has higher readability scores and distinguished between satirical and authentic news.

Della Vedova et al. (2018) utilizes both content-based and context-based strategies to assess whether a given news piece is true or false. They have proposed a machine learning model utilizing three datasets, consisting of Facebook posts and data extracted from BuzzFeed and PolitiFact websites, computed features for a vector of TF-IDF (Term Frequency and Inverse Document Frequency) frequencies, and the number of likes that a given page has obtained from Facebook for computing context-based features. Their experiments show that they could distinguish between real and false news with a high degree of accuracy.

Samonte (2018) aims at creating a detection model for fake news using polarity analysis. The authors extracted editorial articles from popular English-language news websites and manually annotated them by the authors. They have utilized n-grams to compute content-based features processed by a SVM, K-Nearest Neighbor (KNN), and Naive Bayes classifiers and found that KNN classifiers have better prediction rates for fake news detection polarity analysis.

Collins et al. (2020a) produces a synthesis of tendencies for fighting fake news by analysing its detection models considering its different types. The authors describe that fake news can be present in clickbait, propaganda, satire and parody, hoaxes, and others (mainly name-theft, framing, and journalistic deception).

Collins et al. (2020b) presents an overview of the various models for fake news detection, including machine learning, Natural Language Processing (NLP), expert fact-checking, and hybrid expert machines.

Tran et al. (2020) utilizes context-based detection techniques for fake news from Twitter posts. The authors obtain context-based information regarding user account profiles to infer user's credibility, then collect the user's interactions to obtain user opinion and exhortation levels and verify the authenticity of the news through a SVM model with Radial Basis Function (RBF).

Phan et al. (2020) although not primarily focused on fake news detection, it utilizes content-based sentiment analysis to analyse Tweeter posts for producing an improved feature ensemble and Convolutional Neural Network (CNN). Their method consists of obtaining the tweet post and its metadata to extract linguistic features transformed into vectors and further determine its sentiment polarity. Maleszka and Nguyen (2015) utilizes an approach of collective intelligence for the detection of fake news.

Some limitations also are found in these studies. Potthast et al. (2018) and Nguyen et al. (2019) uses complexity, quantity, and readability features for content-based detection. Yang et al. (2017) focuses on the detection of satire from differentiating false news from accurate news, and it does not consider the title of the article within its classification features. Saldanha et al. (2020, december) uses a data source of news coming from Twitter and does not consider the base structure of the news article, including title and body. Saldanha et al. (2020, december) utilizes social media posts from Facebook and does not rely exclusively on a content-based strategy for detection. Samonte (2018) utilizes only the article body and focuses their detection approach solely on the quantity and sentiment attributes.

These works rarely addressed the multiple dimensions of content-based feature extraction and did not contemplate the intentions behind the articles. News sources selection primarily does not consider sources that might present either factual, false, or mixed content veracity. Our approach aims at resolving these issues.

2.2. Research problem

This research aims at classifying fake news using content-based analysis. Concerning content-based properties, news articles present stylometric, semantic, and syntactic features. News articles can be trustworthy or not, and, concerning their intentions, untrustworthy articles can actively untrustworthy (fake news) or passively deceitful (satirical news).

A voting ensemble is a type of classifier where several classifiers calculate the inputs, on which the final result takes into account each classifier's output. This research uses an adapted soft voting mechanism where, instead of adopting probabilities for the computation of the output, it utilizes a weighted mechanism based on accuracy and Cohen's Kappa. Accuracy determines the agreement between training and test data class outputs. Cohen's Kappa is another type of accuracy metric suited for situations where the class distribution is imbalanced. The vote weight output is, in our model, the highest value between the calculated accuracy and Cohen's Kappa score. The final voting ensemble output is the label matching the highest score between the count of all false votes weighted against the false vote weight output and all true votes weighted against the true vote weight output.

Current research problems are the non-usage of all three linguistic features (semantic, syntactic, and stylometric), not considering the unique aspects of the journalistic text and author intentions, and using diverse sources of articles when analysing and classifying fake news articles. Our research problem statement is: comparing journalistic articles originated from news outlets, both true and false, and using all three linguistic aspects for analysis, can we produce a more accurate model utilizing exclusively content-based stylometric analysis? We aim at answering it.

2.3. Methodology

2.3.1. Dataset preparation

We accessed Google Fact Check Explorer during the first twelve weeks of 2021 and selected the most recent fact checks. If the fact check pointed out to a fact check news website, we extracted the full article text and its metadata, stored it into a Microsoft Access database, and labelled it with 'fact check'. From this fact check article, we have obtained all referenced articles and, if they pointed out to a news source, we extracted both textual content and its metadata.

According to the information provided by the fact check article, each referred article was manually labelled either as 'real news', 'false news', or 'satire'. We considered only English language articles and discarded non-textual information (videos, images, audio recordings). After obtaining roughly 200 articles, we have proceeded to automate data extraction from news sources previously classified as unreliable, either manually labelling them as 'fake news' or 'satire', and repeated the same process for reliable sources, labelling them as real news. We utilized the resulting dataset with 714 articles as our primary source of data (referred henceforth as the 'main dataset').

We have utilized the 'ISOT Fake News Dataset', produced by ISOT (Information Security and Object Technology) department at the Univesity of Victoria, Canada (Ahmed et al., 2018, 2017; IMPACT, 2017) as our external dataset (referred henceforth as 'external dataset').

The 'main' and 'external' datasets had their features extracted by a data enrichment and then feature engineering process (see 'Figure 1: Dataset Preparation Process'). First, we run both datasets under the Linguistic Inquiry and Word Count (LIWC) tool, version 2015, (see Pennebaker et al., 2015) to extract linguistic features. We used the 'main dataset' as an input for a feature engineering tailored for each of our voting classifiers. We saved the enriched 'external dataset', the enriched 'main dataset', and its feature-engineered versions to utilize it at the voting ensemble process further.

A 'random dataset', for internal validation, is produced from the resulting output of the enriched 'main dataset' by replacing all numerical values with random numbers and all textual values with random characters.

2.3.2. Model design

Figure 2 ('Voting Ensemble Classifier for Fake News Detection') illustrates the overall workflow. The input module consists of the enriched dataset from the dataset preparation process. The enriched dataset contains the collected articles (including article body, title, author, publisher, class, and if it is authentic or not), and a set of computed features for the article body and title (stylometric: punctuation, readability, diversity; semantic: uncertainty, subjectivity, sentiment, analytical thinking, informality; syntactic: adverbs, verbs, nouns, adjectives, pronouns). We employ the records from this dataset and output them to each component within the 'voting classifier module.'

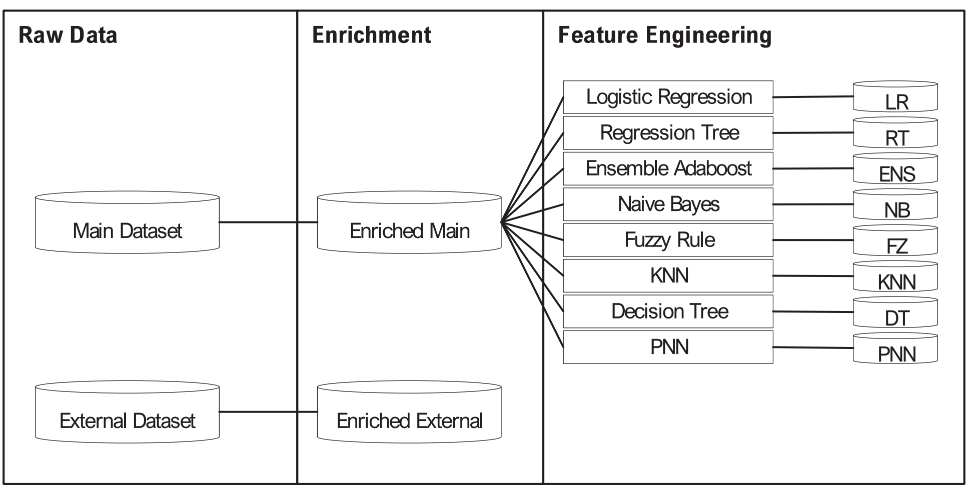

Figure 1. Dataset preparation process.

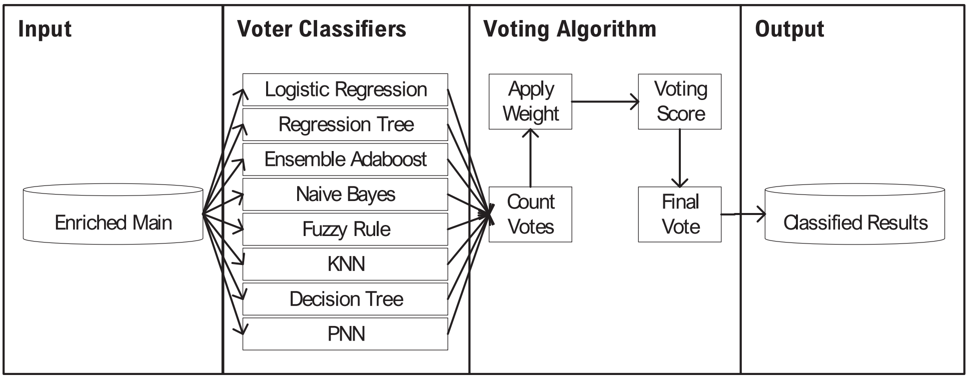

Figure 2. Voting ensemble classifier for fake news detection.

The 'voting classifier module' comprises classifiers that receive the input module's records and then output the classification and accuracy scores. The 'voting classifier module' consists of the data input stream, a predictor node (or a learner node plus a predictor node), and the scorer (which outputs the accuracy and Cohen's Kappa). It delivers its output to the data output stream.

Predictive Model Markup Language (PMML) is a file format available in KNIME for exchanging predictive models from a machine learning algorithm. It provides their reuse and overall stability, essential for our model across different source datasets. We produce this file as an output from the feature engineering step from the dataset preparation process (Figure 1).

Figure 3 ('Exporting Voter Model as PMML') shows the PMML model using the voting classifier module. The PMML Predictor node supports Logistic Regression, Regression Tree, Decision Tree, and Naive Bayes classifiers. Figure 4 ('Voter with PMML Model') illustrates the voter classifier using the PMML Predictor node, which outputs the content to a scorer node.

In the node classifiers not supporting PMML output, we used the native classifier's specific learning and predictor nodes for the non-supported PNN, Fuzzy Learner, Ensemble with Adaboost, and KNN classifiers. The process partitions the input stream into a training and a testing output stream, dismissing the testing output. The learning node receives the training output stream. It produces the model, which utilizes the input stream and the model from the learning node, as represented by Figure 5. It outputs the content to the scorer node.

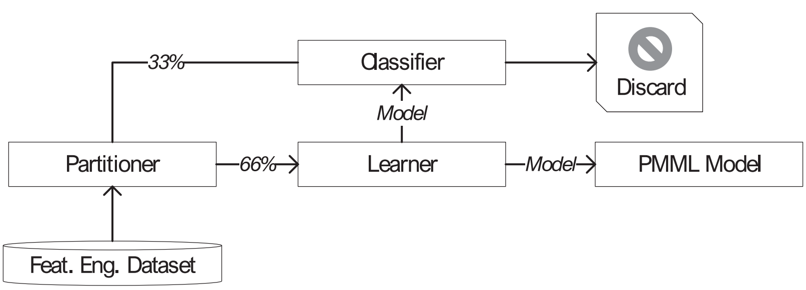

Figure 3. Exporting voter model as PMML.

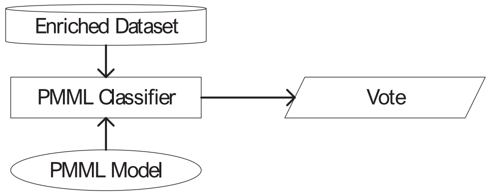

Figure 4. Voter with PMML Model.

The 'voting module' receives all the scorer nodes' outputs and consolidates them into a separate stream. The stream contains the data from the input module, plus the classification, accuracy, and Cohen's Kappa for each record and voter at the 'voter classifier module.' We obtain the following metrics:

- VT = Total amount of 'true votes.'
- VF = Total amount of 'false votes.'
- ATT = Sum of accuracy for 'true votes.'
- ATF = Sum of accuracy for 'false votes.'
- TKT = Sum of Cohen's Kappa for 'true votes.'
- TKF = Sum of Cohen's Kappa for 'false votes.'

The formula computes the 'true voting factor' (VFT):

$$VFT = VT * \max(ATT, TKT) \tag{1}$$

The formula computes the 'false voting factor' (VFF):

$$VFF = VF * \max(ATF, TKF) \tag{2}$$

Where:

- max(ATT, TKT) is the maximum value between ATT and TKT
- max(ATF, TKF) is the maximum value between ATF and TKF

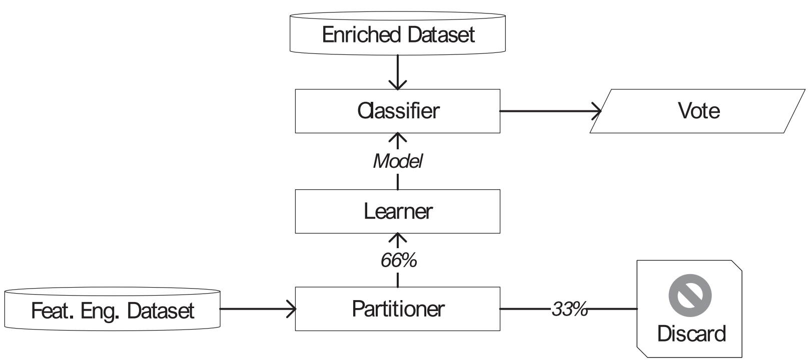

Figure 5. Voter without PMML Model.

Table 2. Accuracy statistics for evaluated datasets.

		Accuracy statistics		*F*-Measure	
Source Dataset	*n*[a]	Accuracy	Cohen's Kappa	False	True
Main	714	0.9635	0.9222	0.970	0.951
ISOT	44823	0.9555	0.9115	0.956	0.955
Random	714	0.6190	0.2199	0.373	0.726

Note: [a]Number of records in the dataset.

The criteria for the predicted output is:

- If VT = 0, then the result is false
- If VF = 0, then the result is true
- If VFT > VFF, then the result is true
- If VFF > VFF, then the result is false
- If VFT = VFF, then the result is false

Finally, the 'output module' produces a dataset with the classified results, including all the fields from the input module, and adding the class of the article as either 'real news' ('true') or 'fake news' ('false').

2.3.3. Experiment details

Data was collected initially using a Google Chrome 90.0.4430.85 running over Microsoft Windows 10 Professional on a Microsoft Surface 4 Pro laptop, Intel(R) Core (TM) i7-6650U CPU 2.20GHz, 16GB RAM, and 256 GB SSD disk. Data was stored using Microsoft Access for Office 365 into a Microsoft Access database; we imported SentiWordNet 3.0 into a Microsoft SQL Server 2019 Express instance, and stylometric features extracted using LIWC 2015 version 1.6.0 (June 26, 2019).

Data were analysed, and we developed all models using KNIME Analytics Platform version 4.3.2 and Python 3.8.5 (on Anaconda distribution version 4.9.2). Data were analysed using KNIME v. 4.3.2. We have used the Chi-Square statistical test for significance evaluation and ROC curves to evaluate its usefulness

3. Results

We collect the ROC Curve, the Cumulative Gain Chart, the contingency table, and accuracy statistics for each input dataset for performance measurement purposes.

As seen in Table 2, the model's accuracy for classifying fake news is above .95 for both the primary and external datasets and .65 when using the random dataset. We present the results of the main dataset for Cumulative Gain Chart and ROC Curves in Figures 7 and 6. Comparatively to the studies mentioned in the Section 2.1 'Literature Summary', the results are listed in Table 3.

4. Discussion

The model's accuracy for classifying fake news is high, above .95 for both the primary and external datasets and .65 when using the random dataset. Furthermore, our model

Table 3. Comparative results of similar studies.

Model	Accuracy
Modified ensemble voter[a]	0.9635
Stylometric	0.55 (Potthast et al., 2018), 0.787 (Nguyen et al., 2019), 0.9839 (Yang et al., 2017)
Syntactic	N/A[b]
Semantic	0.9839 (Yang et al., 2017), 0.425 (Samonte, 2018)

Note: [a]Best score. [b]We did not find a specific content-based syntactic model for direct comparison.

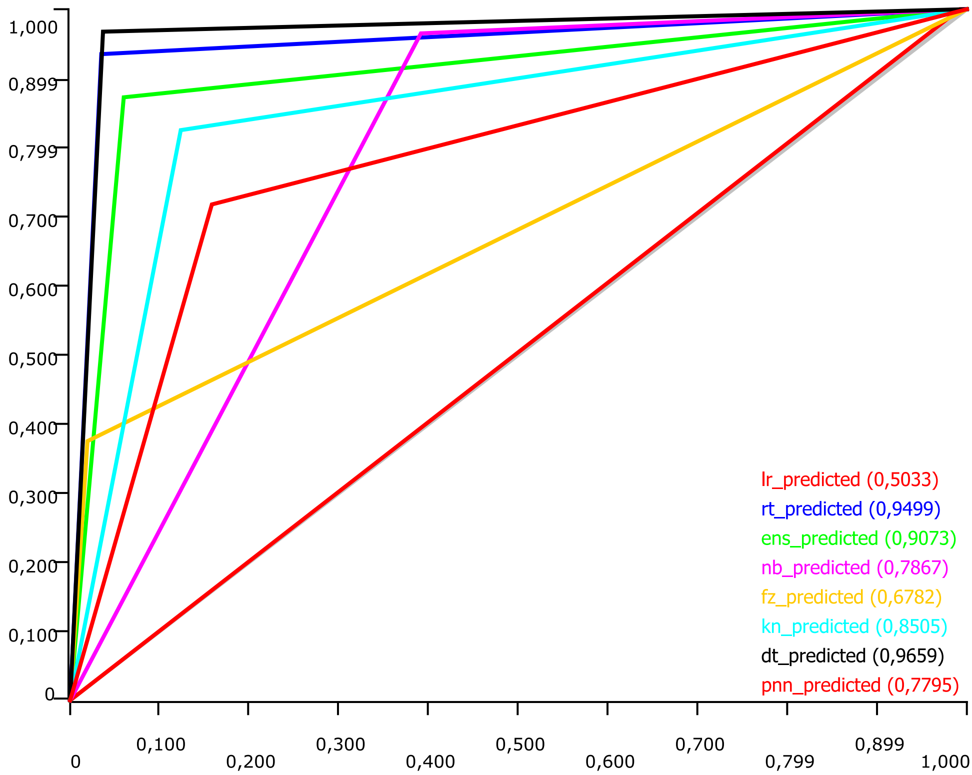

Figure 6. ROC Curve for the Main Dataset All Voter Classifications. (a) Logistic Regression (lr_predicted), Regression Trees (rt_predicted), Ensemble of Classifiers with Adaboost (ens_predicted), Naive Bayesian (nb_predicted), Fuzzy Rule (fz_predicted), KNN (knn_predicted),Decision Trees (dt_predicted), Probabilistic Neural Network (pnn_predicted).

underperforms when using the randomized dataset (0.39245 for our model versus .50000 for ROC Curve baseline). We have a possible explanation that, for this last result, the model was more sensitive to the quality of the data. It utilizes the inputs of other classifiers and their accuracy measures to determine which class an article belongs to. For this reason, we believe that this underperforming metric for a randomized dataset is an acceptable outcome.

5. Conclusion

The discussion about fake news is ongoing. Whether content-based, context-based, or a mixed approach for detection is best at performing such a task, the debate relies upon

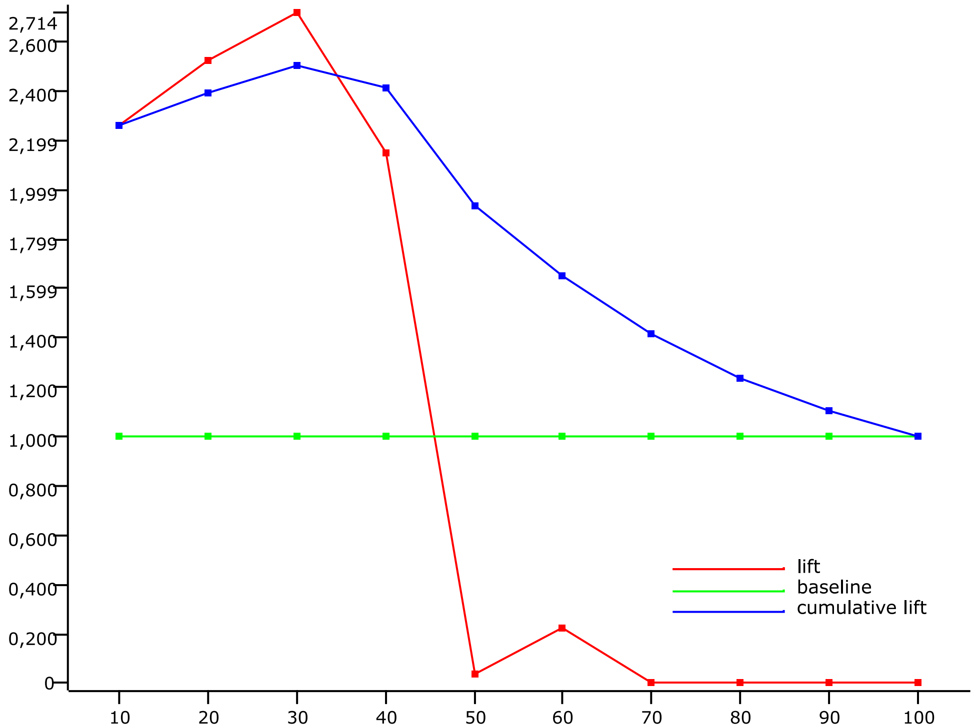

Figure 7. Cumulative gain chart for the main dataset all voter classifications.

the idea of automated fact-checking. Automated fact-checking, by its turn, is heavily dependent on the concept of a computational model for understanding human reasoning and verifying it against any other sources of information. Therefore, an ontological problem.

Our goal with this research was to produce a model for fake news detection relying only on the content, rather than the context, of the article, reducing the need for external dependencies and the issues with ontology.

Our conclusion, given the state-of-the-art research in the field and demonstrated by our experimentation and resources, is that it is feasible to use only content-based features for classifying false news and identifying them against accurate news. We can enhance this classification by the inclusion of data aspects and voting weighting mitigation. These data aspects are stylometric and psychometric measurements from the data.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Notes on contributor

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