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ORIGINAL ARTICLE

Hybrid deep learning model for automatic fake news detection

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Abstract

With the fast advancement in digital news, fake news has already caused grave threats to the public's actual judgment and credibility, in specific, with the wide use of social networking platforms, which provide a rich environment for the generation and dissemination of fake news. To cope with these challenges, several techniques were proposed to detect fake news, but still, there is an urgent need to propose an improved detection technique that provides a high level of detection performance in an automatic manner. Therefore, this article proposes a hybrid-improved deep learning model for automatic fake news detection. The proposed model adopts automatic data augmentation method, called Auxiliary Classifier Generative Adversarial Networks, to artificially synthesize new fake news samples, and then hybridize the Convolutional Neural Network with the Recurrent Neural Networks to detect the fake news efficiently. The proposed model shows superior results against the state-of-the-art models as it provides 93.87% accuracy, 10.39% recall, 93.12% precision in detecting the fake news using Buzzfeed, FakeNewsNet and FakeNewsChallenges datasets.

Keywords Automatic data augmentation · Auxiliary Classifier Generative Adversarial Networks · Convolutional Neural Network · Digital news · Fake news · Recurrent Neural Networks

Introduction

For the time being, the proliferation of social media networking has significantly changed the way users acquire information. Recent survey conducted by Pew Research Center survey, stated that about (68%) American adults get news through social media networking at least occasionally. Fake news are intentional and verifiable spurious news stories, which might spread virally over several social media networking as the users seldom verify the source of the news while sharing any news content that sounds real and true (Ozbay and Alatas 2020; Li et al. 2020). A lot of negative impacts such as social attack and financial loss, might be resulted from the spread of fake news. Large number of high-influence fake news has been witnessed lately, which were spread with different goals and events including Cyber-attacks, presidential election, terrorist plots and natural disasters, and severe weather. Despite the true information later disseminates, in many cases, the fast spread of fake news usually causes destructive and wasteful consequences. Figure 1 illustrates sample of the fake news spread over the social media networking.

In fact, identification of the fake news is undeniably a critical issue for the news sector, journalists, and readers as well; thus, the automated detection tools of fake news have become an urgent necessity (Umer et al. 2020). Since manual detection of fake news is a very tedious and time-consuming task, therefore, automatic identification of fake news has drawn huge attention in the Natural Language Processing (NLP) and Artificial Intelligence (AI) to reduce the burdensome and time-consuming manual activities of true verifying (Lazer et al. 2018; Konstantinovskiy et al. 2021). Deep learning methods such as Convolution Neural Networks (CNN) and its variants (Neculoiu et al. 2016) have been utilized efficiently in solving different NLP problems (Umer et al. 2020).

As one of the most emerging topics nowadays, fake news detection has caught the attention of researchers in NLP and AI fields all over the world. Thus, a massive amount of research has been conducted based on either content or context news features and proposed benchmark datasets. Despite getting significant attention in the research field, yet detection of fake news has not provided a significantly

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Fig. 1 Sample of fake news

enhanced performance because of insufficient context-based news data. Building proper hand-engineered news features (Chong et al. 2017; Fazil and Abulaish 2018) to distinguish the falseness and trueness of such news is a technically challenging process. In contrast to the traditional feature-based technique, deep learning-based detection has the advantage in the sense that it does not need any handcrafting of features, rather it only classifies and distinguishes the optimal feature set on its own for a problem (Mohammed and Daham 2021). With fulminatory advancement, fake news has already caused grave threats to the public's actual judgment and credibility, particularly, with the wide use of social networking platforms, which provide a rich environment for generation and dissemination of fake news. For instance, during the 2016 United State Presidential Election, massive amount of fake news regarding presidential candidates was generated and distributed among different social networking platforms (Jin et al. 2016), as over one hundred fake stories were shared for pro-Trump on Facebook platform more than 30 million times, and over 41 fake stories were also shared for pro-Clinton on Facebook more than 7.6 million times (Allcott and Gentzkow 2017). Such a huge volume of viral fake news has not only damaged candidates' public persona but also has provided illusive voters' judgment. Therefore, it has become vital to detect fake news efficiently, especially on social media networking to block the speedy spread.

However, there are clear differences between fake news and classical fraudulent data/information. As the fake news are intentionally modified by its creators to accomplish the goal of misleading the public. For example, news about the same topic published by several creators has close similarity in most content, but malicious news content is carried out by fake news carriers in objective statements. Although the proportion of these suspicious contents is negligible, this is enough to make the news a harmful fake one. Besides, for classical malicious information, such as spam (You et al. 2020), users instinctively have a prophylactic mentality, which makes them less likely to be beguiled. But for news, users often actively explore, receive, send, and share without being on sentinel about information authenticity. Also, spams are often easier to be prevented or detected due to the abundant orderly messages; so far, detection of fake news is incredibly challenging because news is a time-sensitive content. The proof gathered about past news might not benefit detecting fake news plainly. These features of fake news make the detection task more challenging and complex. Moreover, a considerable volume of misleading and inconceivable information is created by the several users and shared through the social network platforms (Marin and Arroyo 2019; Kaushik and Gandhi 2019; Sahoo and Gupta 2021). It also generated a potential malicious threat to different communities and had a profound negative influence over the end-users via multiple advertisement, electronic shopping and/ or social messaging in terms of 3Vs drawn in Fig. 2.

For the time being, several techniques were proposed to detect fake news, which might roughly be classified into two main categories, namely: (i) detection based on traditional

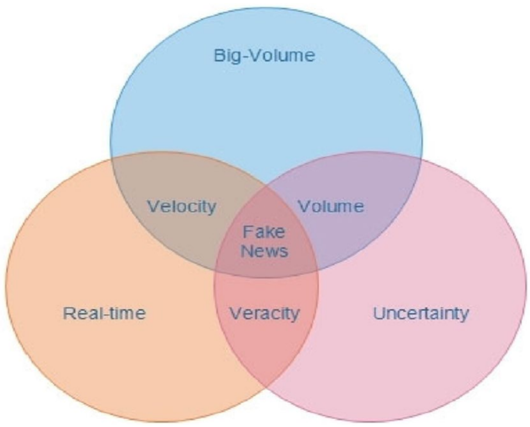


Fig. 2 Fake news in terms of 3Vs (Sahoo and Gupta 2021)

learning (Hakak et al. 2021; Budhi et al. 2021; Machova et al. 2020) and (ii) detection based on deep learning models (Umer et al. 2020; Nasir et al. 2021). In the first category, features are typically extracted from news articles, and then the classifier is trained using these extracted features. On the other hand, detection based on deep learning have provided an enhanced performance in detecting fake news due to its robust abilities of learning informative representations in automatic manner. However, to train deep learning models efficiently, a large amount of labeled data is required (i.e., news should be labeled as real news or fake news). The creation of this labeled data is expensive in terms of efforts and time. Besides, accurate and precise labels might only be provided if the annotators are experts and have adequate knowledge about the news. Moreover, the news articles are characterized by their dynamic nature, which means blighting quality of existing labeled data. Also, part of these news samples might become outdated speedily and could not represent the news articles on recently emerged topics. Thus, to preserve the quality of labeled sample, the annotators should constantly label newly emerging news, which is an infeasible process. To perfectly unleash the strength of deep learning methods in detecting fake news, it is vital to overcome the challenge of labeling fake news efficiently. To do so, the main goal of this study is to improve the detection of fake news using a hybrid deep learning method. The following objectives are formulated to the achieve the main goal:

- To investigate the importance of deep learning over machine learning models in detecting fake news.
- To adapt automatic data augmentation method, called Auxiliary Classifier Generative Adversarial Networks (ACGAN), to artificially synthesize new fake news samples.
- To hybridize CNN with RNN (Recurrent Neural Networks) to detect fake news efficiently.
- To evaluate the effectiveness of the proposed technique by comparing it with state-of-art techniques.

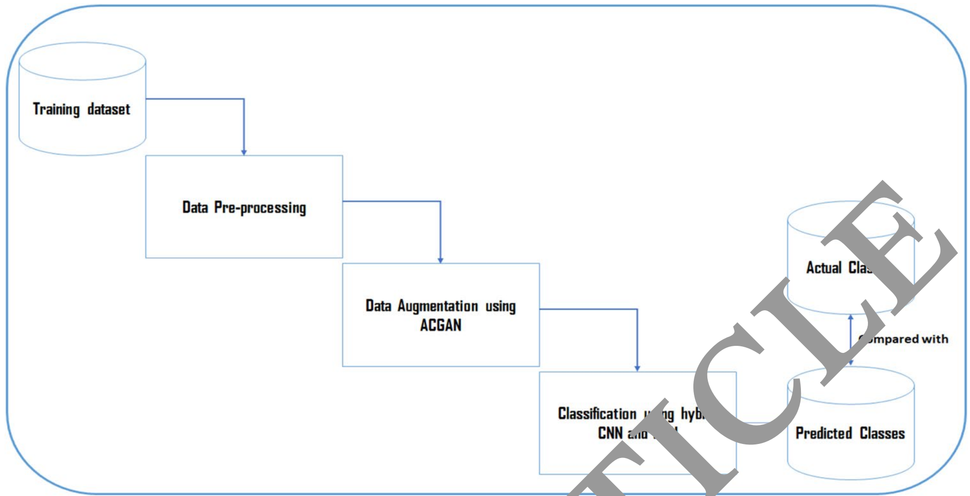
In this article, the main contribution is proposing an automated and intelligent model that can classify digital news with stance labels of either fake or real news. The detection is performed based on the level of correspondence between the title and body/content assigned to titles. A hybrid deep learning model is used to extract the significant features using CNN, then these extracted features are fed into an enhanced RNN model, called Long-Short Term Memory (LSTM), to classify these by getting the high level of features representations. Therefore, the proposed model takes the advantage of both CNN and LSTM. In detail, CNN obtains the text features, then these features set is passed to the embedding layer to vectorize all these extracted features. After that, these vectors are fed to a one-dimensional convolutional layer that aims to extract the significant features by performing 64 filters of five different dimensions. Features with the highest importance are selected by the max-pooling layer. Then, the remaining text features are fed to the LSTM to perform sequence modeling and to discover the hidden relevance of keywords and text contents.

The rest of the paper is organized as follows. "Related works" provides an analysis of related works. "Proposed model" discusses the stages of the proposed model in detail. "Results and discussion" discusses the experimental results and findings. Finally, "Conclusion" concludes the paper with possible future research directions.

Related works

News can be generally categorized into fake or real news based on different aspects such as news author or publisher, title and sub-titles, textual and visual content. Existing studies use news textual content and social context to detect fake news. For instance, in Zhou and Zafarani (1812), four main aspects have been presented to classify news articles as knowledge, style, propagation, and credibility. Knowledge and style exploit the news textual content, while propagation and credibility aspects exploit the social context. Since features of news content might be captured through linguistic and visual cues in the news article (Albahar 2021). Besides, new detection method has been proposed in Sultana and Palaniappan (2020) to detect deceptive spam reviews based on specific features such as number of part-of-speech tags, word counts, etc. Also, a context-free grammar basis is used in Khan et al. (2021), Wynne and Wint 2019) to detect deceptive reviews. Moreover, in Zhang and Ghorbani (2020), various lexical and syntactic aspects of a news article have been explored to specify the misleading content. They have investigated various types of syntactic

Fig. 3 Research methodology



features in detecting fake news. On the other hand, in Reis et al. (2019) the fake news detection technique proposed is based on users' reactions. A bipartite network was adapted in this technique to classify either the news is fake or not are depending on the number of users likes for each news article. RNN was adapted in Parthiban et al. (2020) to acquire contextual features from news articles unlike machine learning methods that need hand-crafted features. They concluded that the use of deep learning produced better results as compared to other state-of-art methods. Also, a hybrid-based fake news detection model that combines the news text is introduced in Ruchansky et al. (2017), its responses and sources features. This model comprises three main modules, namely: (i) Module to capture the temporal users' and articles' patterns engagement with RNN, to provide its lower dimension representation. (ii) Module to assign a credibility weight to a user according to user features using a fully connected layer. (iii) Module to integrate the vector resulting from the first module and weight resulting from the second module. Alhayani et al.(2021) which is responsible for the classification of the news article. Moreover, fake news detection model, called FakeDetector is proposed in Kula et al. (2020). The proposed models adapted gated recurrent unit to extract latent features and adapted Gated Diffusive Unit to combine modeling of news authors, articles, and subjects. Twitter-based PolitiFact dataset was used to assess the effectiveness of the proposed model, and the experiment results revealed that the proposed model achieved 63% classification accuracy. In addition, page-rank-like credibility method is used in Gupta et al. (2012) to evaluate the credibility of each twitter event. First, a classifier method extracts features of users, tweets, and events. Then, basic credibility analysis is conducted through network information of each tweet, events, and their users as well. Finally, a hybrid fake news detection model is based on hybridizing CNN with Long short-term memory (LSTM). The proposed model used two dimensionality reduction methods (i.e., Principal Component Analysis (PCA) and Chi-Square, which are used to diminish the dimensionality of the features' vectors before bypassing them to the classifier. FNC dataset was used to assess the effectiveness of the proposed model, and the results reveal that the proposed model improves the accuracy, F1-score by 4% and 20%, respectively (Umer et al. 2020).

Proposed model

To achieve the objectives of this study, the following methodology will be followed. As shown below in Fig. 3, the followed methodology consists of three main stages, namely: (i) data pre-processing, (ii) data augmentation using ACGAN, and (iii) classification using hybrid CNN and RNN.

Pre-processing

In the first stage, datasets will be collected from online resources (such as: FakeNewsNet,[1] Buzzfeed,[2] and FakeNewsChallenges[3]), which are commonly used by prior studies, such as (Shu et al. 2020; Ghosh and Shah 2018; Ozbay and Alatas 2018), to demonstrate the effectiveness of fake news models. Then these datasets will be pre-processed since they have versatility in their data formats; therefore, it is necessary to preprocess and encode them before feeding them into next stage (Ozbay and Alatas 2018). The pre-processing steps are as illustrated in Fig. 4.

[1] https://www.kaggle.com/mdepak/fakenewsnet.

[2] https://www.kaggle.com/sohamohajeri/buzzfeed-news-analysis-and-classification.

[3] http://www.fakenewschallenge.org/

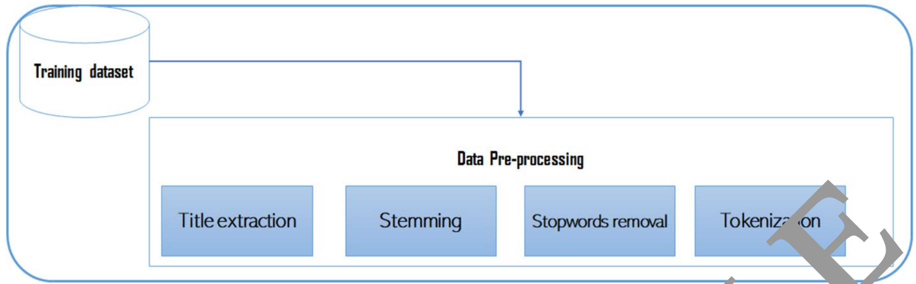
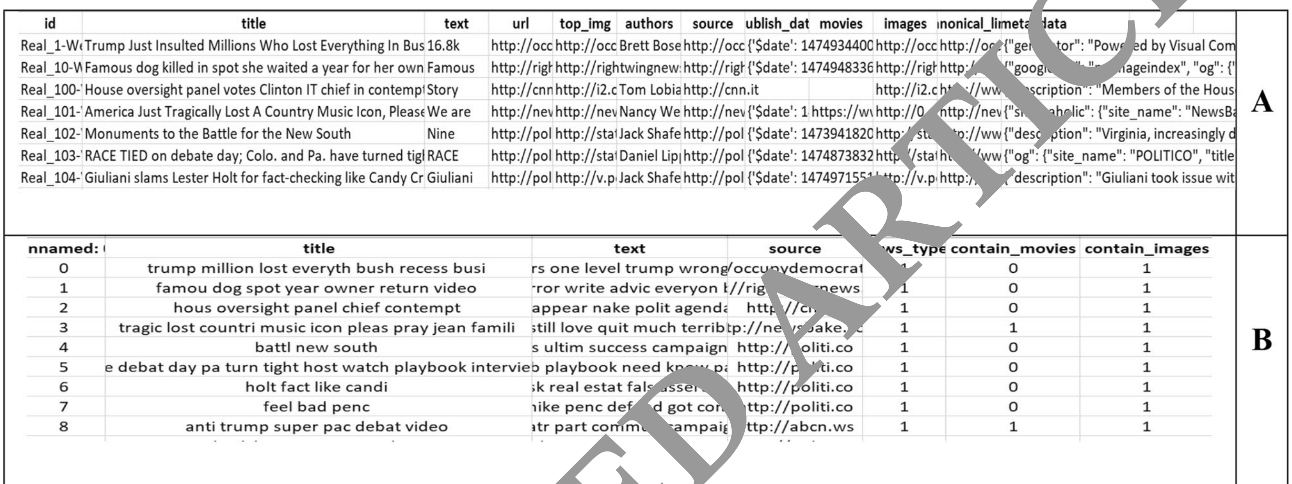


Fig. 4 Pre-processing steps



id	title	text	url	top_img	authors	source	ublish_dat	movies	images	nonical_li	meta_data
Real_1-W	Trump Just Insulted Millions Who Lost Everything In Bus	16.8k	http://occ	http://occ	Brett Bose	http://occ	{'$date': 1474934400		http://occ	http://o[illegible]	{"ge[illegible]tor": "Pow[illegible]ed by Visual Com
Real_10-W	Famous dog killed in spot she waited a year for her own	Famous	http://rigl	http://rightwingnew		http://rigl	{'$date': 1474948336		http://rigl	http:[illegible]	{"googl[illegible]ageindex", "og": {"
Real_100-	House oversight panel votes Clinton IT chief in contempt	Story	http://cnn	http://i2.c	Tom Lobia	http://cnn.it			http://i2.c	ht[illegible]//ww	[illegible]scription": "Members of the Hous
Real_101-	America Just Tragically Lost A Country Music Icon, Please	We are	http://nev	http://nev	Nancy We	http://nev	{'$date': 1	https://w	http://0	http://nev	{"s[illegible]aholic": {"site_name": "NewsBa
Real_102-	Monuments to the Battle for the New South	Nine	http://pol	http://stat	Jack Shafe	http://pol	{'$date': 1473941820		http[illegible]/sta	[illegible]p://ww	{"desc[illegible]ption": "Virginia, increasingly d
Real_103-	RACE TIED on debate day; Colo. and Pa. have turned tigl	RACE	http://pol	http://stat	Daniel Lip	http://pol	{'$date': 1474873832		http[illegible]/stat	ht[illegible]/ww	{"og": {"site_name": "POLITICO", "title
Real_104-	Giuliani slams Lester Holt for fact-checking like Candy Cr	Giuliani	http://pol	http://v.p	Jack Shafe	http://pol	{'$date': 147497155[illegible]		[illegible]tp://v.p	http:[illegible]	[illegible]"description": "Giuliani took issue wit

nnamed:	title	text	source	ws_type	contain_movies	contain_images
0	trump million lost everyth bush recess busi	rs one level trump wrong	/occupydemocrat	[illegible]	0	1
1	famou dog spot year owner return video	rror write advic everyon	t//rig[illegible]news	1	0	1
2	hous oversight panel chief contempt	appear nake polit agenda	http[illegible]//c[illegible]	1	0	1
3	tragic lost countri music icon pleas pray jean famili	still love quit much terrib	tp://ne[illegible]ake.[illegible]	1	1	1
4	battl new south	s ultim success campaign	http://[illegible]oliti.co	1	0	1
5	e debat day pa turn tight host watch playbook intervie	b playbook need kn[illegible]pa	http://p[illegible]ti.co	1	0	1
6	holt fact like candi	sk real estat fals[illegible]sser	http://politi.co	1	0	1
7	feel bad penc	nike penc def[illegible]d got con	ttp://politi.co	1	0	1
8	anti trump super pac debat video	atr part comm[illegible]ampaig	ttp://abcn.ws	1	1	1

Fig. 5 Sample of dataset: **A** before pre-processing, **B** after pre-processing

Before starting any of the pre-processing heavy lifting, all texts are converted to lowercase and any Uniform Resource Locators (URLs) are removed. In Python, a simple RegEx expression can handle this task easily (Alhayani and Abdallah 2020; Alhayani and Llhan 2021). Like URLs, contractions can produce unintended results if left alone. The Aptly package named contractions Python library to the rescue. It looks for contractions and splits them into root words. After that, text normalization, which is the process of simplifying multiple variations or tenses of the same word, is performed. Stemming and lemmatization are two methods of text normalization (Kwekha-Rashid et al. 2021), the former being the simpler of the two. To stem a word, simply remove the suffix of a word to reduce it to its root. As an example, "walking", "walks", and "walked" all are stemmed to "walk". Stemming is not without its faults, however (Hasan and Alhayani 2021; Yahya et al. 2021). We can run into the issue of over-stemming. Over-stemming is when words with different meanings are stemmed to the same root a false positive. Then, the procedure of stop words removal is carried out, as stop words do not add essentially to the meaning of the text and can be removed without affecting the text for the designated purpose. This removal of stop words from the vocabulary caters to noise reduction as well as reduction of dimension of the feature in Python, Natural Language Toolkit (NLTK) library comes in clutch here. A set of both English words and stop words can be downloaded and compared against the input tokens (Abu-Rumman 2021). To detect the fake news, the return tokens are only English and not the stop words. Finally, the process of breaking the raw text into small units, known as tokenization, is carried out. These tokens play a vital role in establishing the understanding of the context and for the development of the model for Natural Language Processing Aldiabat et al.(2018). The whole process of the interpretation of the meaning of the text is made easy through tokenization. Tokenization can be implemented using a variety of methods and approaches. This research has made use of the RegexpTokenizer within the NLTK library and the RegexpTokenizer will employ regular expressions to either match tokens or separators (i.e., include or exclude regex matches). Figure 5 illustrates sample dataset before and after pre-processing.

Automatic data augmentation

Whilst the second stage aims to produce a new synthetic instance generated from the original dataset, to avoid overfitting during classifier training train it efficiently, and thus the

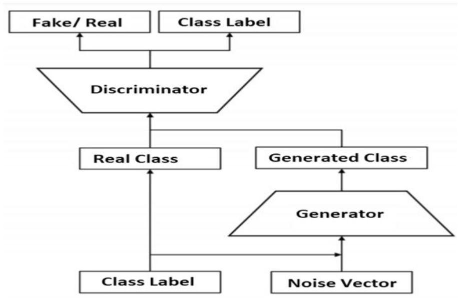


Fig. 6 Architecture of ACGAN

detection (i.e., classification) accuracy will be enhanced. The ACGAN is a variation of the GAN (Generative Adversarial Network). The ACGAN provides high-quality instances derived from original instances with more training stabilization (Chen et al. 2020). Figure 6 depicts the architecture of ACGAN.

The discriminator D receives either as training instance or a synthesized instance as an input from the generator and then outputs a probability distribution $P(S|X) = D(X)$ over possible instance sources. The discriminator maximizes the log-likelihood that it assigns to the correct source where the generator minimizes the second term. The side information can be used to augment the basic GAN framework. In one of the strategies, both the generator and discriminator are supplied with class labels for the purpose of producing class conditional samples. The quality of generated samples can be greatly enhanced by using class conditional synthesis. Every generated sample in the ACGAN has a corresponding class label, $c \sim p_c$ in addition to the noise z. G uses both to generate images $X_{\text{fake}} = G(c, z)$. The discriminator provides both a probability distribution over sources and a probability distribution over the class labels, $P(S|X)$, $P(C|X) = D(X)$. The objective function has two parts: the log-likelihood of the correct source, L_S, and the log-likelihood of the correct class, L_C (Shu et al. 2020).

$$L_S = E[\log P(S = \text{real}|X\text{real})] + E[\log P(S = \text{f ake}|X\text{fake})], \quad (1)$$

$$L_C = E[\log P(C = c|X\text{real})] + E[\log P(C = c|X\text{fake})] \quad (2)$$

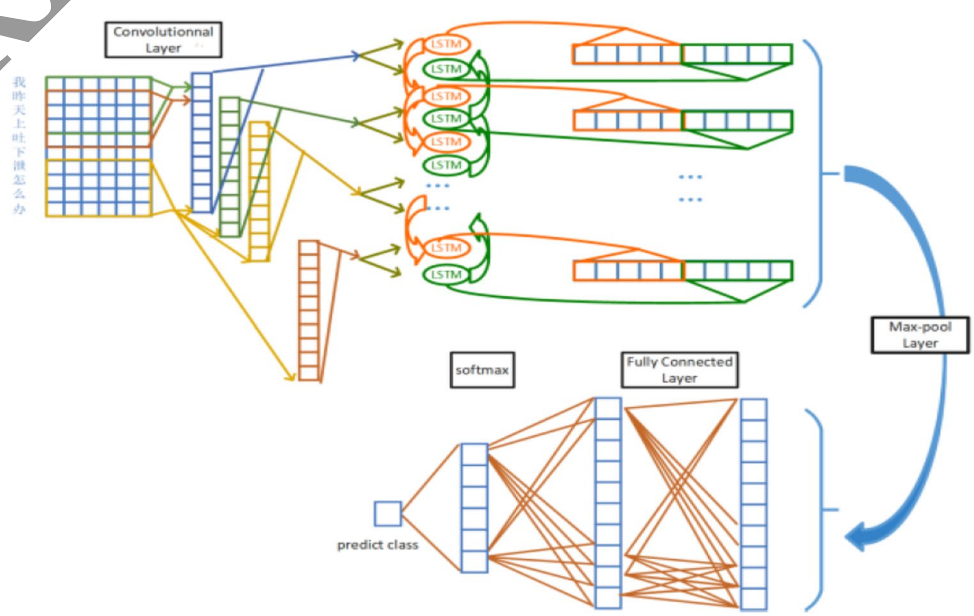
D is trained to maximize $L_S + L_C$ while G is trained to maximize $L_C - L_S$. AC-GANs learn a representation for z that is independent of class label. This model has essential structural differences from another models. This structural modification attributed to the standard GAN formulation produces much improved results to stabilize training. And the ACGAN model the technical contribution of this work has resulted in the form of the ACGAN model.

However, the generated dataset instances along-with the original dataset instances will be used as input for the hybrid model proposed in the next stage (i.e., the third stage).

Hybridizing CNN with RNN

Lastly, in the third stage, the proposed detection model, called CNNRNN-based detection, is used to detect (i.e., classify) fake news. Despite CNN-based detection models are characterized by its high performance in exploiting features derived from spatial data (i.e., digital images), it is improper to dealing with sequential data (i.e., textual data). In contrast, RNN-based detection models have robust capabilities in modeling sequential data. Inspired by their

Fig. 7 CNNRNN- based Detection Model



features, a hybridized model (See Fig. 7), called CNNRNN-based detection model.

CNN-based models exhibit great performances in utilizing features from spatial data such as images. Whereas CNN shows incapability in dealing with sequential data, the RNN-based models deal with sequential data such as texts very efficiently. Therefore, combining together the CNN and RNN together, a hybrid model is proposed which is called CNNRNN. In detail, CNN is put into the front of the RNN, forming a CNNRNN model. $Y = F(X, \theta)$ of CRNN can be represented as:

$$Y = \mathrm{Softmax}(\mathrm{FC}(\mathrm{LSTM}(\mathrm{Pool}(\mathrm{Conv}(X, \theta\mathrm{CONV}), \theta\mathrm{Pool}), \theta\mathrm{LSTM}), \theta\mathrm{FC})). \quad (3)$$

Another combination is to put RNN into the front of the CNN, forming CNNRNN model. $Y = F(X,\theta)$ of CNNRNN can be represented as:

$$Y = \mathrm{Softmax}\,(FC(\mathrm{Pool}(\mathrm{Conv}(\mathrm{LSTM}(X, \theta\mathrm{LSTM}), \theta\mathrm{CONV}), \theta\mathrm{Pool}), \theta\mathrm{FC})). \quad (4)$$

This paper is inclusive of the input data x representing sentences which are sequential and short. Resultantly, a new improved version of CNNRNN model is proposed where CNN is not in front of RNN and the pooling layer is shifted to the back of LSRMM-RNN layers.

This model incorporates the LSRM layer that processes the text features secured through convolution layer and extracts the temporal features of the input data. It is followed by maximum pooling layer, where it compresses and highlights the combination of text and temporal features. This improved CRNN model involves the principle of dealing with the problem as sequential and short. The CNN-RNN model places the pooling layer with prominent features behind the LSRM layer, highlighting the text features as well as the temporal features.

$$Y = \mathrm{Softmax}(\mathrm{FC}(\mathrm{Pool}(\mathrm{LSTM}(\mathrm{Conv}(X, \theta\mathrm{CONV}), \theta\mathrm{LSTM}), \theta\mathrm{Pool}), \theta\mathrm{FC})). \quad (5)$$

Results and discussion

This section provides details about evaluation metrics, hardware specifications and datasets, and experimental results, respectively.

Evaluation metrics

To compare and evaluate the effectiveness of the proposed detection model, the following evaluation metrics are used: accuracy (A), precision (P), recall (R) (Odena et al. 2017). While the following equations are used to calculate the A, P, and R, respectively.

Table 1 Hardware and software specifications

Hardware	Specification
CPU	Core i7-8565 U
RAM	16 GB
HDD	1 TB SSD
GPU	NVIDIA Tesla K40
OS	Windows 10
Implementation environment	Anaconda Spider
Implementation language	Python

Table 2 Buzzfeed features

Feature	Description
Id	Fake or real tag for each news article
Title	Article headline which catches the attention of readers and reflects the news topic
Text	The body of the article
Source	The author or publisher of the news article
Images	The visual cues to frame the story
Movies	A link to video or a movie clip included in a article

$$A = (TP + TN)/(TP + TN + FP + FN), \quad (6)$$

$$P = (TP)/(TP + FP), \quad (7)$$

$$R = (TP)/(TP + FN), \quad (8)$$

where TP, TN, FP, and FN denote true positive, true negative, false positive, and false negative, respectively.

Hardware specifications and datasets

The experiments are performed using a computer device with the specifications as shown in Table 1.

Buzzfeed, FakeNewsNet, and FakeNewsChallenges datasets are used to train and test the proposed model.

The Buzzfeed news dataset contains a complete sample of textual news existing in Facebook environment collected from nine news institutions over 7 days during the 2016 United State election (specifically 19th to 23rd of September, and from 26 and 27th of the same month). This dataset holds the core features as summarized in Table 2:

As illustrated below in Fig. 8, FakeNewsNet dataset contains two main comprehensive datasets (i.e., PoliticalFact and GossipCop) with several categories including news content (linguistics and visual), social context (user, post, response and network), and spatiotemporal information (spatial and temporal).

Fig. 8 Statistics of FakeNewsNet (Ghosh and Shah 2018)

	Category	Features	PolitiFact		GossipCop	
			Fake	Real	Fake	Real
News Content	*Linguistic*	# News articles	432	624	5,323	16,817
		# News articles with text	420	528	4,947	16,694
	Visual	# News articles with images	336	447	1,650	16,767
Social Context	*User*	# Users posting tweets	95,553	249,887	265,155	80,137
		# Users involved in likes	113,473	401,363	348,852	145,078
		# Users involved in retweets	106,195	346,459	239,483	118,894
		# Users involved in replies	40,585	18,6675	106,325	[illegible]0,799
	Post	# Tweets posting news	164,892	399,237	519,581	876,967
	Response	# Tweets with replies	11,975	41,852	39,717	[illegible]
		# Tweets with likes	31692	93,839	96,906	[illegible]1,889
		# Tweets with retweets	23,489	67,035	56,552	[illegible]
	Network	# Followers	405,509,460	1,012,218,640	[illegible]31,413	293,[illegible]1,487
		# Followees	449,463,557	1,071,492,603	619,[illegible]586	[illegible]8,428,225
		Average # followers	1299.98	982.67	1020.[illegible]	933.64
		Average # followees	1440.89	1040.21	1003.14	982.80
Spatiotemporal Information	*Spatial*	# User profiles with locations	217,379	719,33[illegible]	429,[illegible]47	220,264
		# Tweets with locations	3,337	1[illegible],692	12,[illegible]86	2,451
	Temporal	# Timestamps for news pieces	296	[illegible]67	[illegible],558	9,119
		# Timestamps for response	171,301	669,[illegible]	381,600	200,531

Table 3 The real, Fake news with challenges

Headlines	Tokens	Instances	Agree	Disagree	Discuss	Unrelated
2587	372	75,385	7.4%	[illegible]2%	17.7%	72.8%

Besides, the FakeNewsChallenges which is a benchmark dataset consists of more than 75 k labeled instances and 2587 article contents, which linked with 300 titles approximately, and for every claim, there are number of news articles ranging from 5 to 20 articles. The details of the labels for each instance are shown below in Table 3.

Where the agree label indicates that there is a relation between headline and article content (i.e., classified as real news), disagree: There indicates that there is no relation between headline and article content (i.e., classified as fake news). Discuss indicates that there is a little bit of match between headline and article content (i.e., classified as fake news). Unrelated indicates that the topic discussed in the headline is totally irrelevant with content (i.e., classified as fake news).

Experimental results

In the final set of experiments, the proposed CNNRNN-based detection model is trained on 80 k samples and tested on [illegible] k headlines and digital articles. The training task takes 5 h to run 4000 epochs on all training samples and to show the detections results. After that, the results are compared with state-of-the-arts models including CNNLSTM, FakeDetector, CNN-based, and RNN-based fake news detection models. By analyzing all the results, as noticed in Fig. 9, the proposed detection model provides high accuracy ranging from 90.50 to 97.35% with the number of epochs ranging from 1000 to 4000 epochs. Further, the recall (false detection) rate has reduced from 17.19 to 3.219% while the number of epochs increases from 1000 to 4000 epochs. Whilst the recall percentage has wobbly results ranging from 92.09 to 94.16% with 1000–4000 epochs. These results prove that as the number of epochs increases, the greater number of times, the weight is changed in the neural networks and the curve goes from underfitting to optimal to overfitting curve; thus, performance is improved significantly.

As aforementioned, the proposed model has been compared with the other-state-of-the-art models including CNN-based (Salam et al. 2022), RNN-based (Viana 2018), FakeDetector (Kula et al. 2020), and CNNLSTM (Umer et al. 2020) to demonstrate its effectiveness. The results revealed that the proposed model is more effective for detecting fake news and it has impressive results (in terms of accuracy, precision, and recall) compared to the other-state-of-the-art models, as shown below in Table 4.

From the above table, it noticeable that the proposed CNNRNN model archives the highest detection accuracy with 93.87%, followed by CNNLSTM, FakeDetector, CNN-based, and RNN-based models with 91.77%, 86.03%, 83% and 81.07%, respectively. On the other hand, in terms of recall, CNNRNN model archives the lowest recall with 10.39%, followed by CNNLSTM, FakeDetector, CNN-based, and RNN-based models with 12.26%, 13.96%, 15.42%% and 19.33%, respectively. Lastly, in terms of precision, still the proposed CNNRNN model outperforms the other-state-of-the-art models as it achieves 93.12% precision, followed by CNNLSTM, FakeDetector, CNN-based, and RNN-based models with 91%, 90.09%, 90.01% and 87.12%, respectively.

Taking into consideration the accuracy, precision and recall of the experiment results, the proposed CNNRNN model exhibits the most precise and the best performance in detection results when compared with other four

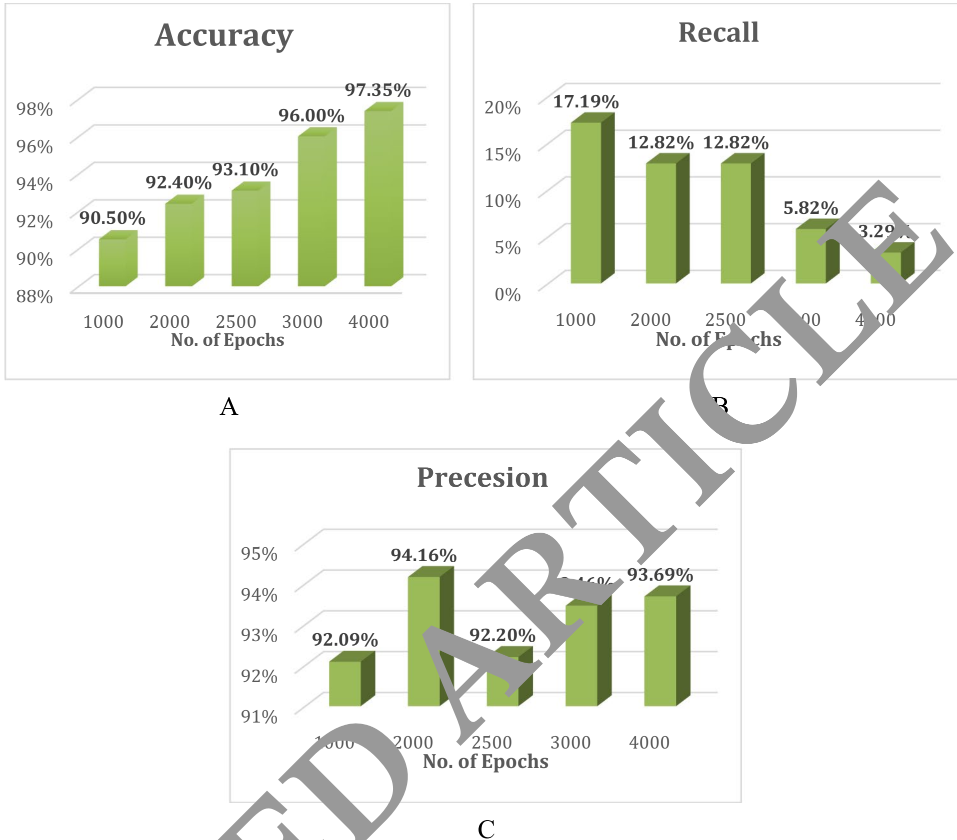


Fig. 9 Evaluation results of the proposed model: **A** accuracy, **B** recall, **C** precision

Table 4 Comparison with state-of-the-art models

Model	Accuracy (%)	Recall (%)	Precision (%)
CNN based	83	15.42	90.01
RNN based	81.07	19.33	[illegible]7.12
FakeDetector	86.03	[illegible]	90.09
CNNLSTM	91.77	12.[illegible]	91
Proposed	93.87	10.3[illegible]	93.12

state-of-the-art models. In the proposed model, CNN model is used to extract textural features in the sentence-level for each textual news, and a RNN model is mainly used to learn the potential patterns and their mutual correlation (i.e., real, or fake). This intelligent-automatic approach might help reduce the spread of fake news, which is a serious problem and often has adverse effects on the society.

Only true and fake digital news is studied in this article. Initially, the features of fake news are often similar to the real news since the news editors post fake news and try to do the best to ensure that the readers consider the news content/body is real. Such reason demonstrates why the prior work in detecting fake news did not always provide overwhelming results. In this article, the experiments are conducted on computer device with suitable hardware specifications as listed in Table 1. These hardware specifications enable the proposed model to process these large datasets efficiently. In addition, Keras library in Python is used, which is considered one of the most powerful libraries used to develop and evaluate deep learning models.

The ongoing and prior works related to automatic fake news detection comprise different hackathons and electronic competitions to provide a commercially available and efficient model, which enclose a state-of-the-art detection, as extensions in web browsers. The existing tool has the ability to mark digital news as true or fake, but does not provide a rating or label beforehand, to describe the credibility that enucleate the real main issue. With enough improvements and inclusion of more input features in the automatic detection model, a future tool can be developed to allow users to find a score for digital articles, as well as suitable and accurate label for digital articled.

Conclusion

This article proposes an automatic fake news detection model based on hybrid deep learning models. The proposed model mainly deals with the headline and the content of the news irrespective of the state-of-the-art models that only consider the individual news' sentences or specific phrases. The proposed hybrid model incorporates automatic data augmentation method, called Auxiliary Classifier Generative Adversarial Networks, to artificially synthesize new fake news samples. And then, hybridize Convolutional Neural Network with Recurrent Neural Networks to detect fake news efficiently. Firstly, data pre-processing performs title extraction, stemming, stop word removal, and tokenization to ensure that the datasets are ready to be fed into the deep learning models. Then, Auxiliary Classifier Generative Adversarial Networks is used to enrich the content of these datasets and ensure avoiding data loss and overfitting during classifier training. Finally, the dataset resulting from the Auxiliary Classifier Generative Adversarial Networks is used to train the hybrid classifier (Convolutional Neural Network with Recurrent Neural Networks) and the testing dataset is used to evaluate the detection performance of this model. On average, this model produces promising results by scoring up 93.87%, 10.39%, and 93.12% accuracy, recall, and precision, respectively, which is considerably better than the other state-of-the-art detection models. It is pertinent to say that pre-processing and automatic data augmentation, reducing the noisy data and overfitting while preserving the high performance of proposed classifiers. As future work, feature selection approaches can be utilized to reduce the data dimensionality and enhance the classification performance. In addition, other textual features might be considered to boost the performance of detection process.

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Conflict of interest The authors declare that they have no conflict of interest.

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