Deep Learning Models to Detect Online False Information: a Systematic Literature Review

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The amount of disseminated information from online content volume is increasing rapidly including trusted and untrusted information that are published by different sources. To counter this problem, we need a comprehensive knowledge of existing methods and techniques emerging in the area of False News Detection (FND).This research survey provides a comprehensive review of most effective Deep Learning (DL) models that are used to detect false news and information. We are focusing in DL models and techniques, which use the textual published content and perform FND based on content features. We have considered the research papers in the last five years starting from 2017 onward. In this research paper, the published articles about proposing and developing FND based DL models are included whether the dataset are collected from social platforms or extracted from other news sources. In addition, this research study helps the researchers to have a complete view of the developed DL models that have been proposed in the field of false information detection, the DL models gaps in FND and how they can be improved.

Keywords: Deep Learning, False Information, Misinformation, Disinformation, Fake News.

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1 INTRODUCTION AND RELATED WORK

The fake news term is a general concept pointing to news pollution [1]. They are usually used for different type of non-verified news including different terms. The definition has been proposed according to the news veracity, intention and other aspects. In most literature such as [2], [3], they used the word "fake" and "false" news alternatively for the type of fabricated news that are meant to mislead readers intentionally or potentially. While others classify fake news, false news, rumor, spam and disinformation as sub categories of misinformation [4]. In our Systematic Literature Review (SLR), we use the following terms changeably as they have been named in literature as “Fake news” [5], “Disinformation”[6], “Misinformation” [7].

Fake News Detection (FND) process is the task of classifying and evaluating published news veracity whether they are true or false news [1]. Deep Learning (DL) have the ability to identify the most effective features for learning process by itself and still performing with higher accuracy and shorter time[8]. There are previous surveys in [2], [6], [9], which cover FND models from different aspects. We are different than those literature by including a summary of developed DL models for false information detection that are based on textual content of the news. We explore the available models and the repository of datasets in Arabic. We are also reporting the type of content whether they are textual or both textual and visual. Moreover, we introduce the training techniques (supervised, semi-supervised or unsupervised), the datasets (source, language, type of input data) and what are the mostly used evaluation metrics for FND deep learning model. Moreover, we are covering the years starting from 2017 till 2021, reporting different research questions (RQs), which will benefit researchers to explore new gaps and challenges to be addressed in FND field. In Section 2, we are clarifying the research methodology that is adopted to conduct this SLR. In Section 3, we are reporting and discussing the answers of our RQs. Finally, we provide a conclusion including summery of our findings and suggestions for future work in the last section.

2 REVIEW METHODOLOGY

We are following Kitchenham [10] SLR protocol, which is conducted through three stages: Planning, conducting and reporting the results of the review. In planning phase, we identify the objective and the need for this SLR. As a result, we define four RQs to be answered then we specify the search terms and best search sources. As explained in the following subsections, we include more details about reviewing scientific articles through different phases.

We evaluate the need to conduct this SLR by addressing the following research questions.

RQ1: What are the DL algorithms, methodologies, and techniques used for detecting false news?

RQ2: What are the different sources of fake information used to perform FND and what’s the dataset language?

RQ3: What are the used features in classification and/ or detection and what’s the input data type?

RQ4: What are the used evaluation metrics and the accuracy of DL FND models?

We select reputable digital libraries and online database such as IEEE Xplore, Springer, ScienceDirect, Scopus, ACM Digital Library, and Elsevier. We use logical operator (“OR”, “AND”) in addition to word synonyms including ("False Information", "Misinformation", "Disinformation", "Fake News"). We use the following synonyms such as "Deep learning" OR "Deep neural network” with the "Detection” for detection techniques.

Once we search with the selected keywords, we get a huge number of published researches relevant to FND different aspects. As a result, to reduce this number and focus our SLR on FND based DL models, we apply the following selection inclusion and exclusion criteria:

Inclusion criteria is limited to researches that have examined DL models for FND. They apply feature-based approach using content textual data input for Arabic and English language. This is regardless the availability of other attributes like author characteristics, semantic meninges, user stance, user profile, etc. We made the search on journal and conference papers for the last five years starting from 2017 and beyond in English language.

Exclusion criteria includes all research papers, which don't have answers for our RQs such as papers proposing FND approach based on feature analyzing. These papers are not related to textual content without discussing new DL model or classification techniques. Moreover, we excluded the research papers proposing FND approaches that are related to early FND, unreliable users source or through stance prediction, or source profiling. After applying these criteria, we ended up with 89 research papers.

In evaluation phase, we prepare an assessment checklist to explore each article's objectives such as DL model, whether using textual-based features, dataset language and other criteria to evaluate the suitability of collected research paper to answer our RQs. The assessment score varies for each article from 1 to 7. Each question on the assessment checklist scores 1 point then we consider all papers that exceed score of 4 points. After this phase, we ended up with 44 research papers.

3 REPORTING REASULTS AND FINDINGS

In this section, we answer each of our SLR research questions depending on our findings and summarize all reviewed research papers starting from the newest to the oldest year followed by article type, input data type, feature type and used deep learning model. Table 1 shows that the number of published researches in FND DL models increasing annually.

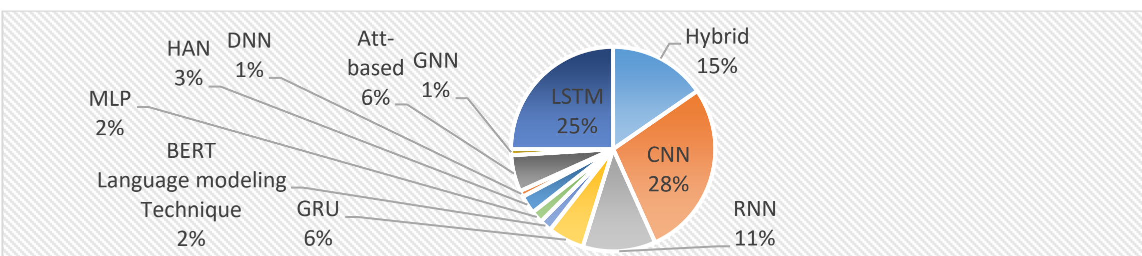
Table 1: Summarization of SLR findings

Year	Type	Input Data	Feature Type	Used Model	Acc.
[11], 2021	Journal	Text, Image	content, context	LSTM	99.4%
[5], 2021	Journal	Text	content	Stacking Approach (ML+DL) Models	99.9%
[12], 2021	Journal	Text	content	CNN, LSTM, Bi-LSTM+attention, HAN, BERT	98.4%
[13], 2021	Journal	Text	content	CNN, RNN, LSTM	87.4%
[14], 2021	Journal	Text	content	CNN+LSTM	98.6%
[15], 2021	Journal	Text	content	CNN+RNN	99.0%
[16], 2021	Journal	Text	content, context	CNN+BERT Transformer	98.9%
[17], 2021	Journal	Text	content	CNN, RNN, CRNN	86.0%
[18], 2021	Journal	Text	content	Linear with (GRU, CNN, RNN)	83.1%
[19], 2021	Journal	Text	content	CNN-LSTM:	98.0%
[20], 2021	Journal	Text	content, context	Hybrid, XGBoost+DeepFake	86.9%
[21], 2020	Journal	Text	content, context	CNN	90.0%
[22], 2020	Journal	Text	content, context	CNN+RNN	94.0%
[23], 2020	Journal	Text	content	Bi-GRU, ELMo with MLP	83.3%
[24], 2020	Journal	Text, Image	content	SeTa -Attention mechanism	97.0%
[25], 2020	Conference	Text	content	CNN, LSTM	98.3%
[26], 2020	Conference	Text, Image	content, context	CNN	72.3%
[27], 2020	Conference	Text, Image	content	BERT, C-HAN, BI-LSTM, CNN	61.9%
[28], 2020	Conference	Text, Image	content	SLD+CNN	x
[29], 2020	Journal	Text	content	CNN	98.4%
[30], 2020	Journal	Text	content	LSTM+GRU, FNN	94.0%
[31], 2020	Journal	Text	content, context	CNN+LSTM	97.5%
[32], 2020	Journal	Text	content	RNN+LSTM	70.6%
[33], 2020	Journal	Text	content	CNN	83.4%
[34], 2019	Journal	Text	content	CNN+Bi-LSTM with att., LSTM	71.2%
[35], 2019	Conference	Text	content	CNN, LSTM	93.4%
[36], 2019	Conference	Text	content, context	RNN, LSTM	77.0%
[37], 2019	Journal	Text	content, context	Att-based CNN	94.8%
[38], 2019	Journal	Text	content, context	RNN-LSTM	74.2%
[39], 2019	Conference	Text	content	Bi-LSTM+MLP	81.0%
[40], 2019	Conference	Text	content	LSTM-HAN	86.0%
[41], 2019	Journal	Text	content, context	Attention Mechanism	93.0%

Year	Type	Input Data	Feature Type	Used Model	Acc.
[42], 2019	Journal	Text	content	CNN	x
[43], 2019	Conference	Text, Image	content	CNN and LSTM	82.0%
[44], 2018	Conference	Text	content	CNN, CNN+LSTM	97.3%
[45], 2018	Journal	Text	content	CNN+Bi-LSTM	44.9%
[46], 2018	Conference	Text	content, context	CNN+RNN, LSTM+CNN, LSTM	82.0%
[7], 2018	Journal	Text	content, context	Bi-LSTM+Attention, LSTM, CNN	80.8%
[47], 2018	conference	Text, Image	content	CNN	82.7%
[48], 2018	Journal	Text	content, context	Bi-GRU+Attention	82.8%
[3], 2018	Journal	Text	content, context	RCNN	43.3%
[49], 2018	Conference	Text	content	RNN Vanilla, GRU, LSTM	21.7%
[50], 2017	Conference	Text	content	GRU, HAN	96.8%
[51], 2017	Conference	Text	content, context	RNN	95.3%

RQ1: What are the DL algorithms, methodologies, and techniques used for detecting false news?

We note from our conducted study results in figure 1 that the most used method for the purpose of detecting fake news is Convolutional Neural Network (CNN), where 28% of explored research papers use CNN model [11-17], [24-34] as it gives high accuracy and promising future in NLP. In CNN, sentence modeling is done by tokenizing the words, which are then transformed in a word embedding matrix. As a result, the formed matrix passed to the input layer of the CNN model to apply convolutional filters to this input and produce a feature map. Pooling layers are then used for applying max pooling to reduce the dimensionality of the feature map. After this process, we get the final sentence representation. Worth to mention that the CNN model goes over multiple feature extraction stages, which allow the model to learn automatically from provided dataset. There is still disadvantage in CNN model, which faces difficulty in presenting the sequential order. As a result, other research articles such as [14], [16], [19] use CNN in combination with Long Short Term Memory (LSTM) model to overcome the memory vanishing problem and record better classification accuracy. In [14], the authors use hybrid FND model with a novel COVID-19 dataset using multiple branches of CNN with LSTM layers by applying supervised learning for content based features. Hybrid models provide higher accuracy by merging two DL models [15].



DNN: Deep Neural Network, GNN: Gated Neural Network, Att-based: Attention based Mechanism, HAN: Hierarchical Attention Neural Network, Bert: Bidirectional Encoder Representation from Transformer, MLP: Multi-Layer Perceptron, GRU: Gated Recurrent Unit, RNN: Recurrent Neural Network.

Figure 1: DL models developed for FND

RQ2: What are different sources of fake information used to perform FND and what's the dataset language?

Datasets are collected from different sources such as: fact checking websites and news websites for true news as in [12]. Most researches used social media platforms, which contain huge content of fake news due to the ease of republishing online content. . The main characteristic of social media contents is that it is limited in terms of word count, making sentences shorter and more concentrated. As a result, this limitation will affect the learning and feature extraction efficiency for DL models. Our research statistics show that 63% of selected research papers have used social media extracted dataset from twitter as in [12], [13], [17], [20], [21], [26]. There are very few researchers who used Facebook and Instagram to include content features extracted from both textual and visual post content as in [11], [24]. On the other hand, 91% of the selected articles used an English dataset language. Few proposed models reviewed in [17], [18], [19], [32] have used Arabic language datasets. This is due to several challenges such as low availability of Arabic datasets and difficulties in training Arabic language dataset related to its characteristic and computational problems at orthographic.

RQ3: What are the used features in classification and/ or detection and what's the input data type? We explore whether the model considered the extracted feature from content feature or they include context features to optimize the model accuracy. We find that 66% of research studies include content based features, while 36% of candidate research papers developed models include both content and context features. This can be considered as another aspect that need to be taken in consideration and which types of dataset input can increase the classification accuracy.

The second part of the research question specifies the type of content whether textual or they use both textual and visual features. As we mentioned previously, our SLR considers content based textual approach but there are 16% of studied articles, which propose DL FND models that combine textual and visual as input type. Extracting features from both types of input data, as well as the models described in [24], [26], [27], [28], [43], [48]. The authors in [24] proposed model that consists of three branches for feature extraction including text branch, image branch and hashtag branch using attention mechanism for textual and visual branches. New attention mechanisms have been developed called Semantic and Task attention (SeTa).It allows the model to indicate the most effective hashtags based on semantic and task level information while the attention mechanism in hashtag branch will indicate the most contributing hashtag in the posts' meaning. Moreover, it indicates on task level which hashtag plays important role in discriminative text detection. They also use Optical Character Recognition (OCR) algorithm to extract text content from images. The three models are concatenated to compose ensemble classification model.

RQ4: What are the used evaluation metrics and the accuracy of DL FND models? The most used metrics for evaluating model performance are precision, recall, Area Under the Curve (AUC), F1-score and the model accuracy, which are used to compare between different proposed approaches. In all literature, accuracy is calculated except few papers don't mention the model accuracy as implied in table 1.

We find that highest accuracy is recorded in [5], which reaches 99.9%. They implement stacking model that is composing of five ML classifiers with Term Frequency- Inverse Document Frequency (TF-IDF) for tokenization. ML models ensemble with additional three DL models including CNN, LSTM, and GRU with embedding for tokenization. As a result, the prediction of each individual model fed to the final classifier to present the news prediction.

4 CONCLUSION AND FUTURE WORK

In conclusion, there are huge gaps can be filled in future work. The research work in FND based on DL models on Arabic language is very limited due to several challenges. There are no adequate dataset for Arabic language and all available datasets are either not enough for extracting features or they have some features that are mostly textual content. Moreover, the dataset size is small comparable to required dataset to be used for DL to extract effective features. Additionally, we notice that the used datasets in the literature are labelled either manually or using Machine Learning (ML) basic classification algorithms, which result in not having high accuracy. There is also single proposed model, which includes the OCR to extract the textual content from image while fake news can be padded within images to avoid FND based on textual content. As a result, we find that there is a big need to propose more FND deep learning models to process multi-module data. Furthermore, we discovered that the accuracy of a single module might vary depending on the dataset used to evaluate it, therefore there is no one-size-fits-all assessment dataset that can be used to test several modules and judge the accuracy of various methodologies. That's why we can't prefer a module over another according to accuracy only unless they are tested and evaluated with similar features and dataset from all aspects. Finally, we find that the most dataset that is related to social media network is limited to Twitter and Weibo. There is very limited work has been done using Instagram or Facebook due to their policies to extract post and user information.

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