Multimodal fake news detection using a Cultural Algorithm with situational and normative knowledge

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***Abstract*—The proliferation of fake news on social media sites is a serious problem with documented negative impacts on individuals and organizations. A fake news item is usually created by manipulating photos, text, or videos that indicate the need for multimodal detection. Researchers are building detection algorithms with an aim for high accuracy as this will have a massive impact on the prevailing social and political issues. A shortcoming of existing strategies for identifying fake news is their inability to learn a feature representation of multimodal (textual+visual) information. In this paper, we present a novel approach using a Cultural Algorithm with situational and normative knowledge to detect fake news using both text and images. An extensive set of experiments have been carried out on real-world multimedia datasets collected from Weibo and Twitter. The proposed method outperforms the state-of-the-art methods for identifying fake news in terms of accuracy by 9% on average.**

***Index Terms*—Fake news detection, Sentiment analysis, Segmentation process, Cultural algorithm**

I. Introduction

With social media sites becoming increasingly popular, user-generated posts can immediately reach a wide audience.Thus, social media has become an ideal location for fake news dissemination. For example, the Pew Research Center stated that about two-thirds (68 %) of U.S adults get news on social media platforms in 2018[1]. The causes for this shift in user habits are implicit in the existence of these social media platforms because the prorating of content on social media is often more frequent and less costly. It is easier to share, discuss and comment on posts with friends and other social media users [1]. Unfortunately, fake news, which usually includes misinformation or even fake images, often takes advantage of this to mislead the users in order to damage a community or an individual, create chaos, and gain financially or politically. For example, by the end of the 2016 presidential election, a report estimated that over 1 million tweets were found linked to the fake news article "pizzagate"[2]. With the last three months of 2016's U.S. presidential election, many people believed that the fake news produced in favor of either of the two candidates was more than 37 million times shared on Facebook and Twitter [2] Thus, dissemination of fake news may cause large-scale negative effects, often influencing or even exploiting public events. And so, automated detection is in great need for reducing the serious negative shortcoming created by the fake news.

Detecting fake news on social media brings several new and challenging work problems. There are several features of this issue which makes it unique for automatic detection. First, fake news is intentionally written to confuse viewers, which makes it nontrivial to identify simply based on news content [3]. The nature of fake news is rather diverse in terms of subjects, formats and media platforms and fake news tries to distort the truth using various linguistic methods besides criticizing true news. Existing work which is specific to textual features only is thus usually not appropriate for the identification of fake news. Further auxiliary information, such as knowledge based and user social user's engagements must also be applied to improve detection [1].Recent advancements have been made to tackle these issues by adding user's social commitments to news content to help to determine which posts are false [4] [5] by giving some promising results. Natali et al. [5] proposed a hybrid model of deep learning to model textual news, user response and post source for fake news detection. Guo et al. [4] created a hierarchical neural network architecture to detect fake news using user engagement with social attention that selects the required user comment. Though the success of above existing fake news detection methods,the use of this supplementary knowledge, in turn, contributes to another important challenge of the data quality itself.

However, the majority of methods focus on detecting fake news using a single modality like using only text or visual content or modeling user engagements to detect fake news. Although there are multimodal fake news detection systems, they tend to solve the problem of fake news by considering an additional sub-task like discriminator of events and finding correlations across modalities. Fake news detection outcomes are heavily dependent on the sub-task, and in the absence of sub-task training, fake news detection performance reduces by an average of 10 %. In particular, our proposed solution detects fake news without any further sub-task being taken into account. This uses both the textual and visual features of a document. The reasons for using multimodal information are

[1]https://www.journalism.org/2018/09/10/news-use-across-social-media-platforms-2018
[2]https://en.wikipedia.org/wiki/Pizzagate$_{c}onspiracy_{t}heory$

as follows: Firstly, various modalities show different aspects of the content. Secondly, information extracted from multiple modalities supplement one another in detecting the validity of data. Lastly, different sources exploit different keywords based on their skills.

The main contribution of the paper can be summarized as follows:

- We designed a multimodal framework for fake news detection using a Cultural algorithm. The proposed model is aimed to detect whether specific given news is real or fake. It takes no further sub-task into account for the detection process.
- Paper's principal innovation is to use the power of natural language processing like sentiment analysis, segmentation process and optimizing it with an evolutionary Cultural algorithm that uses a wider variety of cultural knowledge. Then, the representations from both modalities are concatenated together to produce the desired vector of news, which is finally used for classification.
- Our proposed architecture provides a general model for identifying fake news. The designed multi-modal extractor can be replaced by various versions designed for extraction of features.
- We experimentally demonstrate that the proposed model can effectively classify fake news and outperform existing state-of-the-art models on two large-scale real-world datasets.

The rest of the paper is structured according to this. Section II addresses similar work in the field of fake news identification, with a focus on experiments utilizing multimodal evidence. The detailed description of the proposed method and introduced our architecture model in Section III. Statistical analysis of different types of data set used for experiment and detailed analysis of the observations are shown in Section IV. Finally, we conclude the paper with Section V.

II. Related Work

In this section, we briefly discuss the work related to the proposed model. The main challenge of fake news detection activity is how to identify news through features. Features can be derived from tweets, social context, and even attached images. Therefore, we evaluate existing work from the following two categories: single-modality based and multimodal based fake news detection.

A. Single modality based fake news detection

Most previous research done at the news detection level depended heavily on features of text and user metadata. Textual feature extracts specific writing style [6] [7] and emotional sensation [8] that commonly occurs in fake news content. Potthast et al. [6] demonstrated how to style analysis, network connection, and user reaction would contribute to fake news identification. Shu et al. [7] described how an author's writing style impacts people's views and opinions on reading articles like this. In many fake news identification studies,emotion is considered a significant predictor and most of them use emotion primarily through user stances or simple statistical emotional features. In [8],they proposed a new dual emotion-based approach to detect fake news where it can learn from the content,user comment and representation of emotions from both publishers and users.Textual content of post contains more textual features like statistical or semantic features, which have been explored in many works of literature of fake news detection [9], [1], [10]]. Kim et al. [11] proposed a convolutions neural network model to identify fake news which can distinguish different granularity of text features with convolution filters. In addition to features directly related to the news articles content, auxiliary information can be extracted from user-driven social engagements of news on social media. In [12] , they proposed a novel approach to detect fake news based on news content using a knowledge graph. Ke Wu et al. [13] aims to detect propagation patterns and sentiments using graph-kernel based method. However, social context features are noisy, unstructured and labor-intensive to collect [14].

Visual features extracted from visual elements (picture and video) have been shown to be a salient indicator of fake news detection [15] [1]. However, the value of multimedia content on social media is being verified in very limited studies. Several visual and statistical features have recently been extracted for news prediction [15]. Fake images were recognized using a classification framework based on various user-level and tweet-level features [16]. Marra et al. [12] researched the efficiency of several fake image detectors toward image-to-image conversion using GANs. Though, these models are still hand-crafted and complex to represent visual content.

Even though all of the above mentioned single-modality approaches have been able to deliver promising results, the unstructured nature of social networking data is always a difficulty in the extraction of knowledge. And so, the researchers began experimenting with features derived from different modalities (i.e. text and image) to address this constraint.

B. Multi-modal based fake news detection

Deep neural networks have been successfully applied to various tasks to learn feature representations from multiple aspects. Wang et.al [14] created an end-to-end framework based on Adversarial Neural Network, which can derive event invariant features and can detect fake news on the newly arrived events. Their model have two components: for a textual part, it took word vector embedding as input and created text representation using text-CNN [11]. Image representation from VGG-19 platform pre-trained on Image Net [17] was extracted. Both components were fused together using a fully connected neural network classifier into event discriminator and fake news detector. Author Khattar et al. [18] built a model named MVAE: Multimodal Variational Auto-encoder for Fake News Detection.It uses a bimodal vector autoencoder combined with a conditional classifier for fake news identification tasks. The platform comprises of three main components, an encoder, a decoder, and a fake news detector element. The variable autoencoder is capable of learning probabilistic latent variable models by maximizing the marginal likelihood of

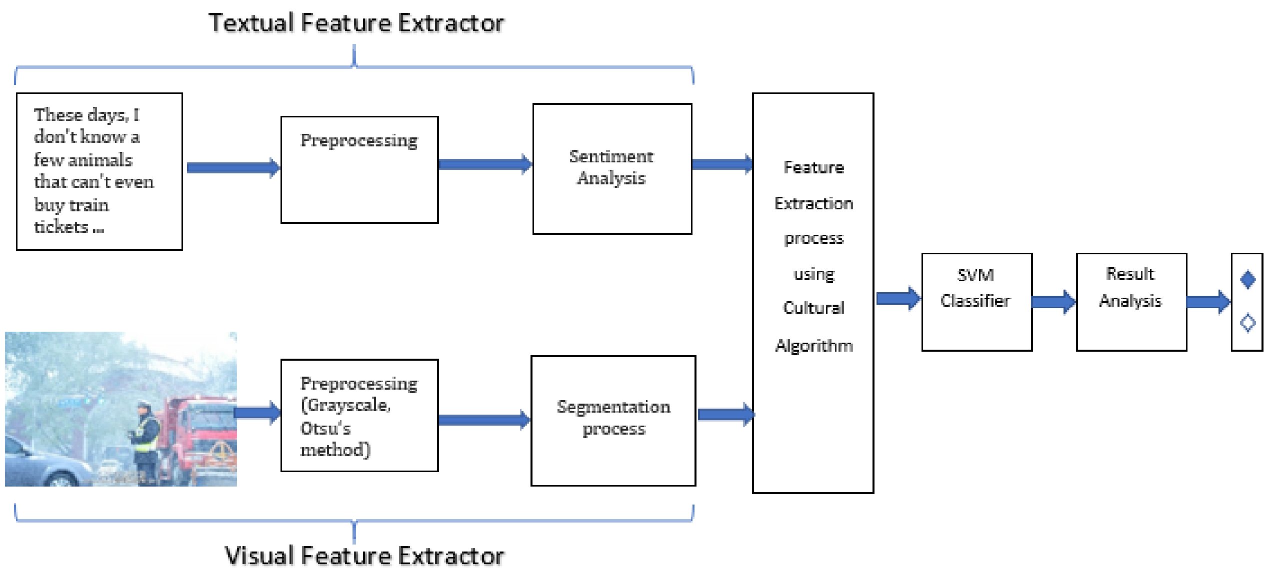

Fig. 1. Architecture of proposed model

observed data. They used bi-directional LSTMs and VGG-19 to extract text and image representation respectively. Shivangi et al. [19], introduced a model named SpotFake-A multimodal Framework for Fake News Detection without considering any other secondary task. They used a language model like BERT to learn textual features and VGG-19 platform pre-trained on Image Net [17] to learn image features. Even though multi-modal based models do well in identifying fake news, consideration of secondary task with fake news detection problem decreases the efficiency performance.

An important step in developing predictive models is determining the best features to be used for building the models. By using the evolutionary approach like Cultural algorithm which uses a wider variety of cultural knowledge [20] for finding an optimal features which can reduces the cost and also make it more efficient. To overcome such problems, we designed a model of fake news detection using a cultural algorithm on two different modalities and distinguished a piece of news content into real and fake without considering any secondary tasks.

III. Methodology

In this section, we introduce our proposed framework of multimodal fake news detection in figure1. The basic idea behind our work is to detect fake news from both the modalities of given tweets independently without considering any other sub-task. We divided our model into three main components. The first one is a textual feature extractor that uses Sentiment analysis to extract meaningful content from textual data. The second component is Visual feature extractor which extracts visual features from the post using preprocessing techniques and Segmentation process. Feature representation from both components were passed through a Cultural algorithm to extract optimum features. The last component is a fake news detector that uses a classifier to detect fake news.

A. Textual feature extractor

Algorithm 1 Sentiment analysis for text

Inputs : Text File τ , the sentiment lexicon x

Output: S = P, N_g, N and Strength S, where P: Positive, N_g:Negative,N:Neutral.

Initialization: $SumPos$ and $SumNeg$ = 0, where
$SumPos$: collects the polarity of positive tokens $t_i -_{s\,mt}$ in τ
$SumNeg$: collects the polarity of negative tokens $t_i -_{s\,mt}$ in τ

begin
  foreach $t_i \in \tau$ **do**
    Search for t_i in x
    if $t_i \in Pos-list$ **then**
      SumPos $\leftarrow SumPos$+t$_{i-smt}$
    else if $t_i \in Neg-list$ **then**
      SumNeg $\leftarrow SumNeg$+t$_{i-smt}$
  if $SumPos > |SumNeg|$ **then**
    $S_{mt} = P$
    S =SumPos/(SumPos+SumNeg)
  else if $SumPos < |SumNeg|$ **then**
    $S_{mt} = N_g$
    S =SumNeg/(SumPos+SumNeg)
  else
    $S_{mt} = N$
    S =SumPos/(SumPos+SumNeg)

In this sub-module, the sequential list of words in the articles is the input to the extractor of textual features. It's first applied to pre-process the information by removing special characters and symbols, and convert them into space characters in order to calculate the frequency of words and their ratio in the textual content.In order to extract informative and meaningful features from the textual content, we employ Sentiment analysis. Sentiment analysis is also known as opinion mining which is used to understand the effective meaning of sentences and phrases. It assigns classification levels to statements made by the authors; also known as polarity. It could be as basic as binary distinction forms such as positive and negative or sometimes neutral. While sentiment analysis from the document goes beyond polarity, it could also involve evaluating the writer's emotional state as furious, nervous, distressed and excited. Some sentiment dictionaries exist to help in the achievement of this task such as [21] and [22]. In the context of our work, we use the text's sentiment to the negative, positive and neutral polarities of a text message.The detailed steps of the sentiment analysis of text are summarized in algorithm 1. We believe that the sentiment of writing a news article may serve as a key element in characterizing the news as false or actual. It will also help to further increase accuracy and consider related feelings and sentiments.

B. Visual feature extractor

The attached images of the news content are input to the visual feature extractor. In order to extract visual features efficiently, the proposed method first preprocess the image, apply image representation to segmentation process and lastly for optimal feature extraction and minimizing it's cost it using the concept of Cultural algorithm.

a) Preprocessing step: In our preprocessing step,we first resize all images to 200*200, convert image to gray scale and use Otsu's binarization method for automatic image threshold. Thresholding creates binary images from gray-level ones by turning all pixels below some threshold to zero and all pixels above that threshold to one.

b) Segmentation process: The segmentation of images is the method of partitioning a digital image into multiple segments (pixel sets, often known as image objects). The segmentation purpose is to simplify and/or change an image's representation into something that is more relevant and simpler to evaluate. Here, we use K-mean, Discrete wavelet transform(DWT) and nine additional features to extract meaningful content from the images. Wavelet transform (WT) is an effective tool for extracting features from pictures because its multi-resolution analytical property enables image analysis at multiple scale rates. Feature matrix formed from these was further passed to a Cultural algorithm to get the best optimal value.

C. Optimization using Cultural Algorithm

All the feature matrix from text and photos is passed through the Cultural algorithm for optimal feature extraction. Cultural algorithms (CA) are a branch of evolutionary computation where there is a knowledge component that is called the belief space in addition to the population component. It was first introduced by Reynolds [23]. It has five knowledge components among which here we have used normative knowledge and situational knowledge. Normative knowledge is a collection of acceptable value ranges for the individuals in the population space whereas , situational knowledge provides a set of important events (e.g. successful/unsuccessful) from an experience of specific individual [24]. Its use as an optimization algorithm to restrict optimization, combinatorial optimization, and continuous function optimization for a wide variety of non-limited domains. Our motive is using this algorithm to find optimal features from both text and images at the best cost. In order to explore the training process of the model,on selecting optimal value at each iteration training cost has been plotted in figure 2.

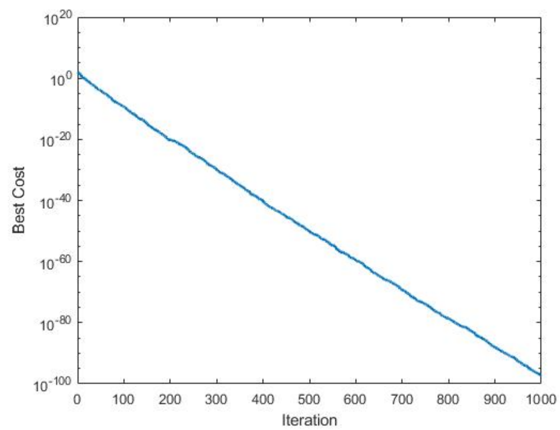

Fig. 2. Cost function

D. Fake news detector

The two optimal feature vectors obtained after passing through Cultural algorithms are passed through kernel SVM. Recently, SVMs have grown rapidly, of which the most popular and effective one is kernel SVM.Here we have used radial based function kernel (RBF) for fake news classification. Since the classifier is trained by a given dataset, so it is possible to achieve high accuracy performance only for the particular training dataset and not any other independent datasets. We need to incorporate cross-validation into our system to prevent over-fitting. Cross-validation will not improve the accuracy of the final classification but will allow the classifier reliable and generalize to other different datasets. Here, we implemented the K-fold cross-validation because of its property, as quick, easy and it uses all data for training and validation. In this study, by means of the trial-and-error process, we empirically calculated K as 10, which implies we assume parameter K varying from 3 to 10 with initial step rising, and then we train the SVM by each value. Finally, we pick the optimum K value corresponding to the valid classification.

Here, a set of m news article containing the text and image information, we can represent the data as a collection as a set of text-image tuples denoted as $A = (A_i^T, A_i^I)_{\mathrm{i}}{}^{\mathrm{m}}.(S_A)$ is process of sentiment analysis for textual part of news article

TABLE I
PERFORMANCE OF PROPOSED MODEL V/S OTHER METHODS ON 2 DIFFERENT DATASETS

Dataset	***Method***	***Accuracy***	***Precision***	***Recall***	***F1***
Twitter	Textual	0.563	0.527	0.539	0.582
	Visual	0.602	0.619	0.518	0.596
	EANN-[15]	0.648	0.810	0.498	0.617
	EANN [15]	0.718	**0.822**	0.638	0.719
	MVAE-[19]	0.656	N/A	N/A	N/A
	MVAE [19]	0.745	0.801	0.719	0.758
	Proposed Method	**0.798**	0.791	**0.833**	**0.760**
Weibo	Textual	0.683	0.635	0.612	0.672
	Visual	0.610	0.624	0.630	0.607
	EANN-[15]	0.795	0.806	0.795	0.800
	EANN[15]	0.827	0.847	0.812	0.829
	MVAE-[19]	0.743	N/A	N/A	N/A
	MVAE[19]	0.824	0.854	0.769	0.809
	Proposed Method	**0.891**	**0.873**	**0.822**	**0.932**

Algorithm 2 Procedure of multimodal fake news detection

Inputs : The multi-model input $\{m_i\}_{i=1}^{N}$,Label $\{n_i\}_{i=1}^{N}$ and the learning rate η

begin

[1] Apply sentiment analysis (S_A) for text and segmentation process for image (S_p);

[2] Create feature matrix of text (f_t) and image (f_i);

[3] Training set $\{f_t, f_i, i = 1, 2, \ldots n\}$ and weight matrix q_i,i=1,2,...n passed to Cultural algorithm for feature extraction (ϱ) and optimal selection(γ);

[4] Calculate training set (S), error set (E) ,and remaining set (R);

[5] Apply kernel classification (K);

[6] Based on test data classify and update it with iteration.

and features obtain from it is represented by (f_t).Similarly, process of visual feature extraction is represented by (S_p) and all the features obtained from images are represented by (f_i) . All features from text and image are fused together by simple concatenate method.This combined representation is taken input to Cultural algorithm for feature extraction by optimal selection denoted by (γ). Optimal features are further used for classification.

IV. EXPERIMENTS

A. Datasets

Our model training is carried out on two datasets, i.e. Weibo dataset and Twitter dataset, which are publicly available. These are the only databases accessible to the best of our knowledge that has combined picture and textual content.

1) Weibo dataset: The Weibo dataset is used in [14] to track fake news. Real news from official Chinese news sources such as Xinhua News Agency was stored in this dataset. The fake news is crawled from May 2012 to January 2016 and checked by Weibo's official gossip debunking system. This system encourages specific users to report suspicious messages, and a committee of trustworthy users is investigating suspicious posts. We follow the same steps of pre-processing done by [14] for a fair comparison. To ensure the quality of the image , we first remove the duplicates and low-quality images. We split the dataset into the training, validation and testing sets in a ratio of 7:1:2 respectively.

2) Twitter dataset: This twitter dataset is released from MediaEval [25] as a part of the challenge which aimed to detect fake content on twitter. The dataset is composed of tweets,images and additional social context information . It is made up of 17,000 individual tweets, related to various incidents. The training set contains 9,000 fake news messages and 6,000 real news items. Here, we have used a developing set as a training set and test set for testing purposes.As we focus on multimodal fake news, we remove the tweets without any text or image and also remove social context information.

TABLE II
THE STATISTICS OF DATASETS

Total number of content	***Twitter***	***Weibo***
Number of real news	6026	4749
Number of fake news	7898	4779
Total number of images	514	9528

B. Performance comparison

In this subsection, we outline our experiment setup and detail analysis of the result of the proposed model in comparison with the current state-of-the-art method. The experiments were carried out on the platform of core i7 processor and 16

GB RAM, running under Windows 10 operating system. The algorithm was in-house developed on Matlab 2018 software.

Table 3 shows the performance comparison of the proposed model with the current state-of-the-art EANN [14] and MVAE [18]. We can observe that the overall performance of the proposed method is better than the current methods in terms of accuracy, precision, recall, and F1 score. Both EANN and MVAE have versions of two types each. EANN-/MVAE- is when fake news classifier is used independently. EANN / MVAE is when the fake news classifier is focused on a secondary task in the model. In the case of EANN, the secondary function is an event discriminator that excludes event-specific features and retains common features between activities. While in MVAE, the secondary sub-task is to discover the correlations across the modalities to improve shared representation.

Our proposed model on the Twitter dataset gains 24.33% and 18% improvement in accuracy over EANN-and EANN respectively. On Weibo dataset output benefit over EANN-and EANN is 9%, and 5.8% respectively. It outperform MVAE- and MVAE by 23.5% and 14.6% respectively as compared to MVAE on twitter dataset.The brief summary of the findings is presented in Table I.

C. Hyper parameter used in the model

We conduct random search iterations on possible combinations of hyper parameters to pick the right permutation of the hyper parameters. The number of possible permutations is reduced in each iteration, based on the previous iteration's results. Within our model, everything is configurable from the number of generations to the number of population size, acceptance ratio and decision variables. In Cultural algorithm , the population size for all runs was 100 and each run was 1000 generation, which is also a stopping criteria. Table III provides a complete list of hyper parameters.

TABLE III
AN OVERVIEW OF HYPER PARAMETERS USED IN PROPOSED MODEL

Parameters	***Values***
#Decision variable	10
Decision variable range	[1,10]
# of iteration	1000
Population size	100
Acceptance ratio	0.35
Learning rate	0.02

V. CONCLUSION AND FUTURE WORK

The current multimodal state-of-the-art methods suffers from a problem of not being able to learn from fake news detection problems as a primary task. To address this issue, we proposed a model of multi-modal fake news detection using a Cultural Algorithm without considering any sub-task. It outperforms the current methods by an average of 9%. Previous literature has tackled the problem of detecting fake news from a variety of angles, such as natural language processing, knowledge graphics, computer vision, and user profiling.There can still be a gain in performance for a larger data collection and more complex approaches that clarify how various modalities play an important role in the detection of fake news.

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