The Journal of Supercomputing (2021) 77:1015–1037
https://doi.org/10.1007/s11227-020-03294-y

DeepFakE: improving fake news detection using tensor decomposition-based deep neural network

Rohit Kumar Kaliyar[1] · Anurag Goswami[1] · Pratik Narang[2]

Published online: 5 May 2020

Abstract

Social media platforms have simplified the sharing of information, which includes news as well, as compared to traditional ways. The ease of access and sharing the data with the revolution in mobile technology has led to the proliferation of fake news. Fake news has the potential to manipulate public opinions and hence, may harm society. Thus, it is necessary to examine the credibility and authenticity of the news articles being shared on social media. Nowadays, the problem of fake news has gained massive attention from research communities and needed an optimal solution with high efficiency and low efficacy. Existing detection methods are based on either news-content or social-context using user-based features as an individual. In this paper, the content of the news article and the existence of echo chambers (community of social media-based users sharing the same opinions) in the social network are taken into account for fake news detection. A tensor representing social context (correlation between user profiles on social media and news articles) is formed by combining the news, user and community information. The news content is fused with the tensor, and coupled matrix-tensor factorization is employed to get a representation of both news content and social context. The proposed method has been tested on a real-world dataset: BuzzFeed. The factors obtained after decomposition have been used as features for news classification. An ensemble machine learning classifier (XGBoost) and a deep neural network model (DeepFakE) are employed for the task of classification. Our proposed model (DeepFakE) outperforms with the existing fake news detection methods by applying deep learning on combined news content and social context-based features as an echo-chamber.

Keywords Social media · Fake news · Deep learning · Echo chamber · Tensor factorization

✉ Pratik Narang
pratik.narang@pilani.bits-pilani.ac.in

Extended author information available on the last page of the article

1 Introduction

Today's world of mobile revolution has made it easy for consumers to share articles and interact with the people over social media. As a result, social media has become a popular source for the consumption of various news articles. In a single day, a large volume of data [1] is produced online using various social media platforms. The major part in the huge data that is generated online is information-based especially, news-based [2]. This ease with which a user can circulate news online has led to an increase in the number of fake news. The false information published with the intention of misleading consumers is known as fake news. Fake news is created in a manner to make it appear like a genuine and credible piece of information and thus is easily shared by the people on social media. Such type of news may manipulate public opinions and is spread with an objective of financial and political gains. This imparts a negative impact [3] on society and hence it is crucial to tackling this problem. Figure 1 shows a few examples of fake news which spread over social media platforms during the 2016 U.S. Presidential General Election [4] and selection of New Air Marshal in India. These fake news hampered the public emotionally and spread a negative impact [5] on the society.

A common instinct to examine whether the news is fake or real is based on the content of the news article. News content-based methodologies [3] focus with respect to extracting different features in fake news content, including information-based and style-based. Style-based methodologies attempt to identify fake news by capturing the manipulators in the writing style. We can use linguistic features like news content to find clues between fake news and real news. But the intention of creating fake news is to mislead consumers. Thus, with the help of

Fig. 1 Examples of some fake news spread over social media. *Source* Facebook®

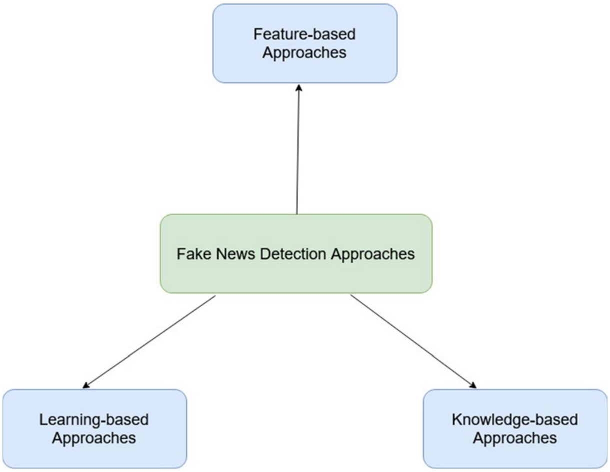

Fig. 2 Approaches for fake news detection

news content, it is a very challenging task for the researchers to detect fake news more accurately. We need to look at the side of social-context for better detection.

Latent information based on the social context like user and news article engagement must also be considered to improve the detection of fake news. Approaches for fake news detection are shown in Fig. 2. Social engagements [6] could be another significant feature for fake news detection. Social context-based methodologies mean to use user social engagements (the relationship among publishers, news pieces and user) as auxiliary data to help recognize fake news. Instance-based methodologies [7] use users' perspectives from relevant post substance to induce the integrity of unique news stories. A user cannot exist as one individual at any social media platform, so another important factor for more accurate classification of fake news is echo-chamber (a group of people with like-minded people).

However, an essential user-based feature is the echo chamber. Echo chambers can play a vital role for the dissemination of fake news. The news articles are shared within these echo chambers if they find story to suit their philosophies. User is not isolated on the web but connected in the form of a community. It is the main reason that this community-based information can play a vital role in fake news detection. The idea is to utilize this kind of echo chambers to obtain user-related and community-related information from the news articles. This refers to the problem of users with the same interests are aggregated together in social circles, and the opposing ideas are rejected and disapproved by the majority.

Fake news detection is a relevant problem in society and is now receiving tremendous attention from the research community as well. It is a challenging task to detect fake news because multiple entities are involved in designing and spreading fake news along with the lack of public awareness and complicated propagation over social media plays a vital role [7]. It is is the main reason that journalists do not care about the damage to the reputation of any person but only economic gain. The complexity of the fake news problem is due to its many faces of fakesters.

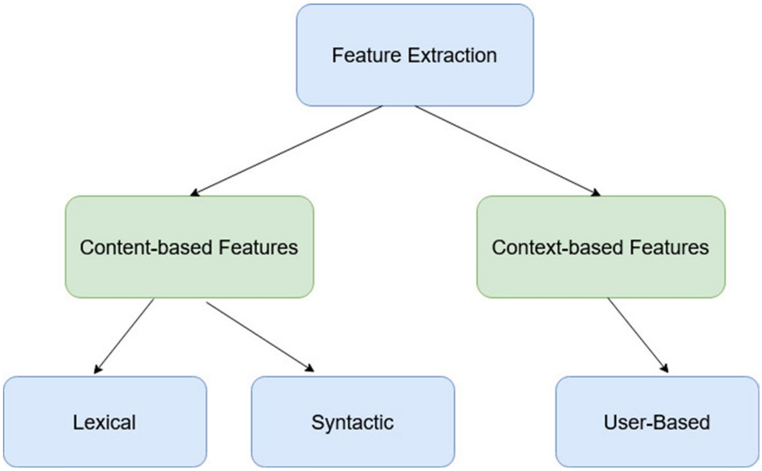

Fig. 3 Type of features for fake news representation

The above challenges create many research questions and demand solid solutions. This work is motivated by the research question mentioned below:

RQ1: Can we build a more accurate system for fake news detection?
RQ1: Would the combination of all content-context-user-level features improve the performance in the fake news detection? (refer Fig. 3)
RQ2: Which classification model (machine learning or deep learning-based) is the most accurate for fake news classification using several context-dependent datasets?

To respond to the above research questions, we propose a useful model (DeepFakE) for fake news detection. In this paper, the news-user engagement (relation between user profiles on social media and news articles) is captured and combined with user-community information (information about the users with having the same perception about a news article) to form a 3-mode (content, context and user-community) tensor. A tensor is a multidimensional array that gives a higher dimensional generalization of matrices. A tensor can be thought of as a data cube and is used when dealing with multi-relational data [7]. For this work, fake news detection is done by combining news content and social context features. Consider this context, the news content is combined with the tensor which represents the social context of the context-specific users. A coupled matrix-tensor factorization results in an underlying representation of both news content and social context. Experiments have been conducted using machine learning as well as deep learning-based models. A machine learning model (XGBoost) and a deep neural network model (DeepFakE) are used for modeling this combined representation for fake news detection. The relevant meaning of the word deep in deep learning refers to the number of layers through which the data are transformed. These extra layers enable composition of features from lower layers, potentially modeling the data. A higher number of hidden layers in the neural network increase order of weights, and it helps to make a higher-order decision boundary. More hidden layer, there are more chances to approach the end goal quickly. We have designed our proposed model containing four hidden layers with the selection of optimal hyperparameters. Our proposed model (DeepFakE) achieved state-of-the-art results as compared to existing methods with a validation accuracy of 85.86 % with BuzzFeed and 88.64% with PolitiFact dataset. The main contributions of this paper are:

- Modeling a deep neural network (DeepFakE) on both news content and social context to achieve state-of-art results for fake news detection.
- Demonstrating the results on a real-world dataset (BuzzFeed & PolitiFact).

The paper is organized as: Sect. 2 discusses the literature review in the field of fake news detection. The proposed method is discussed in Sect. 3. Classification techniques are discussed in Sect. 4. The details of a dataset, experiments and results are presented in Sect. 5, followed by conclusions in Sect. 6.

1.1 Motivation and research goal

Fake news detection is one of the emerging topics that caught the attention of researchers across the world in artificial intelligence. Consequently, a large amount of research has been based on either content-level or context-level features and provided benchmark results. Despite receiving significant attention in the research community, fake news detection did not improve significantly due to insufficient context-specific news data. Creating appropriate hand-engineered features [8, 9] to distinguish the falseness of such statements is a technically challenging task. In contrast to the classical feature-based model, deep learning has the advantage in the sense that it does not require any handcrafting of rules or features, rather it distinguishes the best feature set on its own for an issue or problem.

In our research, the news-user engagement is captured and combined with user-community information to form a 3-mode tensor. In this paper, fake news detection is done by combining news content and social context features. For this detection, the news content is combined with the tensor which represents the social context. A coupled matrix-tensor factorization results in a latent representation of both news content and social context. Further, the deep neural network-based method with optimized parameters is used for modeling this combined representation for fake news detection.

Research Goal Combining News content, social context and echo-chamber-based (user-community-based) information for fake news detection using Deep Learning Techniques.

2 Related work

News can be classified as fake or real based on various aspects like author or publisher, headline, text and visual content. Recent research discusses methods based on news content and social context to detect fake news. Zhou et al. [2] have described four perspectives for examining a news article: knowledge-based, style-based, propagation-based and credibility-based. Knowledge-based and style-based perspectives exploit the news content, whereas propagation-based and credibility-based perspectives exploit the social context.

News content-based features are captured using linguistic and visual cues in the article [7]. Ott et al. [10] have proposed a method for detecting deceptive spam reviews. Features like count of part-of-speech (POS) tags, word counts, n-grams have been considered for deceptive review classification. Feng et al. [11] have detected deceptive reviews on the basis of context-free grammar (CFG) rules. Chen et al. [12] have discussed different lexical, syntactic traits of an article to identify its misleading content. In their research, they have investigated different type of syntactic features for fake news classifications.

Social context-based features are captured on the basis of users, posts and networks [7]. Tacchini et al. [13] have proposed a method to identify fake news based on its user reaction. A bipartite network to classify a news article has been constructed based on the number of user likes for an article. Gupta et al. [14] have evaluated the credibility of twitter events with Page-rank-like credibility approach. Comparison of classifier approach, basic credibility analysis and event graph-based optimization approach is presented. A classifier approach extracts user, tweet and event features. Basic credibility analysis is done by using network information of tweet events and users. Event graph-based optimization approach gives better results as it exploits event similarity. Shu et al. [15] have discussed that social context-based features play an important role in fake news detection as compared to news content-based features. The relationship between publisher, news and user is represented as an embedding to improve fake news detection. Gupta et al. [16] have combined the news content and social context-based features in a tensor. Coupled matrix tensor factorization gives factors which have been used for classification of news article.

Ma et al. [17] have employed recurrent neural network (RNN) to capture contextual features from articles in contrast to machine learning algorithms that require hand-crafted features. The authors conclude that implementation on deep learning framework helped achieve better results as compared to existing techniques. Ruchansky et al. [6] have proposed a hybrid model which combines the text, response and source characteristics of a news article. This technique is divided into three modules. The first module captures the temporal pattern of user and article engagement with RNN to give its lower dimension representation. The second module assigns a credibility score to a user based on user features by employing a fully connected layer. The third module integrates the vector from the first module and score from the second module for classification of the news article. Yang et al. [18] have proposed a TI-CNN (Text and Image information-based Convolutional Neural Network) model. This model combines the explicit and latent features from textual and visual content of the news to classify the news article. Explicit features from textual content include linguistic, psychological perspective, lexical diversity and sentiment analysis. Zhang et al. [19] have proposed a model architecture FakeDetector which combines explicit and latent features obtained from a news article for the classification task. Gated recurrent unit (GRU) is employed for the task of latent feature extraction while Gated Diffusive Unit (GDU) is employed for combined modeling of creators, news articles and subjects [18]. They [19] have investigated the problem of fake news using deep neural network with Twitter-based PolitiFact dataset[1] having 14055 tweets with fack check. These news articles belong to 152 subjects. They have achieved accuracy with 63% for binary class interfaces.. Zhang et al. [20] have proposed proxy-oriented identity-based encryption from lattices for cloud storage. Their results demonstrate that their approach is much more practical when compared with existing schemes. Zhang et al. [21] have investigated an efficient label propagation algorithm (LPA) for community detection. They have conducted different experiments on artificial and real social networks. Their result demonstrates that the proposed algorithm is scalable and exhibits high clustering accuracy. Zhong et al. [22] have investigated a fast Gaussian kernel learning method by solving a specially structured global optimization problem. They have adopted the improved Hoffmans outer approximation method in their investigation. They have achieved good time-efficiency performance as well as better classification performance. Zheng et al. [23] have explored a supervised machine learning-based solution for effective spammer detection using social media data. They have collected a dataset from Sina-Weibo.[2] Experiments have been conducted using SVM (support vector machines)-based spammer detection algorithm. They have achieved with 99.1% true positive rate for spammers. In one of the researches, researchers (Alvaro et.al. [24]) have used three different neural network architectures for fake news classification with the dataset: Getting Real about fake news[3] and Fake News Corpus[4] in their research. They have just considered the text of news articles in their research. They have achieved better classification results as compared to existing models using context-related fake news dataset.

3 Methodology

In this section, the proposed method for fake news detection by taking into account social context [16] is described. The methodology adopted for fake news detection is as shown in Fig. 4.

3.1 Mathematical representations

Scalar is denoted by small letter (e.g., a), matrix is denoted by capital letter (e.g., A), and tensor is denoted by boldfaced capital letter (e.g., $\boldsymbol{A}$).

[1] The dataset can be downloaded from: https://twitter.com/PolitiFact.

[2] The dataset can be downloaded from: https://www.researchgate.net/figure/Dataset-from-Sina-Weibo_tbl1_282028558.

[3] The dataset can be downloaded from: https://www.kaggle.com/mrisdal/fake-news.

[4] The dataset can be downloaded from: https://www.kaggle.com/c/fake-news/data.

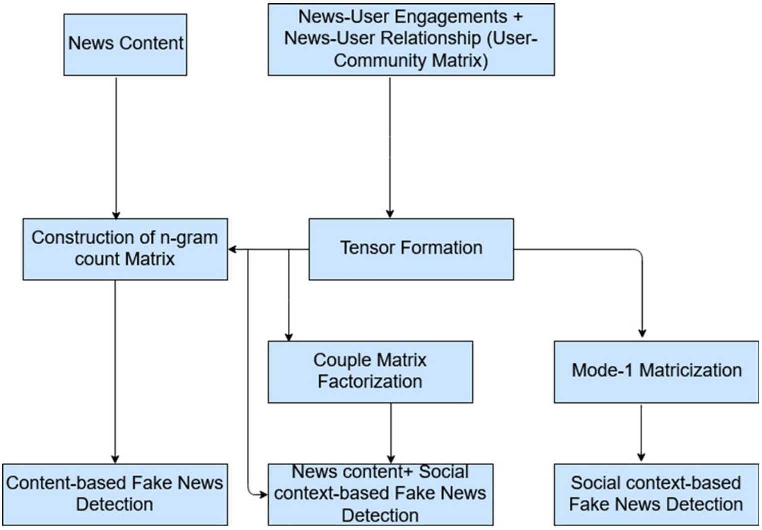

Fig. 4 Proposed methodology

3.2 Construction of n-gram count matrix

The n-gram count matrix gives a representation of the textual content of the news article. This matrix is denoted by N and has dimensions of $(n \times v)$, where n is the total number of news articles in the dataset and v is the number of words in the vocabulary. Every element in the matrix represents the count of occurrence of n-gram in a particular news article.

3.3 Construction of news-user engagement matrix

The news-user engagement matrix gives a representation of the user response to a news article in terms of sharing. This matrix is denoted by U and has dimensions of $(n \times u)$, where n is the total number of news articles and u is the number of users on social media. The elements in this matrix represent the number of times a news article has been shared by a particular user on social media platform.

3.4 Construction of user-community matrix

The user–user relationship given in the dataset is exploited to construct the user-community matrix. Firstly, the echo chambers in the given network of users have been identified. An echo chamber is a community of users sharing common opinions. Meaningful communities have been extracted from the user network by Clauset–Newman–Moore algorithm, which is a computationally resource-efficient algorithm [25]. Every step of this algorithm merges two communities which contribute the most to the global modularity. The detected communities [21] from the user network are thus obtained. User-community matrix has been constructed from these detected communities. The user-community matrix is denoted by C and has dimensions of $(u \times c)$, where u is the number of users in the social network and c is the number of detected communities. It is a binary matrix where only those elements where a user belongs to a particular community are 1.

3.5 Tensor formation

The aim of this paper is to capture social context-based features of a news article. This information can be obtained by representing a news article in the form of news-user engagement along with its propagation in the user community. Thus, following one step further, we propose a tensor modeling of the fake news classification problem, where we capture the latent relation of news articles as well as contextual relation between users. Standard factorization methods [16] have limited effectiveness due to their unsupervised nature. Considering the echo-chambers as closely connected communities within the social network, we represent a news article as a 3-mode tensor of the structure—news, user and user cohort (echo chamber). Thus, we propose a tensor decomposition-based method to encode the news article in a latent representation preserving the user cohort's structure to produce effective results. Our proposed architecture is shown in Fig. 4. A tensor is formed as shown in Eq. 1.

$$T_{ijk} = U_{ij} * C_{jk} \tag{1}$$

The elements in the tensor formed thus depict how a news article has propagated in the echo-chambers. The tensor gives a latent representation of the news article based on its social context.

3.6 Mode-i matricization of tensor

Matricization operation re-orders a tensor into a matrix [7]. A mode-i tensor $\boldsymbol{T}$ can be represented such that $\boldsymbol{T} \in R^{I_1 \times I_2 \cdots \times I_i}$. The mode-i matricization of the tensor $\boldsymbol{T}$ has been obtained from Eq. (2).

$$X_i \in R^{I_i \times (\prod_{n \neq i}^{3} I_n)} \tag{2}$$

The matrix X_1 is mode-1 matricization of the tensor and has dimension $n \times (u * c)$.

3.7 Coupled matrix-tensor factorization [26]

To capture the underlying latent representation of news content and social context together, the collective data are fused by employing Coupled Matrix-Tensor Factorization (CMTF) as presented in [27, 28]. This technique solves the optimization objective, as stated in Eq. (3).

$$\min \frac{1}{2} \| \boldsymbol{T} - [\![T_1, T_2, T_3]\!] \|_F^2 + \frac{1}{2} \| N - [\![N_1, N_2]\!] \|_F^2 \tag{3}$$

In the above equation, $\boldsymbol{T}$ is the tensor with news, user and community information. $[\![T_1, T_2, T_3]\!]$ represents the Kruskal operation on matrices T_1, T_2 and T_3, such that $T_1 \in R^{I_1 \times R}$, $T_2 \in R^{I_2 \times R}$ and $T_3 \in R^{I_3 \times R}$. These matrices are obtained by factorizing the tensor using the R-component PARAFAC procedure [29]. The matrix N is the news content matrix, and N_1 and N_2 are the R factor matrices obtained after non-negative matrix factorization (NMF) [30] of N, where $N_1 \in R^{n \times R}$ and $N_2 \in R^{v \times R}$. Equation (3) can be rewritten as shown in Eq. (4).

$$\min \frac{1}{2} f_1 + \frac{1}{2} f_2 \tag{4}$$

The above optimization problem is solved by computing gradients of the components f_1 and f_2 with respect to factors. The computation of gradients is shown in Eqs. (5)–(7).

$$\frac{\partial f_1}{\partial T_i} = \left(Z_i - X_i \right) T_i^{-i} \tag{5}$$

$$\frac{\partial f_2}{\partial N_1} = - N N_2 + N_1^{-1} N_2^T N_2 \tag{6}$$

$$\frac{\partial f_2}{\partial N_2} = - N^T N_1 + N_2 N_1^T N_1 \tag{7}$$

where

$$Z = [\![T_1, T_2, T_3]\!] \tag{8}$$

$$Z_1 = T_1 \left(T_3 \odot T_2 \right)^T \tag{9}$$

$$Z_2 = T_2 \left(T_3 \odot T_1 \right)^T \tag{10}$$

$$Z_3 = T_3 \left(T_2 \odot T_1 \right)^T \tag{11}$$

$$T^{-i} = T^I \odot \cdots T^{i+1} \odot T^{i-1} \odot \cdots \odot T^1 \tag{12}$$

The symbol $\odot$ in Eqs. (9–12) represents Khatri–Rao product [31]. X_i in Eq. (5) is mode-i matricization of tensor $\boldsymbol{T}$. The final gradient matrix is formed by the concatenation of vectorized partial derivatives with respect to factor matrices. The final gradient to be obtained is as expressed in Eq. (13).

$$\nabla_f = \begin{bmatrix} \mathrm{vec}\left(\frac{\partial f_1}{\partial T_1}\right) \\ \mathrm{vec}\left(\frac{\partial f_1}{\partial T_2}\right) \\ \mathrm{vec}\left(\frac{\partial f_1}{\partial T_3}\right) \\ \mathrm{vec}\left(\frac{\partial f_2}{\partial N_1}\right) \\ \mathrm{vec}\left(\frac{\partial f_2}{\partial N_2}\right) \end{bmatrix} \tag{13}$$

Conjugate gradient algorithm is used for minimization of objective function. The factor matrices obtained after optimization are a lower dimensional representation of the tensor which denotes news, user and community information. The first mode factor obtained after factorization is used as a feature for classification.

4 Classification

The classification of news articles is done on the basis of only news content-based features, only social context-based features and combining both news content and social context-based features.

- News Content-based Classification: The n-gram count matrix which represents only the textual content of news has been used for classification based on news content.
- Social Context-based Classification: The mode-1 matricized tensor represents the interaction of news with users and hence is used for classification based on the social context.
- News Content + Social Context-based Classification: The n-gram count matrix is concatenated with the first mode factor and the resulting matrix is used for classification based on news content as well as social context.

4.1 Machine learning approaches

Experiments have been conducted using a decision tree-based ensemble machine learning algorithm (XGBoost). The detailed description is given below:

4.1.1 XGBoost algorithm

XGBoost [26, 28] is a decision tree-based and fastest ensemble machine learning algorithm that uses a gradient boosting model [28]. XGBoost has been dominating in the field of AI (artificial intelligence) and applied machine learning. XGBoost and gradient boosting machines (GBMs) are both ensemble tree-based techniques that can apply to the standard boosting weak learners (such as CARTs [32]) utilizing the gradient descent architecture. XGBoost enhances the base GBM structure through systems optimization and algorithmic enhancements. XGBoost handles the inefficiency of possible splits during feature selection by looking at the distribution of features [33] across all data points in a leaf and utilizing this information to reduce the search space of possible feature splits.

4.1.2 DeepFakE: a multi-layer deep neural network

We have used a multi-layer deep neural network model [34, 35] in our research for the detection of fake news. The choices of number of dense layers, dropout, the selection of activation function and loss function to make our detection model more efficient and deep optimized are as follows:

Dense layer A deep neural network (DNN) with four hidden layers is designed. This network takes the obtained features as input and classifies the test samples into either one of the categories: fake or real. We can understand the functionality of a dense layer as a linear operation [36] in which every input is connected to every output by some weight. Addition of hidden layers in the neural network helps to improve the model, but only up to a certain point, and further addition of layers can harm the model's performance (it depends upon the complexity of the problem). To get the optimal results, our proposed model consists of four dense layers. Researchers [33, 36–38] have mostly used one or two dense layers before the final softmax layer. With our deep approach, we have taken four dense layers with hyperparameters optimization. In our model, the first dense layer takes the input followed by a dropout and passed to the second dense layer and then the second dense layer passes the information to the third layer and so on before the final softmax layer.

Dropout We can define the dropout as a regularization technique [39–41] which aims to reduce the complexity of any model with the end goal of preventing overfitting [42]. We have applied dropout to dense layers. Application of dropout at each layer of the network has shown good results. Dropout refers to ignoring or dropping units during the training phase of a certain set of neurons which is chosen at random. This means that their contribution to the activation of downstream neurons is temporally removed on the forward pass. We can understand the concept of dropout with an example, the dropout rate is set to 10%, meaning one in 10 inputs will be randomly excluded from each update cycle. In our research, we have taken the value of dropout is 0.2.

Activation Function We have used ReLU (Rectified Linear Unit) as activation function [43]. The main motivation behind to choose ReLU is that it successfully removes negative values from an activation map by setting them to zero in a network. ReLU also increases the nonlinear properties [43] of the decision-making function in the complete network without affecting the receptive fields [43] of the convolution layer. It is the most commonly used activation function in deep learning due to efficient results. It is 0 for all negative values of input z and equal to z for all positive values of input z. It is computationally efficient than sigmoid or Tanh and solves the vanishing gradient problem. The equation of ReLU can be written as:

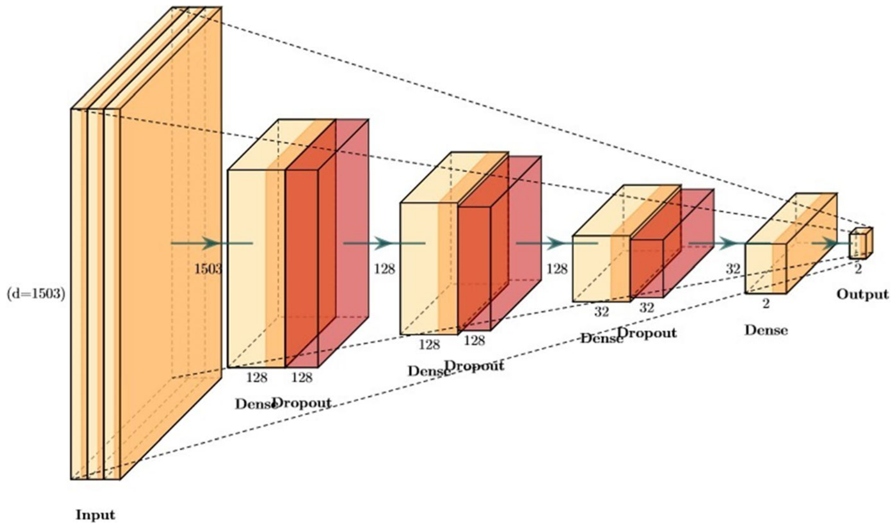

Fig. 5 Architecture of our proposed neural network-based model (DeepFakE)

$$\sigma = \max(0, z) \tag{14}$$

Loss Function (***L***) Cross-entropy loss, or log loss, measures the performance of a classification model whose output is a probability value between 0 and 1. Cross-entropy loss increases as the predicted probability diverges from the actual label. In binary classification, where the number of classes M equals 2, cross-entropy can be calculated as:

$$L = -(y\log(p) + (1 - y)\log(1 - p)) \tag{15}$$

If $M > 2$ (i.e., multi-class classification), we calculate a separate loss for each class label per observation and sum the result.

$$-\sum_{c=1}^{M} y_{o,c}\log\left(p_{o,c}\right) \tag{16}$$

Here, M number of classes, log the natural log, y binary indicator (0 or 1) if class label, c is the correct classification for observation, o, $p$predicted probability observation o is of class c.

In Fig. 5 and Table 1, the layered architecture of our multi-layer DNN-based model (DeepFakE) is shown. This neural network-based is created with 1503 input nodes. It has four hidden layers. First hidden layer has 128 nodes and a dropout of 0.2. Second hidden layer has also 128 hidden nodes with no dropout. Third layer has 128 hidden nodes and a dropout of 0.2. Fourth hidden layer has 32 hidden nodes and a dropout of 0.2. The final output layer has 2 nodes and activation function as SoftMax. The experiments were carried out using the NVIDIA

Table 1 Layered architecture of our proposed deep neural network-based model (DeepFakE)

Layer (type)	Input size	Output size
Dense	1503	128
Dropout	128	128
Dense	128	128
Dropout	128	128
Dense	128	32
Dropout	32	32
Dense	32	2

Table 2 Description of FakeNewsNet dataset

News source	Number of news articles	Number of fake news articles	Number of users
BuzzFeed	182	91	152,57
PolitiFact	240	120	23,865

DGX-1 V100 machine. The machine is equipped with 40,600 CUDA cores, 5120 tensor cores, 128 GB RAM and 1000 TFLOPS speed.

5 Experimental results

5.1 Dataset

The proposed method has been evaluated on BuzzFeed and PolitiFact dataset from the FakeNewsNet Dataset.[5] The dataset contains the following information:

- Real and fake news content: Contains news articles with attributes such as news id, title, text, URL, authors and source.
- News and user engagement: Specifies the number of times a news article has been shared by a user.
- User–user relationship: Specifies the user network on social media.

A brief description of FakeNewsNet dataset is given in Table 2.

5.2 Hyperparameter settings (refer Table 3 for more details)

- Feature Extraction:

[5] The dataset can be downloaded from: https://www.kaggle.com/mdepak/fakenewsnet.

Table 3 Hyperparameters for our proposed deep neural network-based model

Hyperparameter	Description or value
No. of dense layers	4
No. of hidden nodes	128,128,32,2
Dropout rate	0.2
Activation function	ReLU
Loss function	Binary cross-entropy
Output layer	Softmax
Number of epochs	20
Batch-size	32
Learning rate	0.1
Optimizer	Adam

Table 4 Dimensions of features

Features	Dimensions
n-gram count matrix (N)	(182×1500)
News-user engagement matrix (U)	$(182 \times 15{,}257)$
User-community matrix (C)	(15257×81)
Tensor $\boldsymbol{T}$	$(182 \times 15{,}257 \times 81)$
Mode-1 matricized tensor (X_1)	$(182 \times (15{,}257 \times 81))$
Combined content + context matrix	(182×1503)

Sklearn library in Python is used to construct the n-gram count matrix. The number of words in the vocabulary is limited to 1500. The number of communities obtained after Clauset–Newman–Moore algorithm is 81. From Table 2, we can observe that the number of news articles is 182, and the total number of users is 15,257 for BuzzFeed dataset. The number of news articles is 240 and the total number of users are 23,865 for PolitiFact dataset. The dimensions of all the matrices used as features for classification task are given in Table 4.

- Deep Neural Network:

  The DNN with four layers with 128, 128, 32 and 2 hidden nodes, respectively, is designed. ReLU with $\alpha = 0.1$ for hidden layers and softmax for the output layer is used as activation function. The weights are initialized from a normal distribution and scaled using the method presented in [44]. Adam optimizer is used for optimizing the designed DNN. DNN is trained for 20 epochs. Dropout regularization method is employed to avoid over-fitting.

Table 5 Representation of confusion matrix

	Predicted negative	Predicted positive
Actual negative	True negative (TN)	False positive (FP)
Actual positive	False negative (FN)	True positive (TP)

Table 6 Comparison benchmark results using FakeNewsNet dataset (BuzzFeed)

Authors	Precision (%)	Recall (%)	F1-Score(%)
Castillo et al.	73.50	78.30	75.60
RST + Castillo et al.	79.50	78.40	78.90
Shashank et al. (CITDetect)	65.70	100.00	79.20
Shashank et al. (CIMTDetect)	72.90	92.30	81.30
Papanastasiou et al. (CLASS-CP)	85.20	83.00	83.50
DeepFakE-our model	83.33	86.96	85.11

Table 7 Comparison benchmark results using FakeNewsNet dataset (PolitiFact)

Authors	Precision (%)	Recall (%)	F1-Score(%)
Castillo et al.	77.70	79.10	78.30
RST + Castillo et al.	82.30	79.20	79.30
Shashank et al. (CITDetect)	67.90	97.50	79.10
Shashank et al. (CIMTDetect)	80.30	84.20	81.80
DeepFakE-our model	82.10	84.60	84.04

5.3 Performance parameters

In order to assess the performance of our proposed model, we have used the precision, recall, F1-Score, confusion matrices and validation accuracy as evaluation matrices.

5.3.1 Confusion matrix

The information about actual and predicted classifications performed by a classifier is represented by a confusion matrix. Performance evaluation of a classifier is commonly done using the data in the confusion matrix. A confusion matrix for the two-class problem is given in Table 5.

5.3.2 Precision and recall

The measure of the ability of the model to identify the occurrence of a positive class instance accurately is determined by Recall. It is defined as (Tables 6, 7):

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{17}$$

whereas Precision is:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{18}$$

5.3.3 F1-Score

F1 Score is the weighted average of Precision and Recall

$$\text{F1-Score} = \frac{2 * (\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})} \tag{19}$$

5.3.4 Accuracy

Accuracy is a measure of total correctly identified samples out of all the samples. It is defined as:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100 \tag{20}$$

where true positive (TP) = correctly identified, false positive (FP) incorrectly identified, true negative (TN) = correctly rejected, false negative (FN) = incorrectly rejected.

5.4 Experiments

The following approaches have been implemented for fake news detection:

- News content + XGBoost classifier [45]: The input feature matrix for this approach is the n-gram count matrix N. This matrix represents only the textual content of the news article.
- Social context + XGBoost classifier: The features for this approach are only social context-based. The matrix (X_1) obtained after mode-1 matricization of the tensor is used as an input feature matrix.
- News content and social context + XGBoost Classifier: This is a combined approach using both content and context information [46]. The input feature

Table 8 Confusion matrix for news content-based classification using XGBoost classifier (BuzzFeed)

	Predicted negative	Predicted positive
Actual negative	19 (TN)	8 (FP)
Actual positive	8 (FN)	20 (TP)

Table 9 Confusion matrix for social context-based classification using XGBoost classifier (BuzzFeed)

	Predicted negative	Predicted positive
Actual negative	26 (TN)	2 (FP)
Actual positive	7 (FN)	20 (TP)

Table 10 Confusion matrix for news content and social context-based classification using XGBoost classifier (BuzzFeed)

	Predicted negative	Predicted positive
Actual negative	19 (TN)	8 (FP)
Actual positive	8 (FN)	20 (TP)

Table 11 Confusion matrix for news content and social context-based classification using DeepFakE (BuzzFeed)

	Predicted negative	Predicted positive
Actual negative	19 (TN)	4 (FP)
Actual positive	3 (FN)	20 (TP)

Table 12 Classification results using BuzzFeed

Approach	Precision	Recall	F1-Score	Validation accuracy
News content + XGBoost	0.714	0.714	0.714	0.709
Social context + XGBoost	0.74	0.909	0.815	0.836
News content and social context + XGBoost	0.714	0.714	0.714	0.709
News content and social context + DNN (DeepFakE)	0.8333	0.8696	0.8511	0.8649

matrix is obtained after concatenation of the n-gram count matrix with the mode-1 factor matrix obtained after coupled matrix-tensor factorization [47].

- News content and social context + DNN: The combined news content [48] and social context features are also used for classification using DNN, and the results of all these approaches have been compared.

5.5 Results

The classification results are tabulated in Tables 12 and 13.

Table 13 Classification results using PolitiFact

Approach	Precision	Recall	F1-Score	Validation accuracy
News content + XGBoost	0.7454	0.7720	0.7437	0.7880
Social context + XGBoost	0.7868	0.9135	0.815	0.8454
News content and social context + XGBoost	0.8034	0.9520	0.8714	0.8670
News content and social context + DNN (DeepFakE)	0.8210	0.8460	0.8404	0.8864

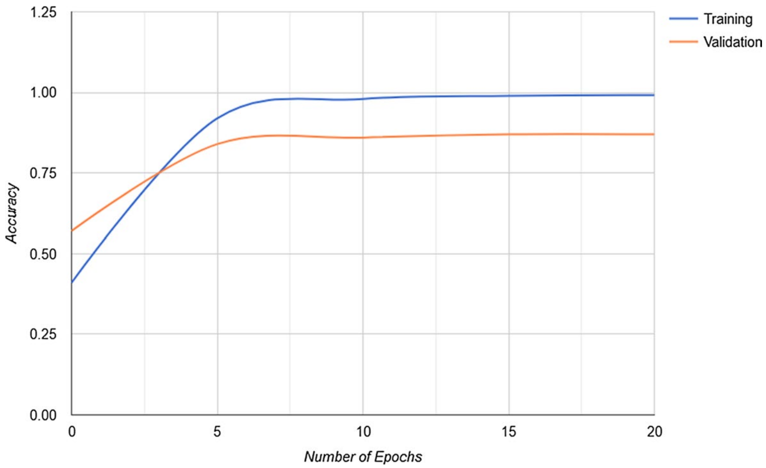

Fig. 6 DNN accuracy and cross-entropy loss curves for combined content and context-based classification

Precision, recall, F1-Score and accuracy have been calculated from the confusion matrix and are used for evaluation of classification results. Table 11 shows that combining news content, and social context-based features give better results by employing DNN as compared to other approaches. The performance of the machine learning algorithm XGBoost classifier is summarized with a confusion matrix. The elements of a confusion matrix give the count of correct and incorrect classifications. The confusion matrices for the machine learning as well as our proposed approach are shown in Tables 8, 9, 10, and 11.

News content-based and combined news content and social context-based classification with XGBoost classifier result in 16 news articles being misclassified. From the confusion matrices, it can be observed that social context-based classification performs the best amongst all three approaches using machine learning.

The DNN accuracy and cross-entropy loss curves after training versus the number of epochs for the classification task based on combined news content and social context are shown in Figs. 6 and 7. It can be observed from the curves that the model has learned well and does not overfit on the training data.

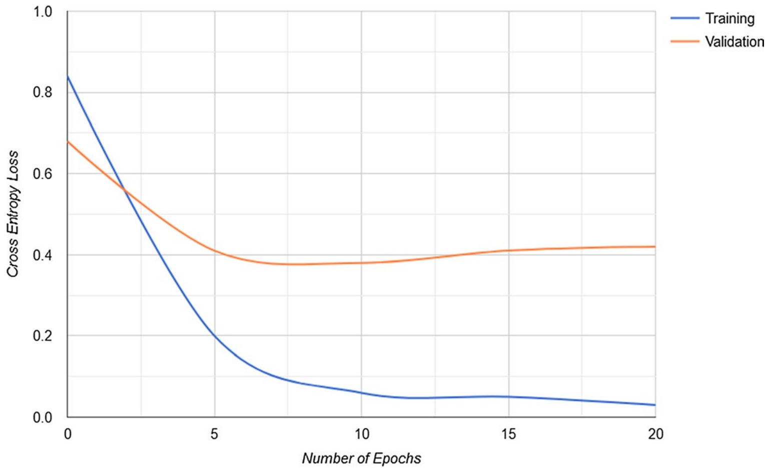

Fig. 7 DNN accuracy and cross-entropy loss curves for combined content and context-based classification

The proposed method outperforms existing fake news detection methods as it considers not only the textual attributes of news articles but also the interaction of news articles with users on social media. The social context of a news article is a latent feature and has been extracted from the tensor representing news-user engagement and user–user relationship. The features obtained after coupled matrix-tensor factorization capture the inter-dependencies within the news, user and community and thus give an overall representation of the news article. From Tables 12 and 13, we can observe the value of different performance parameters. Using our proposed model, the value of precision is 0.8333 and 0.8210, respectively, with BuzzFeed and PolitiFact dataset. High precision relates to the low false-positive rate. We have achieved 0.8333 precision with BuzzFeed dataset, which shows better results. The value of recalls is 0.8696 and 0.8460, respectively, using both the datasets. The value of recall is above 0.50, which is also shows better results. In terms of F1-Score which takes both false positives and false negatives into account. Using our proposed model, the value of F1-Score is 0.8511 and 0.8404, respectively, with BuzzFeed and PolitiFact dataset. The values of F1-Score are higher means better classification results. With our proposed model, we have achieved a training accuracy of 0.9904 and 0.9931 and a validation accuracy of 0.8649 and 0.8864 using BuzzFeed and PolitiFact dataset. We have achieved more accurate results with both news content as well as social context-based features as a combination. This approach can be helpful to improve the performance of fake news detection. The use of our proposed DNN further improves the performance as compared to both traditional machine learning as well as deep learning algorithms. From Tables 6 and 7, we can observe the performance of the existing benchmark models and our proposed model using the context-related fake news dataset. Results demonstrate the superior performance of our proposed method (DeepFakE) for fake news detection compared to other existing benchmarks.

6 Conclusions and future work

A methodology for fake news detection which takes into account news content information obtained from the text of news and social context information which is obtained from the echo chambers has been presented. A coupled matrix-tensor factorization has been used to obtain a latent representation of news articles. This technique is evaluated on the BuzzFeed as well as PolitiFact dataset. A comparative analysis of three approaches: news content-based, social context-based and a combination of news content and social context have been presented. It has been observed that the combined content and context approach gives better results. Employing a deep neural network has further improved the classification result in terms of precision, recall and accuracy as compared to that of XGBoost classifier which is a machine learning approach. The plan for future work is to perform real-time text-based classification of news articles by utilizing these content and context-based features for the real-world dataset (Graph-based dataset).

References

1. Ghani NA, Hamid S, Hashem IAT, Ahmed E (2019) Social media big data analytics: a survey. Comput Hum Behav 101:417–428
2. Zhou X, Zafarani R (2018) Fake news: survey of research, detection methods, and opportunities. arXiv preprint arXiv:1812.00315
3. Sharma K, Qian F, Jiang H, Ruchansky N, Zhang M, Liu Y (2019) Combating fake news: a survey on identification and mitigation techniques. ACM Trans Intell Syst Technol (TIST) 10(3):21
4. Shu K, Sliva A, Wang S, Tang J, Liu H (2017) Fake news detection on social media: a data mining perspective. ACM SIGKDD Explor Newsl 19(1):22–36
5. Persily N (2017) The 2016 US election: Can democracy survive the internet? J Democr 28(2):63–76
6. Ruchansky N, Seo S, Liu Y (2017) Csi: a hybrid deep model for fake news detection. In: Proceedings of the 2017 ACM on Conference on Information and Knowledge Management. ACM, pp 797–806
7. Rabanser S, Shchur O, Gnnemann S (2017) Introduction to tensor decompositions and their applications in machine learning. arXiv preprint arXiv:1711.10781
8. Fazil M, Abulaish M (2018) A hybrid approach for detecting automated spammers in twitter. IEEE Trans Inf Forensics Secur 13(11):2707–2719
9. Chong E, Han C, Park FC (2017) Deep learning net works for stock market analysis and prediction: methodology, data representations, and case studies. Expert Syst Appl 83:187–205
10. Ott M, Choi Y, Cardie C, Hancock JT (2011) Finding deceptive opinion spam by any stretch of the imagination. In: Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, vol 1. Association for Computational Linguistics, pp 309–319
11. Feng S, Banerjee R, Choi Y (2012) Syntactic stylometry for deception detection. In: Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics: Short Papers, vol 2. Association for Computational Linguistics, pp 171–175
12. Chen Y, Conroy NJ, Rubin VL (2015) Misleading online content: recognizing clickbait as false news. In: Proceedings of the 2015 ACM on Workshop on Multimodal Deception Detection. ACM, pp 15–19
13. Tacchini E, Ballarin G, Vedova ML. Della M, Moret S, de Alfaro L (2017) Some like it hoax: Automated fake news detection in social networks. arXiv preprint arXiv:1704.07506

14. Gupta M, Zhao P, Han J (2012) Evaluating event credibility on twitter. In: Proceedings of the 2012 SIAM International Conference on Data Mining. Society for Industrial and Applied Mathematics, pp 153–164
15. Shu K, Wang S, Liu H (2019) Beyond news contents: the role of social context for fake news detection. In: Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining. ACM, pp 312–320
16. Gupta S, Thirukovalluru R, Sinha M, Mannarswamy S (2018) CIMTDetect: a community infused matrix-tensor coupled factorization based method for fake news detection. In: 2018 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM). IEEE, pp 278–281
17. Ma J, Gao W, Mitra P, Kwon S, Jansen BJ, Wong K-F, Cha M (2016) Detecting rumors from microblogs with recurrent neural networks. In: IJCAI, pp 3818–3824
18. Yang Y, Zheng L, Zhang J, Cui Q, Li Zn, Yu PS (2018) TI-CNN: convolutional neural networks for fake news detection. arXiv preprint arXiv:1806.00749
19. Zhang J, Cui L, Fu Y, Gouza FB (2018) Fake news detection with deep diffusive network model. arXiv preprint arXiv:1805.08751
20. Zhang X, Tang Y, Wang H, Chunxiang X, Miao Y, Cheng H (2019) Lattice-based proxy-oriented identity-based encryption with keyword search for cloud storage. Inf Sci 494:193–207
21. Zhang Q, Qiu Q, Guo W, Guo K, Xiong N (2016) A social community detection algorithm based on parallel grey label propagation. Comput Netw 107:133–143
22. Zhong S, Chen T, He F, Niu Y (2014) Fast Gaussian kernel learning for classification tasks based on specially structured global optimization. Neural Netw 57:51–62
23. Zheng X, Zeng Z, Chen Z, Yuanlong Y, Rong C (2015) Detecting spammers on social networks. Neurocomputing 159:27–34
24. Ibrain l, Lloret L (2019) Fake news detection using Deep Learning. arXiv preprint arXiv:1910.03496
25. Clauset A, Newman MEJ, Moore C (2004) Finding community structure in very large networks. Phys Rev E 70(6):066111
26. Torlay L, Perrone-Bertolotti M, Thomas E, Baciu M (2017) Machine learningXGBoost analysis of language networks to classify patients with epilepsy. Brain Inf 4(3):159
27. Acar E, Kolda TG, Dunlavy DM (2011) All-at-once optimization for coupled matrix and tensor factorizations. arXiv preprint arXiv:1105.3422
28. Chen T, Guestrin C (2016) Xgboost: a scalable tree boosting system. In: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. ACM, pp 785–794 (2016)
29. Harshman RA (1970) Foundations of the PARAFAC procedure: models and conditions for an explanatory multimodal factor analysis 1–84 (1970)
30. Lee DD, Seung HS (2001) Algorithms for non-negative matrix factorization. In: Advances in Neural Information Processing Systems, pp 556–562
31. Khatri CG, Rao CR (1968) Solutions to some functional equations and their applications to characterization of probability distributions. Sankhy Indian J Stat Ser A 167–180 (1968)
32. Moreno PJ, Logan B, Raj B (2001) A boosting approach for confidence scoring. In: Seventh European Conference on Speech Communication and Technology
33. Patidar R, Sharma L (2011) Credit card fraud detection using neural network. Int J Soft Comput Eng (IJSCE) 1(32–38)
34. Jain AK, Mao J, Mohiuddin KM (1996) Artificial neural networks: a tutorial. Computer 3:31–44
35. Zurada JM (1992) Introduction to artificial neural systems, vol 8. West Publishing Company, St. Paul
36. Zhong B, Xing X, Love P, Wang X, Luo H (2019) Convolutional neural network: deep learning-based classification of building quality problems. Adv Eng Inform 40:46–57
37. Chen G, Parada C, Heigold G (2014) Small-footprint keyword spotting using deep neural networks. In: 2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, pp 4087–4091 (2014)
38. Wang Y, Ma F, Jin Z, Yuan Y, Xun G, Jha K, Su L, Gao J (2018) EANN: event adversarial neural networks for multi-modal fake news detection. In: Proceedings of the 24th ACM SIGKDDD International Conference on Knowledge Discovery & Data Mining, pp 849–857
39. Wu H, Gu X (2015) Max-pooling dropout for regularization of convolutional neural networks. In: International Conference on Neural Information Processing. Springer, Cham, pp 46–54

40. Wager S, Wang S, Liang PS (2013) Dropout training as adaptive regularization. In: Advances in Neural Information Processing Systems, pp 351–359
41. Srivastava N, Hinton G, Krizhevsky A, Sutskever I, Salakhutdinov R (2014) Dropout: a simple way to prevent neural networks from overfitting. J Mach Learn Res 15(1):1929–1958
42. Vasudevan V, Zoph B, Shlens J, Le QV (2019) Neural architecture search for convolutional neural networks. U.S. Patent Application 16/040,067, filed January 24 (2019)
43. Li Y, Yuan Y (2017) Convergence analysis of two-layer neural networks with relu activation. In: Advances in Neural Information Processing Systems, pp 597–607 (2017)
44. He K, Zhang X, Ren S, Sun J (2015) Delving deep into rectifiers: Surpassing human-level performance on imagenet classification. In: Proceedings of the IEEE International Conference on Computer Vision, pp 1026–1034
45. Natekin A, Knoll A (2013) Gradient boosting machines, a tutorial. Front Neurorobotics 7:21
46. Shu K, Mahudeswaran D, Wang S, Lee D, Liu H (2018) Fakenewsnet: a data repository with news content, social context and dynamic information for studying fake news on social media. arXiv preprint arXiv:1809.01286
47. Papanastasiou F, Katsimpras G, Paliouras G (2019) Tensor factorization with label information for fake news detection. arXiv preprint arXiv:1908.03957
48. Maciej S (2019) Fakenewscorpus Online: https://github.com/several27/FakeNewsCorpus, Accessed 29 Mar 2019

Affiliations

Rohit Kumar Kaliyar[1] · Anurag Goswami[1] · Pratik Narang[2]

Rohit Kumar Kaliyar
rk5370@bennett.edu.in

Anurag Goswami
anurag.goswami@bennett.edu.in

[1] Department of Computer Science Engineering, Bennett University, Greater Noida, India

[2] Department of CSIS, BITS Pilani, Pilani, Rajasthan, India