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Coupled Matrix–Tensor Factorization (Cmtf) And Reinforcement Deep Belief Network (Rdbn) For Fake News Detection In Social Media

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ABSTRACT

Social media's quick information-sharing capabilities have made it a popular platform for individuals to interact with one another and exchange ideas. Artificial Intelligence (AI) and Machine Learning (ML) have been developed for fake news detection on social media, thereby enhancing people's daily lives. It is essential to remove irrelevant features from social media to increase detection accuracy of fake news. High dimensional datasets including content, context, and community-level aspects cannot be handled by effective detection models. In this paper, a novel two-step method has been developed on social media for fake news detection. Initial step, Coupled Matrix–Tensor Factorization (CMTF) method is used to tensor formation. When dealing with labeled data, the class information with factorization procedure is introduced for fake news detection. Second step, Reinforcement Deep Belief Network (RDBN) model is developed for fake news detection. Reinforcement Restricted Boltzmann Machine (RRBM) is created by incorporating the reinforcement learning idea into the trained RBM and Back Propagation (BP) technique for label attachment. Finally the performance of the detection methods has been validated using BuzzFeed and PolitiFact in terms of Precision (P), Recall (R), F1-score (F1), and Accuracy (A).

Keywords: *Social Media, Tensor decomposition, Coupled Matrix–Tensor Factorization (CMTF), Reinforcement Deep Belief Network (RDBN), Reinforcement Restricted Boltzmann Machine (RRBM), Back Propagation (BP), Artificial Intelligence (AI), and Deep learning*

1. INTRODUCTION

Social media has revolutionized news sharing and communication, enabling users to easily access information via smartphones and the rapid advancement of internet technology [1-2]. It has made it extremely difficult for academics to pinpoint the precise location of news pieces' origins [3]. Because social media makes it so easy and flexible to spread information, more fake news is being created to mislead the general public. The term "user-community" refers to the fact that a user is always associated with a certain group of people who share the same beliefs or preferences. Because of their shared views on article sharing, these user groups may be a crucial component in the classification of fake news.

Content-based analysis techniques are challenged in automatically identifying fake news. One of the primary issues with the most complicated natural language processing algorithms, news interpretation is frequently quite complex and calls for "common sense," or an understanding of the political or social context. Additionally, malicious actors frequently write fake news on purpose to look like legitimate news while hiding misleading or manipulative material in ways that are difficult for even highly skilled human specialists to detect [4-5]. Most attempts to detect fake news use content-based methods, which use linguistic (lexical and syntactical) components to detect deceptive cues or writing styles [6]. The main problem with content-based tactics is that they might be typified by fake news that is sufficiently intricate to be difficult to spot [7-8]. The generality of these methods is further limited by the fact that the majority of linguistic traits are language-dependent.

Social context elements include things like user demographics, social network structure, and user reactions. Propagation-based approaches are likely the most intriguing and viable research option for studying the process of news spread over time [9–10]. There have been claims that the proliferation of fake news is comparable to with the purpose of infectious diseases and it can be explained by models of network epidemics [11]. Fake news spreads differently than real news, creating patterns that can be detected automatically [12-13]. Propagation-based features, content-agnostic, generalize across languages, localities, and regions [14].Additionally, individual users typically lack the ability to manipulate the news dissemination patterns in a social network, suggesting that hostile attacks could find it extremely difficult to alter propagation-based features

[15]Additionally, the volume of online content is too great for conventional detection methods that rely on rule-based algorithms and human-based fact-checking. Consequently, there is a need for sophisticated, scalable, and automated fake news identification systems. Machine Learning (ML), and Deep learning (DL) techniques have been developed for fake news detection on social media. Even if the top research communities have given it a lot of attention, there is still a need for an effective detection model that can handle context, community-level features, and content using a factorization approach [16–17].

In this paper, Reinforcement Deep Belief Network (RDBN) algorithm is proposed for fake news detection with extraction of high-level and low-level features. News-user engagement and fake news classification is performed by creating a matrix and detecting false news through RDBN, focusing on article substance and social network. According to classification results, the suggested model achieves the best detection results and performs better than current and suitable baselines for fake news identification. The performance of methods has been validated on a BuzzFeed and PolitiFact.

2. LITERATURE REVIEW

Saleh et al., [18] proposed an OPtimized Convolutional Neural Network- FAKE (OPCNN-FAKE) detection model. ML and DL parameters has been optimized using grid search and hyper opt optimization. N-gram and Term Frequency—Inverse Document Frequency (TF-IDF), Global Vectors (Glove) word embedding features have been extracted from text. OPCNN-FAKE model outperforms other models in cross-validation and testing, indicating its superiority in fake news detection using evaluation metrics. Babar et al. [19] introduced a hybrid N-gram and Long Short-Term Memory (LSTM) to enhance detection results in terms of A, R, and computation time. To categorize fake news, this suggested approach makes use of a classifier. Because of its parallel and distributed platform foundation, it can use big data analytics to construct the DL model. This platform increases the accuracy of the suggested model and speeds up training and testing. A system identifies fake news with high accuracy and low error rate by dividing material into fake and real news categories, integrating Deep Neural Network (DNN) and Spark architecture.

Kaliyar et al., [20] proposed fake news detection with the news article's content. The news, user, and community data are combined for tensor formation which represents social context. BuzzFeed dataset is used for testing, and DeepFakE model and XGBoost classifier are used for classification. Ni et al., [21] developed a Multi-View Attention Networks (MVAN), a unique neural network-based model, are used to identify false information and offer clarifications on social media. The semantic attention and propagation structure attention are combined into MVAN model which ensures fake news detection. Two attention processes are used to identify suspicious people in the propagation structure and important clue terms in texts containing fake news. The experiments are carried out on Twitter 15 and Twitter 16 datasets.

Subhash et al., [22] developed a high-accuracy fake news identification model using Glove and Word2Vec word embeddings and seven deep learning models including Recurrent Neural Network (RNN), LSTM, Bi-directional Long Short-Term Memory (BiLSTM), Gated Recurrent Unit (GRU), Bidirectional GRU, and Convolutional Neural Network-LSTM (CNN-LSTM), and CNN-BiLSTM. FastText and Bidirectional Encoder Representations from Transformer (BERT) models are developed for false news classification. BERT gives better results than other methods in terms of P, R, F1, and A. Verma et al., [23] proposed a Word Embedding over Linguistic Features for false News identification (WELFake). Dataset is preprocessed using linguistic features. Voting classification is combined with the linguistic feature sets with WE. About 72,000 articles are used to test the suggested strategy, which combines data from several sources to produce an objective classification result. This model improves detection accuracy by categorizing real and fake news when compared to predictive-based methods.

Güler and Gündüz [24] proposed a CNN and RNN-LSTM approaches for fake news detection. Evaluation metrics are used to evaluate the results of proposed model, and existing methods on BuzzFeed and ISOT datasets. Kaliyar et al., [25] proposed a Fake News Detection Network (FNDNet) model for fake news detection. FNDNet model, multiple hidden layers are automatically learned by Deep Convolutional Neural Network (DCNN). Performance of proposed model is compared against a number of baseline models. It is trained and tested on benchmark datasets, proposed model demonstrating improved performance metrics.

Chauhan and Palivela [26] proposed a LSTM classifier to distinguish between authentic and fake news. The proposed model utilizes neural networks, gloVe word embedding, tokenization method for feature extraction and vectorization, and the N-grams concept for enhanced performance. Several false news detection techniques are compared using the glove Twitter dataset. Mallick et al., [27] presented a cooperative model for fake news detection using deep learning. The proposed method estimates news trust levels from user comments and ranks the news according to these values. Higher-ranked information is identified as authentic news, while lower-ranked substance is reserved for language processing to guarantee its validity. In the learning layer, user feedback is converted into rankings using a CNN. The CNN model, trained using negative news, outperforms most language processing-based models in P, R, F1, A, and Area under the Curve (AUC) compared to advanced techniques.

Gupta et al.,[28] proposed Community Infused Matrix-Tensor coupled factorization based method for fake news

Detection(CIMTDetect) on social media. Echo chambers are used to obtain a useful and instructive latent illustration of the news story. The news articles are represented as a 3-mode tensor is modeled as echo-chambers within a social network, and encoded using a tensor factorization technique. The news articles community and content data are combined with the matrix-tensor factorization methodology. The efficacy of the Fake News approach is evaluated using two real-world datasets. Papanastasiou et al., [29] proposed a propose CLASS- Canonical/Parafac (CP) factorization, a tensor-based semisupervised approach for classifying fake news posts using network information and the available labeled data. A tensor-based method that makes use of labeled data and network information is suggested for identifying fake news. Users' network connections that spread false information are sufficiently discriminative to aid in the identification of false information. After that, represent a group of posts as a multidimensional tensor and model each post as a network of friendship interactions. Tensor factorization is a technique that links data samples' class labels to their latent representations. In particular, integrate the standard factorization with a classification error term to create a single optimization procedure. The effectiveness of combining CP factorization with tensorial classification is demonstrated through simulations using real-world datasets with P, R, F1, and A.

3. PROPOSED METHODOLOGY

In this paper, content with context-based information is subjected to a tensor factorization-based technique. RDBN model is developed for the fake news detection. Reinforcement Restricted Boltzmann Machine (RRBM) is created by incorporating the reinforcement learning idea into the trained RBM and Back Propagation (BP) technique for label attachment. According to classification results, the suggested model achieves the best detection results and performs better than current and suitable baselines for fake news identification. Results are tested using two new, fictitious real-world datasets (PolitiFact and BuzzFeed). The flow process of proposed system is shown in Figure 1.

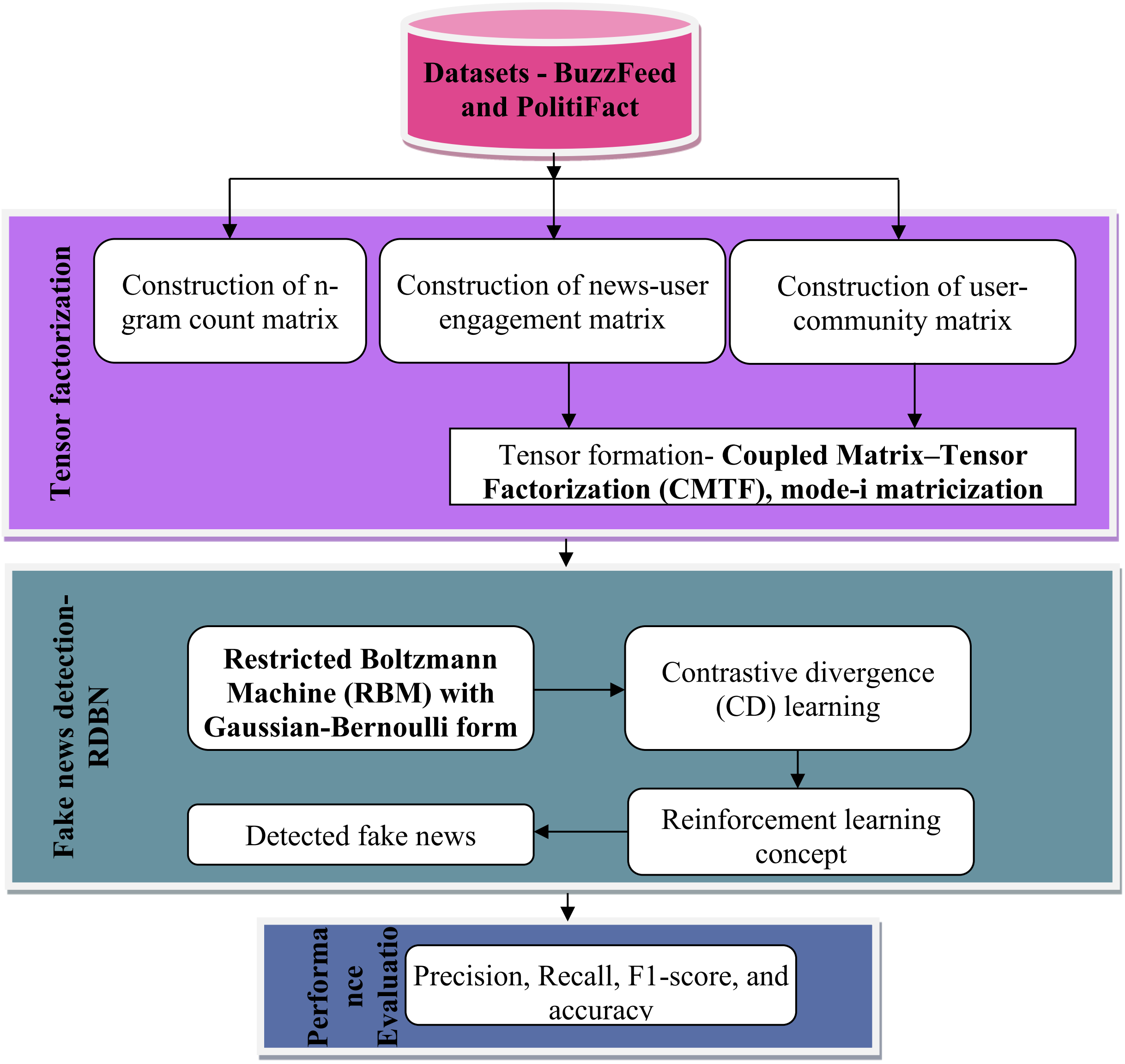

FIGURE 1. OVERALL PROCESS OF PROPOSED SYSTEM

MATRIX FORMATION

The count matrix N, is used to count word sequences in a news story [30].

The news-user engagement matrix (U) represents the number of news stories a user shares on social media is computed by separating the total no. of articles with the number of users [30].

The user-community matrix is a method that considers user relationships in available information, merging 2 communities with contribute to global modularity [30].

TENSOR FORMATION AND COUPLED MATRIX–TENSOR FACTORIZATION (CMTF)

A tensor T is formed as shown by equation (1),

$T_{ijk} = U_{ij} * C_{jk}$	(1)

Tensor is used to illustrate how a news piece spreads throughout a community. The matricization operation can be used to reorder a tensor into a matrix. The CMTF approach is used to merge the combined representation of social context and news information. According to equation, this method resolves the optimization (2),

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

Equation (2), T is the news, user, and community three-mode tensor $[\![T_1, T_2, T_3]\!]$ is denoted as the Kruskal matrices $T_1, T_2, T_3 \in R^{I_1 \times R}, R^{I_2 \times R}, R^{I_3 \times R}$. The equation (2), $N_1 \in R^{n \times R}$ and $N_1 \in R^{v \times R}$ as the R-factor matrices. Equation (2) can be re-written by equation (3),

$$min \frac{1}{2} f_1 + \frac{1}{2} f_2 \quad (3)$$

By calculating the gradients of the components f_1 and f_2 with respect to factors, an optimization problem can be resolved.

$$\nabla_f = \begin{bmatrix} vec\left(\frac{\partial f_1}{\partial T_1}\right) \\ vec\left(\frac{\partial f_1}{\partial T_2}\right) \\ vec\left(\frac{\partial f_1}{\partial T_3}\right) \\ vec\left(\frac{\partial f_2}{\partial N_1}\right) \\ vec\left(\frac{\partial f_2}{\partial N_2}\right) \end{bmatrix} \quad (4)$$

Equation (4) can be utilized to combine partial derivatives of factor matrices to create the final gradient matrix.

REINFORCEMENT DEEP BELIEF NETWORK (RDBN) BASED FAKE NEWS DETECTION

Deep Belief Network (DBN), Restricted Boltzmann Machine (RBM) is used to identify the relevance of a visible layer in a weighted matrix. The weighted matrix inside the DBN was then revised using the reinforce learning concept. To detect fake news, the newly created feature vector is paired with RDBN [31, 32].

RBM

RBM is an energy-based undirected probability graph model with two layers: visible and hidden as illustrated in figure 2(a) [33,34]. It uses weighted parameters W to connect visible units, and equation (5) determines the joint probability distribution of $\mathbf{v} = (v_1, v_2, \ldots, v_N)$ and $\mathbf{h} = (h_1, h_2, \ldots, h_M)$, $v_i \in \{0,1\}, h_j \in \{0,1\}$,

$$P(v, h) = \frac{1}{Z} \exp(-E(v, h)) \quad (5)$$

where Z is described by equation(6),

$$Z = \sum_{v}\sum_{h} \exp(-E(v,h)) \quad (6)$$

Energy function ($E(v,h)$) is defined by equation (7),

$$E(v,h) = -\sum_{i=1}^{N} a_i v_i - \sum_{j=1}^{M} b_i h_i - \sum_{i=1}^{N}\sum_{J=1}^{M} w_{ij} v_i h_j \quad (7)$$

where weight matrix W is denoted as the difference among visible and hidden layers, w_{ij} is denoted as the weight between v_i and h_j, and a_i and b_j represent the bias of v and h. RBM, Gaussian-Bernoulli distribution form since the hidden layer and the visible layer v. Equation (8) defines the energy function,

$$E(v,h) = -\sum_{i=1}^{N} \frac{(v_i - a_i)^2}{2\sigma_i^2} - \sum_{j=1}^{M} b_i h_i - \sum_{i=1}^{N}\sum_{j=1}^{M} w_{ij} \frac{v_i}{\sigma_i} h_j \quad (8)$$

Equation (9) defines $P(h|v,\theta)$ & $P(v|h,\theta)$ with conditional distribution,

$$P(h_j = 1|v,\theta) = s\left(b_j + \sum_{i} v_i w_{ij}\right), P(v_i = 1|h,\theta) = N\left(a_i + \sigma_i \sum_{j} h_i w_{ij}, \sigma_i^2\right) \quad (9)$$

$$s(x) = \frac{1}{1 + exp(-x)} \quad (10)$$

where the Gaussian distribution is denoted by (μ, σ^2). Rather than learning from the training data, the variance parameters σ_i^2 are typically locked to a predefined value and valued $\sigma_i^2 = 1$for for ease of computation. The contrastive divergence (CD) approach is used to train the RBM parameter $= \{a, b, W\}$. Equation (11) updates the θ based on the training data.

$$\Delta w_{ij} = [E_D(v_i h_j) - E_M(v_i h_j)] \cdot \alpha \quad (11)$$

Equation (11), $E_M$is denoted as the expected value of the distribution, E_D is denoted as expected value of the observation, and learning factor α, while maintaining the Δa_i and Δb_j same offset updates.

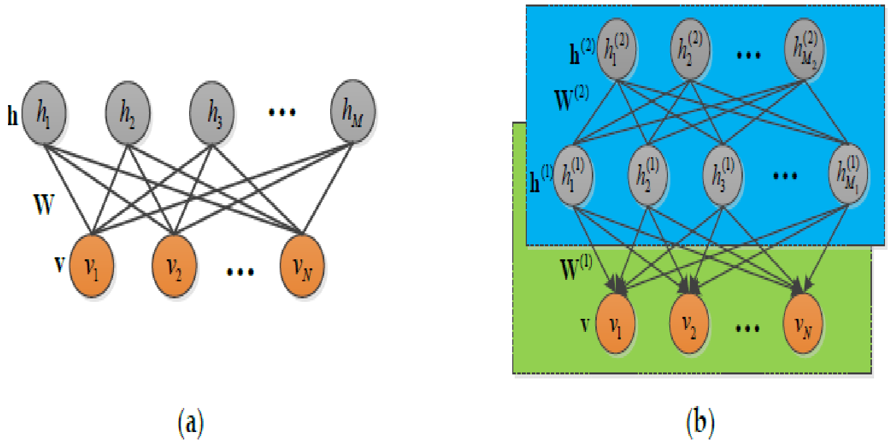

FIGURE 2. (A) RBM; (B) DBN WITH 2 HIDDEN LAYERS

The DBN with 2 hidden layer is shown in Figure 2(b). DBN is a paradigm that consists of numerous hidden layers is directed, whereas the top two are connected in an undirected manner. $W^{(1)}, W^{(2)}, \dots\dots, W^{(L)}, L+1$ are the L weighted matrixes of the L-layer DNB. The offset of the visible layer is represented by $a^{(0)}, a^{(1)}, \dots\dots, a^{(L)}$and $a^{(0)}$. Equations (12–13) define the probability distribution in DBN. DBN consists of hidden layers with two-hidden-layer models having L weighted matrixes and L+1 offset vectors. DBN is defined by equations (12-13),

$P(h_i^{(l)} = 1\|h^{(l+1)}) = s(a_i^{(l)} + W_{:,i}^{(l+1)} T_h(l+1))$	(12)
$P(v_i = 1\|h^{(1)}) = s(a_i^{(0)} + W_{:,i}^{(1)} T_h(1))$	(13)

Equation (9), where $l = 1\ to\ L$, $s(.)$ is the sigmoid function which represents the visible and first hidden layers in a network, consisting of an RBM. Network parameters are maintained after initial RBM training, and subsequent tasks continue until reaching the top layer. The DBN training process involves training former RBMs using unsupervised learning, followed by supervised learning using the Backpropagation (BP) method for optimization.

REINFORCEMENT DEEP BELIEF NETWORK (RDBN)

During the training process, the RDBN model will integrate both supervised and unsupervised learning. First, the initial RBM network parameters are obtained using unsupervised learning. Second, the Reinforcement Restricted Boltzmann Machine (RRBM) is created by incorporating the reinforcement learning idea into the trained RBM. Thirdly, RRBMs includes of RDBN in a stack, and the labels attached to the top layer by the BP method complete the detection network training in the subsequent supervised learning. Figure 3 displays the RDBN construction.

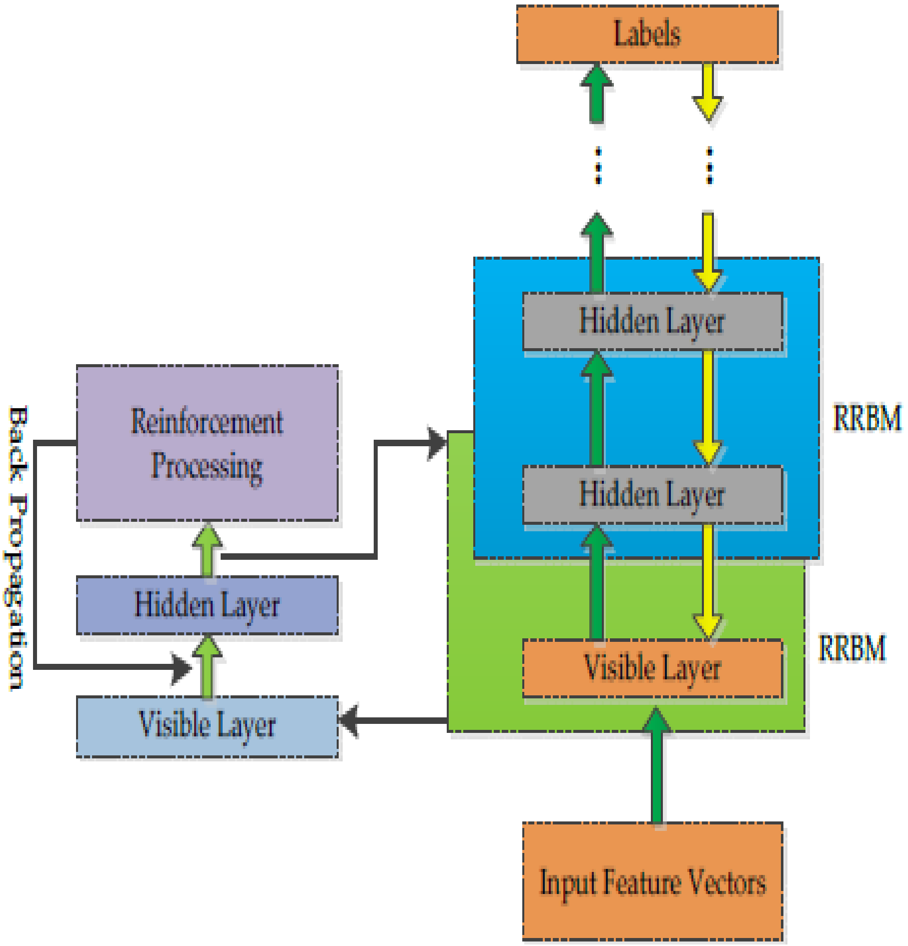

FIGURE 3. STRUCTURE OF RDBN

In RRBM, the representation between neighbouring layers is completed by training the weight matrix. The features of the input fake news are reflected by the weight matrix $W^{(k)}$ distribution. $\widehat{W}^{(k)}$ is subjected to reinforcement processing, threshold ε is computed for each row of $\widehat{W}^{(k)}$, ε is compared with each weight value w_{ij}. For the supervised learning $W^{(k)}$, the old linked weight matrix $W^{(k)}$ will be replaced with the output of Algorithm 1.

ALGORITHM 1. Reinforcement algorithm on $W^{(k)}$ in RRBM
INPUT: $W^{(k)}$, Learning rate α, Tuning factor ρ, γ
OUTPUT: Reinforced weight matrix $\widehat{W}^{(k)}$
PROCESS
Input $\varepsilon = [\varepsilon_1, \varepsilon_2, \dots \dots \varepsilon_N], W^{(k)} = \{w_{ij}^{(k)}\}, \widehat{W}^{(k)} = \{\widehat{w}_{ij}^{(k)}\}, \forall i = 1 \text{ to } N; j = 1 \text{ to } M$

Compute $\varepsilon_i = \frac{1}{M}\sum_j \left\|w_{ij}^{(k)}\right\|$
For $i = 1,2,\ldots,N$ **do**
For $j = 1,2,\ldots,M$ **do**
If $\left\|w_{ij}^{(k)}\right\| > \varepsilon_i$ do
$\widehat{w}_{ij}^{(k)} = w_{ij}^{(k)} + sign\left(w_{ij}^{(k)}\right).\alpha.\rho;$
Else If
$\widehat{w}_{ij}^{(k)} = w_{ij}^{(k)} - sign\left(w_{ij}^{(k)}\right).\alpha.\gamma;$
End If
End For j
End For i
END

4. RESULTS AND DISCUSSION

Classification methods have been implemented using MATrix LABoratory R 2020a (MATLABR2020a) with Intel Core I7-13700K Processor 30M Cache, Up to 5.40 GHZ, LGA 1700, windows 10. Experiments have been conducted to validate the performance of these methods using BuzzFeed and PolitiFact. Totally 75:25 ratio has been used for experimentation. The key components or variables for a learning algorithm during the training and testing of any classification model are known as hyperparameters. There are two primary methods for choosing and refining the context-specific hyperparameters: automatic selection and manual selection. When choosing hyperparameters, there is usually a trade-off among manual and automatic selection.

EVALUATION METRICS

To validate the performance of CIMTDetect, CLASS-CP, DNN-with echo chamber (DNN-EC), EchoFakeD, and RDBN using metrics like precision, recall, f1-score, accuracy based on four constraints,

True Positive (TP): In these cases, the positive class was accurately predicted by the model.

True Negative (TN): The negative class was correctly predicted by the model.

False Positive (FP): In these cases, the model predicted the positive class inaccurately.

False Negative (FN): When the model is unable to recognize the positive class, it marks it as negative.

Precision quantifies the proportion of true positive predictions between all positive predictions. It is described by equation (14),

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (14)$$

Recall quantifies the proportion of real positive cases are accurately detected as positive by the model. It is described by equation (15),

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (15)$$

F1-score is described as the harmonic mean of recall and precision. A model with an extremely high F1-score achieves an excellent balance between recall and precision. It is described by equation (16),

$$\text{F1} - \text{Score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (16)$$

Accuracy is the ratio of correctly identified occurrences to all instances in the dataset. It is explained by equation (17),

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (17)$$

5. RESULTS COMPARISON

In this section, experiment the results of several classification approaches like CIMTDetect, CLASS-CP, DNN-with echo chamber (DNN-EC), EchoFakeD, and RDBN using evaluation metrics in BuzzFeed and PolitiFact dataset in table 1.

TABLE 1. RESULTS COMPARISON OF FAKE NEWS DETECTION METHODS

METRICS (%)	METHODS- BUZZFEED DATASET				
	CIMTDetect	CLASS-CP	DNN-EC	EchoFakeD	RDBN
Precision	82.21	84.15	86.22	87.78	89.66
Recall	84.45	85.76	87.63	88.84	90.15
F1-score	83.32	84.95	86.92	88.31	89.90
Accuracy	83.96	85.35	86.89	88.75	90.56
METRICS (%)	METHODS – POLITIFACT DATASET				
	CIMTDetect	CLASS-CP	DNN-EC	EchoFakeD	RDBN
Precision	81.30	83.64	85.81	87.07	88.39
Recall	82.22	83.45	85.64	86.95	89.58
F1-score	81.76	83.54	85.73	87.01	88.98
Accuracy	82.68	84.72	86.07	88.23	89.67

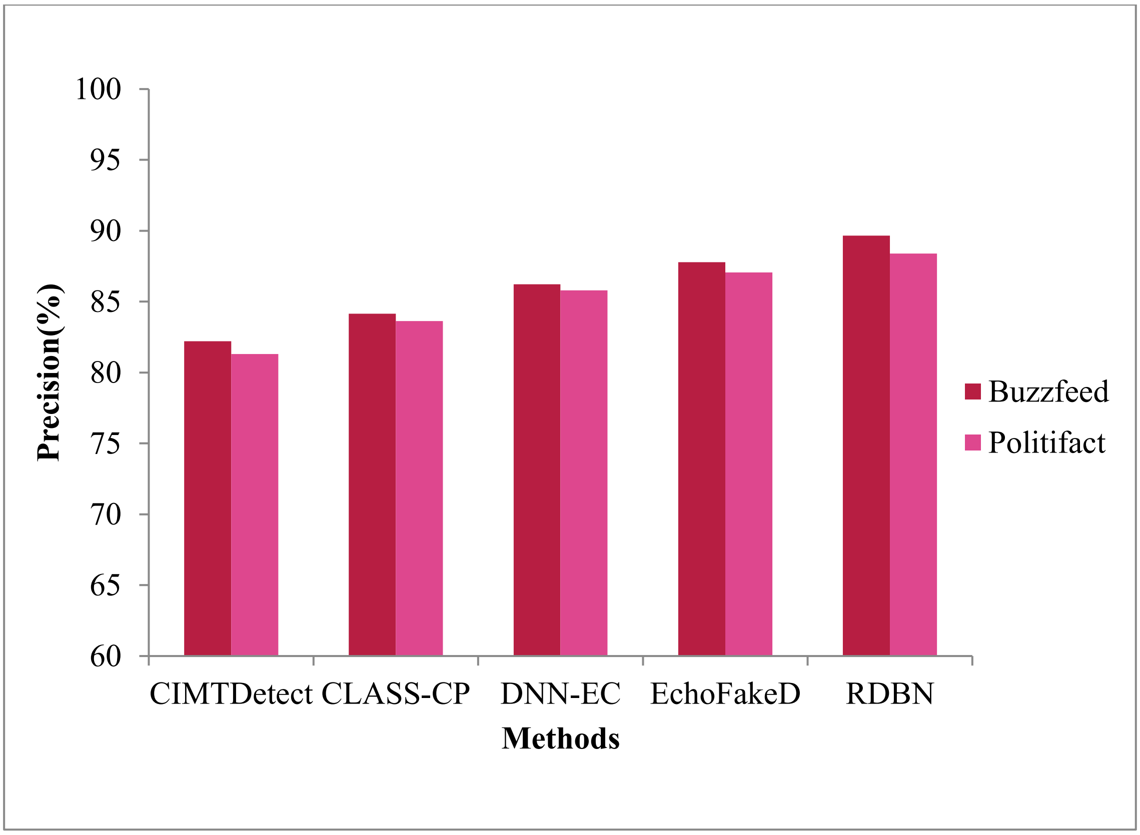

FIGURE 4. PRECISION RESULTS OF BUZZFEED AND POLITIFACT

Figure 4, it can be observed that the precision comparison is evaluated using existing methods, and proposed method. CIMTDect, CLASS-CP, DNN-EC, and EchoFakeD give lowest precision of 82.21%, 84.15%, 86.22%, and 87.78% for

BuzzFeed. CIMTDect, CLASS-CP, DNN-EC, and EchoFakeD give lowest precision of 81.30%, 83.64%, 85.81%, 87.07%, and 88.39% for PolitiFact. RDBN algorithm gives highest precision of 92.88% and 89.36% for BuzzFeed and PolitiFact.

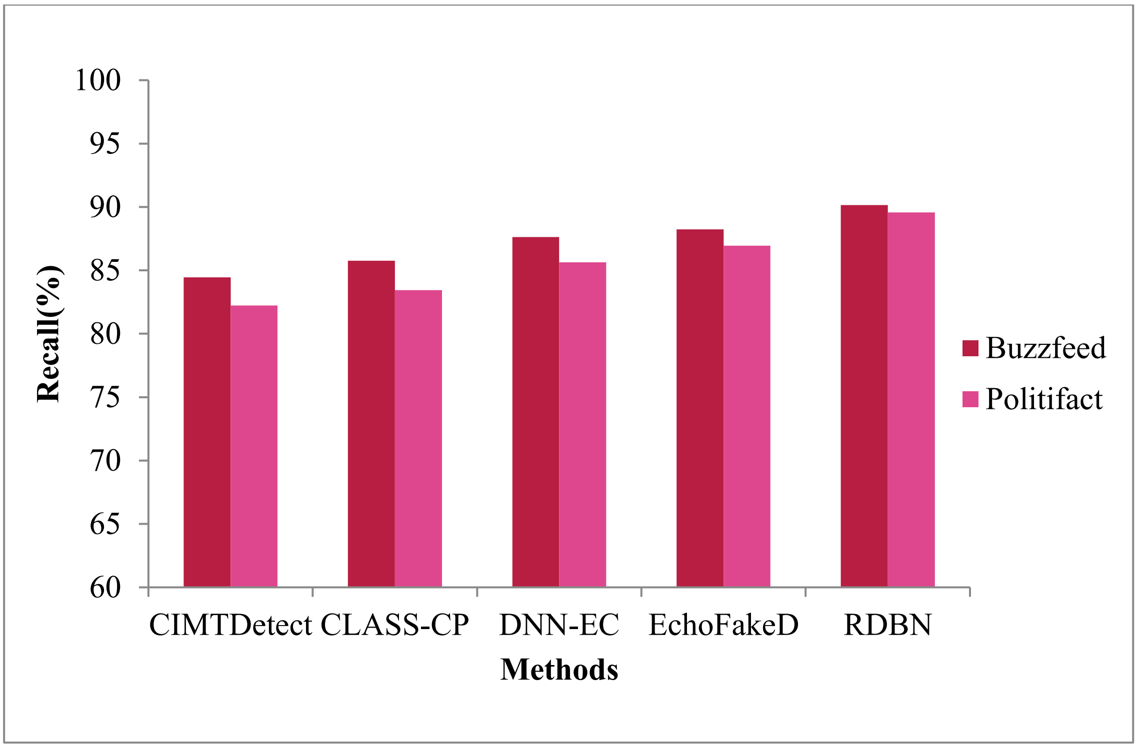

FIGURE 5.RECALL RESULTS OF BUZZFEED AND POLITIFACT

Figure 5, recall is evaluated using existing and proposed method. CIMTDect, CLASS-CP, DNN-EC, and EchoFakeD provide the lowest recall of 84.45%, 85.76%, 87.63%, and 88.84% for BuzzFeed. CIMTDect, CLASS-CP, DNN-EC, and EchoFakeD provide the lowest recall of 82.22%, 83.45%, 85.64%, and 86.95% for PolitiFact. RDBN algorithm provides highest recall of 93.15%, and 92.88% for BuzzFeed and PolitiFact datasets.

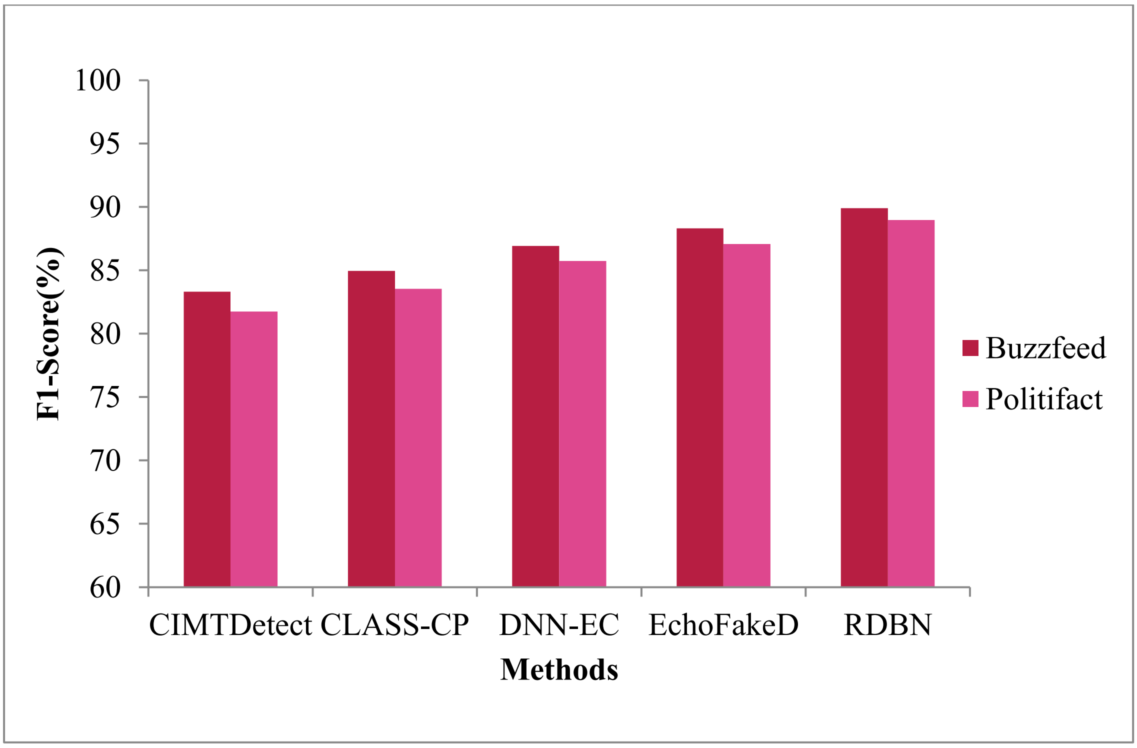

FIGURE 6. F1-SCORE RESULTS OF BUZZFEED AND POLITIFACT

Figure 6, F1-Score is evaluated using existing methods, and proposed method. CIMTDect, CLASS-CP, DNN-EC, and EchoFakeD provide the lowest F1-score of 83.32%, 84.95%, 86.92%, and 88.31% for BuzzFeed. CIMTDect, CLASS-CP, DNN-EC, and EchoFakeD provide the lowest F1-score of 81.76%, 83.54%, 85.73%, and 87.01% for PolitiFact. RDBN algorithm provides the highest F1-score of 94.52%, and 90.63% for BuzzFeed and PolitiFact datasets.

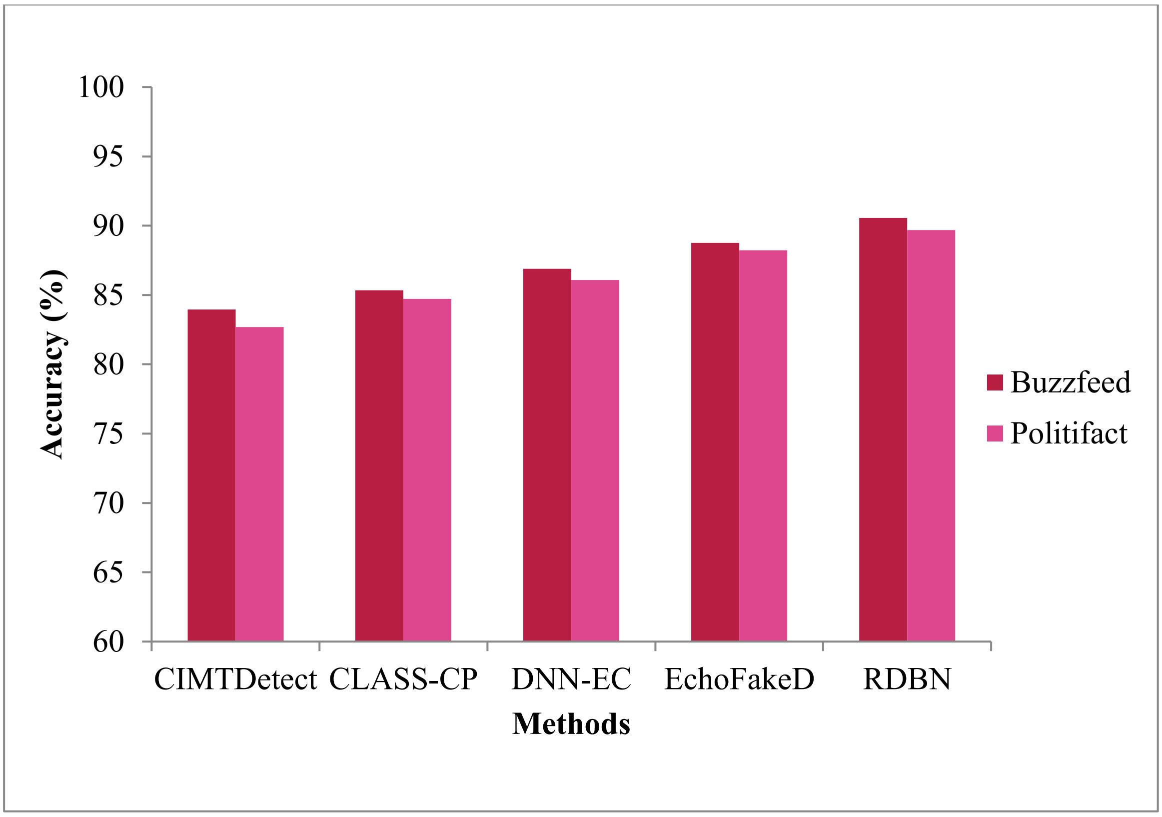

FIGURE 7.ACCURACY RESULTS OF BUZZFEED AND POLITIFACT

Figure 7, accuracy is evaluated using existing methods, and proposed method. CIMTDect, CLASS-CP, DNN-EC, and EchoFakeD give lowest accuracy of 83.96%, 85.35%, 86.89%, and 88.75% for BuzzFeed. CIMTDect, CLASS-CP, DNN-EC, and EchoFakeD give lowest accuracy of 82.68%, 84.72%, 86.07%, and 88.23% for PolitiFact. RDBN algorithm provides highest accuracy of 94.50% and 95.10% for BuzzFeed and PolitiFact datasets.

6. CONCLUSION AND FUTURE WORK

In this paper, novel detection technique is introduced which considers the social environment of news articles to their news content. Initially the FakeNewsNet was used to gather the BuzzFeed and PolitiFact datasets. Secondly, a matrix coupled with a tensor is jointly factorized using Coupled Matrix–Tensor Factorization (CMTF), which minimizes an objective function based on the least square error. The Reinforcement Restricted Boltzmann Machine (RRBM) is used to construct the Reinforcement Deep Belief Network (RDBN), with supervised learning and reinforcement learning finishing the training process. The RDBN model is applied for huge datasets with nonlinear functions, eliminating the need for feature engineering. The RDBN model outperforms other approaches in terms of classification results on PolitiFact and BuzzFeed. Multimodel-based techniques with pre-trained word embeddings are introduced in future research to handle visual information. Furthermore, fact-based and knowledge-based methods are presented to identify false information

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