Received: June 9, 2022. Revised: July 7, 2022.

International Journal of
Intelligent Engineering & Systems

http://www.inass.org/

Fake Review Detection and Emotion Recognition Based on Semantic Feature Selection with Bi-Directional Long Short Term Memory

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Abstract: Customer reviews has a significant role in sale of the product on the e-commerce website and this influences other customers. The fake review affects the trust between the user and seller in the e-commerce website. The existing techniques in detection of fake review have disadvantage of overfitting problem and vanishing gradient problem. The Semantic Feature selection – Bidirectional Long Short Term Memory (SF-BiLSTM) is applied to increase the fake review detection efficiency. The autoencoder based semantic feature selection technique maps the features based on decision tree technique to select the relevant features. This technique helps to learn the features importance related to neighbourhood features that helps to increases the efficiency. The proposed SF-BiLSTM method has the advantage of applying the emotion recognition method in the fake review detection. The four datasets such as Amazon Review, Yelp, Restaurant, and Hotel were used to test the performance of classification. The semantic feature selection technique reduces overfitting problem in existing Convolution Neural Network classification and the mapping of features helps to increase model learning performance. The proposed SF-BiLSTM model has 99.2 % accuracy when compared to the existing methods in fake review detection.

Keywords: Adaptive boosting ensemble, Amazon review, Bidirectional long short term memory, Fake review detection, Semantic feature selection.

1. Introduction

E-commerce websites allow users to write a product review for the purchases to share the details with other customers. Customers' reviews not only influence the social circle and also share the opinion of the product to new customers. Products with positive reviews easily attract potential customers and products with negative reviews detract potential buyers [1]. The fake review affects the entire online review system and also causes credibility loss. Therefore, it's important to automate the fake reviews identification in e-commerce websites to provide truthful information to the user [2]. Big data is a challenging task for the practitioners and academics in an online platform to process the data. Everyday a large amount of data is created from a different source at a great velocity in an online website. Customers generate a large amount of information in blogs, social media, and online review for information about brand that provide potential business value [3]. Many website platforms develop their detection of fake review to gain the trust of users. For instance, Amazon.com uses the 'verified purchases' in the review section, however, this status can be manipulated. Yelp.com uses a filtering algorithm to detect fake reviews tries to strengthen the trustworthiness and validity, considering 16% of restaurant reviews as invalid. ReviewMeta.com updates the product rating by removing the noise of biased review to prevent manipulation and fake review [4, 5].

Reviews of Products has a significant role in influencing the purchase of a product for potential customers. Most customers prefer to buy a product with a high reputation and this is based on the customer reviews [6]. Recently, researchers show a great deal of attention to detecting fake reviews in the business community. Fake review detection is considered an important problem for reflecting genuine and legitimate user experiences and opinions.

Machine learning techniques were highly used in the automatic detection of fake reviews and solving this problem. Furthermore, fake review identification is challenging task since analysis of emotions in text is complex [7, 8]. Recently, deep learning techniques of Convolution Neural Network (CNN) and LSTM models show significant performance in Natural Language Processing [9, 10].

The significant commitment of this paper is:

- Here we have considered KNN, SVM, Random Forest machine learning techniques and LSTM, Bi-LSTM, CNN Deep learning techniques for emotion recognition and fake review detection.
- The proposed Semantic Feature Selection – Bidirectional Long Short Term Memory (SF-BiLSTM) to improve the efficiency of false review identification and emotion recognition.
- The overfitting problem in classification is reduced by using the semantic feature selection approach.
- The classification performance was evaluated using four datasets: Amazon, Yelp, Restaurant, and Hotel from the standard sources.
- Emotion recognition performance is measured by using classification accuracy, F-measure, Precision, and Recall. The performance of fake review detection is measured by using accuracy and F-Measure.
- The proposed SF-BiLSTM method has higher accuracy compared to existing methods.

The paper is formulated as: Section 2 has literature review, section 3 explains proposed method, section 4 provides results and section 5 provides conclusion.

2. Literature review

Hajek [11] applied two neural networks to integrate emotions of consumers and bag-of-words. Three sets of features such as lexicon-based emotion indicators, word embedding, and n-gram were used to learn document-level representation. Four datasets were used to evaluate the two neural networks model to analyse in high dimensional data. In fake review detection, two neural network model has higher efficiency than state-of-art method. The CNN model has an overfitting issue that degrade efficiency of developed model in classification.

Manaskasemsak [12] developed the graph partition method and its extension to find the fake reviews in the dataset. The developed method aims to develop the behavior graph from the reviewer to find the similarity of the behavior in the dataset. A small sub-graph of known fake reviewers and expand the subgraphs to other suspicious reviewers. All the suspect reviewers are hypothesized in developed method and enhance efficiency of fake review detection. The deep learning method is applied to learn lexicon-based emotion indicators and word embedding representation for construction of graph. In fake review detection, the yelp dataset has higher efficiency than existing techniques. The learning performance of the model is low and the method has the limitation of imbalanced data.

Wang [13] applied to roll collaborative training and multiple feature fusion to improve the detection performance of fake reviews. Multiple features in the Initial index system such as behavior, sentiment, and text features were applied to the developed method. The 7 classifiers were used to train initial sample set and a classifier with higher accuracy was selected for the detection process. The classified labels of new reviews are added in new samples to train the model in this developed method. The yelp dataset was used to train and test the efficiency of developed method in detection of fake review. The developed method has lower performance in learning the difference between the samples in the dataset.

Yao [14] applied an ensemble model for detection of fake review in four steps such as classifier ensembling, parameter optimization, feature pruning, and data resampling. The grid search and resampling method was applied to handle data imbalance problem. The unimportant features are dropped in feature pruning and a grid search was applied for optimal parameter settings for the base classifier. Base classifier optimization was integrated using stacking method and majority voting. The classification of fake review in existing method has higher efficiency in developed method. The ensemble method has lower efficiency classification performance.

Budhi [15] applied several pre-processing and textual-based featuring technique for detection of fake review in the system. Ensemble and single classifier were applied for detection of fake review. The imbalance dataset was applied to evaluate the model in detection of fake review. Two dynamic random sampling for textual-based featuring methods to solve the class imbalance problem. The Adaptive Boosting ensemble classifier provides efficient performance in small dataset and the single classifier has higher efficiency in a large dataset. The developed technique has lower efficiency in learning the features for the fake review classification.

Received: June 9, 2022. Revised: July 7, 2022.

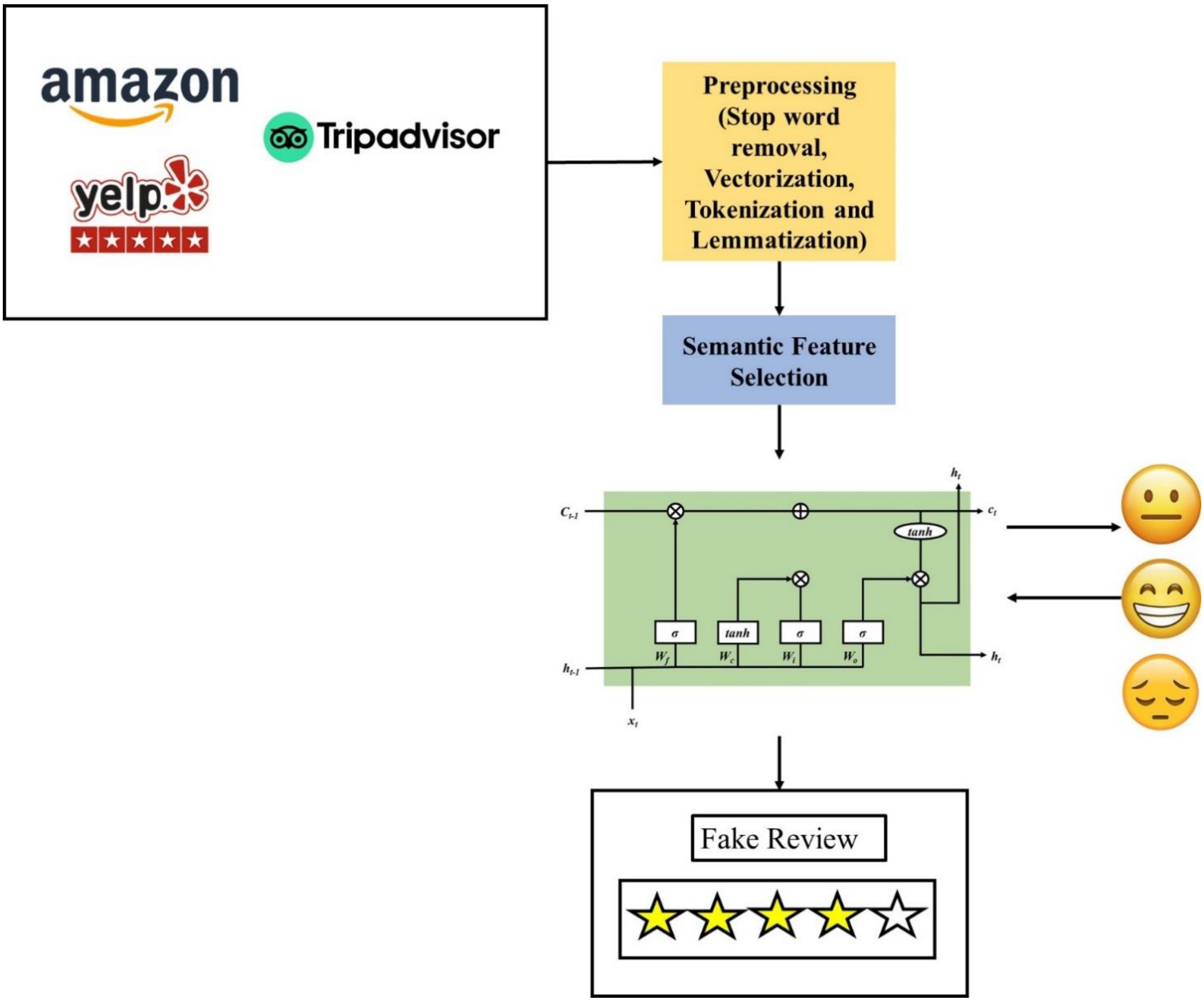

Figure. 1 The block diagram of the semantic features and Bi-LSTM model in fake review detection

3. Proposed technique

This research applies Semantic Feature selection method with Bi-LSTM model for sentiment analysis and fake review classification. The Amazon, yelp and Hotel datasets were applied to test the SF-BiLSTM model in fake review detection. Fig. 1 shows the flow of the model in fake review detection.

3.1 Pre-processing

The stop words are used in the sentence frequently to connect various expressions and complete an appropriate sentence. The stop words are irrelevant for the text analysis, as they do not consider important information.

The vectorization process is a vector spacing technique applied to convert the text in vector value. Vectorization provides product data record of reviews for classification.

Tokenization is the process of partition input text in small segments, as tokens. Tokenization eliminates the punctuations from the text and specific sentences are reduced using filters.

The term stemming and lemmatization are analogous that are applied to reduce the spatiality of a word. For example, words like 'baked', 'baking', 'bake' are converted into a single word 'bake'.

3.2 Semantic feature selection

Semantic feature selection provides artifacts space $X' = \{0,1\}^{d'}$ and maps the instance x (where each feature finds the absence or presence of artifact if it evaluates to 0 or 1, respectively), e.g., sentence x has frequent terms. The image x has artifacts of X and neighbors y of x generates x subsets.

The neighbors y is general, not realistic from the above strategy and conditions from the reference statement. The considered neighborhood expressiveness is reduced and affects the local explanation quality.

The syntactic neighborhood x is replaced with a semantic neighborhood of a more expressive. Each

 DOI: 10.22266/ijies2022.1031.41

Received: June 9, 2022. Revised: July 7, 2022.

original instance is a mapping of x of X to a and instance x belongs to semantic feature space that is related to the classification problem. This process helps replace syntactic neighborhoods.

Unsupervised learning is exploited to learn the mapping between a latent feature space, original space, and corresponding reverse mapping. The original space of semantic features is hidden and these features don't explain the instance x. The x is mapped in semantic latent space Z where features carry information about f performed x classification. This provides more neighbors and realistic instances to be explained.

The neighborhood of x is kept from an operational point of view, as detailed below:

1. Instance x is mapped to instance z of semantic latent space $Z \subset R$, relevant features l is used to characterize the latent space.
2. Random sampling points are used to compute the neighbors of z in Z in the hyper-sphere having radius ρ and centered in z.
3. Sampled points of Z to X are mapped back to obtain neighbors of x.

Mapping Functions: This technique requires the latent space characteristics and Denoising Adversarial Autoencoder (DAAE) is used to perform this process. The DAAE is Adversarial Autoencoders (AAEs) extension that differs from Variational Autoencoders (VAEs) to maintain strong coupling between decoder and encoder. This ensures that the decoder does not ignore encoder produced representation of the sentence and this problem is called posterior collapse, which is frequent in textual data. This architecture provides a good trade-off between reconstruction quality and generation. This architecture maps a similar sentence to a similar latent representation.

Explanation Model: A decision tree is adopted to develop the model g. A rule-based classifier is easy to understand and suitable for the process, local instance is constituting instances that are encoded in a space of features that represent the presence or absence of terms in a common dictionary that are exploited as interpretable components. The tree maximum depth is limited to 3 to guarantee interpretability.

The objective function (Eq. (1)) is computed for fidelity function, its expression is adopted in original space, as given in Eq. (1).

$$\mathcal{F}(x, f, g, \pi) = \sum_{y \in X} \pi(x, y).\left(f(y) - g(y)\right)^2 \quad (1)$$

The original space instances are classified based on model g considering the function π as distance D, measured in Eq. (2).

$$D(x, y) = \sum_{x_i=1} |x_i - y_i| \quad (2)$$

Agreement of x and y in an asymmetric distance highlights on x features characteristics, where x has value 1.

3.3 Bi-directional long short term memory (Bi-LSTM)

The LSTM can retain the important information for the long term based on cell and forget gate. The classification of arrhythmia signals not only requires recent data and also previous data. So, the LSTM model uses the self-feedback method of hidden layer for handling long-term dependence problems [16, 17]. Memory cells and three gates such as input, forget and output gate were used to store information in the LSTM and this helps to handle problem of long-term features [18, 19]. The Bi-LSTM architecture is shown in Fig. 2.

The cell input data of LSTM is denoted as x_t at time t, the h_{t-1} denotes the LSTM cell output of the previous moment, and h_t denotes the LSTM cell output. The calculation process of the LSTM unit is discussed in the following steps.

(1) The W_c denotes weight matrix, b_c denotes the bias, and $\tilde{c_t}$ denotes the candidate memory cell $\tilde{c_t}$, as given in Eq. (3).

$$\tilde{c_t} = \tanh(W_c.[h_{t-1}, x_t] + b_c) \quad (3)$$

(2) Measure input gate i_t, input gate bias is b_i, input gate weight matrix is W_i, sigmoid function is σ. Input gate update state value of memory cell, as shown in Eq. (4).

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \quad (4)$$

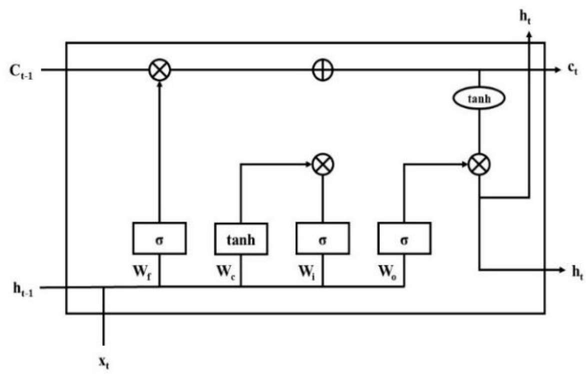

Figure. 2 The architecture of the long short term memory (LSTM) model

(3) Measure forget gate f_t, forget gate weight matrix is W_f, forget gate bias is b_f. Forgot gate uses historical data to update state value of memory cell, as given in Eq. (5).

$$f_t = \sigma(W_i.[h_{t-1}, x_t] + b_f) \quad (5)$$

(4) State value of last LSTM unit is c_{t-1}, and memory cell current moment c_t is measured, as given in Eq. (6).

$$c_t = f_t \times c_{t-1} + i_t * \tilde{c_t} \quad (6)$$

(5) Measure output gate o_t, output gate weight matrix is W_0, output gate bias is b_0. The output gate the output of state value of memory cell, as given in Eq. (7).

$$o_t = \sigma(W_0.[h_{t-1}, x_t] + b_0) \quad (7)$$

(6) Measure output of LSTM unit h_t, as given in Eq.(8).

$$h_t = o_t * \tanh(c_t) \quad (8)$$

LSTM model update, reset, read and keep long-time information easily based on memory cell and control gates. The LSTM model sharing mechanism of internal parameters controls the output dimensions based on weight matrix dimensions' settings.

The Bi-LSTM model applies two LSTM units to process the token sequence in a forward and in a reverse manner. One LSTM unit process the token sequence from left to right and the other from right to left. Based on the previous hidden state h_{t-1} are used to compute the hidden unit function $\vec{h}$ of a hidden forward layer at each time step t. The future hidden state h_{t+1} and current step x_t at the input are used to compute hidden unit function $\overleftarrow{h}$ of a hidden backward layer. Long vector is created for concatenation of $\overrightarrow{h_t}$ and $\overleftarrow{h_t}$ of forwarding and backward context representations.

4. Results and discussion

The semantic features were applied in this research for emotion recognition and fake review detection. Four datasets such as Amazon, Yelp, Restaurant, and Hotel datasets were applied to evaluate the model.

Datasets: Amazon review dataset consists of 21,000 reviews: 10500 truthful and 10500 fake reviews. Yelp dataset consists of 9461 reviews with rating value, verified purchase, reviewer id, product id, and review text [20]. The restaurant dataset consists of 110 reviews: 55 fake and 55 truthful reviews. The hotel dataset consists of 1600 reviews: 800 truthful and 800 fake reviews. The Amazon dataset [21], Restaurant dataset [22], Hotel dataset [23] were used to evaluate the model.

Metrics: Accuracy, precision, Recall, and F-Measure is used to measure the performance of emotion recognition. Accuracy and F-Measure are used to measure the performance of fake review detection. The formula for accuracy, precision, recall, and f-measure is given in Eqs. (9) and (10), respectively.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (9)$$

$$Precision = \frac{TP}{TP+FP} \times 100 \quad (10)$$

$$Recall = \frac{TP}{TP+FN} \times 100 \quad (11)$$

$$F - measure = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (12)$$

System Requirement: The system configuration of Intel i9 processor, RAM of 128 GB, Graphics card of 22 GB, and windows 10 OS to test the model. The Python 3.7 tool was used to implement and test the performance of the developed method. The proposed SF-BiLSTM method and existing methods were trained and tested in the same environment and same dataset.

Parameter Settings: The Bi-LSTM model is set with 50 epochs, 128 batch-size, 0.01 dropout rate, and 6 layers to train and classify the data.

The fake review detection helps to improve the trust between the user and seller in the e-commerce website. Existing machine learning and deep learning in detection of fake review have limitations of existing methods are vanishing gradient problem and overfitting problem. The proposed SF-BiLSTM model is applied to improve model efficiency in emotion recognition and fake review detection. The semantic features were applied in the Bi-LSTM model to improve the performance of classification.

The SF-BiLSTM model is compared with standard machine learning models in emotion recognition as given in Table 1 and Fig. 3. The SF-BiLSTM model has higher performance in emotion recognition than existing methods. The KNN method has unstable performance and SVM has an imbalance data problem. The random forest method has overfitting problem and unstable performance in classification. The SF-BiLSTM model has the

Received: June 9, 2022. Revised: July 7, 2022.

Table 1. Machine learning comparison in emotion recognition

Method	Accuracy (%)	Precision (%)	Recall (%)	F-measure (%)
KNN	81.2	81.5	81.3	81.39
SVM	84.2	83.7	78.2	80.85
Random Forest	83.4	82.5	81.7	82.09
SF-BiLSTM	98.3	98.1	97.8	97.94

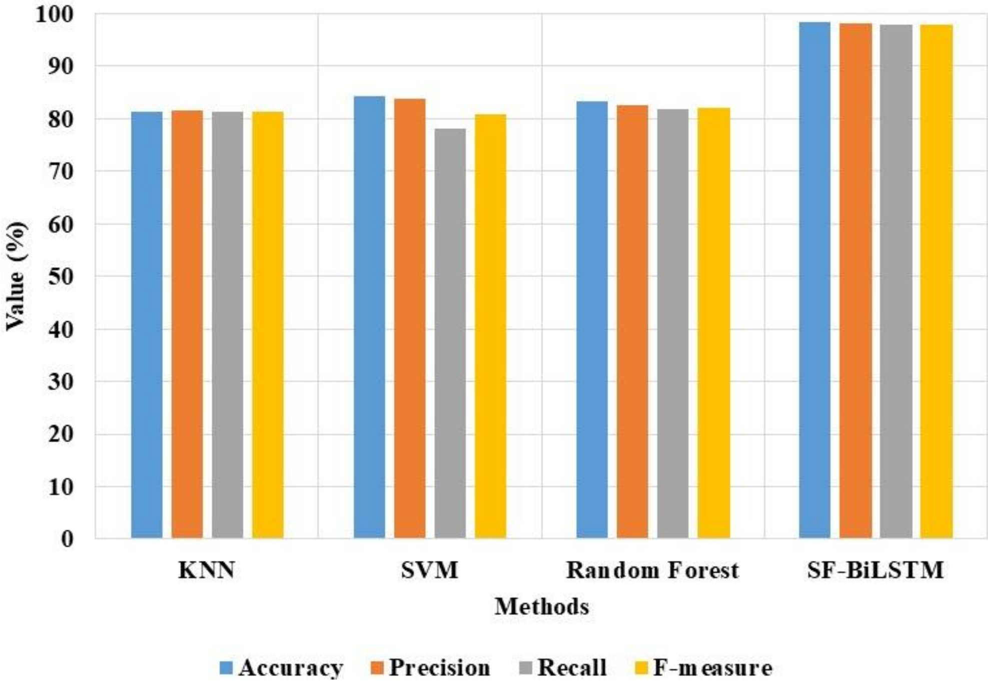

Figure. 3 Machine learning comparison in emotion recognition

Table 2. Deep learning comparison in emotion recognition

Method	Accuracy (%)	Precision (%)	Recall (%)	F-measure (%)
LSTM	88.7	89.1	88.2	88.64
Bi-LSTM	91.5	92.1	91.3	91.69
CNN	93.4	95.4	94.2	94.79
SF-BiLSTM	98.3	98.1	97.8	97.94

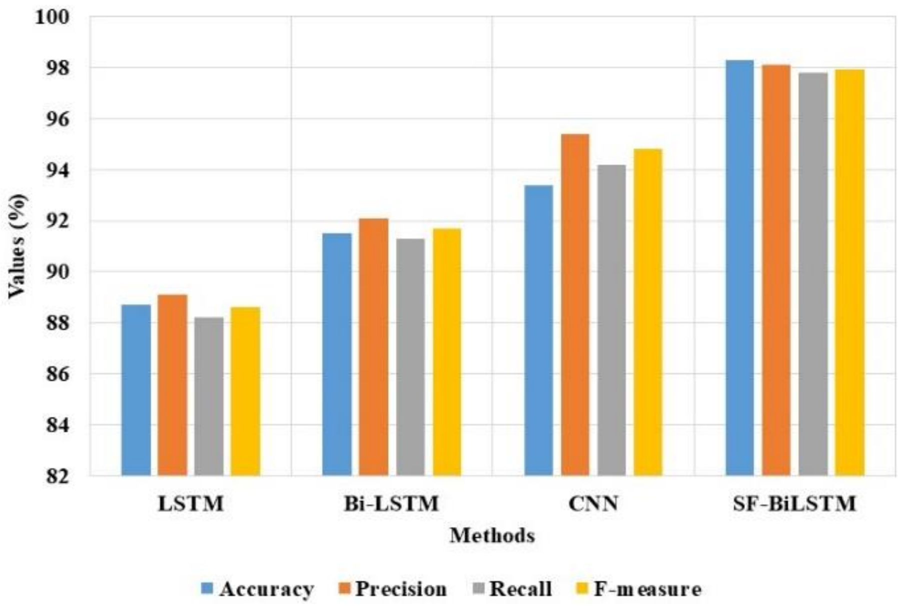

Figure. 4 Deep learning comparison in emotion recognition

Received: June 9, 2022. Revised: July 7, 2022.

Table 3. Machine learning comparison in fake review detection

Method	Accuracy (%)	F-measure (%)
KNN	83.1	85.2
SVM	85.3	85.2
Random Forest	84.4	84.5
SF-BiLSTM	99.2	99.5

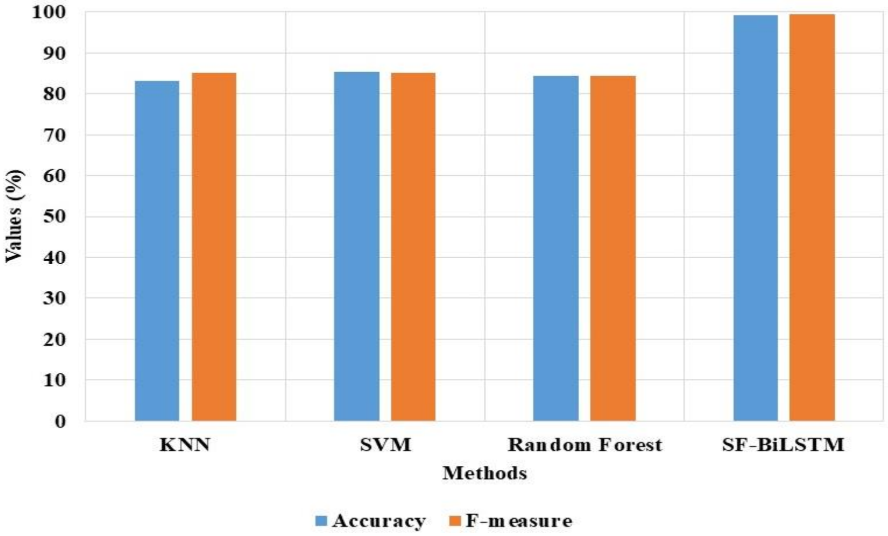

Figure. 5 Machine learning comparison in fake review detection

Table 4. Deep learning comparison in fake review detection

Method	Accuracy (%)	F-measure (%)
LSTM	91.2	91.3
Bi-LSTM	93.4	94.8
CNN	94.5	95.1
SF-BiLSTM	99.2	99.5

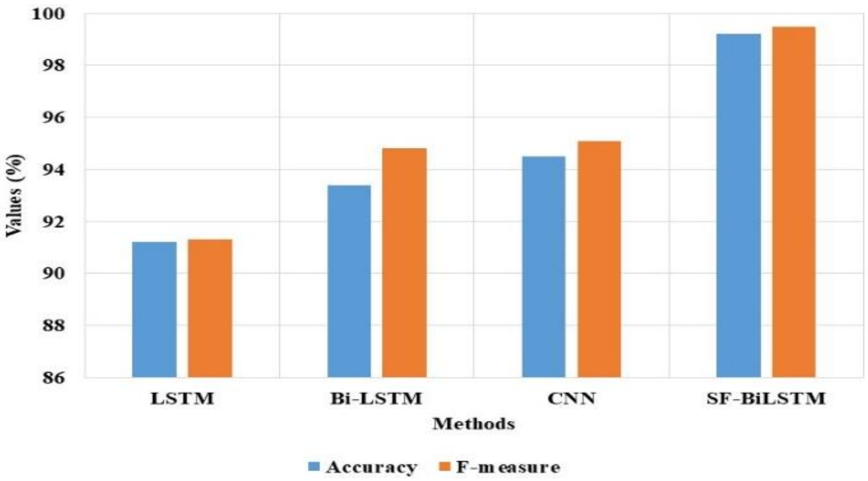

Figure. 6 Deep learning comparison in fake review detection

advantages of semantic features and mapping the data in the encoding.

The SF-BiLSTM method is compared with the deep learning methods in Table 2 and Fig. 4. The SF-BiLSTM method has significant efficiency than existing methods in emotion recognition. The SF-BiLSTM method analyzing the input in a manner of forward and reverse. The semantic feature with the embedding of data improves the classification performance. The LSTM has a lower learning rate and Bi-LSTM has lower performance in feature selection. The CNN model has an overfitting problem for model classification.

The proposed SF-BiLSTM method and the existing method are compared in fake review detection, as shown in Table 3 and Fig. 5. The SF-

Received: June 9, 2022. Revised: July 7, 2022.

Table 5. Existing method comparison in fake review detection

Methods	Accuracy (%)	Precision (%)	Recall (%)	F-Measure (%)
Lexicon-CNN [11]	91.8	91.7	91.5	91.59
Graph Partition [12]	92.5	92.1	93.4	92.74
Collaborative Training [13]	93.7	93.1	92.7	92.89
Ensemble-Majority voting [14]	94.2	94.3	94.5	94.39
Adaptive Boosting Ensemble [15]	96.5	96.2	96.3	96.24
SF-BiLSTM	99.2	99.3	99.3	99.3

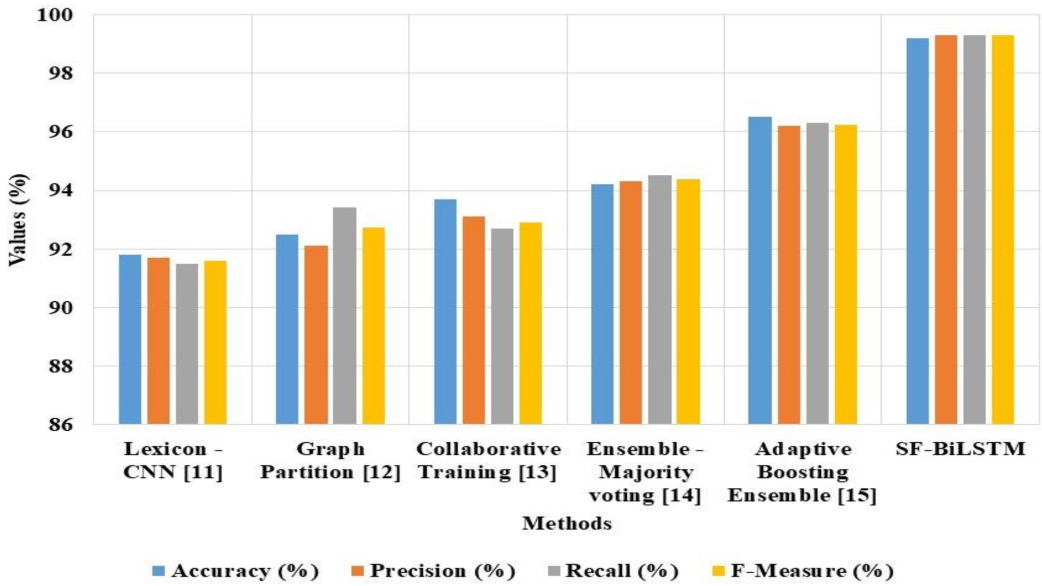

Figure. 7 Existing method comparison in fake review detection

BiLSTM has the advantage of analyzing the data in a forward and reverse manner with semantic features. The existing methods of KNN, SVM, and Random forest has a limitation of unstable performance, imbalance data, and overfitting problem.

The proposed SF-BiLSTM is compared with standard deep learning techniques in fake review detection, as shown in Table 4 and Fig. 6. The SF-BiLSTM method has the advantage of semantic feature selection and analysis of the data in a forward and reverse manner. The CNN model has a limitation of overfitting problems in the classification. The LSTM and Bi-LSTM model has the limitation of overfitting and vanishing gradient problems.

4.1 Comparative analysis

The proposed SF-BiLSTM method is compared with the existing research method in fake review detection. The parameter settings of Bi-LSTM model is set with 50 epochs, 128 batch-size, 0.01 dropout rate, and 6 layers to train and classify the data.

The proposed SF-BiLSTM method is compared with the existing method in fake review detection, as shown in Table 5 and Fig. 7. The SF-BiLSTM model has advantage of mapping the features related to neighbourhood features using autoencoder and decision tree. This technique helps to learn the relevant features for classification and increases the efficiency of the model. The SF-BiLSTM has significant efficiency due to its advantage of semantic feature selection. The Lexicon-CNN [11] model has a limitation of over fitting problem, graph partition method has lower learning performance, and collaborative training has an imbalance data problem. The graph partition [12] and collaboration technique [13] have limitations of overfitting problem in the classification. The ensemble-majority voting method [14] has lower efficiency in learning feature differences in classification. The adaptive boosting ensemble [15] method has lower performance in noisy and outlier data. The proposed SF-BiLSTM method has 99.2 % accuracy and the existing Adaptive Boosting ensemble method has 96.5 % accuracy.

5. Conclusion

Fake Review detection is important for an e-commence website to improve the trust between the user and seller. The existing methods in detection of fake review have the limitation of over fitting problem and vanishing gradient problem. In this work, the SF-BiLSTM is proposed to increase the performance of detection in fake review. The proposed SF-BiLSTM method performs emotion recognition in input data and is used for detection of fake review. The four datasets such as Amazon, Yelp, Restaurant, and Hotel dataset were applied to test SF-BiLSTM model efficiency. Existing methods has the limitation of over fitting and vanishing gradient problems in fake review detection. The proposed method performs semantic feature selection to increase classification efficiency by using the semantic feature selection approach. To proposed method is compared with existing KNN, SVM, Random Forest machine learning techniques and LSTM, Bi-LSTM, CNN Deep learning techniques for emotion recognition and fake review detection. This emotion recognition performance is measured by using various performance parameters like classification accuracy, F-measure, Precision, and Recall. The performance of fake review detection is measured using accuracy and F-Measure. The proposed SF-BiLSTM method has higher efficiency than existing models. In future the developed method can be applied over the LSTM-CNN model to overcome the data imbalance problem.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

The contributions by the authors for this research article are as follows:

Author 1: Collect the data, make contributions to conception and design, analysis, and interpretation of work.

Author 2: Review and analyze the manuscript, participate in drafting the article, or revising it critically.

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