A Novel Deep Learning Approach of Convolutional Neural Network and Random Forest Classifier for Fine-grained Sentiment Classification

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Abstract: Deep learning became more popular in recent years. It is widely used for different machine learning tasks. One such task is sentiment prediction on a text document. Fine-grained sentiment analysis is highly recommended since most of the researchers are focusing on binary sentiment classification. In this work, a new model which combines the benefits of both Convolutional Neural Network (CNN) and Random Forest (RF) Classifier is proposed for fine-grained sentiment classification. The main idea of the proposed model is to achieve maximum accuracy for sentiment classification on large volume of data. The CBOW (Continuous Bag-of-Words) model is used for converting the text input into vector form. Convolutional Neural Network (CNN) is used to extract the features from the input vector. The fully connected layer in the Convolutional Neural Network is replaced by the Random Forest classifier. Then the extracted features are used for the classification process by Random Forest Classifier. A dropout strategy is applied to regularize the CNNRF model to avoid overfitting. Sentiment analysis is performed on product review data by using CNN and RF model separately. The result of the CNN model and RF model is compared with the result of the proposed CNNRF model. The experiment result shows that the combined CNNRF model gave high performance than independent CNN and RF models.

Keywords: Convolutional Neural Network (CNN), Deep Learning, Sentiment analysis, Random Forest (RF) Classifier, Big data

1. Introduction

The birth of e-commerce technology leads to a large number of people to prefer online shopping. Most of the customers are leaving their opinion online. They are posted, shared, tweeted and left on retailers' site also. The opinion of customers may be their experience of the particular product they are considering or the service they are using. Compared with traditional shopping, users can shop at any time and from anywhere. Moreover, the products from an e-commerce platform have come with different varieties and styles. The e-commerce industry, consider social media as an advertising platform. The people are spending more time on different social media and thus the chance for the online purchase is more. The big data collected from these social media will help the business organization to improve their graph of growth. Still, due to the virtual nature of e-commerce platform, the buyers are facing so many problems in a sold product like the bad performance of the product, differences in the description given and the real product and so on. So, it is highly significant to perform customer feedback sentiment analysis on the purchased product. The customer feedback provides a reference for other customers also.

Machine learning classifiers are widely used for performing sentiment analysis on product reviews. The supervised machine learning classifier provide promising outcomes as compared with the unsupervised machine learning classifiers. The supervised machine learning classifiers use labelled data for processing. The classifiers can be Naïve Bayes, Support Vector Machine, Decision Tree Random Forest etc. The volume of data handling is little challenging in the case of machine learning models. This leads to the usage of deep learning in big data environment.

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Big data is mainly generated from social sites and mobile networks. The big data may include structured and unstructured data. The unstructured data does not have a particular form or structure and it is difficult to use for processing task. The structured data can be process, store and retrieve easily. Big data is generally defined by four main characteristics. They are volume, velocity and variety. The size of big data is generally larger than a traditional computer system can handle. Velocity refers to the speed at which the data is generated in real-time. Variety of data such as structured, semi-structured and unstructured data is supported and used by big data environment. Performing sentiment analysis on big data in business field will help the business organization to take timely decision on their production and promotion.

The sentiment analysis of product review refers to the task of analyzing their feeling towards a particular product or service automatically. As deep learning showed remarkable outcomes [1] for processing natural language processing, it has been widely used for sentiment analysis on customer feedback analysis in the business field. In the domain of natural language processing, deep learning is highly used and a variety of deep learning online sentiment analysis is proposed by researchers. Compared with traditional machine learning, human intervention features are not needed for deep learning but it required mass data as support. Different neural network models are used to automatically extract features and the model will learn from errors itself [2]. The neural network uses a layer-by-layer abstraction model and non-linear activation function is used to map different layers; thus, it can use to represent complex features also. The commonly used deep learning models for text sentiment analysis are Recurrent Neural Network (RNN), LSTM, CNN (Conventional neural network), and Gated Recurrent Unit (GRU) [3].

Most of the researches are concentrating on the deep learning neural networks and machine learning methods separately. In this work, a hybrid model is proposed by combining the Convolutional Neural Network and Random Forest classifier for fine-grained sentiment classification. This model can handle large volume of data and maintain the striking features of machine learning classifiers too.

The rest of this paper is organized as follows. Section 2 gives the background details related to this research area. Previous and related works are discussed in Section 3. In section 4, a novel method for fine-grained sentiment prediction is explained. The experimental results are discussed in section 5 and it is followed by section 6 where conclusion of this work is given.

2. Background

In the traditional approach of machine learning, labelled data is given to the model and based on labelled data, the model will predict the class of new data. The feature definition and extraction are done either by feature selection methods or manually. After feature selection and its transformation, it is easy to represent the input that can use by the machine learning algorithm. Currently, many classifiers with machine learning techniques are proposed for sentiment analysis. Nedhaa Baker and Huwida E [4] used Naïve Bayes classifier for sentiment analysis on predicting the presidential election. Manek et al. [5] proposed a Gini-index based feature extraction and SVM classifier. Bahrawi conducted sentiment analysis [6] on twitter data using Random Forest classifier. Although the method of machine learning can extract the features automatically, it often includes human intervention. However, in deep learning, the feature selection and extraction are performed automatically and the model can learn from its errors. In recent years, the approach of deep learning reached a great rank in many fields. The model of the neural network is composed of a layered approach, the layers are using activation function for mapping, so the network can represent complicated features then it tries to find the hidden features from the given text [7]. Figure 1 depicts the differences in the classification of sentiment polarity between machine learning and deep learning. In recent years, the use of deep learning provided a better solution to different problems in natural language processing.

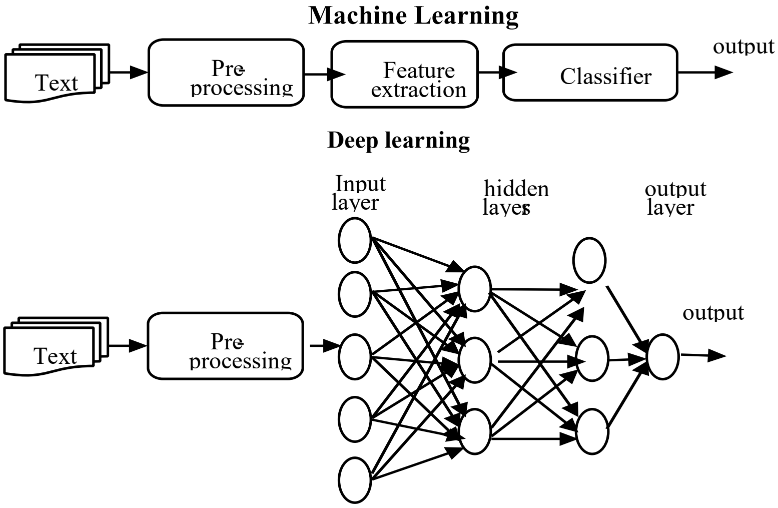

Figure 1. Difference between two approaches for sentiment classification. Top- Machine learning, Bottom-Deep learning

3. Related Work

In this section, previous and related works carried out in the field of fine-grained sentiment analysis which used deep learning methods are discussed.

In 2017, Oscar Araque et al. [8] introduced an enhanced deep learning sentiment analysis model for social application. The model helps to improve the performance of the deep learning approaches by combine it with traditional surface approaches. The authors used six public datasets for their work which collected from twitter and movie reviews. The statistical study shows that proposed model is really suitable for performing aspect-based sentiment analysis in social applications.

Adyan Marendra Ramadhani and Hong Soon Goo concentrated on twitter which is a Social Network Service (SNS) in 2017 [9]. For the experiment, the authors used both English and Korean twitter data from twitter API. They trained the model with 100 epochs and used 0.1 and 0.001 as the learning rate. The detailed graphical representation is also given. The accuracy comparison of both deep learning methods and multilayer perceptron was another highlight of their work.

For fine-grained sentiment analysis, Akshi Kumar et al. [10] proposed a context enriched hybrid deep learning model. Real-time multimodal data is used for their work. Three different types of input used for this model such as info-graphic, text and image. Combination of Convolutional Neural Network (ConvNet) with context semantics of SentiCircle performed sentiment prediction on the text. Visual content sentiment prediction was the job of the Support Vector Machine (SVM). The proposed model achieved 91% of accuracy.

Social media data sentiment analysis is done in 2016 by Zhaoxia WANG et al. [11]. The authors also considered emotion analysis. They developed a social media analytics engine to perform fine-grained sentiment analysis with four classes such as mixed, positive, neutral and negative. According to the authors, this model is capable to apply in different fields such as corporate, leisure, healthcare, private and public sectors.

In 2018, sentiment analysis is performed by shalini et al. on Indian language [12]. Bengali-English code-mixed data is used in this work. Convolutional Neural Network with one hidden layer trained for analyzing the input dataset. The CNN is used for analyzing both Telugu movie reviews and Bengali-English code-mixed data separately and achieved an accuracy of 51.3% and 73.2% respectively.

Most of the current works are concentrating on neural networks rather than the combination of neural networks and supervised machine learning classifiers. The proposed hybrid model provides nice features of both neural networks and supervised machine learning classifiers.

4. Methodology

Nowadays researchers are performing sentiment analysis based on binary classification in which the given document is classified into two categories i.e., positive and negative. This research proposes a novel approach of combining CNN (Convolutional Neural network) and Random Forest (RF) classifier called CNNRF model for fine-grained sentiment analysis which is capable to perform multiclass sentiment analysis. This proposed model is used to classify the sentiment on product reviews into five different categories such as strong negative, negative, neutral, positive and strong positive. The labelled dataset first goes through pre-processing stages, then CBOW model is used to find the vector values for each word in the corpus. The output of CBOW Model is given to Convolutional Neural Network for feature extraction. The CNN consists of five hidden layers. Every hidden layer includes a convolution layer and a max-pooling layer The convolutional layer extracts the features, then the features are transformed by using the max-pooling layer. Finally, the fully connected layer develops the feature space by combining all the features. Last, the feature vector output is fed into the classification process by Random Forest Classifier. Dropout strategy is also applied to this CNNRF model. The overall flow of the system is depicted in Figure 2.

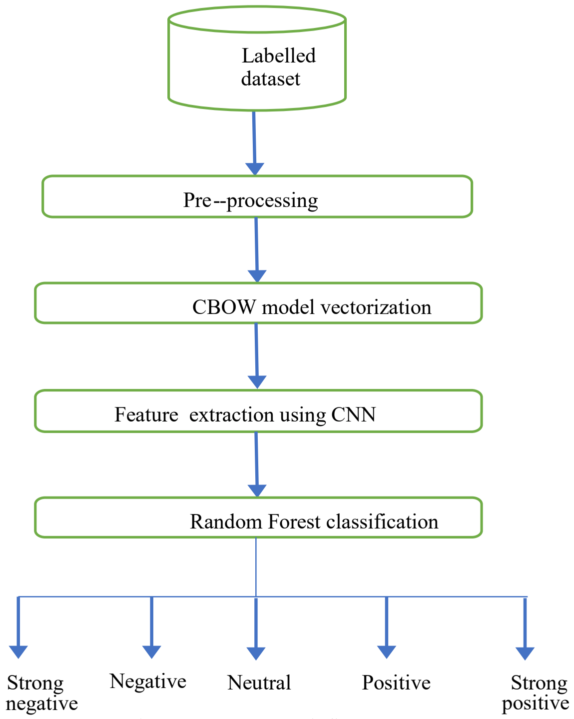

Figure 2. System work flow

A. Pre-processing

The collected input data may contain a lot of unwanted elements and noises. It is very important to clean the input data before processing. Data pre-processing is always necessary to clean the input data and make it suitable for a machine learning model. Number of pre-processing techniques are used in this work and they are

- Tokenization: The collected input data is available in the form of sentences or document, so in the initial stage, these sentences or document is divided into a number of an individual unit called tokens.
- Numbers, special character, stop words and punctuations are also removed since it does not convey any sentiment.
- Stemming: In the stemming process each word is reduced into their root word called the stem. For example, consider the words love, lovable, loving, loves and these words are reduced into their root word called love.

B. Word Embedding-CBOW Model

The machine learning algorithms and deep learning architectures are not able to process text inputs. The plain text should be converted into numbers before classification. For this purpose, word embedding methods are used. These methods will convert the text into numbers and it may keep different representations of the same text. The word embedding can be either frequency-based or prediction-based. One of the widely used prediction-based word embedding methods is Continuous Bag-of-Word model (CBOW). This CBOW will find the target word from the given context. The order of the context word does not influence the prediction process. In this model, the context is represented by multiple words for a given target word. For a given set of sentences, this model loops on each sentence and struggle to find a new word w from the given context. A parameter called "window size" is used to limit the number of words in each context.

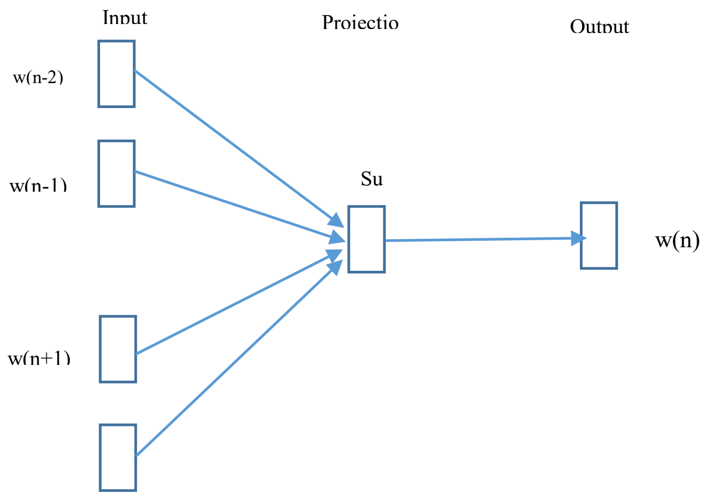

Figure 3. CBOW model

Steps used in CBOW model word embedding are

- First, the input layer receives one-hot encoded-words which are of dimension D where V is the vocabulary size
- The input layer averages them and creating a single input vector
- The input vector is multiplied by W where W is the weight matrix and get a D-dimensional vector
- The resultant vector is multiplied by another matrix of size D×V and get a new V dimensional vector as output
- This V dimensional vector is normalized to make all the entries

C. Convolutional Neural Network

Convolutional Neural networks are deep artificial neural networks which are specifically used for classification and image recognition. It works based on feed-forward architecture. Due to its multi-layer perceptron, the CNN requires only minimal pre-processing of input data. A CNN has an input, output layers and hidden layers also. The architecture of CNN is generated by a stack of different layers that convert input volume into output volume through a differentiable function. Other than input and output layers the CNN has the following hidden layers.

- Convolutional layer: In convolutional layer, sit slide over the given input data to extract features by applying a kernel or filter. This is an important layer which plays a major role in feature extraction. After applying the filter over input data, different activation functions can be applied over the produced output to get a non-linear relationship for the output. The convolutional layer calculates the element-wise product of each word and multiplied by the weight associated with the convolutional filters.

  Consider the input matrix W= [w_1, w_2,…….., w_n], then the equation for the convolutional operation is

  $$w_i = f\left(W_t . W_{[i:i+k-1]} + b\right) \tag{1}$$

  Where $W_t \in R^{k*m}$ which is a weight matrix,
  k - height of the convolutional kernel
  m- width of the convolutional kernel
  b – offset value
  f – activation function.

  The resultant vector after the convolutional operation is represented as

  $$W' = [w_1, w_2, \ldots., w_i, \ldots w_{n-k+1}] \tag{2}$$

- Pooling layer: Pooling typically applied after the convolutional operation. It is considering as another building blocks of CNN. It performs a down sampling operation. The purpose of pooling is mainly to decrease the spatial size needed for representing the inputs and the thereby decrease the total computation and parameters used in a particular network. The pooling operation can be max pooling and average pooling. For this work k-max pooling is used.

  For the input vector w_i, the k-max pooling operation is represented as

  $$x = [x_1, x_2, \ldots. x_i, \ldots., x_{m-k+1}] \tag{3}$$

  $$x_i = \max(w_i, w_{i+1}, \ldots.. w_{i+k-1}) \tag{4}$$

  Where m – dimension of the vector w_i
  max – maximum function

- Fully connected layer: This layer represents the traditional neural network. The features generated by the convolutional layer are fed into this fully connected layer and it will produce the output. The fully connected layer performs two operations on its incoming data i.e., a linear transformation and a non-linear transformation. The linear transformation is performed by using the following formula

  $$Z = W^T . X + b \tag{5}$$

  Where X – input
  W - weight
  b – a constant which is called bias.

The non-linear transformation cannot tackle complex relationship, so one additional component is added to the network which helps to add non-linearity to the data. This new network component is known as activation function. From equation (5), the activation function is represented as

$$Y = Activation\left(\sum(W^T . X + b)\right) \quad (6)$$

The output of this activation function is given to the next hidden layer and will perform the same process. This is known as the forward propagation. Based on the forward propagation result, the error is calculated then the weights and biases are adjusted. This process is called back-propagation.

The vector output of the CBOW model is given as input to the CNN. In this work, 5 convolutional layers and 5 pooling layers are used in CNN. In this proposed framework, most of the time is spent on training the convolutional layer. The main task of the convolutional layer is to extract features from the input and these features are down sampled by a pooling layer. The final fully connected layer takes up the important parameters of the CNN.

D. Random Forest Classifier

Random forest is a widely used supervised classification method which constructs multiple decision trees during the training phase. It works efficiently on a large database. The Random Forest Classifier can be used for both classification and regression. One of the advantages to using this classifier is that it reduces the risk of overfitting and training time. It also provides high accuracy by predicting missing data. There are some important terms related to Random Forest Classifier. They are

- Entropy: Entropy is the measure of randomness or unpredictability on given dataset
- Information gain: It is the measure of the decrease in entropy after dataset split
- Decision node: It is the node with two or more branches
- Root node: Topmost decision node which has used to represent all data
- Leaf node: It is the node which carries the final decisions

Instead of depending on a single decision tree, Random Forest takes the results from different decision trees and based on majority votes, it will predict the final result. The traditional Random Forest Classifier algorithm is as follows.

RandomForestClassifier: Prediction Pseudocode

- Randomly choose f features from total feature F where f<F
- Using the best split point, find node n from f features
- Find best split and split the node n into number of child nodes
- Execute the above steps until reach single node
- To create T number of trees, do the above steps for T times
- The test features are given to the generated forest
- Find the vote for every predicted target
- Select the outcome with maximum vote as the final prediction

The novelty of this work is that we combined the features of Convolutional Neural Network (CNN) with the Random Forest (RF) and proposed a new model called CNNRF model for fine-grained sentiment prediction. The procedure for the proposed CNNRF model is given as

Proposed CNNRF procedure

- Read the labelled dataset D
- Perform pre-processing techniques on each reviews R in the dataset
- For each R ∈ D do the following to find the corresponding vector values
  - For each word $w_t \in R$
  - Define context size K
  - Find context cumulative sum V_t
  - Generate the vector value for w_t as

$$P(w_t|Context(w_t)) = \sum_{t-k}^{t+k} f(V_t\theta)$$

- Vector value is given as input to the CNN for feature extraction
- For each sentences S do the followings
  - From W, find the word vector for all words in $S= [w_1, w_2, \ldots\ldots, w_{n-1}, w_n]$
  - Find the feature value from the convolutional operation $f_i=f\,(v.\ w_{i:\,i+h-1}+b)$
  - Generate a feature vector $F= [f_1, f_2, \ldots\ldots, f_{n-h+1}]$ by combining all feature values
  - To find the most important feature, perform the pooling operation using max{F}
- Perform classification by RF
  - Built decision trees based on random features
  - Perform a vote for each predicted result
  - Select the prediction result with the most vote as the final decision.

5. Experimental Results

For evaluating the performance of the proposed model 3000 Product reviews from UCI database are used as a dataset for this work. Product reviews in the dataset are of five different categories i.e., strong positive, positive, neutral, negative and strong negative. Manual checking is done to ensure that all the reviews come under at least one of these five categories. After this checking, this dataset is used for this work. CNN model is used to extract the features from the input dataset. The attributes in the collected dataset are described in Table 1.

Table 1. Dataset description

Attribute	Description
reviewerID	ID of the reviewer
Asins	ID of the product
reviewerName	Name of the reviewer
Helpful	Helpfulness rating of the review
reviewText	Text of the review
Overall	Rating of the product
Summary	Summary of the review
unixReviewTime	Unix time of the review
reviewTime	Time of the review

First, the input goes through vectorization process by CBOW Model. It will convert the text input data into vector form. This converted form of the dataset is given as input to the CNN. This work builds a CNN with five convolutional layers for sentiment classification.

Table 2. Size of the neural network

Data sets	Number of hidden layers	Number of output labels
Product reviews	5 convolution 5 pooling	5

In this work, the proposed CNNRF model is used for product review dataset analysis. The aim is to perform fine-grained sentiment analysis on product review dataset. Different iteration values are tested for CNNRF. The effect of the value of different iterations is given in Table 3. When the number of iterations increases the model performance will increase then after some point it will fall. From the Table 3 and Figure 4, it is clear that CNNRF model's performance improved when the iterations number is less than or equal to 8. When the value of iteration is greater than 8 the performance is slowly decreasing and it results in overfitting.

Table 3. Iteration number effect on the CNNRF Model

Epoch	Accuracy	Precision	Recall	F1
3	92.1%	91.6%	92.4%	92.0%
5	92.4%	92.4%	91.8%	92.1%
8	92.8%	92.2%	93.2%	92.7%
10	92.2%	92.2%	92.0%	92.1%
12	91.9%	91.7%	92.3%	92.0%
15	91.5%	90.7%	92.1%	91.4%

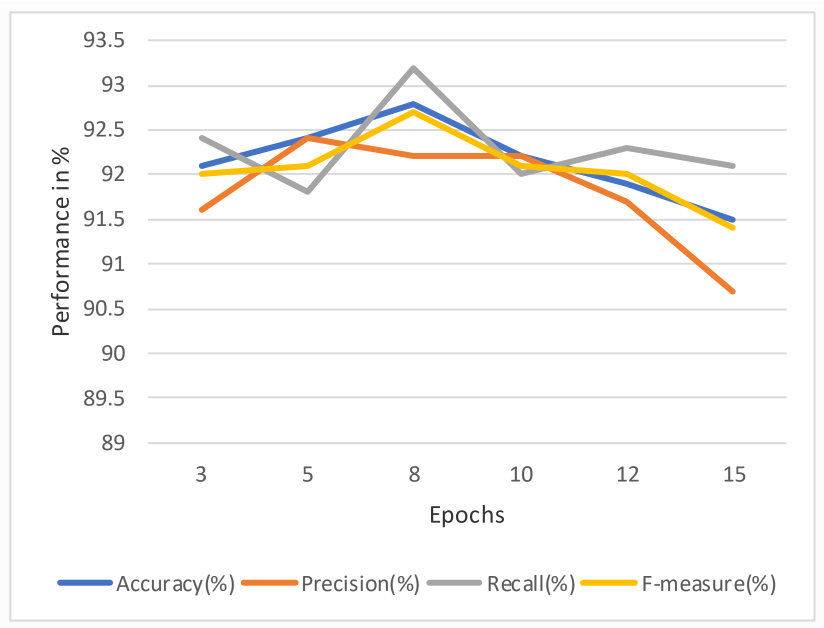

Figure 4. Iteration values on model evaluation

A dropout strategy is used in this work to avoid the overfitting problem of the proposed CNNRF model. In this experiment, different values are tested for dropout. The Table 4 and Figure 5 depict the performance of the CNNRF model based on different dropout values. For the dropout value 0.4, the accuracy of the CNNRF model is high and then it gets fall.

Table 4. Dropout value effect on CNNRF model

Dropout	Accuracy	Precision	Recall	F1
0.2	92.0	91.0	93.0	92.0
0.4	92.7	92.6	92.4	92.5
0.5	92.4	92.4	91.8	91.1
0.6	92.4	92.7	92.1	92.4
0.8	91.6	91	92.5	91.7

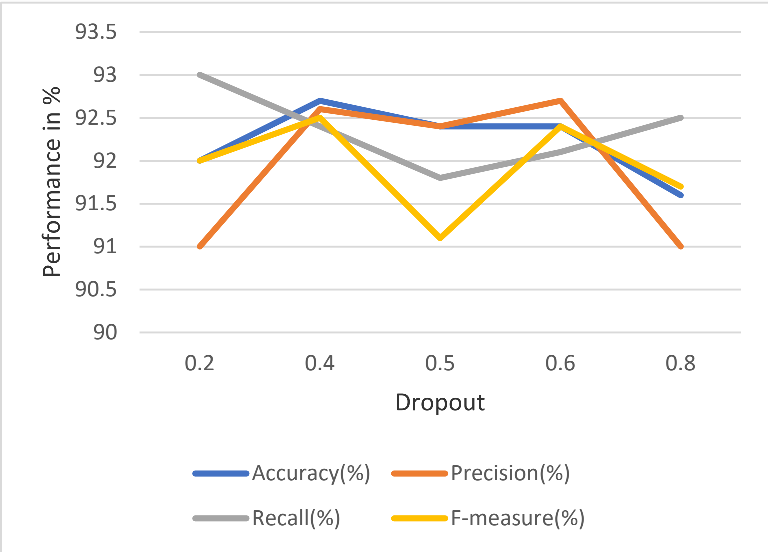

Figure 5. Dropout values on model evaluation

Finally, we performed sentiment analysis on the same product review dataset by using traditional models like CNN and RF separately. The result of this comparison is given in Table 5 and Figure 6.

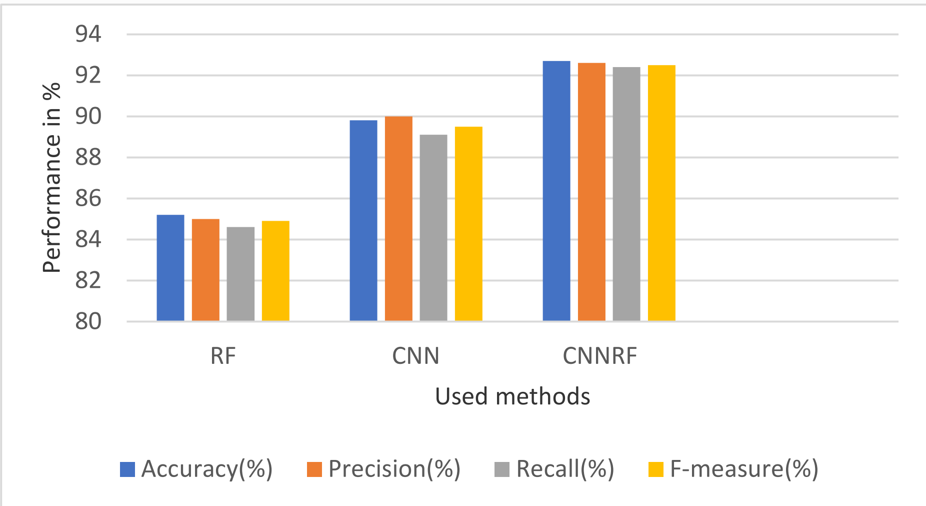

Figure 6. Result Comparison

Table 5. Result obtained for multiclass (five) sentiment analysis.

	Fine-grained sentiment analysis			
Model	Accuracy	Precision	Recall	F1
RF	85.2	85	84.6	84.9
CNN	89.8	90	89.1	89.5
CNNRF	92.7	92.6	92.4	92.5

The result shows that the CNNRF deep learning model provided better performance as compared with the traditional supervised algorithm called the RF. When RF model is used alone for analysis, it provides an accuracy of 85.2%. Then, 4.6% of performance accuracy can be increased by using the CNN model. When a fusion model i.e., CNNRF is used for fine-grained sentiment analysis on product reviews, it results in an accuracy of 92.7%. The proposed CNNRF model gives better performance as compared with traditional CNN and RF models.

6. Conclusion

In this paper, a hybrid model is proposed for fine-grained sentiment classification. The proposed called CNNRF and it combined the features of both deep learning model and supervised machine learning. For getting better performance for large volume of data, the proposed model combined CNN (Convolutional Neural Network) and RF (Random Forest) classifier. It uses CBOW model for vectorization purpose. The important features are extracted using CNN. Classification is performed by RF classifier and it provided accurate result since it takes the major voting method. Different iteration values and dropout values are tried for this model. A detailed comparison is done with independent CNN and RF models. By analyzing the results, it is clear that the performance of the proposed model is higher than the individual performance of CNN and RF models for fine-grained sentiment classification. The dropout strategy also helps to generalize the performance of the CNNRF model.

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