Emotion Detection using Natural Language Processing

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***Abstract*—Online reviews of products, travel destinations, or movies are frequently given as sure opinions. As a result, sentiment analysis and opinion gathering become routine tasks. Consequently, the demand for automated text sentiment analysis has increased. Instead of reading reviews, it is useful to obtain opinions and sentiments regarding a particular subject. The Support Vector Machine, Naive Bayes, Decision Tree, and K-Nearest Neighbor are machine learning approaches, as well as the deep neural network, a Recurrent Neural Network and Long Short-Term Memory (LSTM), are the two main methodologies of sentiment analysis employed in this paper. Additionally, in this work applications of two techniques using three Twitter datasets are done: Netflix, Flipkart, and Tourism. Additionally, visual comparison of several strategies is also shown, and the Recurrent Neural Network experiment results are displayed.**

***Keywords—Text mining, Opinion Detection, Deep Learning, Machine Learning, Emotion Detection*.**

I. INTRODUCTION

The mining of feelings has made blogs and social networks useful resources. To express their opinions on various subjects or products, they are handled by a variety of persons. As a result, gathering statistics about their goods and enhancing results is a resource that is advantageous for businesses and organizations.

In addition, academics are now interested in this vast amount of information to learn what people think. [1]–[3]

Social media are currently creating a ton of rich emotional content data in blogs, Facebook meta posts, and tweets. These data are useful for discovering consumer opinions on a range of subjects and goods. The amount of Twitter's data is severely constrained by the character limit of its generated messages, which is set at a maximum of 150 characters. [4]

There are a good amount of quick tweets on Twitter that were created by users [5]. In order to extract opinions from tweets on Twitter, opinion mining is essential [6]. Researchers have researched sentiment mining in great detail [5], [7], [8].

Furthermore, it's regarded as one of the key areas of data mining where, based on the positive or negative connotations of the data acquired, valuable information might be discovered. Some names for sentiment analysis include opinion mining, sentiment extraction, and product appraisal. In order to get viewpoints on various items or themes, it is also looking via comments or tweets. [6].

Machine learning is mostly used by researchers to categories consumer opinions of brands or businesses.

Machine learning, which is widely defined as a machine's capacity to mimic intelligent human behavior, includes the subfield of machine learning. Artificial intelligence (AI) systems are used to carry out complicated tasks in a manner akin to how people solve issues. [6].

In general, there are three classes of machine learning.

Among them are the following: a) Supervised learning, where practice data is labelled and used to train the model. b) Unsupervised Learning: Where practice data is unlabeled and used to train the model. c) Reinforcement Learning: Unlabeled data are used to train the model. Communication with a dynamic environment is necessary at every level of the system's growth. [9].Recently, Deep Learning algorithms have outperformed existing machine learning techniques in a number of applications, including Computer vision (CV) and speech identification. [10].

Having the ability to gather complicated data once at abstract level in a manner that allows the production of higher-level characteristics in connection to lower-level attributes at such a lesser level of abstraction, this is capable by Deep Learning. The acquisition of intricate nonlinear characteristics in data is also possible using deep learning algorithms. Deep learning algorithms also incorporate several hidden layers to change input. [11].

Furthermore, sentiment analysis uses two separate deep learning techniques, namely A deep learning neural network called a convolutional neural network is made for processing structured data sets like pictures. The state-of-the-art for many visual applications, such as image classification, CNN are extensively employed in computer vision. They also have achieved success in NLP for text classification.[12] and recurrent neural networks [13]. A deep neural unit and long-term memory are two further forms of RNN [4].

Opinion mining techniques include using deep neural networks and machine learning. On the three Twitter databases, Netflix, Flipkart, and Tourism, the two methods were used. The suggested system contains five key phases, which are as follows:

1) *Dataset from CSV file.*
2) *Preprocessing of Data.*
3) *Feature Extraction*
4) *Classification.*
5) *Model Evalution.*

Comparing the two algorithms revealed that the RNN that implemented LSTM had the best degree of accuracy. Five sections make up this essay: The associated works are shown in Section 2. Section 3 describes the suggested system design and method. Section 4 discusses the experimental findings and contrasts ML with recurrent neural network methods. Section 5 towards the end includes the conclusion.

II. RELATED WORKS

I also looked at earlier research on the system that was recommended in this section. Twitter has become more popular as a tool for tracking demand patterns or opinions on certain products or topics. Many scholars have focused their efforts on emotion recognition topics, using classifiers to analyses data from the Twitter dataset. There has been a ton of earlier research on sentiment analysis, including Go and On the Dataset, Alec evaluated the performance of a number of classifiers, including the Naive Bayes, Support Vector Machine, and Maximum Entropy. When they trained a computer using comments and emotional data, scientists got an accuracy of about 80%. [13].

Neethu, M. S., has used machine learning methods including Naïve Bayes classifier, the Support Vector Machine, Ensemble classifiers, and Maximum Entropy to evaluate the Twitter dataset related electrical equipment, such as PCs, mobile phones, laptops, etc. The study employed a novel feature vector that collects user views about products and classifies tweets as positive or negative. Moreover, several classifiers used the new feature representation to achieve about equivalent accuracy. [4].

A method developed by Geetika Gautam and Divakar Yadav analyses customer evaluations and classifies them as either good, negative, or indifferent [14].

In order to learn the sentiment-specific word embedding (SSWE), Tang and Duyu created the Cool system. They used loss function 1 to teach themselves SSWE. They also gathered 10 million tweets without any manual annotation, both of which included positive and negative emotions. Utilization of this data to develop SSWE [15] is also done.

To measure accuracy, precision, and recall, they make use of a variety of methodologies, such as Naive Bayes, Entropy, Support vector machines, and text analytics. The accuracy index of the Naive Bayes approach was greater than the accuracy index of the maximum entropy and the Support Vector Machine methods, which was 87.2%. Gangawane AA and H.B. Torvi classified positive and negative comments gleaned from Twitter data using machine learning. In order to attain a greater rate of accuracy, they also developed a classification model utilizing Bayesian Logistic Regression. They have developed a technique that locates target tweets by using Bigram highlights and Term Recurrence Inverse Document Frequency (TF-IDF) [16].

The quantity of tweets provided Jiang, Long, and others with the data and analysis they needed. The customer opinions are then categorized using the primary analysis, which might be either positive, negative, or a combination of both. This contribution involves a variety of processes, such as the pre-processing of input from an adjective that was taken from the Twitter data was used to build the feature vector after numerous machine learning algorithms, including the SVM, Naive Bayes Classifier, Semantic Orientation based WordNet and Maximum entropy, were used to choose synonyms and similarities. Additionally, a variety of evaluation techniques, including precision, recall and accuracy [17].

III. METHODOLOGY

The proposed system has five processes, as illustrated in Fig. 1: importing a dataset from a Csv format; preprocessing the data; extraction of features; classification; and model assessment. 1, and that each step is thoroughly described:

A. Dataset from CSV

The Twitter datasets from Netflix, Flipkart, and tourism are used. Both a tweet column and a labelling column with both negative and positive labels are present in every dataset. Moreover, splitting the data into two portions: a 25% test dataset for such model's assessment as well as a 75% training dataset for model's training.

B. Preprocessing of Data

Pre-processing, which involves cleaning, preparing, and reducing dataset noise, aids in classifier performance and classification process speed. There are four primary steps to this process.

- Erasing datasets that contain special characters like http://, @, and #.
- Tokenization: In this step, the dataset is divided into a word list.
- Stop words should be eliminated since they frequently repeat themselves and therefore are unneeded.
- The more common stop words in English, for instance, are “a”, “an”, “the”, “I”, “it”, “you”, “and”, “of”.
- Stemming: This process strips derivative words back to their original forms.

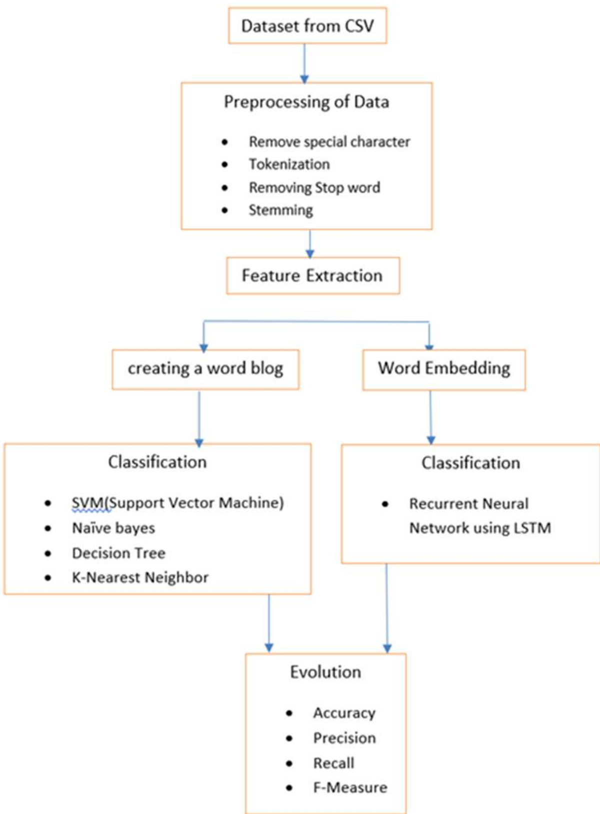

Fig.1. Infrastructure for mining opinions on Twitter

C. Feature Extraction

Words are converted into a vector matrix via feature extraction. Deep neural networks and supervised algorithms are two alternative ways that this stage is carried out.

- Establishing the Words Bag: a collection of words entered for computer learning Also created is a bag of words. building Python libraries and employing the popular vectorizer Count Vectorizer [19].
- Word embedding: word embedding in a deep neural network application. Words and documents with complete vector representations are represented by it.

D. Classification

1) Machine Learning Strategy:

- Naive Bayes

  Popular supervised machine learning methods include Naive Bayes. To calculate the posterior probability of a class, this model is utilized. When each class is given a collection of items, the model's goal is to predict future objects [3].

- Support vector machine

  Using Support Vector Machines, one can categorize linear and non-linear data It transforms data via a nonlinear mapping. A higher dimension using the training data [20].

- Decision Tree

  One of the most popular machine learning algorithms is the decision tree algorithm, and a large part of its appeal stems from its propensity to adapt to virtually any sort of input. This particular supervised machine learning technique breaks up the training set of data into smaller chunks in order to extract patterns that are then used in the classification phase. The information is then presented in an understandable tree format [21].

- K- Nearest Neighbor

  An unclassified sample point receives the categorization of the closest neighbors thanks to the nearest neighbor decision rule. A collection of already categorized points [22]. Recurrent neural networks are thought to have extensions called Long Short Term Memory (LSTM) networks, which essentially extend memory. As a result, it makes sense to be able to draw lessons from significant events that occur across very large time delays. The LSTM units are used for sic buildings. Blocks for an RNN's layers are known as LSTM building blocks. RNNs can remember their inputs for a lengthy period of time thanks to LSTMs.

  This is due to the fact that LSTMs, whose storage is comparable to that of a computer, can perform the basic operations from their storage of writing, read, and wiping data. [23].

2) Deep Neural Network Strategy:

- Recurrent Neural Network

  Recurrent neural networks are a component of powerful deep neural networks (RNN). RNNs feature a memory with a finite capacity, in contrast to traditional feedforward neural networks, which means that the current input at a particular time step also depends on the past inputs. Where working with data that must be consecutive or when order is important, RNNs are the ideal approach. Sentiment analysis is one of such uses because word order regularly changes a word's meaning in context. [12].

E. Evaluation

Recall, accuracy, precision, and F-measure are a few methods for evaluating models [24]. The accuracy is the percentage of twitter comments that were correctly classified to all comments. Recall, accuracy, and F-Measure are defined as:

Recall = True-Positive/ (True-Positive + False-Negative)

Precision = True-Positive/ (True-Positive + False-Positive)

F − Measure = (2 ∗ Precision ∗ Recall)/ (Precision + Recall).

IV. EXPERIMENTAL RESULTS

A. Description of Dataset

To develop the model, three datasets were used. Each dataset was also divided into a 25% testing dataset and a 75% training dataset. Each database is thoroughly described below:

1) 1700 TWEETS TOTAL, OF WHICH 1000 WERE GOOD AND 700 WERE NEGATIVE, MAKE UP THE FLIPKART DATASET.

2) THE 2600 TWEETS IN THE NETFLIX DATASET WERE DIVIDED INTO 1600 POSITIVE AND 1000 NEGATIVE TWEETS.

3) THE 12645 TWEETS IN THE TOURISM DATASET WERE DIVIDED INTO 6000 POSITIVE AND 6645 NEGATIVE ONES.

B. EXCRUMENTAL ANALYSIS

TensorFlow and Keras were used to implement the RNN-LSTM. The architecture of Figure 1 and the network configuration created in Table I are also shown. Word embedding is sent into layer 2, the LSTM network's single input layer.

TABLE I. NETWORK CONFIGURATION

Parameter	Value
Epochs	15
Bunch Size	15
Method for activating a hidden layer	ReLU
Method for activating a output layer	Sigmoid
Optimizer	Momentum
Rate of Learning	0.005
Dropout	.4
Loss Function	Binary_crossentropy

input is divided into two groups, positive or negative, by one output layer. use the ReLU function for three of its hidden levels while using the sigmoid for the activation. The accuracy was found to be greatest when there were four buried layers after multiple failed attempts.

'Algorithms'	'Precision'	'Recall'	'F-Measure'	'Accuracy'
Naïve Bayes	71	68	67	68
K-Nearest Neighbour	65	64	63	80
Decision Tree	70	70	67	80
Support Vector Machine	80	80	80	82
RNN-LSTM	81	80	81	87

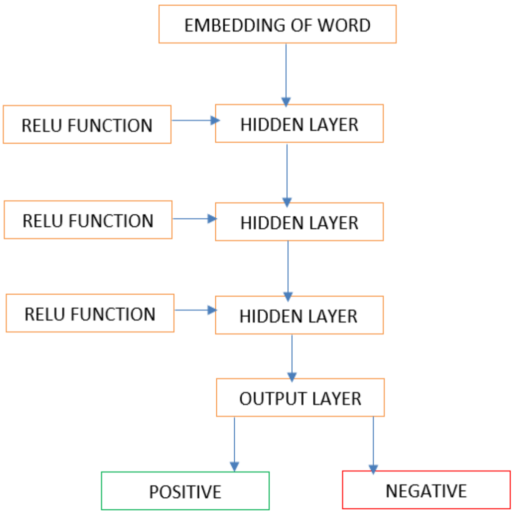

Fig. 2. Architecture of LSTM network

C. Results

a) Dataset of Flipkart:

TABLE II compares several algorithms for the Flipkart dataset using a variety of techniques.

Figure 3 compares the accuracy percentages reported by the following five algorithms: Support Vector Machine, Naive Bayes, Decision Tree, and Recurrent Neural Network utilising LSTM.

The Naive Bayesian approach had the lowest accuracy, at 68%, while the RNN-LSTM model had the best accuracy, at 87%. Additionally, accuracy scores for SVM and Decision Tree are 80% and 82%, respectively.

TABLE II. ANALYZING SEVERAL ALGORITHMS IN COMPARISON FOR A FLIPKART DATASET

'Algorithms'	'Precision'	'Recall'	'F-Measure'	'Accuracy'
Naïve Bayes	73	72	72	69
K-Nearest Neighbour	70	67	66	80
Decision Tree	79	78	77	81
Support Vector Machine	79	78	78	82
RNN-LSTM	82	81	81	88

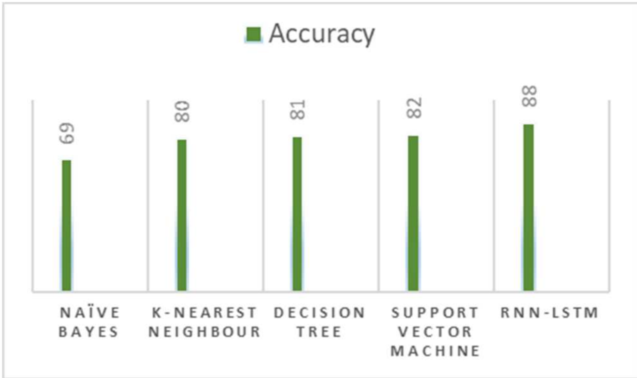

Fig. 3. Comparison of the performance of algorithms for the Flipkart dataset in terms of accuracy.

b) Dataset of Netflix:

For the Netflix dataset, III compares several algorithms utilizing a variety of techniques.

TABLE 3 ANALYZING SEVERAL ALGORITHMS IN COMPARISON FOR A NETFLIX DATASET

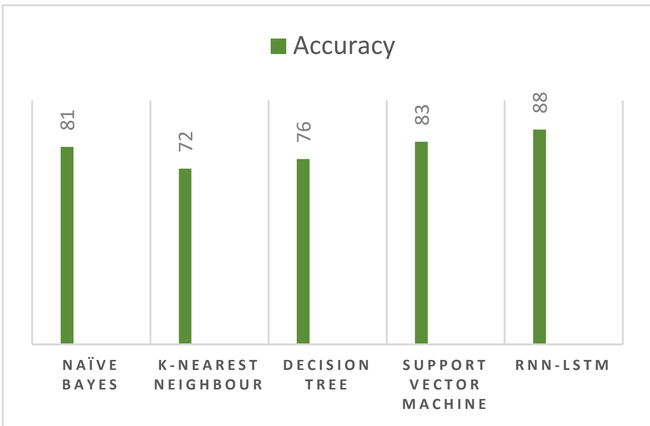

Fig. 4. Comparison of the performance of algorithms for the Netflix dataset in terms of accuracy

The accuracy rates displayed in Fig. 4 were determined using five algorithms: Naive Bayes, Decision Tree, KNN, and SVM. The K-Nearest Neighbor had the least accuracy score of 69% while RNN-LSTM received the greatest accuracy score of 93%. With accuracy rates of 80% and

91%, respectively, the Naive Bayes and SVM algorithms are virtually equally accurate.

c) Dataset of Tourism:

TABLE IV
ANALYZING SEVERAL ALGORITHMS IN COMPARISON FOR A TOURISM DATASET

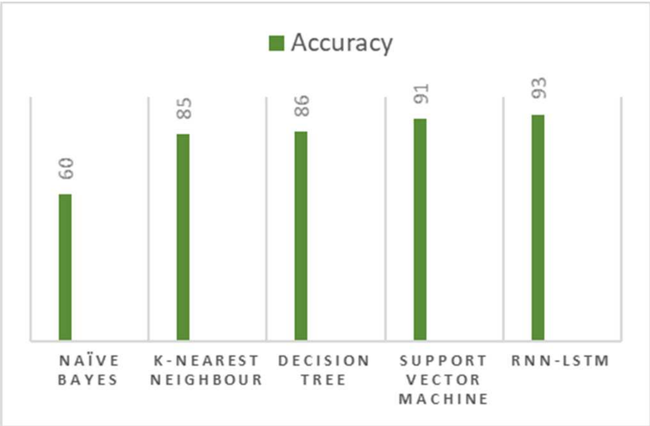

Fig. 5. Comparison of the performance of algorithms for the Tourism dataset in terms of accuracy

Recurrent Neural Network using LSTM, Naive Bayes Classifier, KNN, Decision Tree, and SNN are the five techniques, are compared in Fig. 5. The accuracy of the algorithm using Naive Bayes was lowest at 69%, whereas the accuracy of the RNN employing LSTM was highest at 88%. Support Vector Machine places second with an accuracy rate of 82%. With accuracy rates of 80% and 81%, respectively, KNN and Decision Tree are comparable.

V. CONCLUSION

This study's primary objective is to use RNN-LSTM to classify people's perspectives into negative and positive categories on the basis of the Dataset, and to try comparing the accuracy of the results to that of other machine learning methods such as Support Vector Machine, KNN, Naive Bayes Classifier, and Decision Tree. The study's findings demonstrated that RNN-LSTM seemed to have the best accuracy, attaining 87% for data from Flipkart, 93% for data from Netflix, and 88% once again for data from the tourism dataset.

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‘Algorithms’	‘Precision’	‘Recall’	’F-Measure’	’Accuracy’
Naïve Bayes	80	58	60	80
K-Nearest Neighbour	85	85	85	69
Decision Tree	86	86	86	86
Support Vector Machine	85	83	79	91
RNN-LSTM	81	80	80	93

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