ABSTRACT
In this era of digitalization, Sentiment Analysis (SA) has become a necessity for progress and prosperity in marketing. Sentiment analysis has become a powerful way of knowing the opinions and thoughts of users. The viewpoint of the consumer, such as knowledge sharing would include a lot of useful experience, while one wrong idea will cost too much for the company. SA has many social media data-related problems, such as natural language interpretation, etc. Issue of theory and technique also affect the accuracy of detecting the polarity. There is a problem of text classification such as analysis of sentiments in document level, sentence level, feature based. Document level analysis is done by two approaches: supervised learning and unsupervised learning. Sentence level contains sentences containing opinions. Aspect based analysis have different attributes is performed in customer reviews. Product opinion is taken for knowing the sentiments. Opinions are compared and are extracted as a feature. SA is very important for business purpose because it gives the way for improving their operations and the products they offer. For improving business strategy it plays an important role. It provides many key benefits like impactful decisions, for finding relevant products, improving business strategy, beating competitions, tackling positive or negative issues affecting the product. To overcome such issues, deep learning processes are applied. The work focuses on two main tasks. Firstly, to extract sentiments present in data of social media of customers' reviews and secondly, to use the deep learning process for the sentiments' extraction for customer reviews.

Keywords
Sentiment Analysis, Neural Networks, NLP, Deep Learning, Convolutional Neural Networks, Machine Learning

1. INTRODUCTION
The prime data sources are the frequent use of a web tool, social networking sites, blogging sites, and forms. It enables the user to share opinions, comments, feedback, and discussion on important topics. The demand for online shopping, marketing communication, etc. has grown rapidly due to the rise of the internet and access to its users. It has become meaningful to analyze public opinion to explain their activities and moods and the influence of other opinions. Hussein et al. discuss customer reviews that contain a large piece of information. There is, however, a need for data retrieval since it is buried in behaviors, perceptions, and emotions [1]. Receiving input from consumers will unexpectedly raise earnings. Such reports aid in the happiness of clients. Valuable information is shared by customers, which industries cannot ignore. The Sentiment Analysis tool and the analysis of data help in decision making. Emotions described as mood, behavior, actions, and mind state that influence the life are expressed through conversation. Emotion detection is primarily done by expressions like happiness, surprise, sadness, fear, and anger, etc. Written language is also an effective means of communicating ideas, knowledge, feelings, etc. Emotions are states of mind, which are expressed through words. The objective is the determination of the user’s thoughts whether they are positive, negative, or neutral. Extraction is done at three levels namely Document Level, Sentence Level, and Feature Level.

There are three methods: Lexicon-Based, Machine Learning, and Hybrid. The first is further divided into Dictionary and Corpus-based. And Machine Learning-based technique is also divided into two models; the Traditional model and the Deep Learning model. The traditional model refers to classification such as Naive Bayes, Support Vector Machines (SVM), and Maximum Entropy (ME). Hybrid approach is a combination of a lexicon-based and machine learning-based approach. Deep learning is also a process of machine learning by gaining importance in the area of research. It has been widely used as image datasets extract significant features of an image as shown in Figure 1.

Figure 1: Picture of taxonomy of sentiment analysis Classification Methods of Sentiment Analysis

Work is focused on two main tasks. The first is to extract sentiments in customer reviews; Convolutional Neural Network (CNN) does all the extracting and describing of the feature. The Second Deep Learning Task is the extraction the sentiments for customer reviews. To optimize the classifier's parameters, Classification errors are minimized. CNN emphasizes words that affect from classification and parts of features that are of high thrust. Strapparava et al. mention that sentiment analysis is quite beneficial in fields like health, business, and sports, to name a few [2]. In the business field, companies can know customers behavior for attracting new customers. Companies can improve their product and can improve marketing ways. By understanding the opinion, the recommender system may also
become helpful. Jeong et al. proposed the technique of topic modeling and analyzed sentiments on customer-generated data[3]. Every person has different ways of expression. CNN was implemented in sequential order for the classification of emotions, which utilizes the feature of the sentence for the detection of emotions. For capturing feature of input, a trained word embedding technique is used as the first layer that changes words into a vector. For verification, features are passed to the attending model. Thus CNN takes these features, which are very useful as input. RNN, LSTM, and Random Forest Classifiers are used to compare results. There are mainly two objectives:

1. To Extract sentiments by customer reviews.
2. To design a model of CNN for predicting results.

2. RELATED WORK

Tang et al. proposed a deep learning approach, word embedding, extraction of opinions, etc. that focused to find emotional keywords. The comparison study was done on review data sets. When result was evaluated time was not taken into consideration[4].Yanam et al. applied a basic theory and verified that emotional words represent a real process and category related to keywords [5]. Zhang et al. applied machine learning method for the analysis of sentiments Datasets were used containing scripted dialogs and improvised dialogs. Only improvised data was used. Raw spectrogram was applied as an input[6]. Spoken words were used as a text feature and the TF-IDF approach was used for calculating weights of words. Sharef et.al. proposed sentiment analysis by deep learning method[7]. Liu et al. built a model to analyze emotions and classification was done in categories according to Ekman’s model. Real world common sense knowledge was taken into account for classification which was very expensive[8]. Strapparava et.al. proposed the same words having different senses to solve this problem, a set of same words[9]. Jain et al. proposed a Naïve Bayes Classifier for automatic emotion detection. Many hierachical studies were used to classify emotion categories on a fine-grained level[10]. Jain and Kumar classified emotions by machine learning approaches in multilingual data [11]. According to Jain and Kumar, 2017 buyer thoughts are helpful for buyers and sellers for improving market strategy[12]. Mikolov et al. provided work for word embedding[13]. Paredes-Valverde et al. proposed a sentiment analysis for customer satisfaction by improving services[14]. Alharbi et al. proposed a method of extraction of features to know the behavior of users in which CNN was used[15]. Pham et al. analyzed travel reviews for extraction of sentiment [16]. Preethi et al. proposed a topic modeling technique for customer-generated data. For changing customer needs real-time monitoring tool was used [17]. Vateekul et al. applied polarity based sentiments methods for analyzing tweets [18]. Salas-Zarate et al. used aspect-based sentiment analysis was done. Senti-word net dictionary was used [19]. Satapathy et al. analyse sentiments on mental health data posted by patients[20]. Chorowski et al. recognized attention-based models for speech recognition [21]. Ciregan et al. proposed methods of deep learning process for classification of images and recognition of patterns [22].

DaSilva et al. proposed ANN architectures and training processes using artificial neural networks [23]. Ghazii et al. proposed that for automatic classification of emotions two level classification was done. In the first level positive and negative emotion was classified and last level emotion was fine grained. Different levels of hierarchy are not used at different tasks [24].

Deep neural networks have brought revolutionary change in the field of natural language processing where data features is captured by many layers and gives an output. It provides understanding and capability of learning of feature ad helps in solving complications of artificial intelligence accurately.

3. PROPOSED METHODOLOGY

Two data sets are used for analysis; the first for movie reviews and the second for the Amazon company. These data sets include labeled review data with a score of 0 for negative sentiment and 1 for positive sentiment. The number of comments about a product has a significant effect on awareness, intentions, expectations, and behavior key for selling products respond to demand of customers at the proper time in the right locations. Each word for review is meaningful for decision and helpful for improving satisfactions. These words are full of slangs and misspellings due to many languages. Preprocessing is very necessary for making data normal. Data sets used for analysis were taken from Kaggle.

Labeling is based on the star rating. The one or two stars labeled negative, 3 as neutral, 4, and 5 as positive. Many pages of company were observed for review and these were taken from website. The term used for observing are (“Mobiles,” Bed”, “Chairs”,”Camera”, “Tab”). The three categories of product was made as shown in a Table.

Randomly 59000 reviews were extracted.39500 were used to train classifier and 19500 were used for testing. Reviews of various products are collected as in Table1.

| Table 1: Used Data Sets |
|-------------------------|
| Search Data Sets        | Reviews Numbers |
| Sets for training       | 39,500         |
| Sets for testing        | 19,500         |
| Evaluation sets         |                |
| Kaggle                  | 4,000,000      |
| Electronic Devices      | 65000          |
| Toys                    | 21613          |
| Wooden furniture        | 150,000        |

Data Preprocessing: Preprocessing is very necessary for cleaning raw data. The following methods are applied: Tag removal, filtration of symbols except for (A-Z) and numbers (0-9).

Feature Extraction: This process is done to convert text data into numerical data. Text words are separated one by one and are converted into unique integers. After tokenization, the whole sentence is represented by numerical data. For the classification of review, three machine learning approaches are used: Naïve Bayes’ (Multimonial) , SVM(Linear), and CNN with word embedding.

Data is randomly split into 75% training data and 25% testing data. The model created has four layers. Knowing the accuracy of classification following metrics was used. The prediction of sentiment analysis was done by star rating.

Basic steps used to train CNN model shown in Figure 2.
The algorithm for predicting sentiment polarity is used to assess the efficiency of techniques and accordingly, classification is performed. Algorithm performance is tested by two methods: Word embedding and TF-IDF approach. Sentences are split into words individually and converted into a vector of real numbers called feature vectors. These feature vectors are used as input of this model.

**Embedding Layer**
CNN layer defined depends on a kernel of 3 sizes and 32 filters. It means 32 different features on the first layer. The output of the first layer is $40 \times 32$ neuron matrix. This result is fed to the second layer accordingly. The output matrix will measure $40 \times 16$. The pooling layer is used after the CNN layer for the prevention of overfitting data. The output matrix has a neuron long dimension of $1 \times 8$.

The output layer is a fully-connected layer with a sigmoid function that reduces the vector of height. F-score was derived from precision and recall. Different types of data sets with feature extraction are used. Performance stars’ deep learning technique with word embedding is better than TF-IDF.

Pair of feature vectors and tags that is positive, negative, neutral is fed into a machine-learning algorithm to generate a model, as shown in Figure 3.

**Algorithm applied before feeding into CNN**
1) Each sample tagged term is summed up.
2) For the formation of the training set, low-frequency samples are extracted.
3) The CNN model has been extracted. The first layer of CNN is fully connected to the second layer for future fusion.
that CNN with word embedding is better than other classification techniques in customer reviews as shown by accuracy in Table 3. Future work will be focused on a hybrid approach.

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