Chap 1

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CHAPTER 2

LITERATURE REVIEW

Sentiment Analysis has become the fastest-growing research area in computer science which keeps track of all the activities in the specific area. The main reason for this analysis is to analyse the behaviour of buyers, and observers of any product. With time, data is also increasing day by day on the internet and it is very difficult to analyse each review manually. To analyse the customer's sentiment, sentimental analysis comes into play. Many researches are already carried out on this topic.

The researchers extracted sentiments from the reviews and analyses the outcome to create a business model [70]. Researchers claimed that the presented model is too much robust and has provided high accuracy. They performed analysis using Genderizer and Text blob to detect fake emotions and create a classifier to check the model's accuracy. They performed their analysis on python and R programming languages. They used Support Vector Machine and Multinomial Naïve Bayesian as their leading classifiers. They achieved 80% accuracy with SVM and 72.95 with MNB.

The researchers used current supervised learning (Naive Bayes, Perceptron, and Multiclass SVM) algorithms to forecast ratings of a provided mathematical scale using only reviews [71]. They collect the 1125458 reviews from the Yelp dataset challenge. They used hold-out cross-validation by using 70% of data as training dataset and 30% of data as testing dataset. In this research, the author used precision and recall evaluation matrices to analyze the results.

The researchers in [72] presented the system which classifies the customer reviews and presented the results in charts to visualization. They scrapped the data from amazon through URL and pre-processed it. In this paper, they have applied NB, SVM, and maximum entropy. The proposed methodology integrates the current sentiment analysis techniques and is claimed to increase the accuracy. They presented their result in the form of charts.

The authors built a model for predicting the product ratings based on text using a bag-of-words. These models utilized unigrams and bigrams techniques. They used 2,982,356 reviews of 252,331 unique products of Amazon. They performed analytical operations on the data to find the features and better understanding of features of the product. Between unigrams and bigrams, unigrams produced the most accurate result. And popular unigrams were an extremely useful predictor for ratings for their larger variance. Unigram results had a 15.89% better performance than bigrams [73].

In 2016, the researchers have discussed different feature selection or extraction methods of sentiment. They used the amazon dataset for feature selection and classification of sentiment. They performed pre-processing to remove special characters and stop words. They performed multiword, phrase level, and single word feature extraction and selection techniques [74]. They used Naive Bayes as the classifier. They determined that Naive Bayes performed better at phrase level as compared to a multiword and single word. The main disadvantage of this research is, authors performed a Naive Bayes classifier only and we cannot extract a satisfactory result from which. In different study, they used easier algorithms to understand the problem easily. They collected the data of Hotel Reviews. The system gave the highest accuracy 93.50% on SVM having N-gram aspects as compared to other used algorithms logistic regression and decision trees method [75].

The main contribution of the researchers in this research [76] is to predict rating and to separate the positive and negative words from the dataset with a linear regression model. Tf-Idf is used here as an additional experiment. They evaluate the model with root mean square error. They determined that Yelp reviews could be utilized for rating prediction with the help of the bag of words model. They claimed that TF-IDF searches the most relevant terms from the reviews but unfortunately these terms do not participate in improving the prediction. However, they used unigrams which shows positive effects on their results.

The researchers described which feature of the product is good to expect the aspect-level sentiment analysis and explained the reason why this is in this way [77]. In the first iteration, all the textual data is categorized and it is considered an important aspect for the sentiment analysis. For this purpose, natural language was used on Stanford's CoreNLP package. They collected the restaurant reviews for the analysis. In the start all textual reviews data was pre-processed by using tokenization, lemmatization, removing parts of speech. The next stage is regarding SVM in which authors extract the features through SVM. After the acknowledgment of all features, obtain score can be added for each feature. Thus, this is happened by the use of a training data system.

The researchers analysed the features with the help of Information Gain, which is mostly used in conjunction with the measurement of feature selection. This approach is working in the following steps: First of all, Information Gain is used for every feature, second IG scores related to all properties are arranged high to low and in SVM used k % features. The whole study concludes that when we used 1% best features for information gain, then the accuracy decreased with the value of 2.9% when we utilized complete features [78].

The researchers used a Convolution Neural Network for the performing of sentiment level. For aspect level sentiment classification, the authors proposed a convolution neural network. Their model first developed the CNN to extract the aspect and then applied another approach named as order labelling methodology with Conditional Random Fields (CRF) for the discovery of opinions. Then at the final point, they collect features with each word and implement the convolution neural network and define the sentiment with respect to aspect [79]. They presented a deep learning approach to aspect-level sentiment analysis, which employs a convolutional neural network for aspect extraction and sentiment analysis and CRF for opinion target expression.

They try to present the ABSA on movie review data. They collected the movie reviews. They proposed the methodology to extract the aspect and the sentiment related to the aspect by using the appended crafted rule [80]. They defined the three patterns for the selection of required words: 1: Manual labelling (M), 2: clustering(C), 3: review guided clustering (RC),

They take the 1000 movies data from the IMDB website. In this work, they have tested the efficiency of the approaches on individual sentiments. Moreover, the efficiency of cleaning the sentences have a good effect on the general aspect sentiment mining from the emotions as a whole but it needs to be fixed with effective approaches for combining opinions through different sentiment.

The researcher performed a sentiment analysis on music. In this paper, the dataset of one thousand songs was collected from the web for analysis [81]. They collected around 20,000 emotions from one thousand songs for sentiment analysis towards music. Linear Regression was used to calculate the polarity of sentiments in this research. The authors used 70 % of the total data set to train the model and 30% was used for testing purposes. Researchers performed to analyses the songs on the appended subject like Baseline, Shape, and Contrast of the one thousand songs. The analysis will help the readers to analyses the consequence of emotions and observation of actuality while listing to music.

The researchers performed the analysis and expand the Jazz music dataset. They used the dataset of having 21651 songs of jazz music [82]. The dataset was collected with the help of techniques of information retrieval. The data about songs and the audio features of the songs were also present in the dataset. Researchers worked dedicatedly on searching the features of the songs. It will help to search the related songs to add them in the cluster and to analyze the song either it was the type of jazz music or it is not the jazz music. It will also clarify the purposed of the used dataset. One of the unsupervised Machine Learning techniques K-mean was utilized to create the cluster of the songs of jazz music and other music having different audio features of songs. Later, researchers have a plan to expand their research with the non-supervised algorithm.

The researchers have worked on the integration of data on dissimilar datasets. Dataset, which is used in this research, consisted of national products of the China and United States for many years [83]. The dataset was extracted from different central repositories. The dataset consisted of raw data and information as well. The dataset consisted of the rates of currency exchange Yuan to Dollar and vice versa. In the first iteration, currencies were exchanged with the help of math rules and produced values. Then, they divided the information by eliminating other values or data formats and tags. Researchers gathered data from multiple repositories so that integration of data could be performed. After the integration of data, validation of data was performed to confirm the quality of data.

The researchers performed research on data about the dataset. The dataset contained the actual standards for short-term learning [84]. The dataset consisted of two standards, the first standard consisted of 1623 characters and the second standard consisted of 600 samples. Classification, multiple classification algorithms were used like K-NN and Fine-Tune. One of them K-NN is used to classify each considered item to the closest actual class. Moreover, Fine-Tune cannot do so. Researchers obtained greater accuracy with the help of K-NN of 88.42 as compared to Fine-Tune which was 73.88 %.

B. Gopal performed different modal-based classification on Hindi and Western songs. They used two types of the dataset for analysis. The first dataset consisted of audio song clips and the second dataset consisted of sentiments with eight different classes. The first dataset of AMC consisted of audio song clips while the second dataset consisted of sentiment with 8 different sentiment classes [85]. The dataset of Hindi songs consisted of 500 songs and the second dataset consisted of 1753 audio clips. The dataset of Western songs consisted of 298 songs while 1111 clips in mp3 format. The authors utilized a supervised Machine Learning algorithm for classification purposes like SVM (Support Vector Machine) and FFNNS (Feed-forward neural networks). To determine the accuracy of classification, Ten-Fold validation was utilized. They obtained precision 58.9 % and 59.1% using SVM while on Western music they obtained 70.5 % precision. With the FFNNs algorithm, the precision value was 65.3%, 65.2% of F-measure, and 65.1 of Recall on Hindi music.

M. Bilal performed Sentiment Analysts on Roman Urdu with the help of different machine learning algorithm methods on mobile reviews. The dataset was gathered from sites and blogs. For classification purposes, the Rapid Miner tool was used [86].

A study was performed on the Dimensionality Reduction on Bag of “Pop Corns, Bag of Words” a set of data which was collected from on Kaggle. For this purpose supervised machine learning approach was used to analyze a dataset of 25000 [18].

Sentiment Analysis was performed at the aspect level on mobile reviews dataset of Amazon for analysis. After data pre-processing, they selected features and determine the rating of selected features based on Sentiment Analysis. Data mining association rule was used for the segmentation of the sentences using NL Processing [87]. After opinion orientation of the words simply count the total numbers of positive and negative comments for each feature and finally rate the aspect top to down which has maximum numbers of positive reviews, and at last which aspect that gets minimum positive reviews and maximum the negative.

P. Patil Aspect level Sentiment Analysis was performed on movie reviews. They classify the sentiments at the aspect level and the document level by exploring a sentiment-based scheme. Classification of document level has some linguistic feature, it can range from adverb + adjective to adverb + adjective + adverb combination. While in this paper they advised a domain specific heuristic approach for aspect level classification. Dataset for analysis was collected from different sites. To classify these reviews in positive, negative, and neutral by using the publically available library. To indicating the Aspect, 5- Gram technique was used [88].

A survey was carried on Aspect level Sentiment Analysis to aggregate the people's opinions on the entities that were mentioned within the document. At aspect level Sentiment Analysis, a single entity was analyzed at a single time. Aspect level Sentiment Analysis, a review would generally refer to the entity from the document, so the aspect detection was the major/important part of Aspect Level Sentiment Analysis. Here they can discuss different ways of aspect detection like frequency-based and syntax-based aspect detection. After that in this survey, they talked about the classification methods of supervised and unsupervised. The supervised classification is used for the labeled data for training and testing both. Unsupervised classification is required to operate labeled data only for training the algorithm at testing it can classify the unlabelled data. State of the art Aspect Level Sentiment Analysis proposed in this survey [38].

A solution was purposed of forms and function for Roman Urdu dataset, that was collected by surveying the local universities of Pakistan. The average age of both male and female was 21.01 years in which 103 (88.8%) members from undergraduates 10 (8.6%) were from graduates while 3 (2.6%) from them were Ph.D. scholars. The messages they collected in the form of text messages, the corpus has a total of 4, 46,483 words. In their survey, they see the people prefer to write their messages using the Roman Urdu type of writing. Accordingly, to their study, they analyze the female data was less romantic words than males. And the students of undergraduates have used more friendly words than a graduate student. 73 users used 20 or less friendly words those called low romantic participants. The 41 users were who used 81 or more intimate words were classified as high romantic participants, The research was carried to understand the population way of messaging and classify the users were they adopted low medium or high Romantic way to communicate with others [89].

The emotion ontology was generated for Roma Urdu text data. Dataset was collected from different blogs by using a scraper that contains people's emotions. They classified the emotions into 5 classes (Happiness, angry, hurt, caring, and fear). After data collection, they parse the data through a syntax analyzer that recognizes the syntax structure and contracts a phrase tree, and modify the Figures into the required order. After semantic analyzer through JENA API and checking the ontology of the document classified according to their classes in happiness, angry, hurt, caring, and in fear. They experimented on four documents named (DOCI, DOC2, DOC3, and DOC4). In document 1, 30 sample data was taken ‘n which from 27 were classified correctly and their results precession 93.10% and with recall 90%. In doc2, carried 33 sample data, and their algorithm correctly classified them in number 28. Results with recall a DOC2 was 84.84% and with recession 93.33%. Document 3 has 54 samples and correctly classified 46 results with recalled was 85.18% and with 93.86% with precession and document 4 carried 38 samples ‘in which from 31 correctly classified and recall gives 81.57% and precessions give 91.17% results. Their main goal to design an algorithm to identify the emotions from Roman Urdu text and their algorithm gave better results in the form of precessions and recall [90].

The research was carried to find the hidden pattern in raw text and different pre-processing techniques in text mining were discussed. They extracted useful text data from the raw data with the help of a scraper. Unstructured text data may be extracted from files, spreadsheets or from rational database which contained noisy data as well as HTML tags or Stops Words. Remove these outliers and noise present in data with the help of pre-processing techniques. They discussed a few of them pre-existing pre-processing techniques. Firstly, they talked about data then stemming a process in which, identify the stem/root of the word. Then they discussed N-gram techniques in which N-gram a string, where character extracted from the continuous text. They also talked about TF & IDF. Term frequency a word present in a document and inverse document frequency talked

about a word that was repeated in multiple documents. Through the paper; they tried to help the people in the field of text mining [91].

Sentiment Analysis was performed on multi-languages data Twitter dataset. To perform sentiment analysis, they selected multi-language tweets associated with PGE 2013. The dataset was collected from the users of five capitals of Pakistan and tweets were belonged to legendary political parties of Pakistan. The dataset was gathered with a scrapper from 2001 to 2013. According to the results of Urdu and English tweets [92],

Sentiment Analysis was performed at the Aspect level by using different Machine Learning Techniques and purposed a system for the Aspect level Detection of reviews. Different pre-processing techniques were applied to the extraction of data i.e. (Tokenization, Part of Speech tagging, and Lemmatization) to prepare the data and to remove the outliers as well. A spam detection model was used to avoid model spam or noisy data. After pre-processing and classify the reviews (Positive, Negative, and Neutral) Machine Learning algorithm i.e. (Support Vector Machine and Naive Bayes) were applied to check the rating of the product. According to their reviews products were classified into three categories (Low, Medium, & High). A product that has one or two star ratings classified as a low product, which a product rating was three classified as medium, and a product having 4 and 5 ratings classified as a high product. Their proposed system classified the comment into two classes as Negative and Positive very fast and correctly [93].

A survey was performed on the supervised and unsupervised classification of the document. They classified document classification in three basic methods named rule-based classification, supervised classification, and unsupervised classification. In the rule-based classification of the documents, documents are grouped by predefined rules. This approach is good for small documents and rules are also decided by the writers. In supervised classification, the document was classified based on supervised learning. In this technique, the model is trained using training data which was known as algorithm learning. After model training, the testing data is passed through the model. The unsupervised classification was a method in which classification was achieved through clustering. It simply clusters the data according to the structure or pattern of the data. Unsupervised algorithms worked on a centered based approach, in centered based techniques each document "D" represented Documents Vector VD and centered vector of each class, and Euclidean distance between VD and centered Vector of Class was calculated. Documents having a minimum distance from centered assign a particular class [94].

Some of the Supervised and Unsupervised algorithms were also discussed in this paper. SVM analyses the data and classifies them after recognizing the pattern. Naive Bayes classify the document by the calculation of posterior probability value and classify the documents according to their frequencies. Decision Tree uses a tree-based algorithm to classify the documents. In unsupervised classification, they discussed partitioned clustering. Partitional clustering algorithms develop un-nested and non-overlapping partitions of the documents. It works like first K clusters are defined and partition (P) was constructed, then clustered is redefined by moving the documents from one cluster to another iteratively. In K-mean clustering, K clusters are defined and each document move to that cluster which was near to its centered, Hierarchical clustering techniques make a cluster from top to down and bottom to up and documents are divide into the cluster. Research in the field of Sentiment Analysis was conducted at different times in different domains.

The research was carried on the Amazon dataset and it is organized in Jason format. All the Jason files are consist of many reviews. The dataset contains on review of different sources such as TV, Mobile Phone, Camera, Laptops, Tablets, etc. In pre-processing term researcher passes through the reduction process of stemming, punctuation, stop word, repeated word, etc., and then they converted the dataset into a bag of words. Pre-processing is a significant process in the field of views mining and sentiment analysis. Each sentence was analysed and calculated by sentiment score. For calculating the sentiment score they performed a comparison between dataset and lexicon sentiments. The dataset was compared with sentiment lexicons having 2006 positive and 4783 negative review words and sentiment scores were calculated. The authors used various types of features, learning algorithms, several accuracy measurements. In this work, researchers applied different approaches as the lexicon approach, a dictionary-based approach that was usable within learning techniques. The sentiment analysis was applied to each review of products and then used the machine learning algorithms like SVM as well as NB. Naïve Bayes grew 98.17% accurateness of Camera reviews, while on the other hand Support Vector Machine got 93 [95].

A sentiment analysis was performed by using a Gini Index for feature selection with one of the classifiers SVM was used for the classification of sentiments on large movie review. The results of this study presented that this Gini Index method is helpful for better results for error reduction and accuracy. They proposed a method for review extraction and categorization. The purposed methodology consisted of five steps: Data Source: they collected the most recent reviews from Rediff, Rottentomatoes, Mouthshunt, and Bollywoodhungama. Data Pre-processing: it is contained on transformation, tokenization, and removal of stop words, and mining of opinion words. Feature Selection: the system of selecting features is known as feature selection and it is called attribute selection, and it is mostly used and helpful for the model construction. Representation: the consequence of attributes on the Gini Index is planned and weights are allocated sequentially. Sentiment Classification: it is performed by learning the model from the training dataset and classifying the data based on the trained model. The results explained that the proposed methodology showed greater accuracy than the SVM with 0.65 split ratio [96].

In this paper [97], the dataset was gathered by Kaggle that was consisted of food reviews collected from Amazon from October 1999 to October 2012 (29,30). Dataset consisted of a huge number of data like reviews are contained on 568,454, users consisted of 256,059, products was 74,258, and 260 users that had more than 50 evaluations. In this pre-processing stages, scholars followed the steps: took out the URLs as (www.abc.com), all tags like (#topic), removed all screen name such as (@username), took away all the punctuation marks, symbols as well as numbers, removed all stop words, replacement of emotions within sentiments, the transformation of text to lowercase, exchange the words with roots, reduction of repeated words and retweets. This type of analysis provides help in judging the customers' sentiment. In the same way, in a product-centric approach, the researcher gets success towards the best-reviewed product that was done by several customers. This research explained the consumers' views and emotions towards the products. And the results of this research were additional evidence about the significance of customers' reviews for digital as well as online marketing research. Researchers' most of the work contained on the investigation of customers' opinions and reviews that they took from various E-commerce sites.

The amazon dataset ranging from August 2018 to December 2018 was used in this study [97]. Despite reduced objectives from this research, all the subjective contents were detached for the upcoming examinations of sentiment sentences. They explained that each sentiment sentence must contain one negative and one positive word. All the sentences first of all organized into English words. Each word exists on its semantic role that elaborates on the meaning of words and how a word is used. The semantic role is also known as parts of speech. The English language commonly consists of 8 famous parts of speech. The name of these parts of speech is the following: 'Noun, pronoun, verb, adverb, adjective, conjunction, interjection, and the preposition'. In natural language, part-of-speech (POS) producers organize the words based on POS. Some researchers collect moreover 500 sentiment of reviews on products that is related to 4 major forms: Flash drives, Computers, Mobiles, and Electronics. These were online reviews and set by almost 3.2 million people in front of 10,001 products. They proposed the process of sentiment polarity classification and POS tagging has been described along with detailed descriptions of each step.

Sentiment analysis is a fundamental task of natural language processing used to determine whether the sentiments portrayed in data are positive, negative, or neutral. Sentiment analysis is often performed to help businesses to gather customer feedback on their products and service or whether comprehend customer needs. It has been proved to be a quite efficient text mining technique while aspect-level sentiment analysis is an even more improved technique often implemented on textual data to perform a detailed analysis on customer feedback that helps businesses to produce products and services that are up to customer satisfaction and needs.

Aspect-level sentiment analysis is a text mining technique that groups data by aspect and categorizes the sentiment to each aspect of data. Aspect-level sentiment analyses are performed to evaluate customer feedback by integrating certain opinions on several aspects of any product or service. Aspects are the components or attributes of a product such as a user's review after experiencing a specific product or service, any feature of a product, or customer service provided by an organization. Aspect level sentiment analysis is specifically the positive or negative opinion on a particular aspect that can be any feature or category of a product or service.

Recently, declared that the position features can improve the performance of the model on four different datasets. Therefore, the study proposes a classification model by combining attention mechanism and position features named Multi-Level Interactive Bidirectional Gated Recurrent Unit (MI-biGRU). Word embeddings are developed by position features of a word in a sentence so that the used approach can extract context and features of the targeted term by utilizing a well-constructed model, at last, to pay more attention to the words that are significant for sentiment classification an attention mechanism is used. The correlation between position features and the multilevel interactive attention network has been shown through experimental results [98].

A study focuses on retrieving aspect terms from each record extracted from Amazon customer review data by identifying the Parts-of-Speech and applying classification models including Naïve Bayes and Support vector machines to classify the sentiments from data. While performing the aspect level sentiment analysis feature terms of a product are the key target which depends on the product attributes. In the study, the aspect level sentiment analysis is categorized in three steps; identification, classification, and aggregation. Experiments are performed through applying preprocessing mainly Part-of-speech tagging to each term in a sentence and frequently used words are extracted. Later frequently used aspects are extracted from data through the Apriori feature extraction algorithm and opinion words such as a set of adjectives that best describe the aspect of the product are extracted after applying feature pruning. At last classification algorithms are applied to classify the sentiments into labels including positive, negative, and neutral [33].

In a study by Puspita Kencana Sari et al. Tokopedia review data is used for aspect-level sentiment analysis. The user reviews are classified based on five e-Servqual dimensions including; personalization, reliability, responsiveness, trust, web design, and sentiment analysis positive and negative. The naïve Bayes classification method is applied for the classification of the data because of its support to process large data and high-level accuracy [99].

Pratik P. Patile et al. focused on polarity prediction using a large data set extracted from Amazon customer reviews labeled into three classes such as positive, negative, or neutral. The classification task is performed by logistic regression, naïve Bayes, and support vector machines. Before performing classification, the data has been cleansed by applying some preprocessing methods including tokenization, stop word removal, and stemming. LDA and k-means algorithms are applied to extract and cluster the aspects or topics. The experimental results show that logistic regression has outperformed the other classifiers applied [100].

Ashwath et al. performed a study on aspect-level sentiment analysis by using different notion examination techniques on client audit data. data has been preprocessed by applying stemming, stop word removal techniques and POS tagging is used to extract mainly used terms from the data, that has been further classified by two states of the art machine learning models including, naïve Bayes and support vector machines where Naïve Bayes has the high accuracy score than the other model used [36].

A study proposed a pre-trained language model based on transformer bidirectional encoder representation named SA-BERT. Semantic information of the context of data is encoded into a word vector by Bert. While the text features were extracted by using the attention mechanism on a deeper level to comprehend the semantics of the text information and to accomplish the sentiment analysis task of e-commerce data. The experiments are performed on a JD mobile review dataset that shows the efficiency of the SA-BERT model in aspect-level sentiment analysis [101].

A study focused on developing a hybrid method for aspect-level sentiment analysis with the combination of machine learning approaches and lexicons. It has been proved that the word-level analysis by word cloud visualization provides primary results regarding the customer opinion on a product or service. For review classification, two lexicons named Syuzhet and Sentiment are compared at the sentence level to classify the reviews. Syuzhet package has provided better performance and is used to train labeled text provided by it. The experimental results show that the naïve Bayes has a better accuracy score while using the Syuzhet lexicon package among other applied models [38].

Qiang Lu et al. proposed a model for aspect-level sentiment analysis named interactive rule attention network (IRAN). IRAN is proposed to designs a grammar rule encoder by standardizing the output of adjacent positions to simulates the grammatical functions in the sentence. It also learns attention information from context and target by constructing an interaction attention network. The experiments have been performed on the ACL 2014 Twitter dataset and SemEval 2014 dataset. It has been shown that the IRAN can learn effective features and has shown better performance as compared to the traditional models [102].

Another study presents a continuous learning framework based on naïve Bayes for sentiment classification of a large-scale and multi-domain e-commerce product review. The parameter estimation mechanism has been extended in naïve Bayes to support continuous learning. The experiments are performed in two different domains including; cross-domain sentiment classification and Domain-specific sentiment classification. In cross-domain classification, reviews are taken from different domains, and in domain-specific classification, reviews are taken from the same domain [103].

Yue Han et al. proposed a Pretraining and Multi-task learning model in their study based on Double BiGRU namely PM-DBiGRU. In the proposed model short text-level drug review are used to learn pre-trained weight to initialize related weight for the model for sentiment classification task model. After that two BiGRU networks are executed to produce the bidirectional semantic representations of the drug and target review, and target-specific representation is obtained attention mechanism for aspect-level sentiment classification of drug review. To transfer helpful domain knowledge from the corpus multi-task learning is further utilized [104].

A study used a mobile product review dataset for aspect-level sentiment classification. The data has been initially pre-processed by using tokenization and POS tagging. POS tagging has been used to extract the most frequent terms from the data. later the classification has been performed by using four different machine learning models including Bernoulli Naïve bayesian, multinomial naïve Bayesian, k nearest neighbor, and Support vector machines. The experimental results show that the KNN has the highest accuracy among all the other models on APPLE products and has performed comparatively better than the other classifiers [95].

Table 2.1: Literature Review of Sentiment Analysis

Ref No.	**Dataset**	**Methods**	**Accuracy**
[70] 2016 M. S. Elli and Y. Wang	Amazon dataset	Multinomial Naïve Bayesian (MNB) and support vector machine (SVM)	accuracy80% accuracy with SVM and 72.95 with MNB.
[71] 2015 Y. Xu, X. Wu, and Q. Wang	Yelp dataset	Naive Bayes, Perceptron, and Multiclass SVM	Get best results with the Naïve Bayes.
[72] 2015 A. Bhatt, A. Patel, H. Chheda, and K. Gawande	Extracted from Amazon	NB, SVM, and maximum entropy	Visualizes the sentiment of the review in the form of statistical charts.

Ref No.	Dataset	Methods	Accuracy
[74] 2016 T. Shaikh and D. Deshpande	Used amazon review dataset	Preprocessing (stop words and special characters removal), Naïve Bayes classifier	Accuracy 80%
[76] 2017 M. Wang	Yelp dataset	Tf-IDF, linear regression model.	Unigram RMSE 0.9206 Bigram RMSE 1.0114
[77] 2018 Y. Liu and X. Zhu	COAE data	Support Vector Machine	Improved accuracy
[79] 2017 L. Xu, J. Liu, L. Wang, and C. Yin	Yelp Dataset	Convolution Neural Network, Conditional Random Fields	Used Convolutional Neural Network for aspect extraction and sentiment analysis.
[96] 2017 Mohan, and K. R. Venugopal	Reviews collected from Rottentomatoes, Hungama, Times of India, Rediff and Mouthshut	Gini index for feature selection,	SVM 94.46 NB 87
[82] 2019 G. M. M. Sarria, J. Diaz, and C. Arce-Lopera		IR Techniques, K-mean	Improve query to find related data.

Ref No.	Dataset	Methods	Accuracy
[85] 2018 B. Gopal, P. Dipankar, and S. Bandyopadhyay	Audio songs emotions.	Svm, FFNNS (Feed-forward neural networks)	Compares accuracy of SVM and FFNNS.
[86] 2016 M. Bilal, H. Israr, M. Shahid, and A. Khan	Mobile reviews from blogs	Differenr machine learning algorithm, Rapid Miner tool	Naïve Bayes 97.5% and Decision Tree 93% on only 20 records.
[88] 2016 P. Patil and P. Yalagi	Movie reviews	Extraction of linguistic feature. domain specific-heuristic. 5-gram	SVM 77%
[89] 2019 A. Rextin, A. Kakakhel, and M. Nasim	Data collected from survey.		
[90] 2016 G. Z. Nargis and N. Jamil	Blogs	Data ontology. semantic analyser through JENA API	Algorithm to identify the emotions from Roman Urdu text
[91] 2015 S. Vijayarani, M. J. Ilamathi, and M. Nithya,		Pre-processing, removal of outliers, and noise. TF-IDF	NB 83%

Ref No.	Dataset	Methods	Accuracy
[87] 2014 W. P. Wong, M. Lo, and T. Ram	Amazon	Pre-processing, Data mining.	
[94] 2015 D. Kalita		SVM, Naïve Bayes, Decision Tree	Survey on Supervised and Unsupervised classification of document
[81] 2013 M. Soleymani, M. N. Caro, E. M. Schmidt, C. Y. Sha, and Y. H. Yang	web	Linear regression	
[80] 2016 D. Anand and D. Naorem	Movie reviews	Naive Bayes	Proposed the methodology to extract the aspect.
[96] 2017 A. S. Manek, P. D. Shenoy, M. C. Mohan, and K. R. Venugopal	Rottentomatoes, Hungama, Times of India, Rediff and Mouthshut	Gini index for feature selection,	SVM 94.46 NB 87
[97] 2019 P. Pankaj, P. Pandey, M. Muskan, and N. Sone	Amazon	POS Tagging	like sentiment polarity classification and sentiment analysis.

Ref No.	Dataset	Methods	Accuracy
[97] 2019 P. Pankaj, P. Pandey, M. Muskan, and N. Soni	Amazon	POS Tagging	like sentiment polarity classification and sentiment analysis.
[93] 2017 B. R. Aditya, A. R. Sulthana, A. K. Jaithunbi, and L. Sai	Reviews	Pre-processing, SVM, Naïve Bayes	The proposed system classifies the data in two categories with accuracy
[75] 2017 E. M. S. Mona Mohamed Nasr and Ahmed Mostafa Hafez	Trip Advisor and from DAIS repository	Svm, logistic regression, decision tree	93.80% on SVM Logistic regression 92.75 %
[92] 2013 I. Javed and H. Afzal	Twitter		Sentiment analysis on multi-languages
[83] 2014 J. Hendler	Data set of national products of china.		The main focus on integration and validation of data quality.
[33] 2018 S. Vanaja	Amazon customer review data	POS tagging, Apriori feature extraction algorithm, SVM and NB classifiers	90.42

Ref No.	Dataset	Methods	Accuracy
[98] 2020 X. Wang, X. Chen, M. Tang, T. Yang, and Z. Wang	SemEvals dataset series; SemEvals 2014 laptop sales, and SemEvals 2014, 2015, 2016 restaurants feedback.	Multi-Level Interactive Bidirectional Gated Recurrent Unit (MI-biGRU)	82.54
[69] 2018 B. R. Aditya	Tokopedia customer review data	five e-Servqual dimensions and naïve bayes classifier	90
[111] 2019 S. Yang and H. Zhang	Amazon review data	LDA and k-means algorithms used to extract topics, NB, SVM, and LR are used for classification	81.5
[100] [2019] A. K and V. J	Client audit data	POS tagging, NB, SVM	81.30
[38] 2015 K. Schouten and F. Frasincar	Amazon review data	Syuzhet and Senti-mental lexicons with NB, KNN, SVM classifiers	86.3
[102] 2020 Q. Lu, Z. Zhu, D. Zhang, W. Wu, and Q. Guo	SemEval 2014 and ACL 2014 Twitter Dataset datasets	Interactive rule attention network (IRAN)	81.96

Ref No.	Dataset	Methods	Accuracy
[104] 2020 Y. Han, M. Liu, and W. Jing	SentiDrugs dataset	PM-DBiGRU	78.26
[103] 2020 F. Xu, Z. Pan, and R. Xia,	Amazon Product and movie review dataset	Naïve Bayes	75.68
[95] 2020 M. P. Abraham and K. R. Udaya Kumar Reddy	Mobile review dataset	Bernoulli Naïve bayesian, multinomial naïve Bayesian,	91.5