ABSTRACT

Aspect based sentiment analysis using evolutionary based ensembler

Sentiment analysis is a computational analysis of unstructured textual data, used to assess the person's attitude from a piece of text. Aspect-based sentimental analysis defines the relationship among opinion targets of a document and the polarity values corresponding to them. Since aspects are often implicit, it is an extremely challenging task to spot them and calculate their respective polarity. In recent years, several methods, strategies and improvements have been suggested to address these problems at various levels, including corpus or lexicon-based approaches, term frequency and reverse document frequency approaches. These strategies are quite effective when aspects are correlated with predefined groups and may struggle when low-frequency aspects are involved. In terms of accuracy, heuristic approaches are stronger than frequency and lexicon based approaches, however, they consume time due to different combinations of features. This article presents an effective method to analyze the sentiments by integrating three operations: (a) Mining semantic features (b) Transformation of extracted corpus usingWord2vec (c) Implementation of CNN for the mining of opinion. The hyperparameters of CNN are tuned with Genetic Algorithm (GA). Experimental results revealed that the proposed technique gave better results than the state-of-the-art techniques with 95.5% accuracy rate, 94.3% precision rate, 91.1% recall and 96.0% f-measure rate.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Chapter 1

Introduction

The purpose of this chapter is to introduce the overview of the research, the motivation and impact of sentiment analysis in the area of scientific publications. This chapter further elaborates the problem statement, which is developed through exploration of the literature review and statistical evaluations. Then the methodology is presented along with the scope of the research. Finally , the significance of the research is discussed followed by the structure of the thesis

1.1 Overview of Research

As the web progresses instantly, users generate a huge amount of online information in the form of reviews, blogs, and tweets. This information may include your views on the event, product, or people. It gives institutions and companies an insights to discuss their concerns, enhance service quality and increase competitiveness [1]. The manual analysis of these comments is time intensive, and it is difficult to aggregate and report all the details effectively. Instead, sentiments analysis (or opinion mining) can be implemented. Sentiment analysis aims at extracting the writer's sentiment from the text and presenting it in a simple and cohesive manner [2]. Sentiment analysis also includes information mining, computational linguistics in addition to machine learning. It mainly deals with the examination of the emotions, feelings, extracted reviews mentioned in transcribed text.

Since the mid-2000s, sentiment analysis has become a new field of research. One can observe its effects in different application areas i.e. from product reviews analysis to sales/purchase forecast [3]. Sentiment analysis interacts with the statistical evaluation of opinion, sentiment and subjectivity in text. It can be performed at the review level, which determines the sentiment of the entire text, or at the sentence level, which calculates the sentiment for each sentence. For the better understanding of the opinions communicated in the text, Aspect Based Sentiment Analysis (ABSA), can be used which is a subfield of sentiment analysis [4]. Since sentiment analysis describes sentiment for a review or for a complete sentence, ABSA focuses on detecting reviews aspects in the text and calculating sentiment for each mentioned aspect. ABSA is regarded as a basic task of sentiment analysis and can explain sentiment related to multiple aspects of the text.

In a text, the aspect may be interpreted as a personal perspective or intuition on which a critic makes his decision, for example, the comment "screen size is perfect, battery is good" affirms these comments. You may easily infer that the positive rating comes from the size of the screen, critics or reviewers are comfortable with screen size and battery life. Extraction of information, commonly called the aspect extraction task, retrieve the best aspect from the text and seeks the most important aspect from the textual data. This is valuable as in one review people often consider various aspects of a service or product and each aspect has its own score. ABSA integrates information mining, computational linguistics, and machine learning to handle sentiment analysis, opinion mining. ABSA helps companies for the good understanding of needs and interests of their product and services. This makes a bit more sense than the wider overview, as more precise details helps the company to prioritize specific improvements [5]. Aspects are of two types. The first is explicit aspect whereas the second is implicit aspect [6]. Aspects openly defined in the document are known as explicit aspects and other aspects that are not explicitly included in the document are called implicit aspects. Aspects are called features. That is, the exact reference to the entity that someone will comment on in their comments [10].ABSA is dedicated to explore emotions, opinions, facts, and emotions through human-passed phrases in specific reviews. Browsing all aspects of reviews, tweets, blogs, and comments can identify the emotions and attitudes of particular people [7].

In modern research technology, ABSA classification involves classifying consumer reviews into three categories: negative, neutral, or positive derived from the review text data set. This classification of emotions is called emotional polarity [8]. Sentiment analysis work focuses primarily on supervised learning techniques. One of the main issues of supervision is the representation of documents, and the central issue of document representation is the weight term. The initial methods are mainly rule-based methods [9] and statistics-based methods [10]. While these traditional methods are effective, they largely depends human resources and expertise to perform feature engineering.

Word embedding [11] can clutch syntactic and semantic information of meaningful words, but it can rarely capture emotional information that is essential for an extensive range of sentiment analysis tasks. Most existing technologies are corpus-based and dictionary-based. These methods are less organized than those based on machine learning. Covering English words needs building a large corpus, which is a very difficult task. Most recent techniques are designed to test emotional polarity tasks at sentence level, expression, paragraph, or text without having to consider units or aspects such as notes, cell phones, etc. Although the aspects generally stated as features for instance battery or memory. However, looking at overall sentiment in this way can lead to failure of capturing overall sentiments of a particular review [12].

ABSA seeks to predict the polarity of a particular document for a specific aspect of an entity. The neural network architecture accurately predicted the overall polarity of sentences, but the sentiment analysis of some aspects remains an open question. There are numerous existing methods for polarity estimation at sentence level, they are general (negative, neutral or positive) and may inadequately reflect the theme, especially if the class contains excessive information [13]. Although typical SA focus on predicting the positive and negative polarity of a particular sentence. This task is useful when there is only one aspect and polarity of the specified text. A more common and more challenging task is to predict the various aspects mentioned in the sentence and the emotions associated with each of them [14]. ABSA compares the relationship between all words in the document with an aspect vector. The relationship between aspect and language prevents learning of expression. Majority of the current methods of analyzing opinions are centered on analysis at the text level and can only detect well-expressed opinions.

The purpose of ABSA is to detect all aspects of an entity and the views expressed in each aspect. Extraction of aspect terms from user-generated content and providing opinion is one of the most significant tasks of ABSA. Gloom, wonder, irritation, loathing, pleasure and fear are more informative emotions, yet they are usually eliminated from the text. However, it can be found in a magnificent manuscript to identify the narrator's thoughts [15]. To solve these research problems, a sophisticated and state-of-the-art technique is required. The purpose of the proposed study is to provide a solution to the above problems based on opinion analysis, aspect identification and polarity assessment. VADER (Dictionary of Values and Emotional Reasoning) is used in conjunction with the predictive method to achieve greater accuracy than existing methods. The proposed method has been applied to numerous reviews datasets (hotels, cars, movies) to consider them as positive, negative or neutral and determine their polarity. One of the more interesting applications of this study is to calculating sentiment polarity and test how much positive or negative a review is. The work in this thesis is based on an evolutionary ensembler that aims to extract emotion from text and achieve accuracy [16]. The proposed solution fixes the above-mentioned issues of extracting opinions from the text with respect to the aspect. The results have been compiled with Convulational neural network (CNN) and Genetic Algorithm (GA), where accuracy, precision, recall and f-measure has been improved. Proposed research shows promising results by using CNN with integration of GA and achieved 91.5%

accuracy rate, 95.0% precision rate, 92.3% recall and 94.0% f-measure rate To validate the research further, proposed model is compared with six other classifiers, i-e, SVM, Maximum entropy, Random forest, Stabilized discriminant analysis, Decision tree, Generalized linear model. It has been found that the proposed technique outperforms all other recent methods.

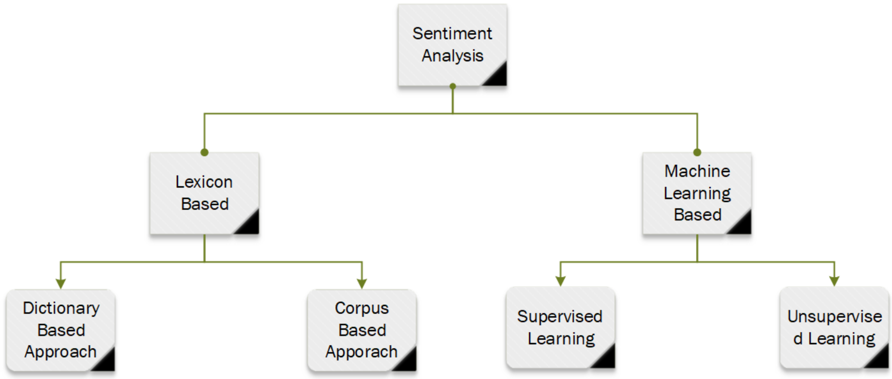

FIGURE 1.1: Areas of research in sentiment analysis

1.2 Motivation

Sentiment analysis or opinion mining can be used to perform computational tests of people's emotions, feelings, methods, and passions for objects, products, organizations, individuals, themes, and their characteristics [17]. The majority of the existing methods of same research problem [18] interested to perceive the whole sentiment of a sentence, section or document regardless of the objects (e.g. hotel) and respects (e.g. services). Such approaches can merely find the overall sentiments, however, flopped to capture the feelings over the aspects by means of an entity as stated in [19] directed the dynamics of this study towards the handling with such kind of problems. This research is interested to suggest a more detailed methodology to evaluate sentiment obtained from user generated text. One of the most interesting applications inspired by this study is to deal more effective deal with increasing number of reviews on the internet [20].

Today, almost every internet user is commenting or reviewing a product that go beyond their capability to read. Every single product, if not thousands, has hundreds of reviews. Several platforms like Amazon, Twitter and social media blogs are aiming to build better means to present their opinions to users. Most of the common approaches summarize the information by considering alike phrases with high frequency over the reviews [21]. These methods will involve the loss of valuable information that excitingly deflects this work into extending ABSA to such large sets of evaluations that a representative model ca instantly built for individual aspects and emotions. ABSA will effectively classify aspects of reviews, and assess the opinion of the evaluator on the merit of the aspect [22].

1.3 Scope Of Research

The scope of this research is to explore the ABSA process in detail in order to enhance the polarity estimation not limited to positive and negative but also with the intensity of the aspects. State-of-the-art techniques are used to analyze reviews at the sentence level, while this study identifies sentiments are at the aspect level through aspect recognition and polarity estimation. This research is embed with the scope of aspect identification that further goes to polarity estimation and polarity aggregation to compute the overall polarity.

1.4 Problem Statement

ABSA aims to determine the polarity of a given text to an entity's specific aspect [23]. Though the existing approaches successfully predict the overall polarity of the sentence, however, SA of certain aspects is an open question [24]. Traditional SA focuses on predicting a given sentence's positive and negative polarities [25]. This task operates when there's only one dimension and polarity of the given text. The prediction of the aspects mentioned in a sentence and the emotions associated with each is a more difficult and complex activity. In ABSA the relation across each word in the document and the aspect vector is compared. The aspect-language relation lacks the ability to learn expressions [26]. Many current techniques of opinion mining are centered on text level analysis and can identify only well-expressed opinions. ABSA's purpose is to define aspects of an entity and state the emotions on each aspect [27]. One of the most important tasks in ABSA is to extract the aspect terms and present opinions from user-generated content [28].

Following Research Questions (RQs) have been identified based on our research problem that would helpful to find solution of the problem.

Q.1. What are the drawbacks of existing approaches and limitation of state of the art techniques in sentiment model?

Q.2. How to solve the aspect identification issue?

Q.3. How to solve the polarity estimation issue?

Q.4. How features can be extracted from the given corpus?

1.5 objective of work

The goal of this research is to outperform current ABSA approaches like lexicon-based techniques [29] and sentence level techniques [30] etc. Such approaches are helpful for finite dictionaries only and may struggle if sentence contains variety of information. The novel polarity estimation approach will help to reduce the binary polarity problem, which classifies emotion only as either positive or negative. The main objectives of the proposed research are: The proposed work can evaluate the polarity of sentiments at the aspect level in order to examine the general theme of a review. The suggested polarity estimation would help to assess the satisfaction of the customer and can help someone to evaluate if their product or service satisfies the standards of the consumer. The proposed framework would be able to capture the hidden emotions in a text and would cover the vagueness of sentiment to classify the reviews efficiently. Build a framework that integrates the polarity of each aspect to estimate the overall polarity of review. Empirically, evaluation to achieve a more reliable methodology for classifying sentiments

1.6 Research Contribution

This research deploys aspect-based sentiment analysis to measure the polarity of sentiments. Some useful steps such as feature extraction, opinion terms extraction and polarity estimation are successfully on available reviews. Compared with existing approaches, the proposed methodology performed well. Contributions in this research are as follows

- An aspect-based sentiment analysis approach has been suggested that allows us to extract useful decisions in the natural language processing and opinion mining domain.
- Data from various datasets can be used to get more sophisticated opinion mining. Data pre-processing ensures more refined and less noisy data.
- In this research, the Convolutional Neural Network and the Genetic Algorithm-based ensembler has been used to gain the accuracy and effectiveness of the sentiment analysis process.
- The proposed technique outperforms the existing state-of-the-art methodologies.

- The aspect identification method can certainly be used in various real-time applications as event identification in digital networking.

1.7 Research Methodology

The proposed methodology comprises of three phases: Semantic feature extraction, Aspect polarity estimation and Aggregation of polarity. The current research approach is being adapted to evaluate the research questions.

Review of Literature

The related literature from google scholar, Elsevier, IEEE, Springer, DBLP, MEDLINE and Cite Seer was retrieved later the in-depth exploration discovered on these sites in nearly ninty research papers. These investigations, alongside comprehensive references are elaborated in Chapter 3. Current ABSA, feature extraction, and event identification approaches are analyzed.

Data Collection

For simulations three type of datasets are used. Web scraping is employed to gather reviews; hotel reviews gathered from "https:/webhose.io/", automobiles reviews are collected from "https://www.cvedia.com/", while movie reviews are fetched from" https://seedmelab.org/".

Preprocessing of data

In this stage, the raw data is converted into structured data. Empty rows, empty cells may be present in the data generated by scrappy, panda library is being used to clean the data and retain only useful data.

Development of Conceptual Model

A structural technique for extraction of features from unsaturated data of hotel, automobiles and movie reviews has been defined.

Semantic features have been extraction

Words are converted into feature vectors in the first layer of the network to extract the semantics and morphological information about words.

CNN Implementation

CNN is being used to extract opinions. Vector form of processed corpus is used to train through CNN classifier.

Use of GA

CNN hyperparameters are tuned using GA to achieve better model simplification.

Drawing Conclusions

Conclusions are drawn based on deep analysis of the results of experimentation for the above objectives 1.2.

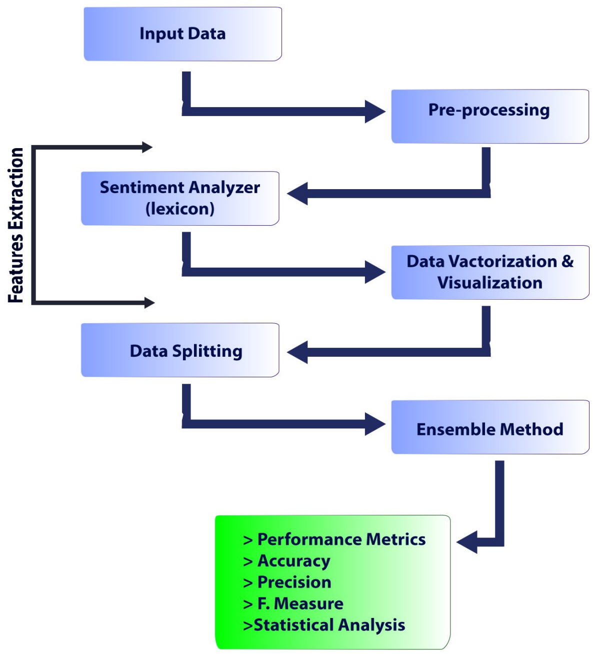

FIGURE 1.2: Graphical view of methodology

1.8 Significance of Work

This research suggested a new approach for extracting aspects and opinions of a given review by applying CNN and GA. This research demonstrates new aspect extraction methods that can really improve the process of reducing dimensionality. This may be more useful when extended to various machine learning, computational approaches and rule-based mining instead of conventional NLP techniques. In fact, this study may be further applied in a medical to forecast numerous amendments in its recent domain. Also, this research will help to extract all possible aspects, define all the views, and then map aspects to respective sentiments. The suggested methodology should help to produce a full, descriptive, and concrete overview of opinions from certain observations. It would help individuals tremendously in making better purchasing decisions. It would also provide the companies with innovative support in making healthier decisions on their services and policies.

1.9 Thesis Structure

The structure of this studies consist of six chapters named as chapter 1 ”Introduction” chapter 2 ”Study of Existing Models for Sentiment Analysis” chapter 3 ”Literature Review” chapter 4 ”Proposed Methodology” chapter 5 ”Results and Discussions” chapter 6 ”Conclusion and Future Work” The flow of thesis structure is shown in Fig. 1.3

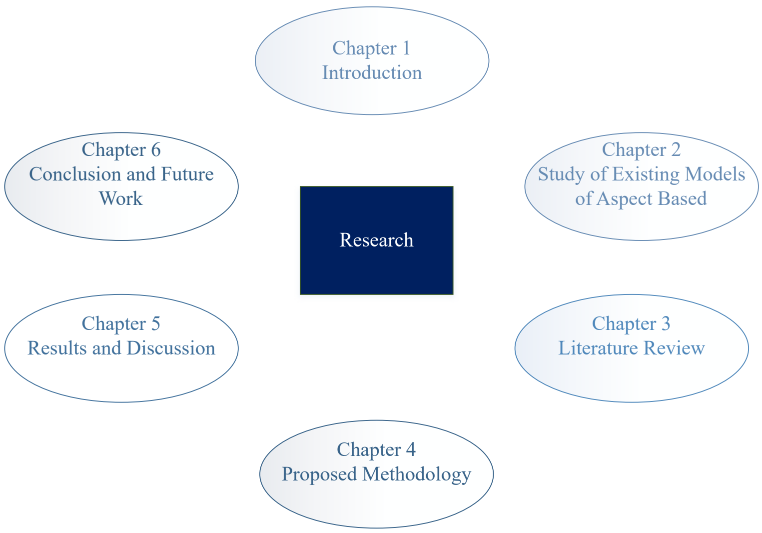

FIGURE 1.3: Thesis structure

Chapter 2

This chapter provides a detailed overview of various models and tools used to perform sentiments analysis. We also discuss various current supervised, unsupervised and lexicon-based methods, their components and metrics for evaluation. Explore their libraries and framework used to build that models.

Chapter 3

This chapter presents the preliminary studies, their comparisons, related studies and there limitations are presented that are commonly used for this problem.

Chapter 4

This chapter presents the model justification, propose model, working of proposed model, datasets characteristics and description of proposed model. The proposed models are based on text reviews sentiment analysis and polarity estimation.

Chapter 5

In this chapter, the suggested methodology has been analyzed on the basis of various experiments conducted on multiple datasets. Extensively discussed the experimental outcomes of our proposed technique and compared the results with existing techniques and their performance with a comprehensive review.

Chapter 6

Eventually, the conclusions of this research along with future orientations in the area of sentiment analysis is presented in Chapter.

Chapter Summary

In sentiment analysis, extraction of aspect and estimation of polarity is a growing area of research that analyses the opinions, emotional states of individuals. It plays an important part in a classification task since the bulk of content is created and published every day on the internet. The significance of this research is obvious from the amount of applications where it could be helpful. This work, suggests a novel technique for calculating and aggregating polarity. The following section includes several basic concepts of the domain.

Chapter 2

SENTIMENT ANALYSIS: AN OVERVIEW

This chapter introduces some basic ideas related to the applied methods in this thesis. The discussion laid the foundation for the field understanding and background of research practice in this thesis. In addition, this section also discusses the specific situations, environments, and event recognition of aspect-based sentiment analysis. It also describes some NLP tools, concepts, and basic models for enhancing sentiment analysis tasks.

2.1 Opinion Mining and Sentiment Analysis

Sentiment analysis is a computational process used to automatically identify and classify a person's views or opinions about an entity (product, event, organization, etc.) [31]. this task is usually accomplished by viewing and transcribing text, but it has been accomplished in other formats, such as recognizing emotions in facial expressions. Therefore, the study of sentiment can require the use of numerous computational linguistics, natural language processing and biometric techniques [32]. Analysis of the sentiment is also called predictive analysis. The differences are relatively small, and are often neglected. Whereas the analysis of emotion is all about the inner moods of a individual in relation to the substance, the analysis of opinion focuses on capturing the emotions conveyed by that person[33]. Although the use of the two concepts is indistinguishable, it should be noted that a person may not convey their view in detail about a particular entity. The exponential emergence of the internet has lead in a substantial amount of digitally captured self-checking data. You can find perspectives on different textual knowledge outlets such as forums, social networks, item reviews, film reviews, etc. Whereas viewpoint interpretation is one of the utmost important research field in the arena of natural language processing (NLP)[34].

2.2 Aspect-Based Sentiment Analysis

The aim of aspect-oriented sentiment analysis, as mentioned earlier, is to recognise aspects of a product that are presented in textual reviews and classify sentiments relying on authorship. You can tackle this multipurpose process together or at different phases.

2.2.1 Aspect Extraction

Aspect extraction is first solved in the user view summary [35, 36, 37] task. Define item characteristics as the goals described in item comments and use those characteristics to create an overview. Comments are summarized in short sentences. When extracting aspects of elements from custom comments, you can categorize them implicitly or explicitly. Aspects are not mentioned, but if they are indirectly mentioned in the input comment, they are processed implicitly, and if they are referenced in the comment, they are called explicitly. For example, the term "cost" is a semantic term of "price" in the sentence "this phone is costly," but the word "price" is clear in the sentence "this phone is expensive." Despite the abstraction of implicit features, such as [38, 39], the majority of published work has concentrated on explicit aspects. The literature describes four main methods to this problem.

The first method focuses on using word frequency to describe elements in a specific area [40]. Assuming an aspect is a noun or noun phrase, the aspect that has the most occurrences in the set of related annotations is considered a candidate for that aspect. Methods based on this theory have recently been used, considering the disparity in the distribution of (aspect) terms in the target domain and the distribution of terms in a common multidomain corpus [41].

The second approach relies on the use in comments of the syntactic relation between nouns and adjectives. Double propagation is a popular algorithm which follows this approach[42]. The third approach produces a supervised model of learning for extraction of a function. The best examples of iterative learning methods are Conditional Random Fields (CRF)[43], and Hidden Markov Models (HMM) [44]. In the aspect extraction process, words and comment expressions are treated as markers, and the expression of opinions is the main state [45]. Training data is marked in pairs and model parameters are conditioned to optimize the probability of introductive analysis text opinions. Popular problems are with the first three processes. Aspects are typically presented in terms. That is how people are likely to use various vocabulary to explain a given idea. Typically the extracted dimension terms are combined by dictionary similarity, synonym, and distance based on classification[46] to overcome this problem.

To solve this problem, a fourth method of simultaneous selection and grouping using topic model is considered. The topic model takes a collection of documents and describes the subjects in the documents (and how they are distributed). So a subject is typically a collection of words. Distribution of topic is the "proportion" of documents that define a topic. Reviews are viewed as records when extracting details, and topics may reflect details of reviews. A topic may therefore be described as reflecting a group of aspects which consists of several aspects. Such dimensions define elements. In this case, explicit and implicit aspects can be found on the method.

Several thematic approaches included in analyzing emotions and features extraction depend on probabilistic latent semantine analysis (PLSA) [47] and latent assignment of Dirichlet (LDA)[48], as well as the concurrent occurrence of terms in text and variations in delivery. The delivery of topics may be somewhat similar because product reviews will contain perspectives on a small range of issues in a given field. Therefore, the aspect extraction thematic model usually extends the global thematic model [49, 50, 51]to overcome this problem and find the best aspect. In this case, in the course of constructing a topic model, the general approach is to differentiate between types of terms such as terms of a particular dimension, words of the global level, context words, words for comprehension etc. Separating certain types of terms would remove the most valuable information in the process of generation.

The approach used in this study is new because it uses an aspect-oriented approach instead of the topic models. Modeling the subject is typically focused on clusters which are difficult to understand. Cluster labeling is a difficult process in itself which requires sophisticated computational algorithms. Moreover, when the content of the review is extensive, the aspect approach can yield better results [52]].

2.2.2 Aspect Sentiment Classification

There are two primary emotion recognition approaches; Regulated and vocabulary approaches. Classification of dictionary-based emotions starts with well-known vocabulary, looking for terms and phrases in textual evaluations, and identifying the target terms that influence them [53]. Usually the assumptions are syntactic and common. When the reference word in the dictionary is beyond the spectrum of the word in terms of general meaning, then if its polarity is positive its polarity is +1. If negative, polarity is -1 and can be based on opinion words. That is the impact on the target, to calculate the polarity. The accuracy of this unsupervised approach is dependent on the intactness of the lexicon and the consistency of the syntactic analysis. The inspection method uses cell levels to determine the polarity of each cell [54, 55]. Aspects of an item that appear in a review with the highest score are considered more positive than aspects mentioned in a negative review. Several aspects of the sentiment extraction and classification process are detailed in the literature review.

2.3 Sentiment Analysis using ML Models

Different machine learning algorithms can be operated to evaluate the knowledge retrieval and classification emotionally. Many of them are discussed in finer detail below.

Naive Bayesian Classification

Another of the well-known classification schemes for text is the naive Bayesian method. Most researchers see their research as incredibly good [70][71]. When there are so many D reports, then each documentation is viewed as a word list. Wdi, k represents the term in the file di, at position k. Each word comes from the $v =< w1, w2 \ldots, wv >$dictionary. The dictionary should consider the placement of all words within the group. There's many predefined classses have $C =< c1, c2 \ldots, cC >$.

$$P[cj] = \sum_{i} P[cj/di]/D \tag{2.1}$$

Where N (ws, di) is the number of times wt appears in the document di, $P(c_d] di) \in \{0\{0, 1\}$ centered on the document category label. Lastly, according to these categories, word probabilities are independent.

$$P[cj/di] = \frac{P[cj] \prod_{k-1}^{di} P[wdi, k/cj]}{\sum_{r-1}^{C} P[cr] \Pi_{k-1}^{di} P[wdi, k/cr]} \tag{2.2}$$

The naive Bayesian classifier assigns the maximum P [cj] to a type of text. Therefore it is a supervised method of study. Bayes classifier is the plainest classifier of probability, centered on the theorem of Bayes. Data classification uses the Bayesian rules to assess the class or category to which a text is most likely to belong.

Support Vector Machine (SVM)

Described in [73] [74]. For a set of categories C = +1, -1 and two pre-classified training sets, a positive set of samples and a set of negative samples:

$$\begin{aligned} Tr^{+} &= \sum_{i=|1}^{n}(d_i, +1) \\ Tr^{-} &= \sum_{i=1}^{n}(d_i, -1) \end{aligned} \tag{2.3}$$

The SVM identifies a hyperplane with the maximum margin (or maximum potential distance between the two groups) splitting the two groups, as seen in Figure 2.1. Every training sample is altered into a specific vector xi at the preprocessing level, consisting of a series of essential functions describing the relevant text di. So at this point, then w if ci = +1. If Xi + b ¿ 0 and cj = -1, that will be W. Xj + and b ¡ 0. Therefore, T +, T- ci. (W.xi + b) ≥ 1 is an optimization problem defined as

Reduce (1/2) ||w|| 2 according to ci. (W. xi + b) ≥ 1. The hyperplane therefore has a maximum distance from both sides up to xi. The classification problem can be expressed as determining which side of the test sample is the hyperplane [56].

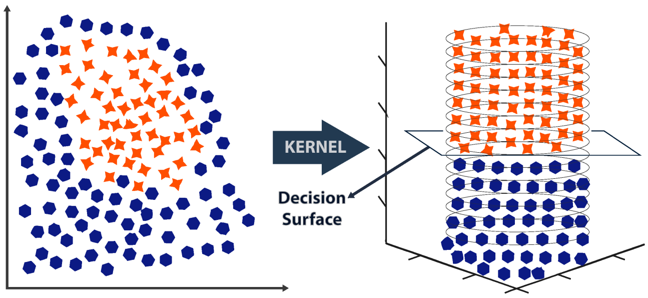

FIGURE 2.1: Illustration of SVM Method

K-Nearest Neighbor (KNN)

KNN is a basic algorithm in machine learning. This algorithm classifies objects as per closest neighbors to them [57]. The class allocated to the object is in the nearest adjacent k. The KNN classification algorithm categorizes aspects or objects in the training data based on their similarity to the instances. KNN chooses objects from the training data depending on their similarity to instances or remote weighted voting. KNN intends for voting based on majority voting or remote weighing. KNN is an unsupervised text classification algorithm, suitable for wide training sets. Consider a set of vector A and M instances labelled with ai, bi. The classifier uses predefined categories N to determine the labels for categories

A. The classification algorithm KNN determines the k closest neighbors of A and uses a plurality vote to decide the labels of categories A. The classifier KNN uses Euclidean distance as a measure of distance [58].

$$\mathrm{Dist}(X, Y) = \sqrt{\sum (Xi - Yi)^2} \tag{2.4}$$

Using CNN, this work focuses on probabilistic classification.

CNN

CNN design is represented in fig. It is formed by a particular layer stack that converts the quantity of input into objective output using a differential method. CNN's constituent layers are:

1. Convolution layer
2. Max-pooling layer
3. Rely layer
4. Back propagation layer

The aim is to use a appropriate number of filters (128) for collecting a large number of features in a given sentence. Similar to image recognition, various filters accumulate different features such as margins, multi-colored field width, turning certain regions into high contrast. The text classification problem expands the concept of similarity to capturing features such as positive mean rather than similarity with different filters, and uses size 2 filters to convey the degree of features. The basic principle is to establish enough basic principles to capture each content descriptor. When using filters, the largest pool should have the highest self-rating of the output vector. The strongest component of the expression is selected from the output of the extracted feature, regardless of the word length. Each example is passed in the n * 1 format. Where n is the expression size / transfer size filter, which is actually used as a draft window for the 3 * 1 instant sentence filter. I really like this car! I like this car, this car is so, very, very, very! ! All filters do not produce the same size result because the operator is split by the same length before being filled. The size of the area (2, 3, 4) is equal to 2, 3, 4 G-words. The first filter of this 3-letter combination assigns different weights to different words of the 3-letter combination. This means that the first index is given a high weight (index 0) and the second index is given a low weight. Therefore, various weights are allocated to the 128 filters, and in some situations certain weights are allocated for accurate prediction. For a given sentence, emotion labels are generated by analyzing its value, assessing the sentence, using the word order in the sentence as feedback, and using hierarchical levels to simplify high-complexity functions. I will. I will. Extraction of the function will take place at the level of the sentence and the character. In architecture, Convolution is the central learning mechanism. The concept of convolution may be simplified by Equation 1. Convolution is a two-function mathematical process, which creates a new function that changes one of those functions. Convolution as implementation for equations of a boring matrix multiplication algorithm.

$$(f * g)(t) = \int_{-\infty}^{\infty} f(t) \cdot g(t - x) \tag{2.5}$$

The symbols (f) and (g) in an expression are functions, input function (g), and function as filter (f). The symbol with the symbol (t) indicates how many times the process terminated. The (∞) character is an input character and can start with any value from positive to negative. The end result is the product of function (f) and function (g). The uniqueness of the network architecture lies in the fact that two convolutional layers are combined to handle sentences and words of any size.

2.4 Parameterization

The hyper-parameters of CNN are tuned using Genetic Algorithm.

Genetic Algorithm

Genetic algorithms are approaches based on natural selection to solve multi-objective optimization problems. GA is very useful when you do not know the optimal range and dependencies of various CNN parameters. As shown in Figure 6, CNN defines hyperplanes between data. This approach illustrates the natural selection cycle, through which the best regenerated individuals are chosen to produce the next generation of offspring. The natural process of selection starts with selecting the best individuals from the population. Descendants inherit their parents' traits, and transfer them on to the next generation. If the parents are healthy, the offspring are likely to be better than the parents and be able to survive longer. This process repeats itself continuously, eventually finding the best generation of people. The general procedure is shown in Figure 2.2. You can use this concept to find the correct solution to your problem. GA selects a best solution

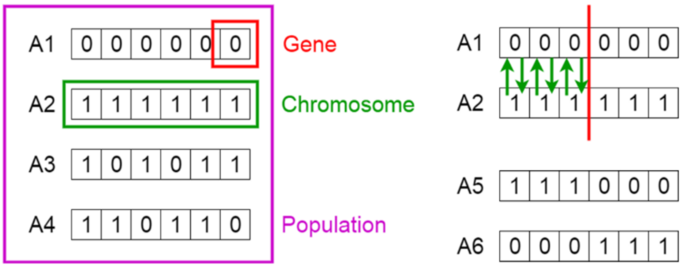

FIGURE 2.2: Genetic algorithm steps

from the set of solutions for specified problem. The genetic algorithm considers five stages.

1. Initial population
2. Fitness function
3. Selection
4. Crossover
5. Mutation

Initial Population : The cycle starts with a community called a "population" All are a solution to a problem that needs to be addressed. Human traits are composed of genes called parameters (variables). Genes interact with strings to form chromosomes. A series of human genes is expressed in a genetic algorithm by a string and a letter, as seen in Figure 2.3. Binary numbers are widely used (strings of the ones and the zeros). We might assume it encodes a gene on the chromosome. Fitness Function: Fitness functions determine a person's health (the ability of one to compete with others). It provides fitness assessments for everyone. The likelihood of choosing the correct breeder is calculated on a scale of agreement. The raw fitness score of objective function is converted into a value

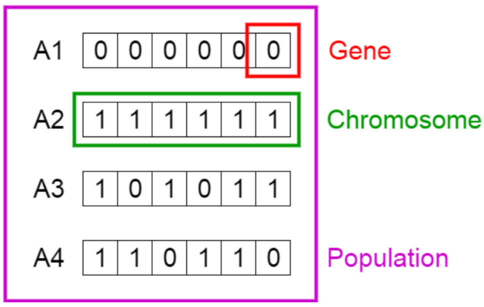

FIGURE 2.3: Initial population

within selected range as in Eq. 11 is happened by fitness scaling.

$$F = \frac{G^{leam} + G^{validation}}{2} \tag{2.6}$$

Selection: The most appropriate artifacts are chosen at this point, and their genes are passed to the next generation. Based on the health assessment, pick two classes of individuals (parents). The taller your physique, the better your chances of reproduction. This choice uses the scaled value of consent to select the next generation parent, and typically applies a high probability of choice to people with higher scale values, as shown in Equation 12.

$$g(x) = \frac{f(x)}{\sum_{x \epsilon p} k} \tag{2.7}$$

The number of copies of each function tx0 in p (k), that is, the number of copies selected by each function tX0 in p (k). The number of objects selected in this way is less than m (usually), the fractional part e (x) is used as p (k) n, and the remaining functions are selected from the maximum number). In general, this technique aims to remove less adaptive features and repeat more adaptive features.

$$CR_{(y)} = n_y^+ / m_y \tag{2.8}$$

In the formula in Figure 13, n + y reflects the number of type y (correct) patterns listed as type y representatives, and my is the number of all type y patterns. Crossover: Crossover is an important step in genetic algorithms. Random exchange points are selected from genes for each pair of parental pairs. Crossovers help genetic algorithms extract the most important characteristics from different people and rearrange them into potentially good children, as shown in equation 14.

$$child = parent2 + R_{cros} \times (parent1 - parent2) \tag{2.9}$$

For example, consider the crossroads shown in Figure 2.4. Offspring are created by exchanging genes between parents until they reach the intersection point. New offspring are added to the population as shown in Figure 2.5.

Mutation :

When new offspring are formed, the likelihood of a particular gene mutating is greatly reduced. This means that you are unlikely to be able to flip the bits in a bit string. Besides mating offspring, the genetic algorithm also produces mutant offspring by randomly mutating the single parent of the current generation. Because mutations contribute to population diversity, the algorithm is more likely

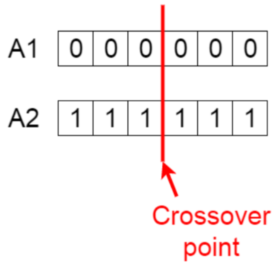

FIGURE 2.4: Selection point for crossover

to generate fitness values that are better suited to individuals. Mutation occur in

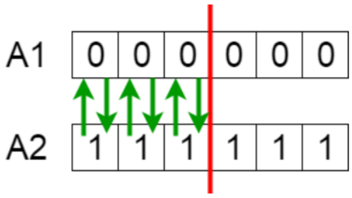

FIGURE 2.5: Exchange of genes between parents

order to preserve demographic diversity and avoid premature fusion.

Termination:

Once the population converges, the algorithm stops (the descendants don't differ substantially from the previous). GA's said to give our dilemma a set of solutions.

The motivation for CNN is to select an integrated model that best suits certain constraints for certain data. The main benefit of CNN is that you can combine multiple knowledge sources to easily add other knowledge. Normally CNNs can be used to estimate distributions of probabilities. It is a concern of optimization[59].

2.4.1 Sentiment Analysis Evaluation

Four metrics are widely used to assess a type of sentiment efficiency. They are precision, accuracy, F1score and recall [60]. A common way of measuring these indices is through:

- True positive (TP): the class of values that are correctly categorized.
- True negative (TN): correctly class as not the class of interest.
- False negative (FN): classified the incorrectly as not the interest class.

- False positive (FP): class of interest is wrongly classified.

These indexes can be defined by the following equations

$$\text{Accuracy} = \frac{TN + TP}{TN + TP + FP + FN} \tag{2.10}$$

$$\text{precision} = \frac{TP}{TP + FP} \tag{2.11}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{2.12}$$

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{2.13}$$

Accuracy is the component of all specific instances of forecast correlated with all instances of forecast. Accuracy of 100% means the expected instance is exactly the same as the real instance. Accuracy is a part of the true positive example of prediction over all positive examples of prediction. Remembering is part of several more positive predictive cases along with all the other pessimistic cases. F1 is the harmonic mean of precision and reminiscence.

2.4.2 NLP Tools for Sentiment Analysis

Sentiment analysis can be functional to a number of tools for the analysis of open source text, including natural language processing for extracting and classifying content. I have not used the tools listed above in this article, but I have briefly introduced them to understand naive users.

- **Opinion Seeking**, first published in 2006, uses an NLP multi-step process. It is designed to recognize subjective verdicts and denote different aspects of subjectivity, such as the subject source (owner) and the words contained in phrases describing positive or negative emotions.

- The NTLK-Natural Language Toolkit is a grouping, clustering, voice tagging and interpretation tool for teaching and study. This contains a number of tutorials and experimental datasets. Written by Stephen Bird, from Melbourne University.

- **GATE-GATE** has a 15-year history and is actively used for various types of computing tasks, including the human language. GATE does a very good job of interpreting text in different dimensions and forms. From large companies to small businesses, from millions of academic groups to projects for students.

- **LingPipe** is a set of Java gadgets for organizing audio content such as substance extraction, conversation (pos) tags, packaging, feature descriptions, etc. It is the most widely developed and used open source NLP toolbox in the enterprise. Acknowledged for speed, reliability and flexibility.
- **OpenNLP** A variety of Java-based NLP may perform the most well-known NLP tasks such as tokenization, splitting of clauses, grammatical labeling, extraction of named items, concentration, parsing, and general connection targeting. Often these tasks are required to further improve the rights of content processing.

2.4.3 Similarity Measure for Sentiment Analysis

There are several methods for extracting and classifying similarity information, such as the chi-square test[61], that can be used to evaluate sentiment. The coefficient of Jaccard[62] and the benefit of knowledge are appropriate but only statistics are suitable for numbers. Similarity tests are distinct from statistics in terms of the sentiment analysis. Word2vec can be used in this article to achieve high precision.

Word2vec

Word2vec, an open source tool which Google licensed under the Apache License 2.0 in 2013, has gradually evolved into a powerful word processing tool[63]. Lately, Word2Vec, one of the terms embedding devices, has gained more and more attention from the scientific community. This model is based on neural networks and is associated with the emergence of so-called deep learning. Arrogant vector spaces are very efficient at computing vector representations of words. In vector space, word vectors arise from words with the same meaning, share a common context, and map to each other. In addition to syntactic information, word representation similarities based on semantic characteristics (such as semantic relations) are usually stored in vector operations performed on vectors of words. This study uses Word2Vec. This is because Word2Vec creates better word embeddings for most traditional NLP tasks compared to other methods. A very efficient tool for extracting features from a specific domain without manual intervention. Moreover, it works fine if the text size is too small, or even just one word. You can give words the right meaning by having a rich corpus context by using word2vec, and they can even function quickly on large datasets. The most important viewpoint in deep learning is that word2vec is used to identify bigger entities to better understand the meaning of terms. The layout includes 3 million terms and sentences of

3 million phrases. By practicing such a large corpus, you can get an accurate relationship. Figure 9 shows a similar relationship between words using the word2vec transformation. Figure 10 shows the relation between the various terms in the Google News dataset. The spacing of the edge shows correlation, and the terms indicate the nodes. Words with the same sentiment label has same vector that renders word similarity easier.

2.4.4 Chapter Summary

Throughout this chapter, we discussed throughout depth the analysis of emotions and the analysis of opinions. Furthermore, in sentiment analysis, we clarified the purpose of sentiment analysis, machine learning and functional classification models, and different assessment models. Last but not least, we will also take a closer look at NLP methods for analyzing sentiments and calculating precision for analyzing sentiments. Throughout this point these definitions are very relevant to explore if one want to get worthier understanding. The next chapter discusses the current literature on sentiment analysis.

Chapter 3

LITERATURE REVIEW

The purpose of this chapter is to provide a critical analysis of the literature on aspect-oriented analysis of sentimentality. We have looked at literature reviews in detail in various aspects: aspect extraction, sentiment analysis, and event recognition techniques. ABSA and its variants are compared with existing technologies. It summarizes the literature on sentiment analysis and highlights the most appropriate guidelines for future research.

3.1 Literature review

According to the latest aspects of the study, ABSA is splinted into two distinct tasks: the aspect extraction and the sentiment analysis [64]. The discussion begins with a comprehensive description of aspect extraction and sentiment analysis algorithms. Aspect detection and extraction technologies fall into four categories [65] frequency, relationship, controlled and thematic [66]. Sentiment analysis is split into three methods: supervised, unsupervised and lexicon-based [67]. The most challenging task in SA is the identification and retrieval of the most accurate and relevant aspects from large textual data. The primary concept of aspect extraction is to retrieve relevant information from a huge corpus [68]. An aspect can be described as "a feature of an object that someone has commented on." For instance, on a mobile phone of a certain brand, its appearance may be "battery life", "camera", etc. It is desirable to recognize this appearance in different ways

3.1.1 Frequency-Based Approach

This technology finds duplicate nouns and phrases from annotations. People use similar vocabulary when commenting on different aspects of objects and grouping them together. Qian and Chea [69] suggested a part of speech (POS) tagger for identifying nouns and noun phrases. Calculate the frequency of these nouns and their phrases. The proposed method performs the task of trimming aspects by calculating the frequency of each word and selecting the most frequent aspect. This technology finds duplicate nouns and phrases from annotations. People use similar vocabulary when commenting on different aspects of objects and grouping them together. Qian and Chea [70] proposed a part of speech (POS) tagger for identifying nouns and noun phrases. Calculate the frequency of these nouns and their phrases. The proposed method performs the task of trimming aspects by computing the frequency of every single word and pick the most frequent aspect.

Papskiy et al. [71] Created an unsupervised data extraction system called OPINE, which separates the focus and conclusions of the project from the audit. OPINE first focuses on learning phrases by making repetitive phrases more visible than time constraints, and then OPINE's main experts evaluate those phrases. The evaluator evaluates the expression of things by calculating, point by point, the mutual information between the expression and the alias associated with the item's category. The recommended method is intended to work with mobile phones and is restricted to this area.

Chu [72] used the TF-IDF scheme to search for frequently used terms in reviews as the main topic. The frequency of using a particular term is calculated based on the quantity of times that word appears in the document (relative to the total number of words in the document). Inverse document frequency is used to calculate the importance of terms. Often some words are displayed, such as "yes," "one," and "and," but they are not important. TF-IDF is a two-tier feature extraction technology. TF-IDF restricts itself by choosing all the most commonly used aspects rather than their semantic relationship with tags.

Selvey et al. [73] proposed an end-to-end model of uncontrolled adaptation of the ABSA domain to solve the problem of sequence marking. New Selective Adversarial Learning (SAL) method for adjusting the estimated correlation vector that automatically obtains potential relationships. Since the SAL method can dynamically learn the placement weight of each word, it can increase the placement weight of more important words to achieve accurate adaptation (at the word level). The proposed method uses sentence structure instead of emotional relevance to extract all aspects. Zheng El [74] aimed to explore the influence of feature selection on opinion analysis in China's online surveys. First, pick the N-char and N-POS as possible emotional characteristics. Use the improved document frequency approach to pick feature subsets and use the logical weighting method to measure the weights of the function. A modern method of automatically classifying user reviews as positive or negative, incorporated into China's online review area. With this approach, traditional POS taggers use sentence structure rather than emotional association to extract all aspects. Moreover, the proposed method is limited to Chinese texts.

3.1.2 Relation-Based Approach

The idea behind this method is to explore the interrelationship between opinion and word aspect. To search and extract rules this method uses grammatical relationships and syntactic patterns between aspect and understanding words. To discover dependencies extracted from annotations, Zhuang et al. [75] uses a dependency analyser. The system performs syntactic analysis and semantic analysis of feature extraction. After syntactic analysis, the connection of the verbal sentence is established through certain dependencies. Aspect sets obtained using this method are too complex, contain a large number of nouns and adjectives, and require some similarity measures to filter out the clipping of related aspects. Wu et al. [76] define as a promising prospect the use of a dependency analyzer to remove the representation of things and action state words. They use concepts as features and propose a feature extraction algorithm based on a new concept analyzer schema to extract semantic features that take advantage of the semantic relationships between words in natural language text. In particular, by allowing emotion to flow from one word to another based on the dependency of the input sentence, you can better understand the contextual role of each word in a statement. While a dependency parser can identify dependencies from a single word, a dependency parser for expression can distinguish between dependencies for expression, so aspect extraction is more accurate.

We have extracted aspects using [77] vector techniques such as money and found similarities between these aspects. New uncontrolled methods have been proposed for significant improvements. They aimed to study the effectiveness of vector representations of ABSA research questions in an attempt to capture ABSA research questions, semantic and emotional information encoded in user-generated content (e.g. product reviews). Rating vectors represent the validity of various text data and the quality of the vectors associated with the domain. Vector representations have been used to compute various vector functions, and extensive experiments have been carried out to prove their effectiveness. In their method, emotional words were observed to be potential candidates for improving the process of analyzing moods, but some implicit opinions and emotions were ignored and not considered.

Qiu et al.[78] uses the double propagation method in which separate interactions exist between words of opinion and aspects, and the same words of opinion and aspects are included in the formulation of laws of extraction. This approach communicates knowledge across the features and emotional vocabulary. A new way of communication that exploits the relation between the emotional language and the functionality of the product. Feature extraction is performed using double propagation. This allows you to highlight several product characteristics in one proposal. However, it turns out that using the parser creates redundant and repetitive aspects that add complexity. Moreover, communication between different aspects obliges a complicated structure like WordNet. Yin et al. [79] proposed an addiction pathway method that can extract related aspects from a large number of aspects. To classify sentiment at the aspect level, a new graph-based attention network (TD-GAT) is proposed that explicitly exploits the relationship between words. Use a dependency graph to convey emotional characteristics directly from the syntactic context of the target aspect. The developed method is based on uncontrolled learning of distributed word representations and dependent paths. The basic idea is to associate the word and its dependency path with inline space. In their method, emotional words were seen as potential candidates for improving the opinion analysis method, but some hidden opinions and emotions were ignored and not considered.

3.1.3 Supervised Approach

Sequence-based approaches infer data structures from the training and apply inferences to untagged information. On a computational point of view, thus, interpretation and its polarity may be viewed as a labeling issue, and trends and syntactic relations are extracted from the labeled data and introduced into the unlabeled data. Hidden Markov Models (HMMs), and Conditional Random Fields (CRFs) are supervised learning methods for aspect extraction. Jin and Ho [80] used the HM lexicalized model to study the mechanisms of feature extraction and expression. Jacob used conditional random fields (CRF) in [81] to train various domain survey sentences for detached domain extraction. However, training uses complex machine learning algorithms, which reduces efficiency.

Wang et al. [82] proposed a Chinese swallow semantic parsing methodology for dimension extraction, and further developed the basic Chinese semantic function annotation model focused on conditional random fields linear classification. This article combines language clues, combining existing linear sequence labeling algorithms, morphology, and other multi-level linguistic clues to reconstruct the Chinese language semantic role labeling model in teaching grammar. Tell me how to build and improve. Linear sequence. However, the proposed method is subject-oriented and works well with developed data. Mutra et al. [83] found that the tone of Twitter messages can provide a rich set of human sentiments. They use supervised learning techniques to identify sentiment in Twitter posts and categorize Twitter messages into four sentiment categories. Class definitions can be very specific. That is, you can train the classifier using full decision bounding methods to accurately differentiate between different classes. In addition, a comparative study of two monitoring methods was carried out. However, unlike unsupervised learning, you cannot discover, cluster, or classify data.

Null et al. [84] proposed aspect-oriented sentiment analysis to find hate in Twitter data. Word embedding is widely used in natural language processing (NLP) applications. This is because their vector representations can capture useful linguistic relationships and semantic attributes between words using deep neural networks. In this model, the relationship between the word embedding function and the aspect can be expressed as a functional expression of the recommendation model. Word2Vec is used to represent words in online learning. POS is used for verbs, adverbs, nouns, and adjectives. The N-gram is used to represent classification features. A text classification usually uses a combination of letters as a function, but only words. However, training usually takes a long time to compute, and classification can also be time consuming, especially if the dataset is very large.

3.1.4 Topic Modeling Approach

Topic modeling is a method of unsupervised research, built to classify topics in textual data. Manuscript includes several subjects, each of which is a probability distribution of words. The two primary models used are pLSA (probabilistic latent weekly analysis) and [85] are LDA (latent assignment to Dirichlet.

The probabilistic model can be applied to previous data. If the data in each category is not balanced, the projections can be poor. In the context of opinion analysis, the topics found in topic models are often referred to as aspects. In this way, topic modeling can be used to extract aspects. It helps to group aspects and encompasses aspects and ideas.

Zhao et al. [86] proposed a method based on maximum entropy and LDA for determining mutually specific understanding words and aspect words. Chen Lin was waiting. [87] We have proposed a Joint Topic Sentiment (JST) model that combines topic and sentiment and focuses on the extraction of point-to-point pairs. Samuel Brody and others. [88] The aspect was discovered using the local LDA model. After checking the aspect, choose an adjective for the word-opinion. Johan Joe et al. [89] focus on automatic aspect recognition. They proposed the Sentence-LDA (SLDA) model, which assumes the verbal aspect of one sentence. The Sentence-LDA has been expanded to the Unified Aspects and Emotions Model (ASUM) to reveal different model opinions. ASUM finds results in the form of aspects and opinions.

Mogh et al. [90] expanded the pLSA model to include potential estimates. Use this combined potential information to extract aspects. LDA and pLSA are important global thematic models [91]. Both models are used for aspect detection in [92]. These models use a set of words representing the document to extract the name of the document. Mukazi et al. [93] proposed two aspects of an extraction model called SAA and ME-SAS. These models represent various aspects of the vocabularies of opinions and emotional terms. Experimental results show that both models produce aspect sets.

Mei et al. [93] used a model to emotionally model the collaborative blog topics. Author in [94] proposed a cluster method for determining aspects based on survey data. Scaffidi et al. [95] Language Modeling Techniques (LMA) were operated to retrive aspects from product reviews. Table 3.1 shows an outline of the above aspect extraction method. Aspect-oriented sentiment analysis is a recent field of study. It's used to determine people's views, emotions, or feelings. Used as a subtask to classify various types of meaning of document. Over the last few years, researchers have been toiling on identifying and extracting minerals. Both supervised and unsupervised machine learning and vocabulary-based methods can be used with various aspect-based sentiment analysis techniques.

3.1.5 Supervised Machine Learning

Supervised approaches are methods of machine learning, which can extract several parameters from data. Vaib et al.[96] utilize supervised machine learning algorithms such as Naves Bayes, Maximum Entropy (ME), and support vector machine for microtext analysis. An incomplete corpus in Natural Language Processing (NLP) makes microtext analysis a daunting task. They applied these techniques to a movie review dataset collected from the IMDB. They were interested in creating an observation model for microtext analysis. This model helps to simplify text and extract important knowledge from unstructured corpora. However, you cannot find unique characteristics for clustering or classifying data. Lamia et al. [97] implemented three conceptual test calculations to discriminate between hypotheses (positive or negative) in the study. The study proposed a sentiment classifier for traveler reviews. It analyzes travelers' reviews of Egypt hotels and categorizes each opinion according to the characteristics of the hotel. We have collected and analyzed traveler sentiment from approximately 5 hotels in Aswan, Egypt, with a total of 11,458 reviews. Sentimental models use three classification methods: support vector machines, decision trees and naive Bayesian, . Then compare the test results to assess the value of your stay. The results show that the naive Bayesian method is extremely accurate. However, training is computationally time consuming and classification is also time consuming, especially if the dataset is very large.

A method of evaluative questionnaires for electronic surveys of patients has been proposed [98]. It also discusses the value of oblique examinations for patients, professionals and healthcare leaders. Applying SVM classifies such texts. Analysis of sentiment provides several advantages, including the usage of patient statistics to achieve the best outcomes and increase the standard of treatment. This article proposes methods and techniques for mood analysis used in the medical field. The author also discusses some of the restrictions imposed. Zhao et al. [99] formalized combinations of the three main types of phrases and carefully designed the corresponding logos. We impose significant restrictions on the Global dimension to reduce the impact of the Global dimension on local distribution. Finally, constraints and associated associations are combined in the LDA to control the distribution of topic words in the learning process. The proposed model can effectively capture the hidden connections in local sentences and further improve the speed of extracting more subtle aspects and words of understanding. An important element of this model is the simultaneous classification of aspects and opinions. However, the proposed model needs to be refined in order to analyze text from various fields and sources. Other types of semi-guided and unsupervised models that impose constraints on the process of creating association rules, such as patient comments, are difficult to collect because they cannot find common ground. Second, when interpreting patient statements, it's difficult to judge and explain the condition of the patient.

Chitov et al. [100] broaden the MG-LDA method and proposed a new method called the Multifaceted Emotional Model (MAS). Suggested model has two parts. The first part contains of the MG-LDA, which sets out the topics that represent the assessed aspects [101]. Other part is a set of mood forecasters for each aspect, aimed at directly linking a specific theme of the model to a specific aspect. This article proposes a combined text and aspect scoring model to extract the text displayed in a summary of opinions. The model uses aspect ratings to find the relevant topic, so you can extract snippets of text describing those aspects without the need for annotation data. However, the proposed technology is domain-specific and will degrade performance at other levels.

3.1.6 Un-Supervised Machine Learning

Methods that do not need to learn parameters are not tracked. None of these technologies can learn from a dataset. Thematic modeling is widely used as a source of mining implementation and association [102, 103]. Two models, pLSA and LDA were presented here. PLSA and LDA calculate a report's semantic thematic distribution by indulging a base term 'line' between 'document' and 'name.' There each set is a replication of odd inert points and each result is the assembly of specific phrases. These models have done a great job, and they show that they help to separate the global perspective from the neighboring perspective. These models provide the best results in key expression extraction and pass. Zhao et al. [104] identified the flanks using vocal markers with maximum entropy. H. Bao et al. [105] deals with overt aspects of emotional phrases. Review each phrase and use emotional phrases in your sentiment analysis. G. Wang et al. [106] proposed an uncontrolled method named weak labeling. You can also calculate negative and positive polarity. For polarity, we used conjunctions and disjunctions.

3.1.7 Lexicon Based Approaches

Dictionary-based approaches contrast with the techniques of machine learning, given that they use dictionaries to evaluate emotions. Tag structures used by Jiang et al. [107] to remove emotional terms from a dataset. They then hired PMI Information Retrieval (PMI-IR) to assess the survey's mood. The tests were carried out on a sports dataset comprising 410 comments and 84% precision was reached by the system. Nasugawa et al. [108] built an relational dictionary of 3,513 terms in it. Two separate repositories, multidomain corpus, and web survey were used. Experimental tests indicate that their technique 's emotional accuracy is 86% and 88% respectively. Chen et al. [107] proposed a new modeling method for performing collaborative modeling. It detects mood from text and uses data mining techniques (comments, blogs, tweets, etc.) to do so. Moore et al. [109] proposed an open quality LibQUAL technology for classifying positive and negative reviews. They applied the planned methods in a review of the Canadian Medium Academic Research Library and produced promising results concerning machine learning algorithms. Benamara et al. [110] also suggested adverb-adjective combination (AAC) technologies for measuring emotions and determining polarity. The foregoing dictionary-based technologies are domain specific and can not be applied to other domains.

Popescu and Etzioni proposed in a review a method for using discriminator relationships to extract aspects of a product [111]. Characteristic relationships occur in categories of aspects and in products. The noun phrases which they obtain also contribute to more evaluations of polarity. A very unusual methodology suggested by Kobayashi et al. [112] is description of presence or feature evaluation. The key aim of this approach is to define facets of a partnership through comments, reviews etc. Retrieve the first pair of aspects through a dictionary quest. Then a special syntax pattern is used to find the appropriate polarity. Zhuang et al. [113] proposed to find the relationship between aspect-point of view pairs based on watching a film about the tasks of mood analysis. Table. 3.3 elaborates the information on aspect-based sentiment analysis.

3.1.8 Critical Analysis

Table 3.2 introduces the limitations and benefits of feature extraction methods. From the above discussion, we can see that different ABSA methods are used in different areas. Each of these four aspects of mining technology has its own strengths and weaknesses. The frequency method is easy and fast, however it lacks low frequency terms. The relationship-based method is effective for selecting infrequent terms, but non-aspectual terms can also be selected. The sequence based method works well for predefined categories, but only works if the training data is correct. Techniques for topic modeling are excellent since they don't require training data, but they don't operate with large datasets as well as skip the right side. Aspect assessment methods also have some advantages and limitations. See Table in ref tbl:Table3.4. The advantages and limitations of aspect-oriented sentiment analysis lead to the following conclusions: Most of the research work is devoted to teaching methods without a teacher and a teacher. Although the supervised learning method is the most commonly used, it requires a priori knowledge, which makes learning very slow. On the other hand, unsupervised technology is much cheaper because it doesn't require training and works well when you don't know the number of classes. Methods based on dictionaries are quick and reliable, but need strong language resources. It may not always be available, only common language dictionaries have been established.

Table 3.1: Aspect Extraction Techniques Summary

References	Model	Domain	Language
Frequency Based Approaches			
[44]	POS	Product Review	English
[45]	OPINE	Product Review	English
[46]	TF-IDF	News	Turkish
[47]	SAL	Product Review	English
[48]	N-char-gram and N-POS-gram	Reviews	Chinese
Relation Based Approaches			
[49]	Dependency Parser	Product Review	English
[50]	Dependency Parser	Reviews	English
[51]	vector-based methods	Product Review	English
[52]	Double propagation	Reviews	English
[53]	Dependency Path	Reviews	English
Sequence based Approaches			
[54]	Lexicalized HMM	Reviews	English
[55]	Conditional Random Fields	Reviews	English
[56]	shallow semantic parsing	Reviews	Chinese
[57]	HMM	Movie Reviews	English
[58]	Bi-Normal Separation	Reviews	English
Topic Modeling based Approaches			
[59]	PLSA and LDA	Reviews	English
[60]	Joint Sentiment Topic	Documents	English
[61]	LDA	Reviews	English
[62]	Joint Topic	Reviews	English
[63]	Sentence LDA	Reviews	English

Table 3.2: Aspect Extraction Techniques Comparison

Aspect Extraction Method	**Strength**	**Limitation**
Frequency-based	simple and Operative.	- Emphasis on recurring words and neglect low-frequency terms. - Required controller preprocessing for tuned data
Relation-based	Operative while discovery less frequent aspect.	While identifying usable aspects, occasionally it may yield non-aspect.
Sequence-based	Astounded frequency and relative based approaches	May demand predefined sets of aspects
Topic Modeling-based	No requisite of training data	Needs large capacity of data. Only catches rough and common aspects

Table 3.3: Aspect Based Sentiment Analysis Methods Summary

Aspect based Sentiment	**Strength**	**Limitation**
Supervised Learning	-Accurate and reliable results. - Regularly used	- Works not healthy when input data is defined and labels are undefined. - Requirement of past knowledge
Unsupervised learning	- Works well on undefined information. - No requisite of prior information.	- Moderate, Precise and Consistent Results. - Slow
Lexicons based approaches	- Fast and consistent. - Precise.	- Needs influential linguistic resources which are not always available.

TABLE 3.4: ABSA Techniques

References	Models	Domain	Language
Supervised Machine Learning			
[71]	NB,ME, and SVM	Product Reviews	English
[72]	Machine Learning	Hotel Reviews	English
[73]	SVM	Patient Reviews	English
[74]	LDA	Product Reviews	English
[75]	MG-LDA	Tweets	English
Un-supervised Machine Learning			
[76]	PLSA	Product reviews	English
[77]	Random latent topics	Product Reviews	English
[78]	POS taggers	Product Reviews	English
[79]	Vector Based	Product Reviews	English
[80]	conjunctions and disjunctions	Movie Reviews	English
Lexicon Based Approaches			
[81]	PMI- Information Retrieval	Product Reviews	English
[82]	Sentiment lexicons	Customer Reviews	English
[83]	LibQUAL	Library Reviews	English
[84]	Discriminator relation	Tweets	English
[85]	Dictionary based	Tweets	English

3.1.9 Outcomes of literature

As we have disused several machine learning models and deep learning for aspect-based sentiment analysis were proposed. However, the findings of these processed models are:

1. Majority of the current methods for assessing polarity are centered on corpora and dictionaries [104]. These methods are not as effective as those based on machine learning. It takes a huge corpus to cover English words, which is challenging. Also, the corpus is handcrafted and may not cover all content. In addition, dictionary technologies may not work if the text content has changed.

2. uses a variety of existing technologies to incorporate emotional words used to evaluate polarity, including positive or negative numbers, deprived of considering the intensity of polarity or ambiguity of emotional words. Divide into two groups [105].

3. The project needs to enhance the accuracy of current polarity estimation methods by employing enhanced methods to a narrower portion of emotions (latent emotions, aspect ratio).

4. Tweets generally do not grasp the rules of English grammar, but you can analyze these tweets to identify specific events that may be new. It is especially difficult to identify the event because it is something new and has never happened before.

3.1.10 Chapter Summary

This chapter deals with the new developments of aspect-oriented study of emotions and case identification. From 2017 to 2020, we explored work conducted in all subfields of aspect-oriented sentiment analysis. Much work has been done in this area, but it is clear that it is still in its infancy based on the latest technology reviews. Obviously, the best aspect compared to the traditional aspect is 70-80% when using aspect-based sentiment analysis. Many machine learning algorithms are used for aspect based sentiment analysis, including supervised and unsupervised learning. The writers have deployed an ABSA semi-guided algorithm. Only over the last decade lexical strategies have become more and more relevant. The biggest downside to utilizing the vocabulary approach is that the vocabulary consists of a small number of words, and vocabulary is also in progress with several of the major languages. The combination of new vocabulary techniques and machine learning capabilities creates algorithms that can take languages and concepts to a whole new level and perform sentiment analysis based on aspects of complex language structures for more information. It also speeds up the aspect-based sentiment analysis process.

Chapter 4

PROPOSED CONCEPTUAL FRAMEWORK

This chapter outlines a theoretical conceptual structure focused on defining factors that contribute to the evaluation and aggregation of polarities. Numerous tools and techniques like Valence Aware Dictionary and Sentiment Reasoner (VADER) Word2vec, Convolutional neural network (CNN) and Genetic algorithms (GA) are used to advance the efficiency and accuracy of the proposed conceptual framework. This chapter provides detailed steps and a graphical representation of each step to help the reader better understand the entire research process.

4.1 Justification of the model.

To tackle the outcomes of literature a solution was needed so, here is a solution to all the deficiencies raised in the previous chapter. It was ensured that the proposed implementation of the methodology would be equal or superior to state-of-the-art techniques as regards polarity estimation and aspect recognition. The proposed methodology has been compared with machine learning approaches for assuring reliability in the space of sentiment analysis.

4.2 Proposed model

The data used in our proposed model is collected through web scrapping using python pursed by its preprocessing. Features are then extracted from the data and supplied to the models for the classification. The semantics features are separated from the specified domain and total scored is determined based on initial features extraction using VADER. After that Word2vec is design to process the given corpus by utilizing unsupervised neural network and at the end vector form of processed corpus is used to train through CNN classifier. Classification is performed and CNN hyperparameters have been tuned using GA to achieve greater simplification of the model. The model suggested for the method of the sentiment analysis is shown in the Fig. 1.2

4.2.1 Data Collection and Dataset Description

In the proposed model, three types of data set (hotel, automobiles, and movies) are used to perform sentiment analysis. Web scraping technique is used for review collection; hotel reviews collected from "https: //webhose.io/ ", automobiles reviews are collected from "https: //www.cvedia.com/" while movie reviews are fetched from " https://seedmelab.org/". The raw view of dataset is shown in Fig. 3. The reviews are splinted into positive and negative categories. This simplifies the task and makes it easier to distinguish various aspects of positive and negative views.

Hotel_Adc	Additional	Review_D	Average_S	Hotel_Nar	Reviewer_Nationality	Negative_Review	Review_Tc	Total_Nun	Positive_Review	Review_Tc	Total_Nun	Reviewer_Scor
s Gravesa	194	8/3/2017	7.7	Hotel Arer	Russia	I am so angry that i made this	397	1403	Only the park outside of the	11	7	2.9
s Gravesa	194	8/3/2017	7.7	Hotel Arer	Ireland	No Negative	0	1403	No real complaints the hotel	105	7	7.5
s Gravesa	194	########	7.7	Hotel Arer	Australia	Rooms are nice but for elderl	42	1403	Location was good and staff	21	9	7.1
s Gravesa	194	########	7.7	Hotel Arer	United Kingdom	My room was dirty and I was	210	1403	Great location in nice surrou	26	1	3.8
s Gravesa	194	########	7.7	Hotel Arer	New Zealand	You When I booked with you	140	1403	Amazing location and buildir	8	3	6.7
s Gravesa	194	########	7.7	Hotel Arer	Poland	Backyard of the hotel is total	17	1403	Good restaurant with moder	20	1	6.7
s Gravesa	194	########	7.7	Hotel Arer	United Kingdom	Cleaner did not change our sł	33	1403	The room is spacious and bri	18	6	4.6
s Gravesa	194	########	7.7	Hotel Arer	United Kingdom	Apart from the price for the b	11	1403	Good location Set in a lovely	19	1	10
s Gravesa	194	7/9/2017	7.7	Hotel Arer	Belgium	Even though the pictures sho	34	1403	No Positive	0	3	6.5
s Gravesa	194	7/8/2017	7.7	Hotel Arer	Norway	The aircondition makes so mu	15	1403	The room was big enough ar	50	1	7.9
s Gravesa	194	7/7/2017	7.7	Hotel Arer	United Kingdom	Nothing all great	5	1403	Rooms were stunningly decc	101	2	10
s Gravesa	194	7/6/2017	7.7	Hotel Arer	France	6 30 AM started big noise wo	75	1403	Style location rooms	4	12	5.8
s Gravesa	194	7/6/2017	7.7	Hotel Arer	United Kingdom	The floor in my room was filfy	28	1403	Comfy bed good location	6	7	4.6
s Gravesa	194	7/4/2017	7.7	Hotel Arer	Italy	No Negative	0	1403	This hotel is being renovated	59	6	9.2
s Gravesa	194	7/4/2017	7.7	Hotel Arer	Canada	The staff in the restaurant co	35	1403	It was very good very histori	15	1	8.8
s Gravesa	194	7/3/2017	7.7	Hotel Arer	Italy	No Negative	0	1403	This hotel is awesome I took	82	26	10
s Gravesa	194	7/3/2017	7.7	Hotel Arer	United Kingdom	Very steep steps in room up t	38	1403	Great onsite cafe Amazing bu	14	8	6.3

FIGURE 4.1: Unprocessed reviews

4.2.2 Data preprocessing

Preprocessing of data is being used to convert raw data into a valuable and usable format. In this step, raw data is transformed into structural, information data. . Empty rows, empty cells may present in the data collected through scrappy, panda library is used to clean the data and keep the useful data only as shown in Fig. 4.2. Data preprocessing is important in data mining because it directly impacts the success rate of the project. Data is considered to be impure if the attribute, attribute values is missing or it contain anomalies or outliers and null or incorrect information. The existence of any of these would harm the credibility of the results.

4.2.3 Feature Extraction

Words are converted into feature vectors in the first layer of the network to extract the semantics and morphological information about words V words represent word vocabulary V^{char} represent character vocabulary. Given sentence contain n words (w1, w2, w3 ....wn) And changing Wn (every word) into vector, according to Eq. 4.1.

$$Vn = \{r^{word}, r^{wchar}\} \tag{4.1}$$

While r^{word} words is word level embedding and r^{wchar} is character level embedding. It is intended to capture semantic and syntactic word-level embedding of information, while embedding at the character-level is anticipated to capture type and morphological information.

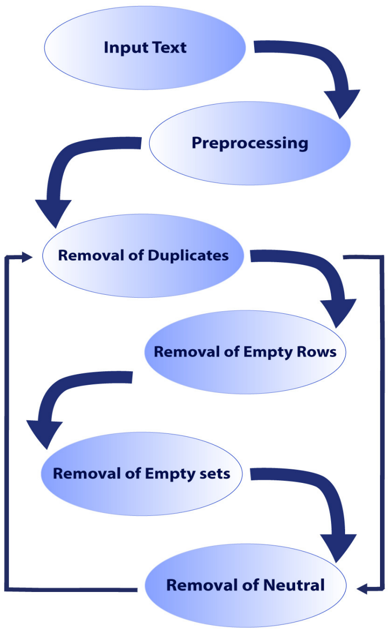

FIGURE 4.2: Preprocessing Steps

4.2.4 Word level embedding

The embedding of the word level is encrypted into the embedding matrix $W^{word} \in R^{dword} * V^{word}$ utilizing column vectors. The embedding of the word level coincides with the individual column $Wi^{word}$and R^{dword},by which i^{th} is produced. Word W is term level embedded by matrix vector product, as seen in Eq. 4.2.

$$R^{word} = V^{w} W^{word} \tag{4.2}$$

Where V^{w} represents the dimension of the-word vector. In index W have a value of 1 0 in their places. W^{word} matrix is a parameter for learning and dword is embedding word level size. In this paper, word level embedding is performed by word2vec.

4.2.5 Character level embedding

All words used essential methods of extracting type and morphological information from the words and thought these words identified important characteristics of the classification stage. For example, sentiment analysis of Twitter data uses various hashtags to display important information, such as # ihateit, and various adverb information, ending with a suffix, such as angry. Convolution generates local blur around the words around each character and connects them for character-level embedding using the max operation. The specified word is a composition of m characters.

$\{k_1, \quad k_2, \ldots, k_m\}$ every character km is converted in to an embedded character $V_m^{|char|}$, according to Eq. 4.3. Embedding metrics have embedded character encoded in column vectors. $W^{char} \varepsilon \left|v^{char}\right|$. Each character k

$$\mathrm{R}^{char} = \mathrm{v}^{\mathrm{k}} \mathrm{W}^{char} \tag{4.3}$$

V^k represent the size of $\left|v^{char}\right|$. v^k have value 1 and index at number 0 at other position. $\left\{r_1^{char}, r_2^{char} \ldots \ldots \ldots \ldots r_n^{char}\right\}$ is convolutional layer input. The convolutional apply matrix vector operation on every character k^{char} from the list of characters. $\mathrm{x}^{\mathrm{m}} \varepsilon \mathrm{r}^{char} \mathrm{R}^{dchar}$ as in Eq. 4.4. That is the embedding character contain its left neighbor $(r^{char} - 1)/2$ and right neighbors $(r^{char} - 1)/2$

$$X^n = \left(k_{n-(rchar-1)/2}^{char}\right)/2 \cdots k_{n+(rchar-1)/2}^{char}\Big)^{\mathrm{T}} \tag{4.4}$$

According to Eq. 4.5, the vector k^{char} has J^{th} element determined in the CNN via convolution layer which is the w which is the embedding character stage.

$$\left[\mathrm{K}^{wchar}\right]_{\mathrm{j}} = \max_{1<\mathrm{n}<\mathrm{N}} \left[\mathrm{W}^0 \mathrm{X}_{\mathrm{n}} + \mathrm{a}^0\right]_{\mathrm{j}} \tag{4.5}$$

Later, local characteristics are extracted using the same matrix around each window character in the given term.

4.2.6 Analysis at Sentence Level

A sentence y contains m words $\{w^1, w^2, \ldots w^n\}$ which are then changed to word level joints and embedding level characters $\{v^1, v^2, \ldots v^n\}$ Next stage consists of phrase level extraction representation while extracting phrase level characteristics we may have following problems.

1. Distinct size of sentence.
2. The sentence may hold significant information = at any position.

These problems are solved by using CNN to calculate the remaining feature vectors of wide sentences. If used for abstraction of a character-level function, CNN still operates along lines. Using the max operation to create a fixed-size feature vector for the sentence, create local features for each word, and then connect. According to Eq. 4.6,Matrix vector operation performed on each word in the sequence

$\{u^1, u^2, \ldots u^n\}$

$$X_n = \{u_c \ldots u_d\} \tag{4.6}$$

where the $c = n - \frac{u^{nod}-1}{2}, d = n + \frac{u^{nod}-1}{2}.$ convolutional layer computed the j th element whom vector $r^{st} \in R^{c^{1/4}}$ as in Eq. 4.7.

$$\left[r^{st}\right]_j = 1 < m < M \max\left[w^1_{x_m} + a^1\right]_j \tag{4.7}$$

$where \quad w^1 \in R^{c^1_u} \times \left(d^{\text{word}} + c^0_u\right) k^{word}$. At last r^{st}_x vector that contain feature vector global comparative with x sentence is handled through two layers of neural network. To extricate one or more representation level and every sentimental level t ε T score is then calculated, according to Eq. 4.8.

$$S(x) = w^3 h\left(w^2 r^{st}_x + a^2\right) a^3 \tag{4.8}$$

Where learning parameter is given by $w^2 \varepsilon R^{hu*c1u}$ and vectors are given by $w^3 \varepsilon R^{|T|*Hu}$

4.2.7 Negative Training

The system is trained over a training set $A,$ to limit the negative probability. A sentence is passed to the system contain parameter set θ and each sentiment label is computing $\tau\varepsilon$ T. These scores are converted into giving the label with conditional probability distribution plus network parameter set θ and then softmax operation is applied over $\tau\varepsilon$ T score, as in Eq. 4.9.

$$P(\tau|x, \theta) = \frac{e^{S_\theta(x)_i}}{\sum_{\forall i \in T} e^{S_\theta(x)_i}} \tag{4.9}$$

The stochastic gradient descent is applied to limit the negative log gradient as in Eq. 4.10.

$$\theta \longrightarrow \sum_{(u,v) \in A} -\log P(v|x, \theta) \tag{4.10}$$

(U , v) is a term related to corpus instruction, and V promotes the corresponding label.

4.2.8 Put the model into work

We use the reviews of different datasets. for example taking a review from hotel dataset "Room were nice but the breakfast were not good for elderly". This text is

Algorithm 1 classification of reviews upon testing

```
procedure INPUT DATA – DATASET OF MOVIE REVIEWS, HOTEL REVIEWS AND AUTOMOBILES REVIEWS(a, b)
    System Initialization
    Read the value
    while test data exist do
        The negative and positive content of each comment is explained using Vader
        Evaluation of features extracted from reviews (service, cleanliness, cost, location, car, bad, etc.)
        Summary of each feature ratings is calculated → Σ
        Compare each functional level summary with the original threshold → Δ
        if summation is greater than threshold then
            positive tag will be labeled to the review
        else
            Negative tag will be labeled to the review and disregard neutral labels
        end if
    end while
    Combination of preprocessed dataset and list of feature vectors
    Word level embedding
    input to CNN
    make pattern
    while GA optimization do
        if Optimized value satisfied then
            Max-Soft learner
        else
            go to make pattern
        end if
    end while
    Classification using ensembler
    Sentiment prediction
    Statistical analysis
end procedure
```

splitted on the basis of positive and negative part. At first the pre-processing will be performed. The preprocessing will extract the nouns, adverbs, verb, adjective etc from the review. Then the text will be cleaned by removing punctuation, stops words, words with numbers, lemmatize the text, text with one letter and then combine them all for further process. We then use Vader lexicon for feature extraction. The features extracted from the above mentioned review are *room*, *nice*, *breakfast*. Furthermore, we add some simple text like number characters and word in text/review. After feature extraction, the review text is then converted to binary using word2vec. Same texts would have identical representations as well and this is why we may use such vectors as training functions. We have to train a Doc2Vec model first by feeding the data in our text. Through adding this model to our comments we are able to get certain vectors of representation. The data is then assigned to classifier for training and identifying the aspects. Our proposed ensembler performs better in finding the aspects from reviews document. The whole scenerio is shown in Fig. 4.3.

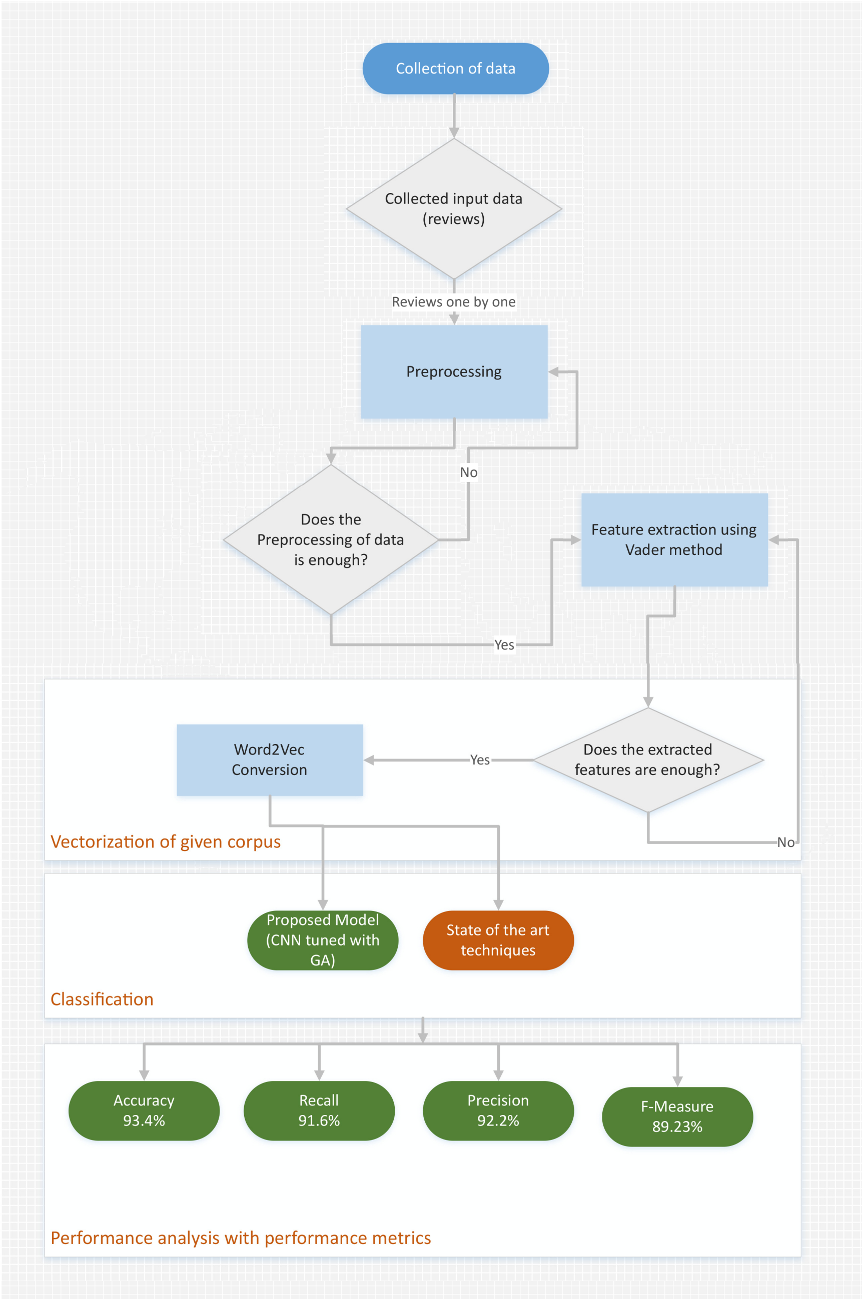

FIGURE 4.3: Scenario of our work

4.2.9 Chapter Summary

This chapter discusses shortcomings associated with existing models and introduces a model offering both sentiment identification and polarity estimation. The working of the model is examined along with its application in sentiment analysis. It is also justifiable that the proposed model is distinct from others. The suggested model has the potential to perform polarity accumulation.

Chapter 5

Simulation results

It is observed in experimental observations that the extraction of semantic features produces exceptionally refined data. Information gathered by examining the particular domain reviews decreases the false negative and false positive rates that produce better accuracy. Table 5.4 demonstrates the contrast of the precision ,

TABLE 5.1: Detailed results on Automobiles Dataset

Parameters	**SVM**	**DecTree**	**LDA**	**LinMod**	**RF**	**LogReg**	**Proposed**
Accuracy	85.5	67	65	78.5	83	80	93
95% CI	(0.84, 0.87)	(0.65, 0.68)	(0.64, 0.66)	(0.75, 0.80)	(0.82, 0.85)	(0.78, 0.82)	(0.90, 0.95)
Information rate	0.6	0.62	0.6257	0.635	0.624	0.625	0.629
P0-value	2.20E-16	2.20E-16	2.20E-16	2.20E-16	2.20E-16	2.20E-16	2.20E-16
Kappa	0.7112	0.6828	0.4429	0.637	0.6712	0.7179	0.7321
Mcnemar's	0.4107	0.002628	0.00992	0.7273	0.0953	0.0013	0.5203
Pos Pred value	82.8	70.6	84.8	74	80.8	85.6	88.4

accuracy and recall of different classifiers such as SVM, maximum entropy, random forest, stable discriminant regression, generalized linear model and decision tree. CNN has been found to produce significant improvement of 91.6% , 93.4% , 92.2% , 89.23% in precision, accuracy, recall and f1 measure, respectively.

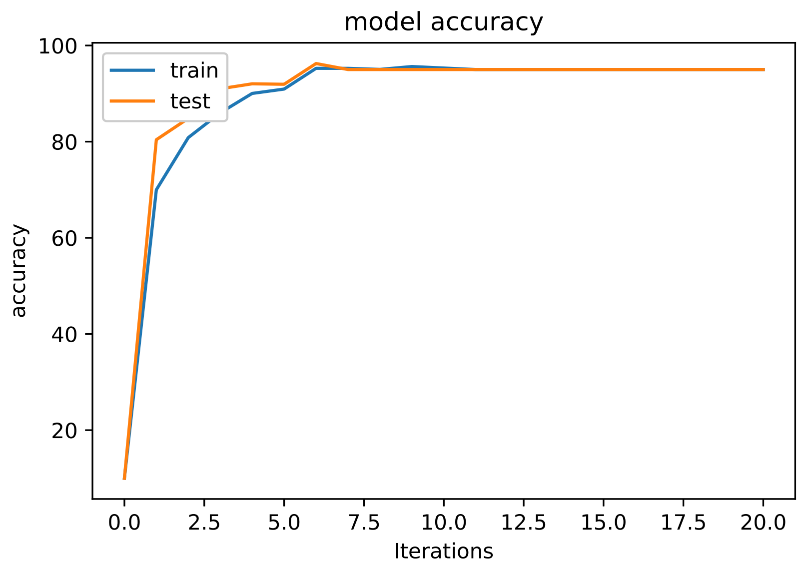

FIGURE 5.1: Accuracy vs iterations

The proposed method was contrasted with the SVM, resulting in high precision rate and f-score value for both positive and negative marks, as seen in Table 5.2. The exactness and rate of failure of the proposed process as seen in Fig. 5.1 and Fig. 5.2. The graph shows that the percentage of precision increases as the number of training iterations and evaluations increases, and as the number of iterations reduces, the percentage of error declines.

Fig. 5.3 graphically illustrates the performance of the integrated method on a hotel dataset. The accuracy of ensemble approach for hotel datasets is higher than the

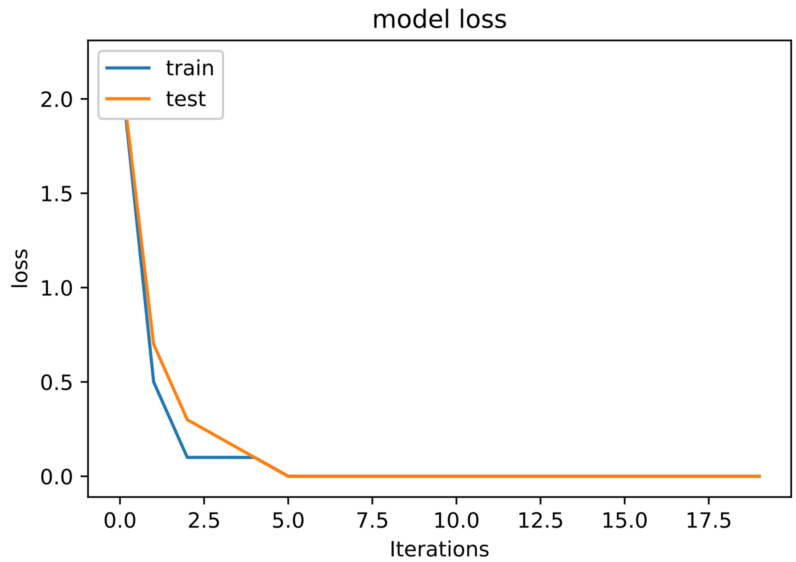

FIGURE 5.2: Loss vs iterations

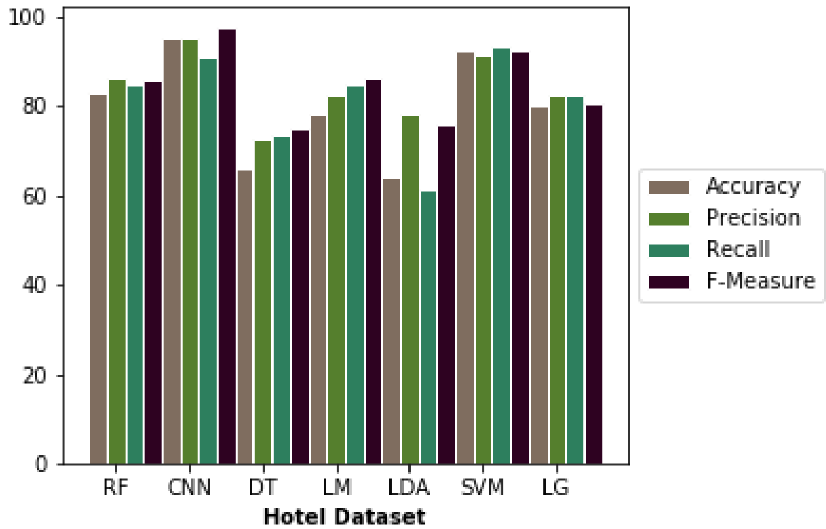

FIGURE 5.3: Performance on hotel dataset

comparison techniques. The ultimate effect of the CNN-GA hybrid model is better than other state-of-the-art approaches, shown in Table. 5.2.

The efficiency of the optimized solution for hotel data is clearly seen in Table 5.2. Compared with the prior art, the proposed method has the highest precision, accuracy, f-measure and recall. The performance of integrated method is 4% better than SVM, 23% better than decision trees, 17% better than LDA, and 10% better than RF, and 12% better than LG.

Table 5.2: Performance Analysis on Hotel Dataset

Models	Precision	Accuracy	Recall	Fmeasure
Proposed	95.5	94.3	91	96.6
DT	72.71	67.0	74.52	75.44
SVM	91.5	92.3	90.2	92.34
LDA	78.53	65.0	62.43	76.75
LM	82.36	78.5	84.85	86.10
RF	86.3	83.0	84.8	85.69
LG	82.36	80.5	82.85	81.10

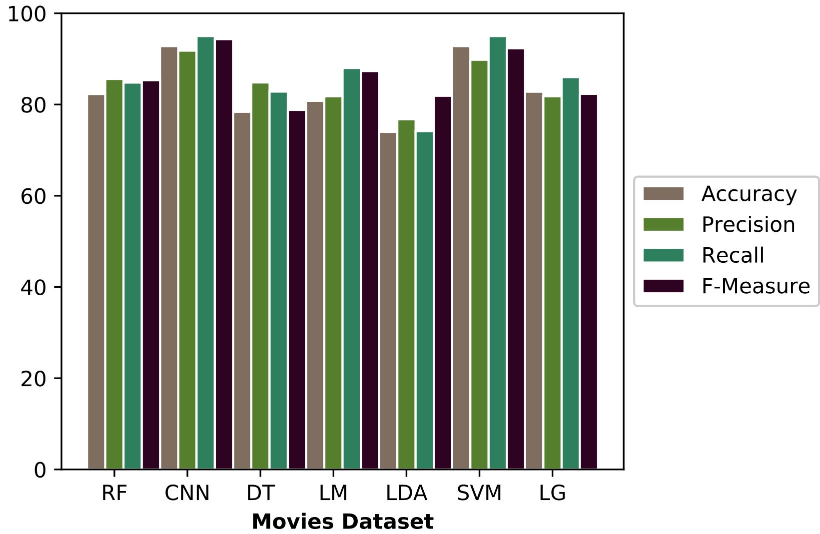

Figure 5.4: Performance on movies dataset

Fig. 5.5 graphically illustrates the performance of the integrated method on automobiles dataset. Table 5.4 clearly demonstrates the performance of the suggested method for automobile data. Evaluated with the prior art, the proposed method has the highest recall, precision, f-metric and accuracy. The performance of the integrated method is 6% better than SVM, 21% better than decision trees, 15% better than LDA, and 11% better than RF, and 10% better than LG.

The movie review dataset is used as the standard benchmark dataset for IMDB. In Fig. 5.4, it can be observed that the outcomes of the integrated method (GA with CNN) are much better than the benchmark algorithm (RF, DT, LM, LDA, SVM, and LG). GA based integrated methods provide superior performance in terms of accuracy, precision, recall, and f measurements. The results are shown graphically in Fig. 5.4 and in tabular in Table 5.3. In Table 5.3, from an accuracy perspective, the performance of the integrated method is 2% better than SVM and 6% better than RF. The accuracy of the integrated method is 91.5%, while

TABLE 5.3: Performance evaluation on Movies Dataset

Models	Precision	Accuracy	Recall	Fmeasure
Proposed	91.5	95.2	92.3	94.0
DT	75	79	85	82
SVM	89.4	92.5	88.8	90.3
LDA	89	80	75	85
LM	87	86	88	90
RF	90.8	87.5	84.8	88.0
LG	87	88	86	85

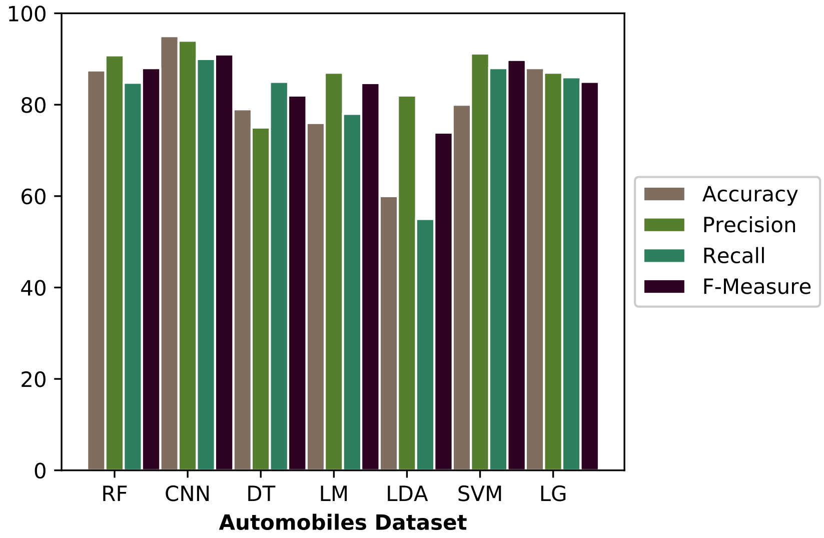

FIGURE 5.5: Performance on Automobiles Dataset

the accuracy of RF and SVM is 90.8% and 89.4%. In addition, the performance of integrated approach is significantly better to other existing technologies in recall and f-measure.

TABLE 5.4: Performance Evaluation on Automobiles Dataset

Models	Precision	Accuracy	Recall	Fmeasure
Proposed	91.6%	93.4%	92.2%	89.23%
DT	70%	70.6%	81.20%	77.59%
SVM	85.8%	84.8%	89.9%	87.33%
LDA	76.75%	74.0%	74.15%	81.90%
LM	81.8%	80.8%	88%	87.33%
RF	82.3%	85.6%	84.8%	85.33%
LG	81.8%	82.8%	86%	82.33%

Fig. 5.5 presents the performance effects of the new vehicle data-sets systems and integration processes. The proposed method has excellent performance on

automobiles dataset in terms of precision, accuracy, f-measure and recall. The findings are further listed in the Table5.4. Table 5.5 shows the performance index

Table 5.5: Comparison of proposed model with SVM model

Parameters	Proposed Model	SVM
Labels	2	2
Data points	200	200
Accuracy	88.4	84.8
Label	NEG	NEG
F-score	89.23% TP: 185 FP: 6 TN: 9 FN: 0	87.69% TP: 168 FP: 4 TN: 23 FN: 5
Label	POS	POS
F-score	78% TP: 185 FP: 6 TN: 9 FN: 0	64% TP: 166 FP: 6 TN: 25 FN: 3

values in percentage format, showing that the proposed method performs well with all metrics as compared to SVM. Table 5.6 shows the detailed results for the different iteration levels and the different iterations for accuracy, loss, progress, and Base Learning Rate. For different parameters, we compare the outcomes of

Table 5.6: Performance Evaluation w.r.t iterations on Movie and Hotel Datasets

Iteration	loss	Accuracy	Time Elapsed	Base Learning Rate
0	9.5881	38.91%	1s 1ms	1.00E-04
1	0.4045	80.78%	0s 703us	1.00E-04
2	0.0755	92.34%	0s 586us	1.00E-04
3	0.0833	92.34%	0s 622us	1.00E-04
4	0.0851	91.56%	0s 563us	1.00E-04
5	0.0692	92.19%	0s 547us	1.00E-04
6	0.0702	92.03%	0s 531us	1.00E-04
7	0.0662	92.34%	0s 531us	1.00E-04
8	0.0654	92.03%	0s 531us	1.00E-04
9	0.0657	92.19%	0s 539us	1.00E-04
10	0.0649	92.19%	0s 531us	1.00E-04

the recommended classifier with all six other classifiers in Table 5.1 and conclude that the proposed approach outperforms nearly all the provided classifiers for all test parameters. It can therefore be concluded that the recommended approach is 93.0% more accurate than all six comparator classifiers. The result comparison table supports the Ensemble methods given.The findings of the analysis clearly demonstrate that the proposed method produces improved performance in terms of accuracy, precision and f-measurement. SVM has the best accuracy on such datasets which are based on positive and negative scores based on experimental settings.

Chapter 6

Conclusion and future work

6.1 Conclusion

This article presents an effective classification method for sentiment analysis using Convolutional neural network and Genetic Algorithm. Semantic characteristics are mined and then, along with the proposed CNN-based ensembler, SVM, maximum entropy, random forest, stable discriminant analysis , decision tree, generalized linear model, multiple models are training. Using data collected through CNN execution and analysis, domain-specific reviews reduce false positives and false positives and improve accuracy. To achieve optimal values, we adjust the CNN hyperparameters using a genetic algorithm. The experimental findings show that the proposed approach beats all other recent approaches, with 95.5%,94.3 %, 91.1%,*and*96.6 %, respectively, for precision , accuracy, recall and f-measurement.Future strategies are to integrate parallel computing to speed up computation and explore metaheuristic-related features. A preferred work is to have a web-based ontology framework automation to incorporate sentiment analysis on social sites.

6.2 Future work

We will examine the efficiency of our proposed scheme in aspect-based multilabeling subject matter in the future. In addition, case studies of the text of multilabeling articles would be highly beneficial to test the efficiency of the same technique.

Chapter 7

References

[1] Kumar, Ravindra, Husanbir Singh Pannu, and Avleen Kaur Malhi. "Aspect-based sentiment analysis using deep networks and stochastic optimization." Neural Computing and Applications (2019): 1-15

[2] Cambria, Erik, et al. "Sentiment analysis is a big suitcase." IEEE Intelligent Systems 32.6 (2017): 74-80

[3] Al-Smadi, Mohammad, et al. "Human annotated arabic dataset of book reviews for aspect based sentiment analysis." 2015 3rd International Conference on Future Internet of Things and Cloud. IEEE, 2015.

[4] Al-Moslmi T, Omar N, Abdullah S, Albared M (2017) Approaches to cross-domain sentiment analysis: a systematic literature review. IEEE Access 5:16173–16192

[5] Jianqiang Z, Xiaolin G (2017) Comparison research on text preprocessing methods on twitter sentiment analysis. IEEE Access 5:2870–2879.

[6] Wei W, Gulla JA (2010) Sentiment learning on product reviews via sentiment ontology tree. In: Proceedings of the 48th annual meeting of the association for computational linguistics. Association for Computational Linguistics, pp 404–413.

[7] Karagoz, P., Kama, B., Ozturk, M., Toroslu, I. H., & Canturk, D. (2019). A framework for aspect based sentiment analysis on turkish informal texts. Journal of Intelligent Information Systems, 53(3), 431-451.

[8] Khan, J., Alam, A., Hussain, J., & Lee, Y. K. (2019). EnSWF: effective features extraction and selection in conjunction with ensemble learning methods for document sentiment classification. Applied Intelligence, 49(8), 3123-3145.

[9] Abdi, A., Shamsuddin, S. M., Hasan, S., & Piran, J. (2019). Deep learning-based sentiment classification of evaluative text based on Multi-feature fusion. Information Processing and Management, 56(4), 1245-1259.

[10] S. Rezaeinia, R. Rahmani, A. Ghodsi, and H. Veisi, "Sentiment analysis based on improved pre-trained word embeddings", Expert Systems with Applications, Vol.117, No.44, pp.139-147, 2019.

[11] Souma, W., Vodenska, I., & Aoyama, H. Enhanced news sentiment analysis using deep learning methods. Journal of Computational Social Science, 1–14 (2019).

[12] Rezaeinia, S. M., Rahmani, R., Ghodsi, A., & Veisi, H. Sentiment analysis based on improved pre-trained word embeddings. Expert Systems with Applications, 117, 139–147 (2019).

[13] Tang, D., & Zhang, M. Deep Learning in Sentiment Analysis. In Deep Learning in Natural Language Processing (pp. 219–253). Springer (2018).

[14] Rani, S., & Kumar, P. Deep Learning Based Sentiment Analysis Using Convolution Neural Network. Arabian Journal for Science and Engineering, 1–10 (2018).

[15] Heikal, M., Torki, M., & El-Makky, N. Sentiment Analysis of Arabic Tweets using Deep Learning. Procedia Computer Science, 142, 114– 122 (2018).

[16] Li, L., Goh, T. -T., & Jin, D. How textual quality of online reviews affect classification performance: a case of deep learning sentiment analysis. Neural Computing and Applications, 1–29 (2018).

[17] Alharbi, A. S. M., & de Doncker, E. Twitter sentiment analysis with adeep neural network: An enhanced approach using user behavioral information. Cognitive Systems Research, 54, 50–61 (2019).

[18] W. Huang, G. Rao, Z. Feng, and Q. Cong, ”LSTM with sentence representations for Document-level Sentiment Classification”, Neurocomputing, Vol.308, No.45, pp.49-57, 2018.

[19] M. Fikri and R. Sarno, “A Comparative Study of Sentiment Analysis using SVM and SentiWordNet”, Indonesian Journal of Electrical Engineering and Computer Science, Vol.13, No.3, pp.902-909, 2019].

[20] Priyantina, R. A., & Sarno, R. (2019). Sentiment Analysis of Hotel Reviews Using Latent Dirichlet Allocation, Semantic Similarity and LSTM. International Journal of Intelligent Engineering and Systems, 12(4), 142-155.

[21] Shuang, K., Yang, Q., Loo, J., Li, R., & Gu, M. (2020). Feature distillation network for aspect-based sentiment analysis. Information Fusion.

[22] Meškelė, D., & Frasincar, F. (2020). ALDONAr: A hybrid solution for sentence-level aspect-based sentiment analysis using a lexicalized domain ontology and a regularized neural attention model. Information Processing & Management, 57(3), 102211.

[23] Liu, N., & Shen, B. (2020). Aspect-based sentiment analysis with gated alternate neural network. Knowledge-Based Systems, 188, 105010.

[24] Chauhan, G. S., & Meena, Y. K. (2020). DomSent: Domain-Specific Aspect Term Extraction in Aspect-Based Sentiment Analysis. In Smart Systems and IoT: Innovations in Computing (pp. 103-109). Springer, Singapore.

[25] Koupaei, D. M., Song, T., Cetin, K. S., & Im, J. (2020). An assessment of opinions and perceptions of smart thermostats using aspect-based sentiment analysis of online reviews. Building and Environment, 170, 106603.

[26] Mowlaei, M. E., Abadeh, M. S., & Keshavarz, H. (2020). Aspect-based sentiment analysis using adaptive aspect-based lexicons. Expert Systems with Applications, 148, 113234.

[27] Ren, F., Feng, L., Xiao, D., Cai, M., & Cheng, S. (2020). DNet: A lightweight and efficient model for aspect based sentiment analysis. Expert Systems with Applications, 113393.

[28] Tan, X., Cai, Y., Xu, J., Leung, H. F., Chen, W., & Li, Q. (2020). Improving aspect-based sentiment analysis via aligning aspect embedding. Neurocomputing, 383, 336-347.

[29] Liu, N., & Shen, B. (2020). ReMemNN: A novel memory neural network for powerful interaction in aspect-based sentiment analysis. Neurocomputing.

[30] Yang, C., Zhang, H., Jiang, B., & Li, K. (2019). Aspect-based sentiment analysis with alternating coattention networks. Information Processing & Management, 56(3), 463-478.

[31] Al-Smadi, M., Al-Ayyoub, M., Jararweh, Y., & Qawasmeh, O. (2019). Enhancing aspect-based sentiment analysis of Arabic hotels' reviews using morphological, syntactic and semantic features. Information Processing & Management, 56(2), 308-319.

[32] Chauhan, G. S., Agrawal, P., & Meena, Y. K. (2019). Aspect-based sentiment analysis of students' feedback to improve teaching–learning process. In Information and Communication Technology for Intelligent Systems (pp. 259-266). Springer, Singapore.

[33] Liu, N., Shen, B., Zhang, Z., Zhang, Z., & Mi, K. (2019). Attention-based Sentiment Reasoner for aspect-based sentiment analysis. Human-centric Computing and Information Sciences, 9(1), 35.

[34] Tang, F., Fu, L., Yao, B., & Xu, W. (2019). Aspect based fine-grained sentiment analysis for online reviews. Information Sciences, 488, 190-204.

[35] Alqaryouti, O., Siyam, N., Monem, A. A., & Shaalan, K. (2019). Aspect-based sentiment analysis using smart government review data. Applied Computing and Informatics.

[36] Shuang, K., Yang, Q., Loo, J., Li, R., & Gu, M. (2020). Feature distillation network for aspect-based sentiment analysis. Information Fusion.

[37] Meškelė, D., & Frasincar, F. (2020). ALDONAr: A hybrid solution for sentence-level aspect-based sentiment analysis using a lexicalized domain ontology and a regularized neural attention model. Information Processing & Management, 57(3), 102211.

[38] García-Pablos, A., Cuadros, M., & Rigau, G. (2018). W2VLDA: almost unsupervised system for aspect based sentiment analysis. Expert Systems with Applications, 91, 127-137.

[39] Zainuddin, N., Selamat, A., & Ibrahim, R. (2018). Hybrid sentiment classification on twitter aspect-based sentiment analysis. Applied Intelligence, 48(5), 1218-1232.

[40] Ma, Y., Peng, H., Khan, T., Cambria, E., & Hussain, A. (2018). Sentic LSTM: a hybrid network for targeted aspect-based sentiment analysis. Cognitive Computation, 10(4), 639-650.

[41] Pham, D. H., & Le, A. C. (2018). Learning multiple layers of knowledge representation for aspect based sentiment analysis. Data & Knowledge Engineering, 114, 26-39.

[42] Amplayo, R. K., Lee, S., & Song, M. (2018). Incorporating product description to sentiment topic models for improved aspect-based sentiment analysis. Information Sciences, 454, 200-215.

[43] Mai, L., & Le, B. (2018, March). Aspect-based sentiment analysis of vietnamese texts with deep learning. In Asian Conference on Intelligent Information and Database Systems (pp. 149-158). Springer, Cham.

[44] de Kok, S., Punt, L., van den Puttelaar, R., Ranta, K., Schouten, K., & Frasincar, F. (2018). aggregated aspect-based sentiment analysis with ontology features. Progress in Artificial Intelligence, 7(4), 295-306.

[45] Rahman, M., & Kumar Dey, E. (2018). Datasets for aspect-based sentiment analysis in bangla and its baseline evaluation. Data, 3(2), 15.

[46] Weismayer, C., Pezenka, I., & Gan, C. H. K. (2018). Aspect-based sentiment detection: Comparing human versus automated classifications of TripAdvisor reviews. In Information and Communication Technologies in Tourism 2018 (pp. 365-380). Springer, Cham.

[47] Peng, H., Ma, Y., Li, Y., & Cambria, E. (2018). Learning multi-grained aspect target sequence for Chinese sentiment analysis. Knowledge-Based Systems, 148, 167-176.

[48] Rathan, M., Hulipalled, V. R., Venugopal, K. R., & Patnaik, L. M. (2018). Consumer insight mining: Aspect based Twitter opinion mining of mobile phone reviews. Applied Soft Computing, 68, 765-773.

[49] Sabeeh, A., & Dewang, R. K. (2018, July). Comparison, classification and survey of aspect based sentiment analysis. In International Conference on Advanced Informatics for Computing Research (pp. 612-629). Springer, Singapore.

[50] Schouten, K., & Frasincar, F. (2018, June). Ontology-driven sentiment analysis of product and service aspects. In European Semantic Web Conference (pp. 608-623). Springer, Cham.

[51] Álvarez-López, T., Fernández-Gavilanes, M., Costa-Montenegro, E., & Bellot, P. (2018, June). A proposal for book oriented aspect based sentiment analysis: Comparison over domains. In International Conference on Applications of Natural Language to Information Systems (pp. 3-14). Springer, Cham.

[52] Marcacini, R. M., Rossi, R. G., Matsuno, I. P., & Rezende, S. O. (2018). Cross-domain aspect extraction for sentiment analysis: A transductive learning approach. Decision Support Systems, 114, 70-80.

[53] Moreno-Garcia, J., & Rosado, J. (2018, June). Using syntactic analysis to enhance aspect based sentiment analysis. In International Conference on Information Processing and Management of Uncertainty in Knowledge-Based Systems (pp. 671-682). Springer, Cham.

[54] Kumar, Ashok, and S. Abirami. "Aspect-based opinion ranking framework for product reviews using a Spearman's rank correlation coefficient method." Information Sciences 460 (2018): 23-41.

[55] Wu, S., Xu, Y., Wu, F., Yuan, Z., Huang, Y., & Li, X. (2019). Aspect-based sentiment analysis via fusing multiple sources of textual knowledge. Knowledge-Based Systems, 183, 104868.

[56] Do, H. H., Prasad, P. W. C., Maag, A., & Alsadoon, A. (2019). Deep learning for aspect-based sentiment analysis: a comparative review. Expert Systems with Applications, 118, 272-299.

[57] Liu, N., & Shen, B. (2020). Aspect-based sentiment analysis with gated alternate neural network. Knowledge-Based Systems, 188, 105010.

[58] Wallaart, O., & Frasincar, F. (2019, June). A hybrid approach for aspect-based sentiment analysis using a lexicalized domain ontology and attentional neural models. In European Semantic Web Conference (pp. 363-378). Springer, Cham.

[59] LI, L., ZHOU, A., LIU, Y., QIAN, S., & GENG, H. (2019). Aspect-based sentiment analysis based on dynamic attention GRU. Scientia Sinica Informationis, 49(8), 1019-1030.

[60] Gupta, C., Jain, A., & Joshi, N. (2019). A Novel Approach to feature hierarchy in Aspect Based Sentiment Analysis using OWA operator. In Proceedings of 2nd International Conference on Communication, Computing and Networking (pp. 661-667). Springer, Singapore.

[61] Tran, T., Ba, H., & Huynh, V. N. (2019, March). Measuring Hotel Review Sentiment: An Aspect-Based Sentiment Analysis Approach. In International Symposium on Integrated Uncertainty in Knowledge Modelling and Decision Making (pp. 393-405). Springer, Cham.

[62] Chauhan, G. S.,& Meena, Y. K. (2019). YouTube Video Ranking by Aspect-Based Sentiment Analysis on User Feedback. In Soft Computing and Signal Processing (pp. 63-71). Springer, Singapore.

[63] Soh, C., Yu, S., Narayanan, A., Duraisamy, S., & Chen, L. (2019). Employee profiling via aspect-based sentiment and network for insider threats detection. Expert Systems with Applications, 135, 351-361.

[64] Ma, R., Wang, K., Qiu, T., Sangaiah, A. K., Lin, D., & Liaqat, H. B. (2019). Feature-based compositing memory networks for aspect-based sentiment classification in social internet of things. Future Generation Computer Systems, 92, 879-888.

[65] Areed, S., Alqaryouti, O., Siyam, B., & Shaalan, K. (2020). Aspect-Based Sentiment Analysis for Arabic Government Reviews. In Recent Advances in NLP: The Case of Arabic Language (pp. 143-162). Springer, Cham.

[66] García-Díaz, J. A., Cánovas-García, M., & Valencia-García, R. (2020). Ontology-driven aspect-based sentiment analysis classification: An infodemiological case study regarding infectious diseases in Latin America. Future Generation Computer Systems.

[67] Ahmed, M., Chen, Q., Wang, Y., & Li, Z. (2019, August). Hint-embedding attention-based LSTM for aspect identification sentiment analysis. In Pacific Rim International Conference on Artificial Intelligence (pp. 569-581). Springer, Cham.

[68] Ikram, M. T., & Afzal, M. T. (2019). Aspect based citation sentiment analysis using linguistic patterns for better comprehension of scientific knowledge. Scientometrics, 119(1), 73-95.

[69] Zeng, D., Dai, Y., Li, F., Wang, J., & Sangaiah, A. K. (2019). Aspect based sentiment analysis by a linguistically regularized CNN with gated mechanism. Journal of Intelligent & Fuzzy Systems, 36(5), 3971-3980.

[70] Demir, S., Alkan, O., Cekinel, F., & Karagoz, P. (2019). Extracting Potentially High Profit Product Feature Groups by Using High Utility Pattern Mining and Aspect Based Sentiment Analysis. In High-Utility Pattern Mining (pp. 233-260). Springer, Cham.

[71] Truşcă, M. M., Wassenberg, D., Frasincar, F., & Dekker, R. (2020, June). A Hybrid Approach for Aspect-Based Sentiment Analysis Using Deep Contextual Word Embeddings and Hierarchical Attention. In International Conference on Web Engineering (pp. 365-380). Springer, Cham.

[72] Mohan, I., & Moorthi, M. (2020). Topic flexible aspect based sentiment analysis using minimum spanning tree with Cuckoo search. Journal of Ambient Intelligence and Humanized Computing, 1-8.

[73] Zhuang, L., Schouten, K., & Frasincar, F. (2020). SOBA: Semi-automated Ontology Builder for Aspect-based sentiment analysis. Journal of Web Semantics, 60, 100544.

[74] Shahid, S., Singhal, S., Mahata, D., Kumaraguru, P., & Shah, R. R. (2020). Aspect-Based Sentiment Analysis of Financial Headlines and Microblogs. In Deep Learning-Based Approaches for Sentiment Analysis (pp. 111-137). Springer, Singapore.

[75] Liu, G., Huang, X., Liu, X., & Yang, A. (2020). A novel aspect-based sentiment analysis network model based on multilingual hierarchy in online social network. The Computer Journal, 63(3), 410-424.

[76] Xu, Q., Zhu, L., Dai, T., & Yan, C. (2020). Aspect-based sentiment classification with multi-attention network. Neurocomputing, 388, 135-143.

[77] Lv, Y., Wei, F., Zheng, Y., Wang, C., Wan, C., & Wang, C. (2020). A span-based model for aspect terms extraction and aspect sentiment classification. Neural Computing and Applications, 1-11.

[78] Habimana, O., Li, Y., Li, R., Gu, X., & Yu, G. (2020). Sentiment analysis using deep learning approaches: an overview. Science China Information Sciences, 63(1), 1-36.

[79] Da'u, A., Salim, N., Rabiu, I., & Osman, A. (2020). Recommendation system exploiting aspect-based opinion mining with deep learning method. Information Sciences, 512, 1279-1292.

[80] Da'u, A., Salim, N., Rabiu, I., & Osman, A. (2020). Weighted aspect-based opinion mining using deep learning for recommender system. Expert Systems with Applications, 140, 112871.

[81] Kirilenko, A. P., Stepchenkova, S. O., Kim, H., & Li, X. (2018). Automated sentiment analysis in tourism: Comparison of approaches. Journal of Travel Research, 57(8), 1012-1025.

[82] Arif, M. H., Li, J., Iqbal, M., & Liu, K. (2018). Sentiment analysis and spam detection in short informal text using learning classifier systems. Soft Computing, 22(21), 7281-7291.

[83] Qiu, J., Liu, C., Li, Y., & Lin, Z. (2018). Leveraging sentiment analysis at the aspects level to predict ratings of reviews. Information Sciences, 451, 295-309.

[84] Lee, G., Jeong, J., Seo, S., Kim, C., & Kang, P. (2018). Sentiment classification with word localization based on weakly supervised learning with a convolutional neural network. Knowledge-Based Systems, 152, 70-82.

[85] Alayba, A. M., Palade, V., England, M., & Iqbal, R. (2018, August). A combined CNN and LSTM model for arabic sentiment analysis. In International Cross-Domain Conference for Machine Learning and Knowledge Extraction (pp. 179-191). Springer, Cham.

[86] Valdivia, A., Luzón, M. V., Cambria, E., & Herrera, F. (2018). Consensus vote models for detecting and filtering neutrality in sentiment analysis. Information Fusion, 44, 126-135.

[87] Chaturvedi, I., Cambria, E., Welsch, R. E., & Herrera, F. (2018). Distinguishing between facts and opinions for sentiment analysis: Survey and challenges. Information Fusion, 44, 65-77.

[88] Chen, J., Yan, S., & Wong, K. C. (2018). Verbal aggression detection on Twitter comments: Convolutional neural network for short-text sentiment analysis. Neural Computing and Applications, 1-10.

[89] Alqaryouti, O., Siyam, N., & Shaalan, K. (2018, September). A sentiment analysis lexical resource and dataset for government smart apps domain. In International Conference on Advanced Intelligent Systems and Informatics (pp. 230-240). Springer, Cham.

[90] Jabreel, M., Hassan, F., & Moreno, A. (2018). Target-dependent sentiment analysis of tweets using bidirectional gated recurrent neural networks. In Advances in hybridization of intelligent methods (pp. 39-55). Springer, Cham.

[91] Ma, X., Zeng, J., Peng, L., Fortino, G., & Zhang, Y. (2019). Modeling multi-aspects within one opinionated sentence simultaneously for aspect-level sentiment analysis. Future Generation Computer Systems, 93, 304-311.

[92] Onan, A. (2019, August). Deep learning based sentiment analysis on product reviews on Twitter. In International Conference on Big Data Innovations and Applications (pp. 80-91). Springer, Cham.

[93] Wang, Y., Sun, A., Huang, M., & Zhu, X. (2019, May). Aspect-level sentiment analysis using as-capsules. In The World Wide Web Conference (pp. 2033-2044).

[94] Mostafa, L. (2020, April). Machine Learning-Based Sentiment Analysis for Analyzing the Travelers Reviews on Egyptian Hotels. In Joint European-US Workshop on Applications of Invariance in Computer Vision (pp. 405-413). Springer, Cham.

[95] Fernando, J., Khodra, M. L., & Septiandri, A. A. (2019, September). Aspect and Opinion Terms Extraction Using Double Embeddings and Attention Mechanism for Indonesian Hotel Reviews. In 2019 International Conference of Advanced Informatics: Concepts, Theory and Applications (ICAICTA) (pp. 1-6). IEEE.

[96] Rietzler, A., Stabinger, S., Opitz, P., & Engl, S. (2019). Adapt or get left behind: Domain adaptation through bert language model finetuning for aspect-target sentiment classification. arXiv preprint arXiv:1908.11860

[97] Rana, T. A., & Cheah, Y. N. (2019). Sequential patterns rule-based approach for opinion target extraction from customer reviews. Journal of Information Science, 45(5), 643-655.

[98] Tang, J., Lu, Z., Su, J., Ge, Y., Song, L., Sun, L., & Luo, J. (2019). Progressive self-supervised attention learning for aspect-level sentiment analysis. arXiv preprint arXiv:1906.01213.

[99] Abdi, A., Shamsuddin, S. M., Hasan, S., & Piran, J. (2019). Deep learning-based sentiment classification of evaluative text based on Multi-feature fusion. Information Processing & Management, 56(4), 1245-1259.

[100] Luo, H., Li, T., Liu, B., & Zhang, J. (2019). DOER: Dual cross-shared RNN for aspect term-polarity co-extraction. arXiv preprint arXiv:1906.01794.

[101] Song, M., Park, H., & Shin, K. S. (2019). Attention-based long short-term memory network using sentiment lexicon embedding for aspect-level sentiment analysis in Korean. Information Processing & Management, 56(3), 637-653.

[102] Bouras, D., Amroune, M., Bendjenna, H., & Azizi, N. (2020). Techniques and trends for fine-grained opinion mining and sentiment analysis: Recent survey. Recent Advances in Computer Science and Communications (Formerly: Recent Patents on Computer Science), 13(2), 215-227.

[103] Chakriswaran, P., Vincent, D. R., Srinivasan, K., Sharma, V., Chang, C. Y., & Reina, D. G. (2019). Emotion AI-Driven Sentiment Analysis: A Survey, Future Research Directions, and Open Issues. Applied Sciences, 9(24), 5462.

[104] Augustyniak, Ł., Kajdanowicz, T., & Kazienko, P. (2019). Comprehensive Analysis of Aspect Term Extraction Methods using Various Text Embeddings. arXiv preprint arXiv:1909.04917

[105] Khotimah, D. A. K., & Sarno, R. (2019). Sentiment Analysis of Hotel Aspect Using Probabilistic Latent Semantic Analysis, Word Embedding and LSTM. International Journal of Intelligent Engineering and Systems, 12(4), 275-290.

[106] Gan, C., Wang, L., Zhang, Z., & Wang, Z. (2020). Sparse attention based separable dilated convolutional neural network for targeted sentiment analysis. Knowledge-Based Systems, 188, 104827.

[107] Pergola, G., Gui, L., & He, Y. (2019). TDAM: A topic-dependent attention model for sentiment analysis. Information Processing & Management, 56(6), 102084.

[108] Hu, M., Peng, Y., Huang, Z., Li, D., & Lv, Y. (2019). Open-domain targeted sentiment analysis via span-based extraction and classification. arXiv preprint arXiv:1906.03820.

[109] Hu, M., Peng, Y., Huang, Z., Li, D., & Lv, Y. (2019). Open-domain targeted sentiment analysis via span-based extraction and classification. arXiv preprint arXiv:1906.03820.

[110] Truong, Q. T., & Lauw, H. W. (2019, July). VistaNet: visual aspect attention network for multimodal sentiment analysis. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 33, pp. 305-312).

[111] Chen, F., & Huang, Y. (2019). Knowledge-enhanced neural networks for sentiment analysis of Chinese reviews. Neurocomputing,

[112] Lu, Q., Zhu, Z., Zhang, D., Wu, W., & Guo, Q. (2020). Interactive rule attention network for aspect-level sentiment analysis. IEEE Access, 8, 52505-52516.

[113] Tang, J., Lu, Z., Su, J., Ge, Y., Song, L., Sun, L., & Luo, J. (2019). Progressive self-supervised attention learning for aspect-level sentiment analysis. arXiv preprint arXiv:1906.01213.