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ABSC-HMLT: Aspect Based Sentiment Classification Using Hybrid Machine Learning Techniques

Mr. Ganesh N. Jorvekar[1] Dr. Tripti Arjariya[2] Prof. (Dr.) Mohit Gangwar[3]

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Abstract: Methodologies such as Aspect Based Sentiment Classification make use of a series of texts as input in order to assess interactions pertaining to a certain object. These texts may include comments posted on social media platforms or product evaluations. Illustrations of entities include a product like a mobile phone and remarks about an entity like a restaurant. Another illustration of an entity is a restaurant. The systems look for the traits and attributes of the entity (restaurant) that are cited the most frequently, such as "service" and "food," and then attempt to determine the sentiment associated with those qualities. A number of previous technologies, for example, presented the aspect based sentiment analysis as a collection of separate subprojects, such as the aspect extraction subproblem and the sentiment assessment subtask. The purpose of this paper is to introduce a framework for an aspect-based sentiment classification as well as recommender systems. This approach will not only recognise the aspects in a highly efficient manner, but it will also be capable of performing classification tasks with a high level of accuracy using traditional machine learning techniques such as Random Forest (RF), Naive Bayes (NB), Decision Tree, Support Vector Machine (SVM), Artificial Neural Network (ANN) algorithms, and Hybrid Machine learning technique. The performance of the framework was assessed through tests on real time datasets. The framework assists tourists in finding the best venue, hotel, and restaurant in a region. It is observed from the experimental findings that the performance accuracy of proposed hybrid machine learning technique is better as compared to conventional machine learning classifier.

Keywords: *Aspect Based Sentiment Classification, Sentiment Analysis, Machine Learning.*

1. Introduction

The role that a social media play in the dissemination of information about everything and anything within a fraction of a second is a crucial one in the modern world [16]. Because of this, regular people started engaging and interacting with one other on social media. The figures from the year 2020 revealed a jaw-dropping amount of 600 million twitter posts in a single year, which can be expressed as 8,000 tweets every second, so defining Twitter as a dynamic media network. People are open about their thoughts and feelings, and this might take the form of reviews of goods or services, among other things, which can eventually lead to a massive quantity of data being stored on the internet. It is possible to mine a great deal of hidden information from this unorganized digital data using a technique called Sentiment Analysis (SA). The influence of word-of-mouth advertising has been equalised by customer feedback in such a manner that the same thing drives the buying choice of lakhs of clients regionally all over the globe. A single paragraph of writing can have a direct and immediate effect on the mindset of a potential customer. It is completely foolish to consider the idea of manually processing each review comment that was posted by a large number of customers. When it comes to analysing the pattern that lies beneath any given purchasing behaviour, SA is the ideal answer that can be depended upon. Within the realm of Natural Language Processing (NLP), among the research subfields that are expanding at a rapid rate is called Sentiment Analysis.

The method of extracting attitudes and views from a textual document with the assistance of NLP and categorizing those extracted attitudes and opinions on the premise of polarity, such as favourable, unfavourable, or neutral, is referred to as SA. SA is not a single problem, as is the case with the majority of the research fields in NLP; rather, it is a collection of difficulties. The analysis of sentiment can be performed on a document on a variety of different levels, including the sentence level, the aspect level, and the overall document level.

Aspect based sentiment classification (ABSC), is a fine-grain degree of SA job that seeks to determine the sentiment of multiple parts of an entity based on the textual data associated with that item [17, 18, 19, 20]. An item is a single, easily recognisable thing or scenario in

[1]*Ph.D. Research Scholar, Department of Computer Science and Engineering, Bhabha University, Bhopal, Madhya Pradesh, India*
[2]*Head, Department of Computer Science and Engineering, Bhabha University, Bhopal, Madhya Pradesh, India*
[3]*Director (Alumni Cell), B. N. College of Engineering and Technology, Lucknow*
[3]*mohitgangwar@gmail.com*

SA. Entities can also be situations. It might be a person, a location, a movie, or even a product. It might be anything. The entity could be defined in the text information using a variety of distinct sets of words, also known as features that provide details about the entities; these characteristics are referred to as "aspects" of the entity that they correspond to [21, 23]. The entity might be described in more detail by referring to a number of its qualities, along with a number of corroborating words or even phrases that express feelings regarding those aspects. ABSA makes an effort to locate the pertinent aspects that detail the entity in addition to their supporting words, and then assesses the polarity or emotion of those aspects.

Aspect-based sentiment classification can be utilized to construct meaning of all customer feedback, such as recognising particular aspects that customers like or dislike about the brand, obtaining useful, granular-level perspectives from consumer feedback, analysing service or product testimonials to explore the failures and successes of their product, and make comparisons to those of their competitor's, monitoring how customer emotion changes towards specific attributes and features of a good or service, and monitoring how customer emotion changes towards particular attributes and features of a products and services [27, 28].

Consider the statement about a guitar: "This instrument looks so wonderful, but the audio quality is indeed not up to the expectation." The term "instrument" is the subject of this analysis, and the "look" and "audio quality" are the two characteristics that should be taken into account. An ABSC for a statement of this type needs to tag a favourable feeling for the quality of the 'look' aspect, but an unfavourable sentiment for the 'audio quality' side.

In a manner analogous to that of the general SA, the ABSA employs a multiple stage analysis. A great number of strategies and methods have already demonstrated their effectiveness in completing sequences of tasks [22, 24]. The ABSC workflow begins with the pre-processing of the text data, which involves removing any terms that are not pertinent to the analysis. During the phase known as "pre-processing," the data that has been provided should be converted into an appropriate format so that it may be further handled for the particular activity. In SA, the data will be put through a series of processing operations, like as tokenization, elimination of stop word, negation processing, and so on, in order to have it cleaned up and changed to a format that is more appropriate. Tokenization refers to the act of breaking down text content into a number of distinct units known as tokens. The construction of vectors and the removal of words from the text that are not needed can both benefit from tokenization.

Negation handling is a vital step in the pre-processing stage because, if it isn't done correctly, the real polarity direction of the text will be inverted compared to the result. Because they do not contribute anything to the meaning of the textual material, special characters, punctuation that stands independently, and number tokens are eliminated. Following the completion of tokenization is the process of stemming, which searches the textual data for the real base word of each of the given words. This is a highly important consideration in SA when machine learning is being used, once the pre-processing step of word embedding has been completed. Word embedding refers to the process of translating the token of phrases into a format that is compatible with vectors. Although they sound extremely similar to one another, words like "aircraft" and "aeroplane" have entirely different connotations. Word embeddings are utilised in order to ensure that a machine is capable of comprehending the nuanced differences in meaning. This is accomplished by converting the text into some other dimension. In addition to that, these vectors will be input into a machine learning algorithm in order to extract aspects and feelings. In the third stage, comparable aspects of the item from the texts are recognised, and then the relevant words that describe the sentiment of the detected aspects are discovered. This process is repeated until all of the relevant aspects have been identified. In the final step, an accurate identification of the sentiment orientation of words carrying an emotion is carried out.

In addition, the job of the ABSC can be broken up into two parts: the aspect category SA part and the aspect term SA part. The aspect category SA represents a level of separation of aspects that is on a more coarse-grained scale, whilst the later one represents a level of separation of aspects that is on a more fine-grained scale. Aspects like as music, dance, and so forth are examples of the SA category. On the other side, instances of the aspect word SA include things like drums, hip-hop movement, and other such things. The adaptability of ABSC is considered to be one of its primary advantages. The text document can be simply analysed using ABSC, and the analysis can be perform the best at a fine-grained level [25, 26].

The effort of manually analysing large amounts of text is a laborious one because it is nearly difficult to do it on a fine-grained level and yet in a limited amount of time. This makes the task particularly challenging. Also, ABSC will be evaluating certain aspects of texts such as reviews and comments, among other things, so that businesses and individuals will be able to zero in on those specific aspects of their item or service about which customers are expressing dissatisfaction or offering suggestions for improvement. Because of this, the relevant businesses or individuals will be able to save a significant amount of time as well as money. Because ABSC is included in SA, there is not a single issue that needs to be resolved. ABSC provides results that are both more comprehensive and accurate compared to document level and phrase level sentiment analysis. The discovery of features, the determination of the words that support those aspects, and the categorization of the feelings associated with those specific aspects are the three primary responsibilities of ABSC [18, 19, 21]. The application of methods that are based on machine learning has made the process of text analysis in ABSA both simple and time-effective nowadays. ML approaches like as SVM, CNN, and LSTM, amongst others, have been applied in a number of studies for the purpose of ABSA. A framework for an aspect-based sentiment classification recommender system is presented in this paper. This structure will not only recognise the aspects in a very effective way, but it will also be capable of performing classification tasks with a high level of accuracy utilising machine learning techniques.

The study field of aspect-based sentiment classification has seen a lot of activity in recent years, and it has a wide range of potential applications. There is still a significant problem with accuracy, which has a negative impact on the categorization of reviews and ratings. Using a methodology that combines hybrid machine learning with aspect-based sentiment analysis, the suggested strategy enhances the effectiveness of aspect-based sentiment analysis. The structure of paper is fragmented into several sections. Related work of various methods of aspect based sentiment classification using machine and deep learning techniques is described in section II. In section III, proposed research methodology of ABSC using hybrid machine learning technique is described in detail. In Section IV, experimental findings and discussion is described in detail. Finally, Section V, conclude the proposed methodology.

2. Literature Survey

The objective of the study by M. N. H. Hridoy et al. [1] is to determine the emotion of Bangla news stories depending on the aspect. Individuals in every region of the globe would prefer to go through the headlines of newspapers first so that they can prepare their brains with a synopsis of the content of the news rather than focusing on the actual news article. There is a possibility that this influence will be good, negative, or neutral. There are numerous different ways to get to the bottom of what each person is really thinking. Aspect-based sentiment evaluation has been applied to the current situation. Furthermore, for this investigation in Logistic Regression (LR), Multinomial and Bernoulli Naive Bayes, Voting Classifier, SVM, RF, MLP Classifier, and SGD Classifier, the tiny training classification models data-set was used. In the trial, Bernoulli Naive Bayes performed was implemented far better, achieving the highest F1 score possible of 70.75.

By creating the multi-aspect attention (MAA) paradigm and combining it with the BiLSTM neural network, which is referred as MAA-BLSTM neural network, W. L. Kay Khine et al. [2] hope to be able to forecast the sentiment score of every individual aspect in the evaluation into one of three categories. The BiLSTM network, in contrast to unidirectional LSTM, processes the input in both directions, namely forward and backward. As a result, the BiLSTM network is able to comprehend the context more thoroughly than LSTM. The hyperparameter tuning strategy is regarded as another high-performing model within the scope of this particular research study. Tests are run on data taken from restaurants and laptops that were included in SemEval (2014, 2015, and 2016) datasets, and the results are compared to those obtained by alternative LSTM-based algorithms. In conclusion, the study's findings demonstrate that the suggested sentiment model achieves an accuracy of 89.9% on the eatery dataset and 82.1% also on laptop dataset, both of which are superior to existing LSTM methods' levels of performance.

According to V. Yadav et al. [3] recently, the popularity of shopping online has been rapidly growing because of the ability it provides to purchase products from everywhere, at any moment, and also due to the ease with which one can easily compare the features of different products based on the reviews of previous buyers. The process of assessing the feelings and opinions expressed by customers in reviews of a product is known as sentiment analysis. When this study is carried out on a more in-depth level, it will be possible to define the customers' attitude of every product function. The area of aspect-based sentiment analysis is concerned with assessing and classifying the opinions that are stated on a variety of characteristics that are included in these opinions in order to provide suggestions that are definitive. In the product reviews that can be found on Indian e-commerce sites, an effort was made to uncover a variety of texts written in Indian. The purpose of this paper is to investigate the development and study of the ABSA prototype on Hindi feedback in order to evaluate the entire interpretation of the Hindi text that was entered. Specifically, the goal is to grade each paragraph according to whether it is fractious, favourable, neutral, or negative.

An overview of the newly proposed solutions to the challenge of aspect-based sentiment analysis may be found in H. Liu et al. [4]. There are now three primary methods that are considered to be mainstream: lexicon-based methods, conventional machine learning techniques, and deep learning techniques. An in-depth analysis of the most recent developments in the field of deep learning is presented in the following survey article. Introduced here are a number of widely employed benchmark data sets, evaluation measures, and the effectiveness of the many deep learning approaches that are currently in use. In conclusion, the existing challenges as well as some potential avenues for future research are given and explored.

J. Wang et al. [5] provide a summary and an analysis of the recent accomplishments that ABSA has made in the deployment of various deep learning models in regards of their comprehensiveness, accuracy, and level of detail. In addition to this, it provides a summary of the obstacles and difficulties that ABSA is currently facing and looks ahead to the future growth and enhancement of ABSA utilizing the knowledge it currently possesses.

AWARE is a benchmark dataset that consists of 11323 app reviews that have been tagged with aspect phrases, categories, and sentiment. This dataset was introduced by N. Alturaief et al. [6]. The reviews were gathered from three different categories: games, networking sites, and efficiency. Content analysis was used to develop the aspect categories for each area, and domain experts were consulted to validate the categories in regards to importance, thoroughness, overlap, and granular level. Annotations of several aspect types and sentiment polarity were done using crowdsourcing, and quality check processes were carried out. The aspect words were tagged using a completely autonomous Natural Language Processing (NLP) technique, and the results were confirmed by annotators; as a consequence, the aspect terms were right 98% of the time. In the end, machine learning benchmarks are constructed for three activities: I aspect word extraction through the use of a POS tagger; (ii) aspect category categorization; and (iii) aspect sentiment classification through the use of both Support Vector Machine (SVM) and Multi-layer Perceptron classification methods. Each of these tasks is performed separately.

S. Datta and colleagues [7] make the discovery that there is a possibility of improving the knowledge-driven ABSA in terms of its efficiency and effectiveness. Building a comprehensive evaluation on various machine learning techniques applied to movie data is one approach that may be used to address these issues. The primary objective of this study is to analyze the results of the sentiment analysis performed on movie datasets in order to carry out comparative research using classifiers such as K-Nearest neighbour, DT, SVM, NB and Neural Network (NN). In this kind of research, the categorization accuracy can be enhanced by retrieving the significant characteristics and aspects from their respective contexts. As a part of the pre-processing step, the input video data is subjected to having stop words removed, having punctuation removed, having lower case conversions conducted, and having stemming performed. During the aspect extraction phase, the opinion words are gathered, and then the aspects are retrieved by calculating the polarity value and the word2vectorThe various machine learning techniques, such as KNN, Decision Tree, Naive Bayes, SVM, and NN, take the feature extraction as their input. The findings of the experiments and an in-depth analysis of how each of the five ways can produce better focus towards improving performance are presented.

A. Nazir et al. [8] emphasised on the problems and difficulties that are associated to the extraction of various aspects and their relating emotions, relational linear interpolation among aspects, interconnections, interdependences, and contextual-semantic interaction between two data items for enhanced sentiment accuracy, and forecasting of sentiment evolution versatility. These problems and difficulties are linked to the retrieval of various aspects and their appropriate sentiments. An exhaustive review of recent developments is presented in the form of a summary that is organised according to whether or not they contributed to bringing attention to and finding solutions for the problem of aspect extraction, aspect sentiment classification, or sentiment development. In addition to this, the reported performance of each investigated research of Aspect Retrieval and Aspect Sentiment Analysis is presented as a means of demonstrating the quantitative assessment of the proposed method. In this paper, we propose and analyse future research paths by doing a critical analysis of the recent solutions that were presented. These recent solutions will be beneficial to researchers and will be valuable for enhancing sentiment categorization at the aspect-level.

The article by P. P. Shelke et al. [9] offers a variety of strategies for predicting both aspects and sentiments. It has been determined that IMAN has an accuracy of 83.59 on Restaurant. Increases in precision, accuracy, recall, and F1 calculation are seen in observations made with the CNN-GA Hybrid model. In conclusion, research potential were found in feature- or aspect-based sentiment analysis.

Latent Dirichlet Allocation (LDA) is utilised for the purpose of feature extraction by H. Samy et al. [10], and the class connection rule Apriori algorithm is utilised for the purpose of aspect-based sentiment analysis. The method outperformed established machine learning algorithms such as naive bayes and SVM by achieving an average accuracy of 5.68% and 7.58% after being implemented to a dataset consisting of Angry Birds game app reviews.

N. Dehbozorgi et al. [11] developed a model with the purpose of determining whether or not there is a correlation between the emotions gleaned from the speech of students working in groups and their overall performance. The findings of the polarity sentiment investigation shows a significant and positive association between the good feelings that students had for their groups and their personal levels of success in the class. This research goes one step further by analysing the emotional content of the students' group discussions across multiple classes. The procedure is broken down into two stages: 1) separating out the various categories of feelings, such as happiness, frustration, and anxiety, and determining the degree to which they are correlated with students' performance through the use of cooperative speech in a first-year training program (CS1); 2) performing an aspect-based analysis of emotional states. The supervised machine learning technique and rule-based frameworks on voice datasets are the approaches that have been selected for implementation. After performing some preliminary processing on the text, various categories of emotions were uncovered. The Part of Speech (POS) tagging is what enables aspect retrieval, and trends are then recovered from the aspects that have been detected. In the end, the K-Nearest Neighbor (KNN) algorithm was trained using the mixture of emotion categories and aspect patterns as feature vectors to forecast students' achievement.

Using a lexicon-enhanced long short-term memory (bidirectional LSTM), Z. Ren et al. [12] proposed a lexicon-enhanced attention network (LEAN). LEAN not only identifies the words that convey an emotion but also focuses on the data that pertains to particular aspects of a sentence. In addition, making use of the knowledge included in lexicons increases the adaptability and resiliency of the model. The findings of the tests done on the SemEval 2014 dataset revealed that the model obtains a performance that is considered to be state-of-the-art when it comes to aspect-level sentiment categorization.

Deep learning as well as machine learning approaches were integrated in Y. Zhang et al. [13] 's construction of a sentiment model analysis that was based on the ideas of ensemble learning. In addition, the developed framework is used to perform a sentiment classification for customer reviews about restaurants. Restaurant reviews are an example of an application that is user-oriented and location-based, both of which are common in 5G networks. To be more specific, a multi-aspect-labeling framework is designed, and an ensemble aspect-based model that is derived from the idea of ensemble learning is suggested. Both of these models are designed to anticipate the consumer's genuine feelings regarding their usage and their eagerness to consume the product again, as well as to enhance machine learning model on the basis that was developed. The algorithm's predicted performance can only be evaluated inside a single domain at a time.

J. A. Wahid et al. [14] established a hybrid text conceptual approach in order to carry out aspect-level research on public emotions. The methodology is comprised of three layers: first, the elements from the data were derived and grouped by making use of the of the well-known LDA topic modelling; second, the sentiments were derived and the dataset was termed by making use of the linguistic inquiry and word count (LIWC) lexicon; and finally, in the third layer of the approach, the aspects were modelled into sentiments, and the sentiments were again categorised using well-known machine learning classification algorithms. Experiments with real datasets give favourable outcomes when compared to current aspect-oriented sentiment analytical techniques, and the technique with different variants of classifiers performs better than current methods with maximum F1 scores of 91%. Experiments involving real datasets give favourable results when compared to existing aspect-oriented sentiment analysis approaches.

An aspect-level sentiment analytical framework that was built on XLNet-LCF was proposed by D. Ma et al.[15]. The model acquires contextual semantic information in a bidirectional manner by way of XLNet pre-training. Additionally, the model represents a context focus method to encapsulate the local context of the framework with the aspect word as the emphasis, which could also efficaciously minimize the impact of various aspects. The multi-head self-attention technique was coupled with deeply extracting the semantic elements in the global context to develop an emotional weight matrix in order to address the issue of inter - connection among emotionally charged words. In the end, the matrix was normalised so that the training speed could be increased, and then it was input into the emotional analysis layer so that the emotional polarity could be determined. The model is validated by using the Laptop dataset, the Cafe dataset, and the Twitter dataset. According to the findings, the actual quality of the XLNet-LFC model is superior to that of the comparison model. The prediction accuracy of the XLNet-LFC model's sentiment classification reach 80.1%, 85.2%, and 81.3%, while the F1 values reach 76.6%, 77%, and 7.14%.

3. Research Methodology

The following architecture depicted in figure 1 provides a high-level summary of the proposed methodology for the classification and recognition of aspects. In the first step of the process, reviews written by tourists regarding tourist destinations such as hotels and restaurants are gathered from a wide range of social media platforms and blogs. At the second step, noise and redundancy are removed, and the reviews that have been cleaned are rewritten as sentences. In the third step, employing a hybrid approach to the identification of aspects, aspects are extracted from preprocessed datasets. Step 4 involves the application of machine learning techniques, which are then used to categorise the identified features as having either a positive or negative attitude.

Data Collection: During this step, reviews are gathered from many major social media sites by employing a crawler and various application programming interfaces (APIs). The datasets each contain a varied number of reviews in their respective categories. There are a total of 2000 reviews pertaining to restaurants, with 1000 being favourable and 1000 being negative. There are a total of 4000 reviews available, with just 2000 being good and the remaining 2000 being negative. In this particular case study, the city of Mumbai will serve as the focus of attention.

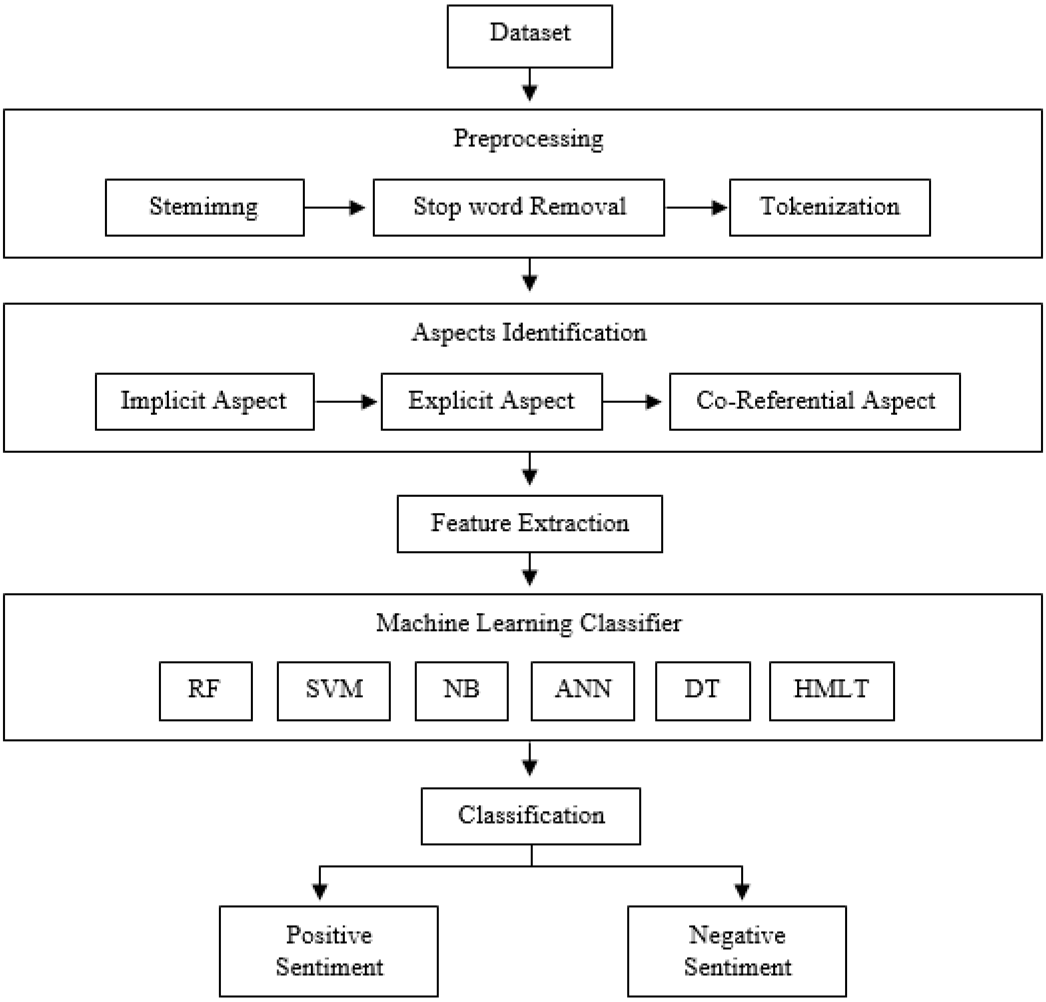

Fig. 1: Proposed ABSC-HML framework

Data Preprocessing - Data pre-processing makes possible sentence-level aspect-based classification by removing repetition and ambiguity that are inherent in the data, as well as transforming the comments into sentences. First, phrases are retrieved by locating the delimiters within each sentence (e.g. full stop, exclamation mark or question mark). The following step is the elimination of superfluous information, such as repeated sentences. At long last, terminology that was unclear, unspecific, or misspelt has been amended. The elimination of stop words, stemming, and tokenization are some of the approaches that can be used to preprocess data. Stop word removal is a process that gets rid of stop words such as is, are, they, but, and so on. Using the tokenization process, special characters and images will be removed. The stemming technique removes the suffix and prefix and identify the original words like e.g. 1. Closed- close, crossed – cross.

Aspect Identification: The purpose of the process known as aspect recognition is to identify features of a tourist destination that are significant and pertinent to that destination. The purpose of this paper is to present a hybrid technique for the identification of aspects. This method is capable of identifying both explicit and unconscious aspects from reviews of tourism destinations based on categories.

Data Classification: It occurs when an algorithm that uses machine learning labels each component of a consumer review as either positive or negative. This is accomplished by taking into account all components and their links to sentiment terms. For instance, a tourist may provide a positive evaluation of the restaurant's meal but a negative assessment of the service. The quality of this review is determined by the emotional words and phrases that are connected to the different parts. When numerous components of the scenario are taken into consideration, the complexity of the problem increases; machine learning techniques are very beneficial and effective.

Algorithms

Algorithm 1: Stop word Removal

Initialize m,n

for m=1 to number of words in files

for n=1 number of words in the list of stopword

if Words(m)==Stopwords(n)

then remove words(m)

end if

end for

Algorithm 2: Tokenization

Initialize feature vector feat =[0,0..0]

for tkn in text.tokenize() do

if tkn in dict then

tkn idx=getindex(dict,tkn)

feat[tkn idx]++

else

continue

end if

end for

Algorithm 3: Stemming

Ip = Normalz(ip)

if normalzValdt(ip)

then return ip;

for every rule in rules do if ip match with rule

then

Stem = RetrieveStem(ip,rules)

if not TestStemSize(Rule)

then

end for

return input

4. IV. Result and Discussion

For the purpose of evaluating the performance, empirical assessment is done to compare and contrast the traditional machine learning algorithms with the proposed hybrid machine technique. The Windows platform is utilized for the construction of the simulation platform, which is constructed using the Java framework. The operation of the system does not need for the installation of any specialised hardware; rather, the programme can be executed on any conventional machine.

The following is a description of the metrics that are utilised during the evaluation process:

Precision: The term "precision" refers to the ratio of the amount of true positives to the total number true and false positives.

F1 Score: The F1 Score is determined by multiplying the product of Precision and Recall by twice over the total by both Precision and Recall. Recall

Recall: The term "recall" defines as the ratio of the number of true positives to the total number of true positives and false negatives.

Accuracy: Accuracy can be seen as the ratio of the total number of predictions generated to the total number of correct forecasts generated.

Consider the following table 1, which depicts the performance of conventional machine learning algorithm and proposed HMLT for hotel dataset.

Table 1: Performance of conventional ML classifiers and proposed ABSC-HML for hotel dataset

Classifier	Accuracy	Precision	Recall	F-Measure
RF	0.90	0.91	0.93	0.94
SVM	0.93	0.94	0.92	0.95

NB	0.83	0.87	0.94	0.90
ANN	0.90	0.93	0.95	0.94
DT	0.91	0.92	0.93	0.95
HMLT	0.97	0.98	0.99	0.99

It is observed from the table 1, that the performance accuracy of proposed HMLT is better as compared to other conventional machine learning techniques for hotel datasets.

Consider the following figure 2, which depicts the comparative analysis of conventional machine learning classifiers and proposed ABSC-HML for hotel dataset.

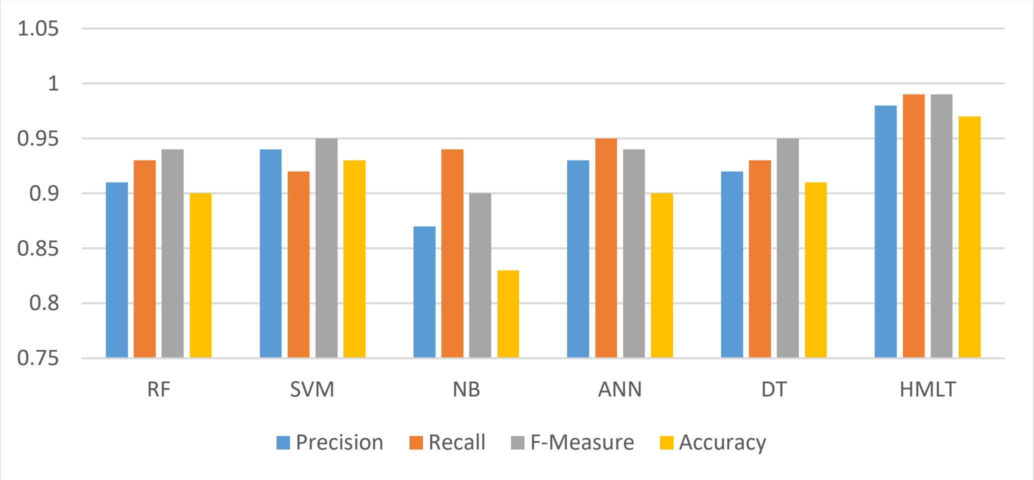

Fig. 2: Comparative Analysis of conventional ML classifiers and proposed HML technique for hotel dataset

It is observed from the above figure 2 that the performance accuracy of HMLT is 97% is better as compared to other conventional machine learning techniques

Consider the following table 2, which depicts the performance of conventional machine learning algorithm and proposed HMLT for restaurant dataset.

Table 2: Performance of conventional ML classifiers and proposed ABSC-HML for restaurant dataset

Classifier	Accuracy	Precision	Recall	F-Measure
RF	0.87	0.89	0.91	0.92
SVM	0.90	0.92	0.91	0.93
NB	0.81	0.87	0.92	0.89
ANN	0.87	0.89	0.91	0.92
DT	0.89	0.90	0.92	0.93
HMLT	0.94	0.96	0.97	0.98

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Consider the following figure 2, which depicts the comparative analysis of conventional machine learning classifiers and proposed ABSC-HML for restaurant dataset.

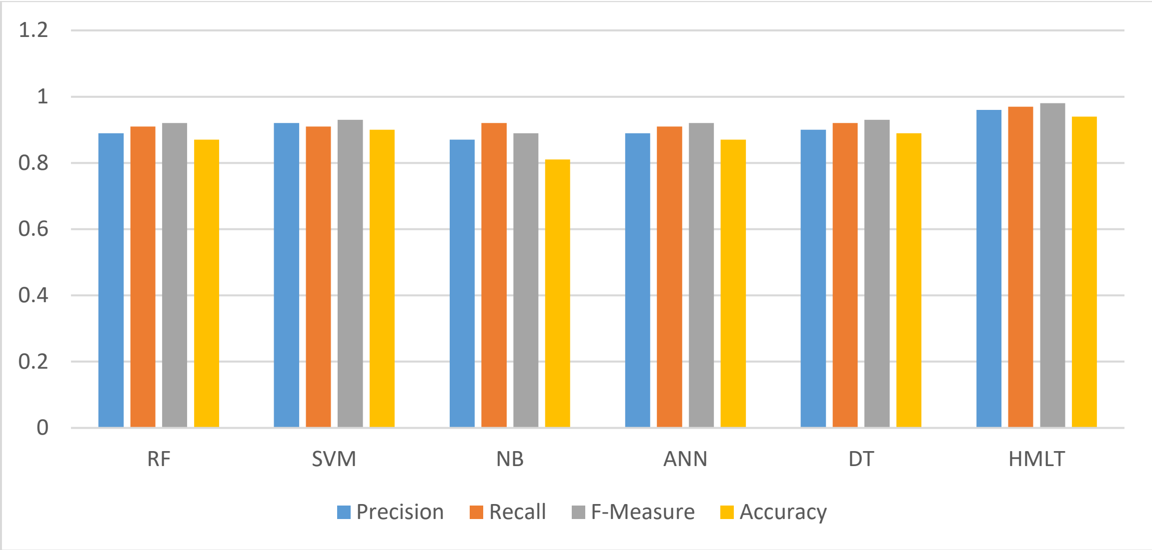

Fig. 3: Comparative Analysis of conventional ML classifiers and proposed HML technique for restaurant dataset

It is observed from the above figure 3 that the performance accuracy of HMLT is 94% is better as compared to other conventional machine learning techniques

5. V. Conclusion and Future Scope

The proposed HML-ABSC system presented an aspect-based sentiment classification framework that categorizes feedbacks about aspects into favourable and unfavourable. Within the confines of this framework, a method for the extraction of hybrid features is proposed. This procedure removes both explicit and implicit elements from the opinions of tourists. It will first extract common nouns and words or phrases from the comments text, after which it will use WordNet to group nouns that are similar. In the initial step of the process, the Stanford Basic Dependency analysis is performed on every sentence to weed out opinionless and irrelevant phrases. The last step is to extract features from the remaining phrases using N-Grams and POS Tags in order to train the classification methods. Lastly, in order to train the classification model, machine learning techniques are applied to the features that were extracted. According to the findings of the experiments, the suggested HML performed significantly better than other traditional ML classifiers. This is something that can be seen. To further enhance the quality of the user experience, future research will concentrate on scalability as well as ways to reduce the total response time.

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