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A Review on Aspect Based Sentiment Analysis Using Machine Learning Algorithms

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Abstract:

Text analysis is done using Aspect-Based Sentiment Analysis (ABSA) technique which separates thoughts into components and determines the emotional response to each. The expansion of platforms for social media like Facebook, Twitter, and Instagram, as well as e-commerce websites like as Amazon and Flipkart, Customers have been able to submit feedback to businesses based on their happiness and thanks to technological advancements. To improve overall predictive accuracy, a classifier in the ensemble is deployed. XGBoost, Support Vector Machine, and Random Forest are models that used in Ensemble classifier. The Framework is completed in four stages. The Data Augmentation step comes first, followed by Feature extraction and Ensemble Classifier Training, Evaluation, and Model Deployment. Finally Comparing and contrasting the results of each model with Ensemble Classifier.

Keywords: Aspect-Based Sentiment Analysis, XGBoost, Support Vector Machine(SVM), RandomForest,Word2Vector,WordNet, Round-trip Translation.

I. INTRODUCTION

An aspect of natural language processing is sentiment analysis (NLP) method for identifying the positivity, negativity, or neutrality of data. It is frequently called "opinion Mining". Textual data is often subjected to sentiment analysis to assist companies in tracking brand and product sentiment in customer feedback and better comprehending client requirements.

Three levels can be reached in sentiment analysis:

1.Document level

2.Sentence Level

3.Aspectlevel

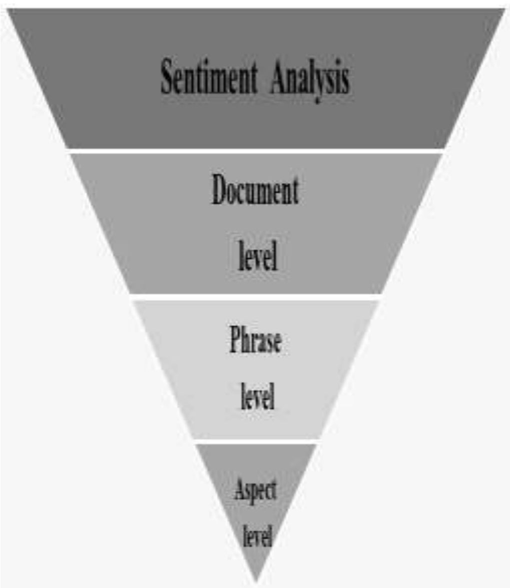

Fig1: Sentimental Analysis

In this survey aspect-oriented analysis is used which is the finest-grained of all levels of analysis.

Aspects refer to the qualities or elements of a good or service, including "the ease of integrating new software," "the response time for a question or complaint," or "the user experience of a new product."

The following is a list of what ABSA can uncover:

Aspects: The category, Trait, or subject being discussed.

Aspect-based sentiment analysis (ABSA) separates data into aspects and establishes the emotion connected to each. Aspect-based sentiment analysis, which links particular sentiments to various characteristics of a good or service, can be used to analyze customer feedback. People today have more viewpoints than they have ever had before. Whatever service we receive, we are either satisfied or disappointed. We can also swiftly express ourselves owing to social media. There are numerous reviews, customer satisfaction surveys, consumer complaints, and other sources of data. Businesses can use this data to better understand their customers' complaints and make data-driven decisions about how to enhance their services. By analyzing customer feedback data, categorizing it according to each component, and determining the sentiment associated with each, this technique allows businesses to learn more about what their customers genuinely desire. Customers regularly debate various elements of service on social media, making it challenging for robots to give the genuine meaning of each sentence. When a consumer writes a review for a restaurant they recently visited, for example, they normally provide the following information: "I like the meal here. "Instead, they'll write a comprehensive assessment of their entire stay, including: "I despise how long I have to queue.

To perform Aspect-based sentiment analysis machine learning algorithms was used. For any machine learning algorithm the process is as follows:

1. gathering data

2.Configuring the Data

3. Selecting a Model

4. Teaching the Model

5. Assessing the Model

6. Parameter tuning

7. Prediction-making

[1] This research suggests a caps-BiLSTM capsule network model for sentiment analysis using BiLSTM.The model starts out by taking as input a word embedding representing a sentence. The output vector is used to predict the polarity of sentiment following feature extraction and iterations of dynamic routing. The performance of the network in the capsule module is enhanced by the dynamic routing algorithm's ability to uncover more hidden features and give important features more weight. The datasets used here include the Stanford Sentiment Treebank, the Internet Movie Database, and Movie Review (MR) (SST).The algorithms employed are LSTM, SVM, BiLSTM, LR-LSTM, and caps-BiLSTM, with the caps-BiLSTM method having a relatively high accuracy rate of 91.96% on IMDB. The caps-BiLSTM network performs favourably in the sentiment analysis job due to its validity in feature extraction and accuracy in classification.

[2] The fundamental contribution of this study is in sentiment analysis, which makes an effort to foresee aspect sentiments in order to improve associated communication and automated decision-making in the social IOT.

The datasets that are being used for the sentiment analysis are TWITTER, RESTUARANT, and LAPTOP. The aspect granular sentiment analysis technique based on the Bi-GRU is proposed.

This enhances the performance of sentiment classification by integrating aspect information into the model and paying closer attention to the impact on sentiment classification. These algorithms include RNN, MultiACIA, TD-LSTM, and LSTM. Alternative RNN variant models should be investigated for improved performance on the issue because the accuracy was ineffective.

[3] For converting knowledge from document-level sentiment classification to aspect-level sentiment classification, they proposed the Transfer Capsule Network model in this research. The databases include reviews from the laptop and restaurant domains. The PBAN, PRET+MULT, and AF-LSTM algorithms are employed. When compared to other baselines, pretraining and multitask learning (PRET+MULT) produced overall greater performance.

They made use of TransCap's copious document-level labelled data to solve the problem of lack of aspect-level labelled data.

[4] This paper investigates end-to-end ABSA and proposes a novel multitask network (MTMVN) architecture. Here, the CMLA-ALSTM, and DECNN-ALSTM are employed. The datasets that were employed were from the fields of laptops and restaurants, respectively. Through multitask learning, additional precise aspect boundary and sentiment polarity information can help with the primary task. On three benchmark datasets, MTMVN outperforms the other end-to-end approaches in terms of performance by 0.37%, 0.17%, and 0.54%, respectively. The three benchmark datasets show how well MTMVN performs in comparison in comparison to the baselines on the entire ABSA job.

[5] The examination of people's beliefs, emotions, attitudes, and judgments about various items or entities as expressed in written language is referred to as opinion mining. The task of tokenizing involves breaking up huge pieces of data into smaller tokens. A review paragraph or multi-line review is broken down into single sentences for feature level examination. Each opinionated remark is categorised in this stage as either favourable, negative, or neutral. Because we need to identify the opinion target for each sentiment phrase stated in sentences at this level of analysis, Aspect-based sentiment analysis has considerable challenges with co-reference resolution. The involved steps are as follows: 1) Data extraction and preparation 3. Feature extraction and reduction, Sentiment detection, and 4) Classifying emotions 5) Summarizing emotions.

[6] The infectious condition known as coronavirus is caused by the SARS-CoV-2 virus (COVID-19**)**. 4 million instances and more than 226 million fatalities had been recorded globally as of October 25, 2021. We assigned each tweet one of 'positive,' 'negative,' and 'neutral' polarity scores utilising the trained hybrid deep learning model proposed by Ref. There were 11616 tweets in the model that was trained using a Persian database. The suggested model demonstrated the efficacy of using Persian data to train deep learning classifiers and was based on CNNLSTM architecture. In this architecture, CNN was applied to textual input data as an LSTM feature extractor. Word2vec was also employed in the suggested model as a word embedding. We assigned positive (1), negative (1), and neutral (0) labels to both datasets using the model.

[7] Predicting the price of stocks is a popular topic with lots of potential right now. The Krizhevsky developed CNN model was widely applied to image identification (Srivastava & Biswas, 2020; Ying et al., 2021). The majority of CNN's structure is composed of the input layer, convolution layer, pooling layer, fully connected layer, and output layer. The convolution layer's convolution kernel is primarily used by CNN to pick the classified feature set. The benefits of convolutional A recurrent convolutional neural network combined sequence modelling, word embedding for stock price research, and information extraction from financial news (RCN),The three gate networks in the LSTM model Compared to RNN, input gate, forget gate, and output gate perform better.

[8] Social media's usage is increasing and the ease with which messages may be posted, Social media attitudes and opinions provide the most up-to-date and comprehensive data. Giving a thorough introduction and presenting fresh perspectives on this topic are the objectives of this paper. For opinion mining, SentiWordNet is a lexical resource that is often used. SWN-based lexicon The learning and classification procedure for support vector machine models uses SWN-V, which is generated from SWN with updated sentiment scores.

[9] People's lives are relying more and more on healthcare data. The elderly may be able to avoid some sudden diseases by using healthcare data properly and securely, while younger individuals can keep track of their health. For the secure transmission of medical data, DDSRP offers mutual authentication techniques and secure routing. In comparison to the other two protocols, DDSRP's normalised routing overhead has significantly improved. DDSRP specifically addresses the issue of GrD-significant OTBR's overhead when there is a high node density.

[10] As a result of the enormous volume of opinionated material that Internet users are constantly producing, Both in academia and business, sentiment analysis has greatly increased in prominence. BERT is the first thoroughly unsupervised, bidirectional language representation model to be created. Utilizing RNN called LSTM, ELMo creates word embeddings (LSTM). A process known as wordpiece tokenization is used to initially process the text input for the BERT model.

[11] Due to its numerous uses, Recently, aspect-based sentiment analysis (ABSA) has drawn increased interest. The Aspect Multi-Sentiment (MAMS) collection contains sentences that each have at least two independent aspects with different sentiment polarities. When compared to previous ABSA datasets, the MAMS dataset is more difficult because each sentence in the dataset has at least two components with different sentiment polarities. In order to determine the sentiment polarity with respect to the aspect words and extract aspect terms from the phrases, we asked three accomplished researchers who specialise in natural language processing (NLP) to do so.

[12] Sentiment analysis is a challenge in the field of natural language processing. Finding an opinion associated with a piece of text involves determining whether it is favourable, negative, or neutral. The given text only has one aspect and polarity, which is the context in which this task operates. Predicting the elements mentioned in a statement and the emotions connected to each one would be a more difficult and general assignment. The term "aspect-based sentiment analysis" refers to this overall activity (ABSA). The degree of polarity (high, mild, or moderate) is also discovered using a technique called opinion mining. It examines the emotions, ideas, and attitudes after gathering reviews on many websites.

[13] Regional language data has significantly increased on the Internet in recent years. It removes language boundaries, allowing people to voice their opinions. 170.2 million people use Urdu as a language of communication. Sentiment analysis is employed to understand public opinion. Urdu sentiment analysis has gained more attention from researchers in the recent past. The least amount of attention has been paid to using deep learning methods for sentiment analysis in Urdu. In terms of Urdu text processing, there is a lot of territory to cover. By experimenting with Deep Learning Techniques for Urdu Text Sentiment Analysis in Combination with Several Word Vector Representations (UTSA).The effectiveness of deep learning methods like attention-based LSTM. CNN, CNN-LSTM, and LSTM (BiLSTM-ATT) are tested for sentiment analysis.

[14] A basic function of Aspect extraction is aspect-based sentiment analysis. An extracting clear aspects approach for formal and informal texts is presented in this paper for supervised aspect extraction.

Due to the fact that customer reviews utilise both professional and casual language, the new algorithm combines 126 aspect extraction methods to cover both types of texts. There are 126 rules in total, some of them are dependency-based and others are pattern-based rules from past research, as well as freshly created rules meant to address the shortcomings of earlier rules. Several aspect extraction rules have also not been thoroughly investigated in earlier research. However, many of these 126 rules should be dropped because they are unnecessary. Consequently, a more thorough selection of the included rules is needed.

[15] Social networking websites are now prevalent and well-liked for expressing a wide range of emotions in brief phrases. These feelings range from joy to sorrow to fear to anxiety. The media has recently assimilated into everyday life. On social media, people want to post about every single event in their lives. Social media is now utilised to display pride or esteem through publishing images, text, videos, etc. Users express their thoughts on hot-button issues, politics, film reviews, and other topics in the text, which is a key component of information sharing.

It is possible to understand the sentiment being represented by the audience by analysing brief texts. The general sentiment or opinion conveyed by a reviewer about a film is identified via the sentiment analysis of IMDb movie reviews. It is possible to understand the sentiment being represented by the audience by analysing brief texts. The general sentiment or opinion conveyed by a reviewer about a film is identified via the sentiment analysis of IMDb movie reviews. the sentiment analysis model, which distinguishes between good and negative reviews with clarity. The suggested model distinguishes between a favourable review and an unfavourable review. Utilizing hybrid characteristics makes it easier to understand the context of movie reviews. and improves classification accuracy because knowing the context of the reviews is crucial for classification.

[16] Due to its many uses, Recently, aspect-based sentiment analysis (ABSA) has drawn increased interest. The majority of the currently used ABSA algorithms have been used on tiny labelled datasets. However, there are a huge amount of reviews in actual datasets like Amazon and TripAdvisor. As a result, using these methods on huge datasets could lead to ineffective outcomes. These approaches currently in use extract a sizable number of variables, the majority of which are unrelated to the study domain. On the other hand, throughout the extraction procedure, some of the periodic relevant components are left out. The effectiveness of the ABSA method is adversely impacted by these restrictions. The suggested approach's extracted elements are used to generate a total review sentiment score once each extracted feature's weight and rating have been determined. Aspect-based sentiment analysis method that was applied to a genuine Amazon dataset and created for unbalanced large-scale reviews. The method entails four distinct jobs, the first of which involves using a hybrid methodology to extract the key elements from three different domains—movies, books, and dining establishments.

[17] Twitter is the third-most popular online social network (OSN) in the world, behind Facebook and Instagram. It provides a clear data access API and a simple data model when compared to other OSNs. This makes it the ideal environment for social network studies, which try to look at patterns of online behaviour, the structure of the social graph, attitudes toward different entities, and the nature of malicious attacks in a vibrant network with hundreds of millions of users. Indeed, during the past ten years, more than ten thousand research articles have used Twitter as a significant study platform. The majority of research that makes use of Twitter has great review and comparison studies, but there have been few attempts to map the whole study landscape. With an emphasis on sentiment analysis, spam, bots, fake news, and dangers including hate speech, as well as the structure and properties of the social graph, we attempt to map the current study fields in Twitter in this article. Additionally, we outline Twitter's fundamental data schema and the optimal procedures for data access and sampling.

[18] A rapidly expanding field of study in Natural language processing and text classification (NLP)is sentiment analysis. This method has become a crucial component of a variety of applications, including business, marketing, advertising, and politics. Although there are several methods for sentiment analysis, word embedding techniques have recently gained a lot of popularity in applications for sentiment categorization. Right now, Word2Vec and GloVe are two of the most trustworthy and useful word embedding methods for turning words into useful vectors. These approaches, however, do not take into account the emotion of words, and they require a sizable corpus of texts for training and producing precise vectors. Due to this, Pre-trained word embeddings that were trained on other sizable text corpora are routinely required by researchers due to the tiny size of some corpora. Because some corpora are modest in size, researchers must frequently use pre-trained word embeddings that were developed using larger text corpora, like Google News, which has roughly 100 billion words. Benchmark sentiment datasets and various Deep learning models were employed to assess the precision of our method.

[19] The latent information in linguistic expressions can be processed and analysed to disclose the user's or people's feelings. Sentiment analysis, sometimes referred to as Opinion mining, also known as review mining, attitude mining, and other similar terms, is the practise of computationally identifying viewpoints in textual information. One of the three primary forms of Aspect-level sentiment analysis is sentiment analysis of emotions, which sentiment is determined using granule level processing orientations by utilising the various characteristics of entities. The creation of machine learning and deep learning techniques has left a profound influence on aspect-oriented sentiment analysis. The recent literature on aspect-based sentiment analysis utilising machine learning algorithms is surveyed and reviewed in this study.

[20] More focus has been placed on Multimodal Aspect-Based Sentiment Analysis (MABSA),recently as a crucial sentiment analysis task. To identify finely detailed aspects, viewpoints, and their alignments across modalities, earlier approaches either I either utilised individually pre-trained vision-language models that ignore cross-modal alignment or (ii) employed vision-language models that were pre-trained using generic pre-training tasks. For both pretraining and downstream duties, we recommend the Vision-Language Pre-training framework for MABSA (VLPMABSA), a unified multimodal encoder-decoder architecture, to address these shortcomings. We also create three various task-specific pre-training exercises from the linguistic, visual, and multimodal perspectives. According to experiment results, our method performs generally better on three MABSA subtasks than the cutting-edge methods. Additional research reveals the effectiveness of each pretraining task.

[21] From a given text, the aforementioned traits must be extracted in order to ascertain their corresponding sentiment polarity, A fine-grained sentiment analysis task is utilised called aspect-based sentiment analysis (ABSA). The majority of the Arabic ABSA techniques now in use primarily rely on time-consuming pre-processing and feature-engineering efforts, as well as the utilisation of outside resources (e.g., lexicons). Aspect term extraction (ATE) and aspect category recognition, two ABSA tasks, must be carried out in Arabic, this work proposes a transfer learning approach using language models that have already been trained. The proposed models are based on the Arabic translation of the BERT model. variations in BERT implementation, such as techniques that are feature-based and fine-tuned, are contrasted. The paper's key findings are as follows: 1. Low-resource environments are more suited for fine-tuning. 2. Creating tailored downstream layers improves the output of the standard fine-tuned BERT model. The studies were carried out on a reference ABSA dataset of Arabic news posts. According to the findings, which show an overall improvement of more than 6% for the ATE test and more than 19% for the ACD task, our models outperformed baseline strategies and associated activities.

[22] When working on a In a new legal matter, attorneys and other legal professionals are expected to have thoroughly investigated related precedent that are comparable to the current case since they can offer useful information that can directly affect the outcomes of the current court case. Therefore, creating approaches that can automatically extract data from texts containing legal opinions pertaining to prior court cases might be seen as a key instrument in the legal technology ecosystem. Finding favourable and unfavourable facts or arguments in court cases is one of the most crucial and time-consuming tasks in court case analysis. This study is based on the Aspect-based Sentiment Analysis approach. Therefore, creating approaches that can automatically extract data from texts containing legal opinions pertaining to prior court cases might be seen as a key instrument in the legal technology ecosystem. One of the most crucial and labor-intensive tasks in court case analysis, our study focuses on identifying favourable and unfavourable facts or arguments in court cases. In this study, legal information extraction is carried out building on the idea of aspect-based sentiment analysis. In this essay, we present a method for predicting the sentimental weight of phrases used in court documents referring to the people concerned. To complete this objective, the suggested method uses an a fine-grained approach to sentiment analysis that is aspect-based.

[23] Processing textual information and assigning sentences a positive or negative attitude is called sentiment analysis. The sentiment polarity of the ABSA dataset is weakened by the fact that the majority of phrases in the sentences with the same aspect have several identical sentiment polarities in a dataset that only has one attribute of sentiment polarity. In order to produce This study uses the SemEval 14 Restaurant Review dataset, which combines two versions of the datasets ATSA and ACSA and symmetrically separates each document into individual sentences. The ATSA data collection stands for Analysis of Aspect-Term Sentiment. The abbreviation for this dataset is Aspect Category Sentiment Analysis. This research integrates the most recent NLP development trend, merges capsule network and BRET, and presents a method to accurately extract the polarity of emotional variables and symmetrically recreate the complicated relationship between aspect contexts and proposes the baseline model CapsNet-BERT.

[24] investigating consumer preferences and opinions regarding items requires the use of target-based sentiment analysis . Despite the fact that various traditional deep learning-based techniques have been put forth in the past, several helpful signals, such as Still, contextual, lexical, and syntactic cues are not fully considered and used. This study suggests a novel method for ABSA that takes into account contextual, lexical, and syntactic information. In order to use the complete context to accurately portray a target in an ABSA statement, a novel sub-network is first established. Additionally, lexicon embedding is used to take into account more lexical clues. Third, dependency attention, a brand-new attention module, is suggested to elaborate the attention-inferring syntactic dependency cues between words. Results of experiments on four benchmark data sets show how effective our suggested aspect-based sentiment analysis.

[25] Through sentiment analysis at the aspect level and visual analytics, this study examines client happiness. To determine the effect of COVID-19 on traveller sentiment in various ways, we gathered and studied the TripAdvisor flight reviews from January 2016 to August 2020 the use of word embedding techniques such bidirectional encoder representations from transformers and deep learning, has received little attention in Up to now, research has focused on information systems, management, and tourism, especially for aspect-level sentiment analysis.

[26] In this study, the model is assessed using two separate datasets. LSTM networks often learn implicit knowledge from data successfully, but they are unable to learn explicit knowledge, such as common sense facts. In this paper, Sentic LSTM, an extension of the LSTM, is put forth. is an effort to consciously combine explicit and implicit knowledge. The concept-level input and token-level memory are created via a unique output gate in the Sentic LSTM cell. This study also recommends a Sentic LSTM hybrid method expansion. The hybrid approach consists of the LSTM and a recurrent additive network that imitates sentient patterns.

[27] In this paper, experiments are done with reviews of restaurants and laptops. SemEval is used to collect labelled test data. Using a noise-resistant loss function and a domain-knowledge BERT, In this study, a three-step semi-supervised hybrid method known as the CASC model is created. For each kind of aspect and sentiment, a limited selection of seed words is used in the initial stage to build corresponding semantically consistent class vocabularies. The second stage labels a portion of the training corpus's phrases using these generated vocabularies and POS tags. By using Noise is produced when data are labelled using a semi-automated manner.

[28]This study suggests a straightforward but efficient method for combining lexical data with an attention LSTM model. By combining lexical data with deep neural network power and already-existing language resources, the LSTM model makes the framework more adaptable and durable without the need for additional labelled data. The dataset is the restaurant domain dataset from SemEval 2014 Task 4. Reviews of restaurants are included in the data, which include characteristics such as "food," "pricing," "service," "ambiance," and "other," as well as polarities such as "positive," "neutral," and "negative."

Given a statement and an aspect, the goal is to forecast the polarity. The corpus contains 973 test instances and 3,518 training examples.

The range of test accuracy is 80.06 to 83.45. However, the initial paper mentioned 83.1.

[29] The most recent methods for dealing with aspect-based sentiment analysis challenge are summarised in this study. CNN, RNN, LSTM, GRU, RecNN, and Memory Network are the algorithms. The primary driver for the use of MNs is the requirement for long-term memory to store conversational context or knowledge of questions and responses. One of the main issues with sentiment analysis is getting high accuracy with annotation. Effective aspect data annotation becomes a critical issue since It directly affects the operation of neural network models, a crucial part of ABSA.According to experimental findings, Using CAN on the ATAE-LSTM raises F1 score and accuracy by 6.46% and 5.39%, respectively.

[30] The enhancement of the aspect level granularity is a current area of interest for sentiment analysis research, serving two unique purposes: aspect extraction from product reviews, sentiment analysis of target-dependent tweets, and sentiment categorization. Deep learning algorithms have emerged as a potential means of reaching these objectives due to their capacity to capture both syntactic and semantic textual data without the need for complicated feature engineering. LSTM, GRU, and CNN standard and variant methods (GRU). Research would benefit more from a more concept-centric approach that links knowledge bases with deep learning techniques. RNN and RecNN both perform similarly, with accuracy values between 69 and 72%.

II. METHODOLOGY

Dataset:

Semeval_14 dataset is used**.** The dataset is about restaurant reviews. The dataset contain 6000 reviews containing the following features:

1.Id

2.Review

3.Aspect term

4.Aspect_category

5.Polarity

Following aspect terms are present in the dataset:

1.Food

2.Service

3.Anecdotes/miscellaneous

4.Ambience

5.Price

Following polarities are present in the dataset:

1.Positive

2.Neagitive

3.Neutral

4.Conflict

Below diagram represents the process of the model.

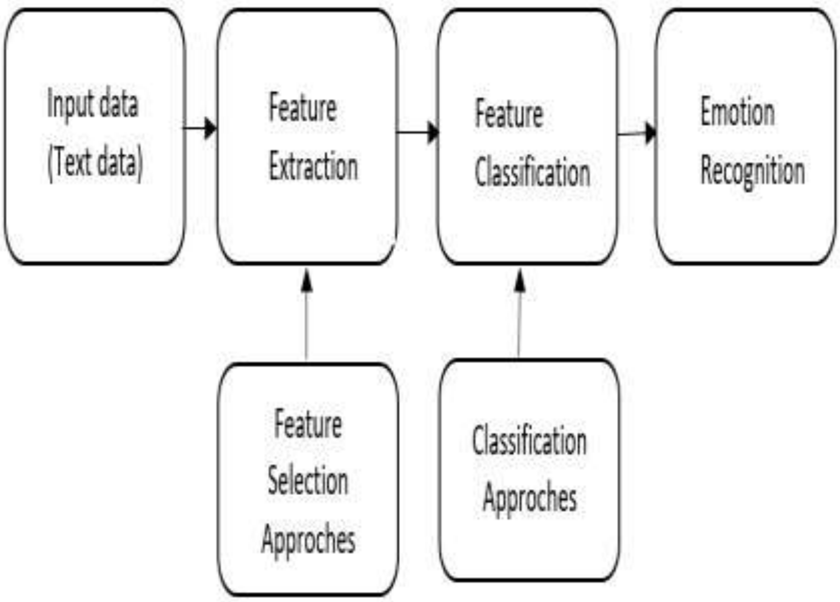

Fig 2:Process flow Diagram

There are four phases to the Framework. 1.Data Augmentation.

2.FeatureExtraction&EnsembleClassifier Training.

3.Evaluation.

4.Model Deployment.

1. Data Augmentation:

Data Augmentation emerged as a novel method for enhancing performance and ensuring reliability. DA employs three approaches:

1.Word2Vec

2. WordNet

3. Round-trip translation

2.FeatureExtraction and Ensemble Classifier Training:

2.1 Preprocessing:

This stage is critical for getting data ready for analysis. Deleting numerals, punctuation, converting all text lowercase, and removing stop words are all part of the preprocessing. Removing redundant words from headline data, such as headline.

2.2 Feature Extraction:

Textual data must be analyzed , to remove particular terms (tokenization), then encoded as numbers or floats for use as input to machine learning algorithms (Feature Extraction or Vectorization). The Count Vectorizer from Scikit-learn is used in this operation. This allows us to represent text features in a very flexible way. These characteristics are essential for the project.

2.3 Ensemble Classifier:

Ensemble classifiers are machine learning algorithms that work together to produce greater overall predicting accuracy than any single method. The goal of utilizing ensemble classifiers was to increase performance because ensemble classifiers are widely used in text classification and ensembles are used to maximize the benefits of learners while minimizing their disadvantages.

Three models are used in Ensemble Classifier listed below:

1.XGBoost

2.Support Vector Machine

3.Random Forest

These performance measures can be used to gauge the model's effectiveness:

1.Accuracy

2. Precision

3.Recall

4.F1 score

5.Support

6.Confidence

4. Model Deployment:

Fourth step is Model Deployment, after completion of model development, Model is deployed in the server by using Heroku app.

III. CONCLUSION AND FUTURE SCOPE

An ensemble classifier is utilised in this study to improve the model's performance.

Predicting polarity by ensemble classifier gave accurate results than the individual models.Future Scope of this model is to perform Due to language modelling, Aspect Based Sentiment Analysis using Transformers in Deep Learning Algorithms will produce better outcomes.

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