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Sentiment Analysis of Twitter Tweets for Mobile Phone Brands

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Abstract- **Sentiment Analysis is a method of extracting useful insight from text or expressions that help make decisions for different fields like establishing a new business, purchasing electronic products, or overall community analysis. Different techniques for sentiment analysis have been used in various researches. This research used a machine learning classification technique to perform sentiment analysis with and without Stopwords on unigram features and Bigram words. We used the Support Vector Machine, Maximum Entropy, Naïve Byes, Logistic Regressions machine learning classifiers using Python. NLTK and scikit learn packages used to perform sentiment analysis in this work with Twitter API. The performance of classifiers is measured in terms of Accuracy, Precision, Recall, and F-measure. Results showed that the current method for calculating sentiment from tweets is better than previous methods, as results showed improved accuracy. It is also observed that Bigram features accuracy after removing Stopwords from data has been improved. By analyzing our results, it is observed that logistic regression gives the best performance, and we achieved 93.74% accuracy; using all feature sets and Maximum Entropy also provides significant results. By comparing previous sentiment analysis results with our results, it is evidenced that our techniques of finding sentiment are significant.**

***Index Terms*—** **Opinion mining, Sentiment Analysis, Feature Extraction, Machine Learning, NLTK, Bigram words.**

I. INTRODUCTION

Sentiment Analysis is studying one's behavior and views towards judging an item or people groups [1-8]. Sentiment Analysis is performing analysis on text, which is in human written languages [1]. Sentiment Analysis could be useful in several ways as it may make decisions about purchasing or judging some political personalities by examining other people's views [2]. These opinions could easily be collected from many places on the web like blogs, social media sites such as Twitter, Facebook, Linked In, or online purchasing sites such as Amazon, eBay, and online stores [6]. It also helps companies to analyze their products or service's popularity and suggestion to improve their flaws. In current years, Sentiment analysis is an active area of research. Multiple ways are utilized to store vast volumes of information; different algorithms and models are required to discover assessment from individuals' surveys and make them valuable learning. These instruments and procedures are utilized to change a large number of raw information into valuable data to assist organizations and groups in making decisions [5].

Combine machine learning and social engineering approaches are now used to find the right sentiments [8] as following natural language in sentiment analysis may lead to the right and accurate judgment of the review and semantic organization. For the right Sentiment Analysis, two main techniques play the primary role; one is data mining, and the other one is Natural language processing. Natural Languages are used as an interface between human written languages and computers [3]. Whenever a choice is made, it relies upon the others' assessments, which they made on various social networking media [1]. Finding opinions from emotions is comfortable, while finding them from text is challenging and may require much effort. Sentiment Analysis is the way of finding one's point of view about an element. Other sentiment analysis challenges include Named entity recognition, finding the main subjective and objective in a sentence. What is the main idea of a sentence; in a sentence, an object refers to which thing or idea? If you do not know the author, you have no idea about the sentence's actual meaning: it represents a wrong concept or a good, Capitalization, spelling mistakes, lack of proper punctuation, grammatical mistakes [2, 3]. Different strategies have been proposed for Sentiment Analysis. During this research, the primary technique that may follow is Machine learning with some dictionary-based approaches [4, 9 -11]. As an analysis of the current techniques, it is concluded that mining reviews for analyzing negative, positive, or neutral, Logistic regression provide higher accurate level results.

People express their thoughts towards a thing by their opinions, feedback, and suggestions about an entity or an object [1,12]. There are many ways to express opinions as one can express his opinion on Twitter, provide his reviews on Facebook or different blogs and social networks. It's in trend to view others' opinions about a product before purchasing it online or from a local site. As on social media, there are hundreds of opinions about a product, so opinion-mining techniques are used to classify opinion on polarity bases to make a better decision [6, 7].Data mining techniques can apply to image, multimedia, and web mining to get great insights. Web mining is also a subfield of data mining commonly used for Sentiment Analysis [14-19]. It is easy to capture sentiment from images, audio, or videos, but it is somewhat tricky and may go wrong-sided when finding sentiment into text [2, 18]. A word that has positive mining may use as a negative sense into another one, like "lengthy," "hard," "sensitive".

Sentiment Analysis is used to collect people's opinions in short reviews, their emotions in reviews, people's feedback about a product, a social event, a service. Sentiment Analysis categorize these opinions into different categories like "Positive", "Negative" "'neutral", "happy", "sad"," annoying" [6]. Sentiment analysis is generally studied at different levels such as article level, Phrase level, and aspect or feature level [2]. Sentiment analysis is the study of finding a negative or positive direction from people's reviews about a product or service to help buyers decide. Different techniques are in practice on data at a sentence or word level, Document-level sentiment. The analysis may be about a specific product to check its negative or positive impact [3]. If a document is based on multiple entities, this technique isn't suitable for its sentiment analysis [7]. Different techniques such as Terms presence and their frequency, Term-based Features, Parts of Speech (POS), syntax are used for document Sentiment examination depending on three kinds of, i.e., dictionary-based, machine learning-based methods, and linguistic analysis-based methods. There are three approaches used by Machine learning for sentence or feature level. The main sentiment analysis methods at sentence or feature levels are Naïve Byes, Maximum Entropy, SVM, and Decision Trees [5, 7, 11]. Figure 1 describes the structure of machine learning approaches used for Sentiment Analysis.

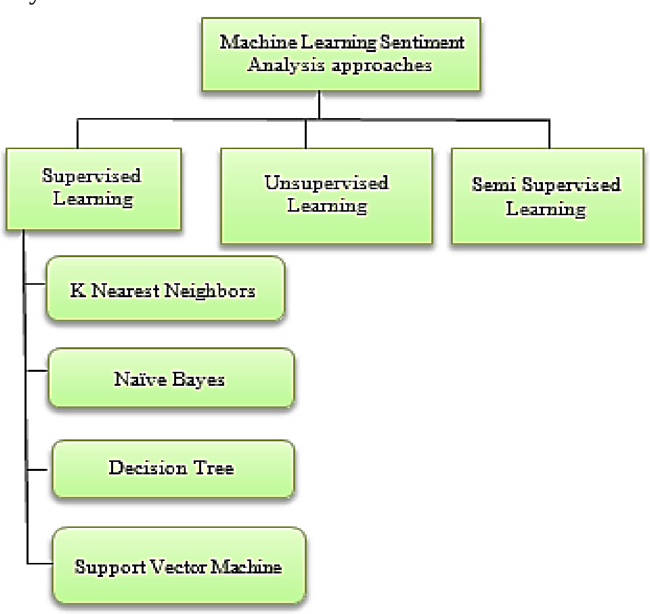

FIGURE 1: SENTIMENT ANALYSIS APPROACHES USING MACHINE LEARNING

Different types of applications of sentiment analysis are available online [7, 16]. Primary applications of Opinion mining and sentiment analysis are as given below:

On social media, opinions about products may come from different areas with different intentions; some may give them a positive way, some into harmful, and others into a neutral base [7, 9, 20-21]. As different companies give negative reviews about their competitor's product to benefit them, opinion mining and sentiment analysis applications can classify these reviews into "spam" or "not spam" contents [7, 13, 21]. Product or service purchasing are applications through which people can compare different brands' products. They can check people's reviews about these products as people's feedback that use these products and services are highly beneficial. Buyers can quickly evaluate these comparative products using opinions [7, 18]. By using products and services improved quality applications, products, or services, manufacturing companies can collect opinions about their products to improve their quality. A company can review the l local government's latest marketing trends and policies regarding these products [9, 10].

By using sentiment analysis, users' opinions should be considered to make better and peoples friendly policies. Decision-making applications can give a useful analysis of people's opinions on decision making [7, 10]. Sentiment Analysis is a systematic procedure that starts by extracting text from different web resources like blogs, review sites, social media sites like twitter and Facebook [18]. Opinion text summarizes subjective knowledge for different purposes, like improvements in business or economic shopping experience. Opinions are categorized as "Positive" or "negative," or they may suggest some right decision [8, 14]. Sentiment Analysis methods involve the following series of steps:

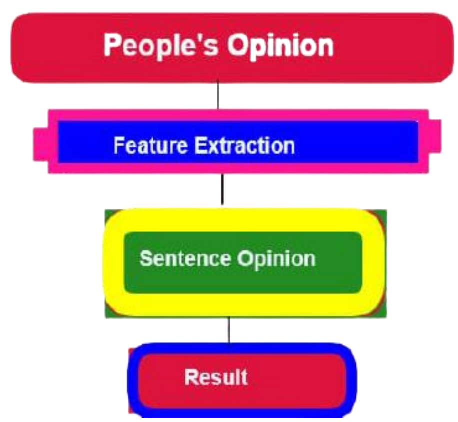

FIGURE 2: PROCESS OF SENTIMENT ANALYSIS

Figure 2 describes the detailed process of sentiment analysis from tweets extraction, feature generation from these tweets to final result finding as positive or negative opinion. These steps are described in the following section in detail. In the Opinion Extraction step, data is gathered from different sources using opinion extraction techniques. Different retailer websites, social networks, and research companies provide sources in the form of free software or modules to extract data [4, 10]. Different languages like Python, R are used with multipurpose packages like NLP, NLTK; WordNet's are used to process data.

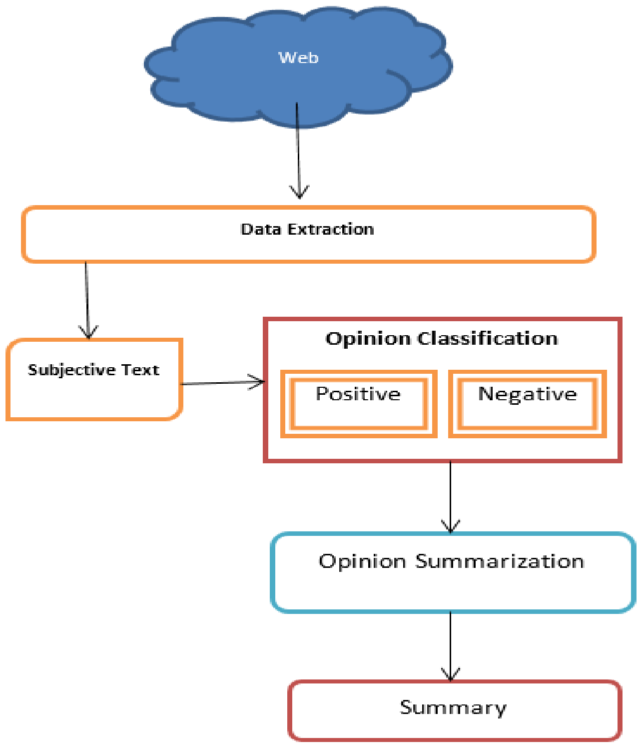

FIGURE 3: PROPOSED SYSTEM FOR SENTIMENT ANALYSIS

Figure 3 shows a detailed process of finding tweets or opinion from the web, then finding subjectivity as a word is a subjective word or objective then the classification of these subjective words either into a positive class or a negative class, all tweets then summarized as how much into a positive class or in a negative class finally a detailed summary of whole processing tweets should be provided at the end.

A. CONTRIBUTIONS

This study is based on supervised machine learning methods to analyze tweets' sentiment using different machine learning classifiers. The main methods followed during this work for feature set extraction and generation are Ngram, Bigram, and stop word filter. The underlined method found relevant material for Sentiment Analysis quickly and improved the previous method's efficiency level. The current method is based on supervised machine learning techniques. The proposed method aimed to improve the sentiment analysis process's accuracy on short reviews about products available on websites or social media. This method improved sentiment analysis in recent years, and the Accuracy level of different sentiment analysis techniques was analyzed. This research aims to give a better solution for Machine learning techniques on sentiment analysis, which helps the business-relevant people fine-tune their business needs and benefit from the technology better.

II. LITERATURE REVIEW

The ideal opinion-mining apparatus would be to work on a set of facts about an entity, produce a list of product features (distinct quality attributes), and collect public opinions about each of them. It works on finding some other more solid conclusions regarding them (poor, outstanding, good). M. Trupthi et al. [2] proposed a system to extract data from SNS services using Twitter stream API. This work is done in three folds; in the first phase, all preprocessing and training are done; in the second phase, scoring and classification are done based on filtered data, and in the final phase, their data represents on a web-based application. They utilize the NLP unigram Naïve Byes classification technique. All tweets are considered as a probability distribution for a positive, negative, or neutral class. Input for classification training was a set of 2 million tweets that were gathered from different sources. All extracted tweets loaded into Hadoop and then preprocessed using map-reduce. All words with their probability scores and class are then stored in MongoDB. The results show that on different filters, this web-based app gives different results as a filter of "ISIS" gives mostly negative scoring, while on the "Education" filter, it gave mostly positive results. Overall performance was efficient in real-time tweets classification.

Ali Hassan et al. [4] proposed a system to analyze election-related tweets' polarity using different sentiment analyzers and machine learning classifiers. As Tweets were in English and Urdu, a language translator was utilized to convert tweets into the English language. For polarity and subjectivity detection of political tweets, SentiWordNet, Text blob, and word sense disambiguation, analyzers have been used. Weka's environment is used to check the validity of results gathered from the sentiment analyzer. A.k. Soni [5] proposed a system for sentiment analysis of Twitter tweets. For classification, they use two machine learning classifiers Naïve Byes and Maximum Entropy on N-grams features. Data for this classification gathered from Twitter using Twitter API and tweepy as the main library on Twitter for fetching data according to the filter. Getting sentiment from these data machine learning classifiers applies to it. They proposed Maximum Entropy with Google translator as it gives a higher accuracy of 74% compared to previous multilingual models.

Marouane Birjali et al. [16] proposed a method to find grounds behind suicide. They use Twitter as a source for data collection. They gathered data from Twitter using Twitter4J about suicide reasons and different circumstances, which results in suicide attempts. They use Weka, an efficient data-mining tool for machine learning-based experiments. For further accuracy of the results, word net has been used. They proposed an algorithm to compute semantic analysis between tweets by dividing them into a training set and a test set divided by following WordNet. The final results show that the algorithms suggested by them can extract and predict suicide ideation using tweets; also, the accuracy improved using WordNet. Jan Der IU Pahwa [17] proposed multiple languages sentiment extraction from short text or sentences. The task was challenging because other languages have limited data as compared to the English language. The previous methods were based on converting multilingual to English, but their approach does not need this conversion. For this work, a vast amount of unstructured data utilized from other languages, and using this unstructured data, a CNN layer also trained, highlighting the importance of pre-training the model. They examine the model on various datasets, including the SemEval sentiment prediction benchmark (Task4).

The performance of these models is acceptable. The network performance is also acceptable for a single language model. Results show that proper training of the model using a single

CNN can be utilized for multilingual analysis. In their research, Hema Krishnan et al. [18] analyze some specific mobile phone popularity through sentiment analysis. Each mobile phone popularity analyzed by considering their sentiment score, five mobile phone brands considered for this experiment are Samsung, Motorola, nexus, iPhones, and Lenovo. The lexicon-based method was used for assessing popularity and implemented using R and MongoDB. The latest 500 tweets related to each phone brand extracted. By studying the plots, it concluded that the various Samsung phone tweets have sentiment scores between –1 and +2. Different range of scores shows the sentiments of the people regarding cell phone purchasing. Customers should make an excellent decision to buy a new phone brand by analyzing its popularity.

Neelima et al. [20] present a sentiment analysis idea on Twitter, especially for Indian users. The said idea has been implemented by gathering data from Twitter. The search is based on different topics in different languages. This raw extracted data is converted into the English language using Google translator and used for polarity classification of data corpus. They experiment with these datasets using Machine learning techniques. They use the Naïve Byes and Maximum Entropy Classifier and comparison of these two. The Results Show that this technique gives better results than previous techniques on sentiment analysis. They work with Hinglish (Hindi in English), but the proposed technique can be used with any other language. Xujuan Zhou et al. [24] worked on the Australian federal election 2010. Their main interest has been to analyze the sentiment of the two political candidates Julia Gillard and Tony Abbot. The tweets' focus has been to automatically analyze whether a tweet poses a positive or negative sentiment. The dataset they utilize is gathered from Twitter during the election and is two weeks' duration. The total number of tweets used is 57000, which is divided into 57 different files. Their results show how much of them are positive, negative, or neutral.

T. JHANSI RANI et al. [28] experiment to find the best n-gram model for sentiment analysis using word-level features. Different machine learning classifiers such as Naïve Byes, k-nearest neighbor, support vector machine, decision tree classifiers, and different n-gram models are used for sentiment analysis. Results prove that the unigram word model is better than other word models as it gave the best F1 score of 0.83 for sentiment classification. SVM classifier gives better performance in all n-gram model experiments as compared to others. Halal tourism is growing very fast, the authors of [27] analyzed 85,259 tweets to examined halal tourism trends. They also analyzed the sentiment valence of tweets in relation to halal tourism, and identified the popular destinations which appear in tweets. Their results showed that Japan is the most-popular destination for halal tourism. In another study the authors [26] evaluated the most popular smart phones brand in India for the ease of Indian smart phones users by Twitter tweet sentiment analysis. They focused on consumers who express their sentiments on social networking sites about a particular brand.

III. TEXT PREPROCESSING FOR SENTIMENT ANALYSIS

Text preprocessing is the process of normalizing text. NLP is a systematic computerized way of automatically understanding and normalizing human language. Different tasks such as Automatic text summarization, tokenization, linguistic analysis, sentiment analysis spam detection are done utilizing NLP tools [9, 16]. Through NLP, computers are being enabled to understand human languages. SIRI and Google are an example of NLP [7]. Natural language processing Toolkit (NLTK) is a suite of program tutorials and datasets broadly utilized for linguistic analysis. It's a Python-based suit and main distribution done under GPL open source licenses. NLTK includes capabilities of tokenization, stemming, lemmatization on the text. NLP used different machine learning classification algorithms for processing our input or raw text. NLTK is a library that has an excellent function for text preprocessing [22]. To evaluate the sentiment's validity, a method is tested using four performance parameters Precision, Recall, Accuracy, f1-Score [23]. TP Belongs to reviews which are labeled to correct class either true or false, FP belongs to reviews with are labeled to false class as Negative review into Positive class, FN belongs to reviews as not unfavorable but labeled by negative class. The equation to measure these matrixes is as mentioned below:

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (1)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (2)$$

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FN+TN+FP}} \quad (3)$$

$$\text{F} - \text{measure} = 2 * \frac{\text{Precission}*\text{Recall}}{\text{Precission}+\text{Recall}} \quad (4)$$

IV. METHODOLOGY

In this research, a machine learning technique was applied to users' reviews gathered from Twitter. Some datasets are also checked through Machine-learning Classifiers and use language features to learn text's sentiment-related features. A final method is an integrated approach to combine methods and models from lexicon-based and machine learning approaches. The main packages which are used for text preprocessing are the NLP toolkit (NLTK) and Scikit-Learn. Machine learning classifiers Support Vector Machine, Naïve Byes, Maximum Entropy, and logistic regressions are used from NLTK and Scikit-Learn. Twitter API is used to get data daily about different mobile brands. An extensive preprocessed dataset for mobile brands is gathered from free internet sources, consisting of 500 positive and 500 negative tweets, a dataset of 1, 00000 positive and negative reviews, and some other datasets tested using this model.

Datasets are divided into train and test sets. A classifier is trained on these datasets by using different machine learning algorithms. After analysis, results are gathered to measure the accuracy of the classifier. All datasets used to get sentiments are normalized before testing through a machine learning model. After preprocessing and frequency measuring, the dataset is divided into training and test set for further analysis. Train and test sets provide different classifiers for analyzing accuracy and cross-validation, results of different classifiers.

A. SUPERVISED LEARNING RESEARCH METHODOLOGY

A Supervised Machine Learning approach is used, which figures out how to extract sentiment scoring for each review using supervised classification techniques. The main tools used for data extraction, preprocessing, and classification are python 2.7 with NLTK. All processed tweets are converts into positive or negative groups. After this, these groups of tweets are divided into Training and Test set. Useful extracted feature vectors are then tested using classifiers that are trained on Positive and negative tweet sets. Using a classifier, the test dataset divides into positive or negative categories [9, 23].

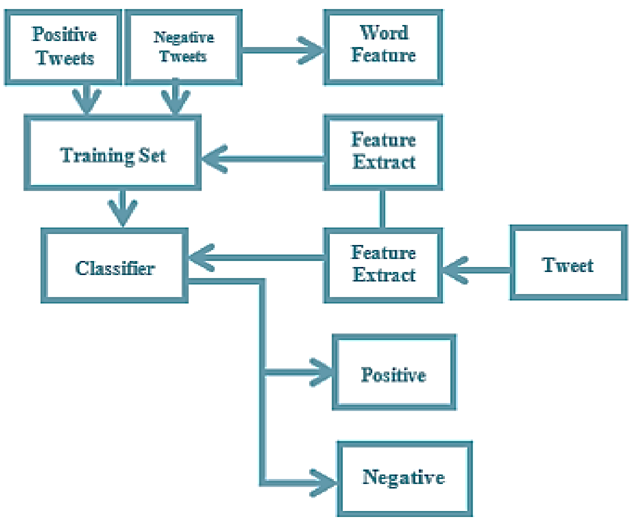

FIGURE 4: TWEETS CLASSIFICATION PROCESS

Figure 4 shows the tweet's classification procedure into the positive and negative classes according to their subjectivity description. Here positive and negative tweets are provided in the form of text or .csv files from which features are extracted; some are provided as a training set for the classifier to train it for new data. Then features are provided to the classified from new tweets processed by trained classifiers that positively or negatively tag them.

B. LEXICON BASED APPROACH

Lexicon Based approach for Sentiment Analysis aims to analyze, design, and implement sentiment analysis over Twitter data for mobile companies; to infer mobile popularity. For sentiment analysis, four top mobile phone companies, "Samsung", "Huawei", "Iphone6", "Iphone7", are selected. Python's main packages for sentiment analysis tweet fetching and preprocessing are Jason, CSV, matplotlib, panda, and Nltk. The main steps to apply this approach are; gather data from Twitter about specific topics in real-time, apply to preprocess to normalize extracted data, giving a starting polarity score, applying tokenization on text, and checking tokenized term present in the sentiment dictionary.

V. RESULTS AND DISCUSSION

This research is based on the training of different machine learning models. For feature set generation techniques followed during this study are Bag of words, stop word filtering, and Bigram collection.

A. SENTIMENT CLASSIFICATION RESULTS

On sentiment analysis, previous methods are based on removing unwanted data items during preprocessing. This research experiment is performed on a unigram word feature set and Bigram words. By examining feature sets with and without Stopwords removal, performance varies.

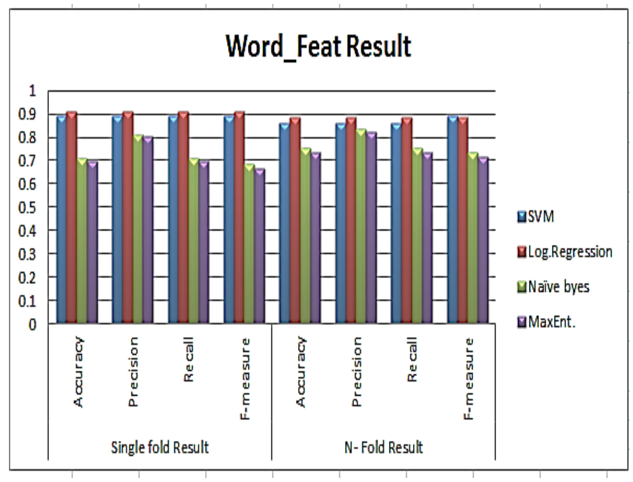

FIGURE 5: CLASSIFICATION RESULTS

Figure 5 shows the results of different classifiers on single-word features. It examines that single word features accuracy without removing Stopwords from data for support vector has 81%, the accuracy of logistic regression is 93%, for Naïve Byes 71%, and Accuracy of Maximum Entropy is 67%. N-fold results also show higher accuracy of logistic regression, 88.6%, and 86.0% for support vector machine, 83.2% for Naïve byes, 73.4%for Maximum Entropy.

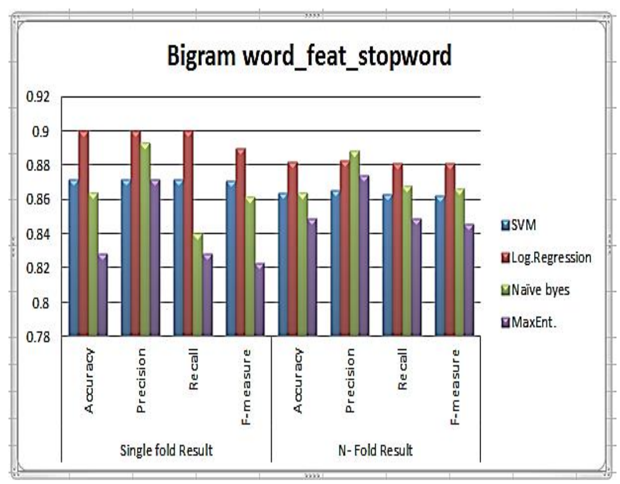

FIGURE 6: COMBINE RESULTS OF BIGRAM WORD FEAT WITH STOP WORDS

Figure 6 shows Bigram word features results of different classifiers. Bigram word fractures accuracy after removing Stopwords from data for support vector has 87%; Accuracy of logistic regression improves to 90%, for Naïve Byes Accuracy 86% and Accuracy of Maximum Entropy 72%. Here logistic regression Accuracy is higher than all other three classifiers. N-fold results also show higher accuracy of logistic regression, 88.2%, and 86.4% for support vector machine, 86.4%for Naïve byes, 84.9%for Maximum Entropy. A dataset of 1000 tweets with 500 positive and 500 negative tweets is used to check Accuracy, Precision, and Recall. Results obtained by 1000 tweets dataset by different feature sets are here:

B. ALL DATASET RESULTS

Table I shows different datasets description, the total number of tweets, the number of positive tweets, and negative tweets in each dataset.

C. PERFORMANCE EVALUATION OF UNIGRAM FEATURE

Table II shows detailed evaluation results using different classifiers. Best accuracy has been obtained from 100,000 tweets dataset where logistic regression gives 93.74% Accuracy; Maximum Entropy returns 93.18% Accuracy; support vector machine gives 92.93% Accuracy while Naïve byes return 88.51% Accuracy. In future, it can be expanded by using feature sets of different languages to check whether it improves accuracy.

TABLE I: Datasets Size

Dataset	Dataset size	Positive Tweets	Negative Tweets
Sentiment analysis Dataset 1,00000 tweets [24]	99000	58000	41000
1000 tweets [25]	1000	500	500
Amazon labeled dataset [22]	1000	500	500
Amazon mobiles Dataset [21]	356549	78105	278444
IMDB dataset [27]	857	498	359
Yelp dataset [23]	1000	500	500

These results could be improved by increasing the training dataset; as we improve our model's training, it improved accuracy. BY using a large dataset, resulting accuracy may also improve. As all words and all Bigrams are used in this study in the future, using the best words and best Bigrams can improve accuracy. These all feature sets are of the same language.

TABLE II
EVALUATION RESULTS

Dataset	Classifier	Accuracy (%)	Precision	Recall	F-measure
Sentiment analysis Dataset 1,00000 tweets [24]	Naïve Byes	88.51	63.11	70.73	65.64
	Maximum Entropy	93.18	96.58	50.66	65.64
	Logistic regression	93.74	80.31	59.22	63.24
	Support vector	92.93	71.72	65.15	67.70
1000 tweets [25]	Naïve Byes	71.2	80.88	71.2	68.75
	Maximum Entropy	69.6	80 .17	69.6	66.68
	Logistic regression	91.2	91.2	91.2	91.20
	Support vector	88.4	88.4	88.4	88.39
Amazon labeled dataset [22]	Naïve Byes	76.8	76.91	76.8	76.7
	Maximum Entropy	74.4	74.80	74.4	74.3
	Logistic regression	77.2	77.4	77.2	77.1
	Support vector	80.0	80.03	80.0	79.9
Amazon mobiles Dataset [21]	Naïve Byes	41.57	63.03	62.23	41.55
	Maximum Entropy	77.54	42.95	49.73	43.90
	Logistic regression	77.82	66.89	65.15	65.88
	Support vector	76.29	65.09	64.67	64.87
IMDB dataset [20]	Naïve Byes	80.0	85.53	76.4	77.3
	Maximum Entropy	63.25	76.8	56.2	49.57
	Logistic regression	78.13	83.68	74.35	75.01
	Support vector	81.86	85.97	78.8	79.8
Yelp dataset [23]	Naïve Byes	76.0	76.55	76.0	75.87
	Maximum Entropy	72.8	73.39	72.8	72.62
	Logistic regression	80.0	80.17	80.0	79.9
	Support vector	76.8	76.86	76.8	76.78

A. COMPARISON OF ACCURACY OBTAINED BY DIFFERENT METHODS

TABLE III shows that this method of extracting N-grams features from tweets is efficient compared to previous methods. Vishal A. Kharde et al. [29] work is closely related to the proposed work. They consider Unigram and Bigram words as their feature vectors for sentiment analysis with and without stop words. Here Results show that our results are high than [29] as on unigram with Naïve Byes, their method got 73.65% Accuracy while our resulting accuracy is 78.4, also with support vector machine, and their method got 76.68% Accuracy while our results show 87.6% Accuracy. We also experiment on different datasets using the current method and find that our accuracy is higher than Vishal A. Kharde et al. [29] results as their method is nearly the same as our approach. As we increased our training set data, accuracy improves; furthermore, it improves the resulting accuracy when we apply the Stopwords filter. This research work is focused on a single language that may be used to find the sentiment of different language-based tweets.

TABLE III
COMPARISON OF ACCURACY OBTAINED BY DIFFERENT METHODS

Author	Method	Obtained Accuracy	
		Unigram	Bigram
Shyamasundar LB [26]	Naive Bayes	85.81%	87.23%
	SVM	86.73%	87.78%
T. Jhansi Rani et al. [28]	SVM	70.16%	68.37%
	Naïve Byes	63.39	62.47
Ankita Gupta et al. [25]	KNN & SVM	67.78%	
Vishal A. Kharde et al. [29]	Naïve Byes	73.65	76.44
	Maximum Entropy	74.93	-
	SVM	76.68	76.44
Proposed work (unigram and Bigram features with stopword filter)	Naïve Byes	88.51	89.4
	Maximum Entropy	93.18	90.8
	Logistic Regression	93.74	95.0
	Support Vector Machine	87.6	87.2

VI. CONCLUSION

This research used supervised machine learning approaches for sentiment analysis of Twitter tweets. The main classification methods used for classification are Support Vector Machine, Maximum Entropy, Naïve Byes, and logistic regression. Dataset for sentiment analysis for tweets about mobile phone brands and other products gathered through Twitter stream listener app using tweepy and some tweets datasets from Kaggle and other free resources. A dataset of 500 positive and 500 negative tweets has also been used to check the model's performance on Unigram and Bigram word features with and without using the Stop words filter. The results of these large datasets show that this model gives the best results for medium-sized data, but for a high volume of datasets, its accuracy goes down. For sentiment analysis, Logistic regression gives the best accuracy of 93.74%.

The Maximum Entropy also gives better performance on all datasets. These results have been improved by increasing the training dataset for the training of the model. As we increased our training dataset, resultant accuracy improves; further, when we applied the Stopwords filter, it improves the resulting accuracy. We also experiment on different datasets, and a comparison of our work with previous work is also made. This comparison shows that our accuracy is higher than previous works' results. This research work focuses on the English language written tweets to find sentiments using supervised machine learning techniques. In the future, we can use deep learning methods to perform sentiment analysis.

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