# A COMPRESSIVE REVIEW ON SOCIAL SENTIMENT ANALYSIS PERFORMANCE OF SUPPORT VECTOR MACHINE FOR POLARITY DETECTION USING VARIOUS DATASETS

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*Abstract*— **Social Sentiment analysis is the use of natural language processing (NLP) to analyze social conversations online and determine deeper context as they apply to a topic, brand or theme. Our net sentiment score and brand passion index show how users feel about your brand and compares across your competitors.Exponential development in versatile innovation and small scale figuring gadgets has prompted a gigantic augmentation in online life clients, who are constantly posting their perspectives and remarks about specific items and administrations, which are in their utilization. These perspectives and remarks can be very advantageous for the organizations which are intrigued to think about the general conclusion with respect to their offered items or administrations. This kind of general supposition generally can be acquired by means of polls and studies, which is no uncertainty a troublesome and complex assignment. Along these lines, the profitable data as remarks and posts from smaller scale blogging locales can be utilized by the organizations to kill the imperfections and to improve the items or administrations as per client needs. Be that as it may, removing a general assessment out of an amazing number of clients' remarks physically can't be plausible. The term sentiment analysis incorporates the classification of specific content as positive, negative or impartial, is known as polarity detection. Support Vector Machine (SVM) is one of the broadly utilized machine learning calculations for sentiment analysis. In this exploration, we have proposed a Sentiment Analysis Framework and by utilizing this system, investigated the exhibition of SVM for printed polarity detection. We have utilized three datasets for the analysis, two from twitter and one from IMDB surveys. For execution assessment of SVM, we have utilized three unique proportions of preparing data and test data, 70:30, 50:50 and 30:70. Execution is estimated as far as exactness, review, and f-measure for each dataset.**

*Keywords*— ***Sentiment Analysis, Polarity Detection, Data Classification, Machine Learning, Support Vector, Machine, SVM, social media.***

### *I. Introduction*

This Online textual data is expanding step by step, particularly because of web-based life (Facebook, Twitter) and other blogging sites. The associations can utilize this huge measure of data with the assistance of sentiment analysis devices/strategies to screen their customers' reaction in regards to items or benefits and can make brief move to settle their issues, for example, expanding the quality or diminishing the costs and so forth. For sentiment analysis, generally three methodologies are utilized: dictionary based, machine learning based and a half and a half [1],[2]. The dictionary-based methodology utilizes dictionaries of weighted words as opposed to utilizing any preparation set, the specific weighted words are utilized with their sentiment direction for recognizable proof of by and large sentiment from a given content [3]. A portion of the outstanding dictionary based strategies incorporates SentiStrength 3.0, SentiWordNet, WordNet, Linguistic Inquiry and Word Count (LIWC), Affective Norms for English Words(ANEW) and SenticNet as talked about in [4]. Some outstanding machine learning strategies are Maximum Entropy, Stochastic Gradient Descent, Random Forest, SailAil Sentiment Analyzer, Multi-Layer Perceptron, Naïve Bayes, Multinomial Naïve Bayes and Support Vector Machine as talked about by [5]. In a regulated machine learning approach, first, the preparation dataset is expected to prepare the calculation. Preparing dataset incorporates the predefined yield class with which the calculation makes the guidelines and get itself prepared and after that group, the genuine information data likewise called test data [11], [1]. While vanity metrics such as follower count and likes are easily tracked, measuring tone and sentiment can be trickier. The following tools can help.

Quickly and easily filter mentions and sort by sentiment using Hootsuite Insights. You can also track sentiment by keywords and set up automated assignments by chosen keywords.

For example, you could set up your Twitter mentions on Hootsuite to scan for tweets containing positive terms such as "thank you," "love," and "amazing."

You can also be sure to search for sentiment-signaling emojis, such as the thumbs up or smiley face.

Hootsuite Insights provides an overview of sentiment with an easy-to-read meter. This allows you to quickly see how your brand is doing from a sentiment point of view, and monitor for any changes.

A crossbreed approach is a blend of dictionary based and machine learning-based methodologies, this methodology, for the most part, returns better outcomes. Most normally utilized mixture strategies/devices incorporate pSenti [6], SAIL [7], NILC_USP[8] and Alchemy API [9] as talked about in detail by [10]. This exploration expects to examine the presentation of Support Vector Machine (SVM) for polarity detection with three datasets. Additionally, three proportions of preparing data and test data are utilized for similar analysis: 70:30, 50:50, 30:70 to check the dimension of reliance of results on the level of preparing data. SVM is one of the generally utilized administered machine learning calculations for sentiment analysis and was formally presented by [12]. It is a pervasive machine learning based classification technique which has demonstrated to be exceedingly viable in order of conventional writings and for the most part beat Naïve Bayes classifiers as clarified by [13], In this investigation, we have proposed the Sentiment Analysis Framework (SAF), which comprises of four stages: Dataset, Preprocessing, Classification, and Results. Preprocessing stage further has five stages: Term Frequency-Inverse Document Frequency (TF-IDF), Stemming, Stop Words, Tokenizing and Words to Keep.

## II. RELATED WORK

Before The Prompt increment of online substance has produced an exceptionally massive effect on our day by day lives, in terms of social joint efforts as well as in pretty much every viewpoint: from internet business to governmental issues. A few devices and calculations are accessible to separate and arrange the sentiments from online client created content to positive, negative or nonpartisan. In [14], the creators have utilized three diverse machine learning calculations: Naïve Bayes, Decision Tree and Support Vector Machine for sentiment classification of Arabic dataset which was gotten from Twitter. The creators have pursued a structure for Arabic tweets classification where two extraordinary sub-undertakings were performed in pre-preparing, Term Frequency-Inverse Document Frequency (TF-IDF) and Arabic stemming.

Pak and Paroubek(2010) [1] proposed a model to group the tweets as a goal, positive and negative. They made a Twitter corpus by gathering tweets utilizing Twitter API and naturally clarifying those tweets utilizing emojis. Utilizing that corpus, they built up a sentiment classifier dependent on the multinomial Naive Bayes strategy that utilizations highlights like N-gram and POS-labels. The preparation set they utilized was less productive since it contains just tweets having emojis.

### SENTIMENT ANALYSIS

Sentiment analysis can be characterized as a procedure that mechanizes mining of demeanors, opinions, perspectives, and feelings from content, discourse, tweets and database sources through Natural Language Processing (NLP). Sentiment analysis includes ordering opinions in content into classes like "positive" or "negative" or "impartial". It's additionally alluded to as subjectivity analysis, opinion mining, and examination extraction.

The words opinion, sentiment, view, and conviction are utilized conversely yet there are contrasts between them.

- Opinion: An end open to question (in light of the fact that various specialists have various opinions )
- View: abstract opinion
- Belief: intentional acknowledgment and scholarly consent
- Sentiment: opinion speaking to one's sentiments

As of late a ton of work has been done in the field of "Sentiment Analysis on Twitter" by various specialists. In its beginning period, it was expected for paired classification which appoints opinions or surveys to bipolar classes, for example, positive or negative as it were.

Parikh and Movassate(2009) [2] actualized two models, a Naive Bayes bigram model, and a Maximum Entropy model to group tweets. They found that the Naive Bayes classifiers worked much superior to anything the Maximum Entropy model.

Go and L.Huang (2009) [3] proposed an answer for sentiment analysis for Twitter data by utilizing inaccessible supervision, in which their preparation data comprised of tweets with emojis which filled in as boisterous marks. They assemble models utilizing Naive Bayes, MaxEnt and Support Vector Machines (SVM). Their component space comprised of unigrams, bigrams, and POS. They presumed that SVM outflanked different models and that unigram was progressively powerful as highlights.

Kamps et al. [12] utilized the lexical database WordNet to determine the enthusiastic substance of a word along with various measurements. They built up a separation metric on WordNet and determined the semantic polarity of descriptive words.

Xia et al. [13] utilized a gathering system for Sentiment Classification which is acquired by consolidating various capabilities and classification methods. In thier work, they utilized two sorts of capabilities (Part-of-discourse data and Word-relations) and three base classifiers (Naive Bayes, Maximum Entropy and Support Vector Machines). They connected group approaches like the fixed blend, weighted mix and Meta-classifier mix for sentiment classification and got better precision.

Luoet. al. [14] featured the difficulties and effective strategies to my opinions from Twitter tweets. Spam and fiercely fluctuating language make opinion recovery inside the Twitter testing task.

# III. Research methodology

### APPROACHES FOR SENTIMENT ANALYSIS

There are mostly two strategies for sentiment analysis for the Twitter data:

### 3.1 Machine Learning Approaches

Machine learning based methodology utilizes a classification system to arrange content into classes. There are essentially two sorts of machine learning methods

**3.1.1. Unsupervised learning:**

It doesn't comprise of classification and they don't furnish with the right focuses at all and thusly depend on grouping.

**3.1.2. Supervised learning:**

It depends on the named dataset and accordingly the names are given to the model during the procedure. These named datasets are prepared to get important yields when experienced during basic leadership.

The accomplishment of both this learning strategy, for the most part, relies upon the choice and extraction of the particular arrangement of highlights used to distinguish sentiment.

Various machine learning procedures have been detailed to group the tweets into classes. Machine learning systems like Naive Bayes (NB), most extreme entropy (ME), and support vector machines (SVM) have made extraordinary progress in sentiment analysis.

**3.2 Lexicon-Based Approaches**

Vocabulary based technique [20] utilizes sentiment lexicon with opinion words and match them with the data to determine

polarity. They allocate sentiment scores to the opinion words depicting how Positive, Negative and Objective the words contained in the lexicon are.

Vocabulary put together approaches chiefly depend with respect to a sentiment dictionary, i.e., a gathering of known and precompiled sentiment terms, states and even figures of speech, created for customary sorts of correspondence, for example, the Opinion Finder vocabulary;

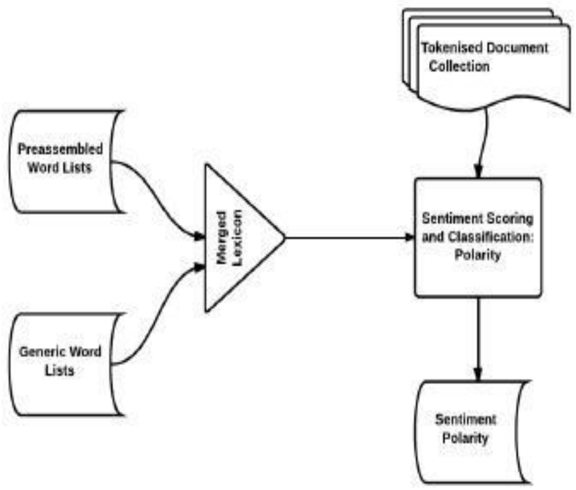



**Fig 1.Lexicon-Based Model**

**There are Two sub-classifications for this methodology:**

**3.2.1.Dictionary-based:**

It depends on the utilization of terms (seeds) that are typically gathered and clarified physically. This set develops via looking through the equivalent words and antonyms of a lexicon. A case of that lexicon is WordNet, which is utilized to build up a thesaurus called SentiWordNet.

Disadvantage: Can"t manage area and setting explicit directions.

3.2.2. Corpus-Based:

The corpus-based methodology has the goal of giving word references identified with a particular space. These lexicons are created from a lot of seed opinion terms that becomes through the inquiry of related words by methods for the utilization of either factual or semantic procedures.

• Methods are dependent on insights: Latent Semantic Analysis (LSA).

• Methods dependent on semantics, for example, the utilization of equivalent words and antonyms or connections from thesaurus like WordNet may likewise speak to an intriguing arrangement.

The motivation behind this examination is to break down the presentation of SVM during the classification of pre-named tweets and surveys as positive, negative and impartial. In this examination three datasets are utilized, two from Twitter [25], [26] and one from IMDB surveys [27]. 'Sentiment Analysis Framework is proposed in this examination (Fig. 1), which is

a customized type of 'Exploration Method Framework' trailed by [14]. The proposed structure comprises of four stages: Data set, Preprocessing, Classification, and Results. Dataset stage manages the addition of data into WEKA condition on which the classification must be performed. Preprocessing Phase manages the procedure of standardization of strings into a vector group, which will be the contribution to the classification calculation. It has further five stages: 1) Term Frequency-Inverse Document Frequency (TF-IDF), 2) Stemming, 3) Stop Words, 4) Tokenizing and 5) WordstoKeep. Classification stage manages the working of the classification calculation in WEKA. Result stage manages the generation of results as tables and charts. In this examination, Classification is performed multiple times (on each dataset) with various proportions of preparing and test data. Lastly, the outcomes are closed and examined.

A. Weka

We have utilized Weka for execution assessment of SVM with various datasets. Weka (Waikato Environment for Knowledge Analysis) is mainstream and broadly utilized data mining programming created in Java language at the University of Waikato, New Zealand [40]. One reason for its wide acknowledgment is that it has GUI for simple access to its functionalities like utilizing calculations for data analysis, prescient demonstrating, and representations. Further favorable circumstances of this product incorporate its overall population permit and its convenience.

B. Data Sets

Three datasets are utilized in this examination. In the first dataset [25], tweets are identified with the accompanying four subjects: 'Apple', 'Google', 'Microsoft' and 'Twitter'. It contains 571 positive, 519 negative, 2331 impartial and 1689 superfluous tweets. In the second dataset [26], tweets are identified with all major U.S. aircraft from February of 2015 and arranged as 2362 positive, 9178 negative and 3099 nonpartisan. Third dataset [27] taken from Internet Movie Database (IMDB) audits and contains 1000 positive and 1000 negative writings.

Table 1. Datasets Detail

| Source | Positive | Negative | Neutral | Irrelevant | Total |
|---|---|---|---|---|---|
| Twitter[25] | 571 | 519 | 2331 | 1689 | 5110 |
| Airline[26] | 2362 | 9178 | 3099 | - | 14639 |
| IMDB[27] | 1000 | 1000 | - | - | 2000 |

Dataset stage expects to download the important dataset from the online network and change it into CSV/ARFF configuration to use in WEKA Workbench [28]. Straightforward CLI can be utilized to change over content records into ARFF organization utilizing "weka.core.converters.TextDirectoryLoader" work has appeared in Fig. 2.

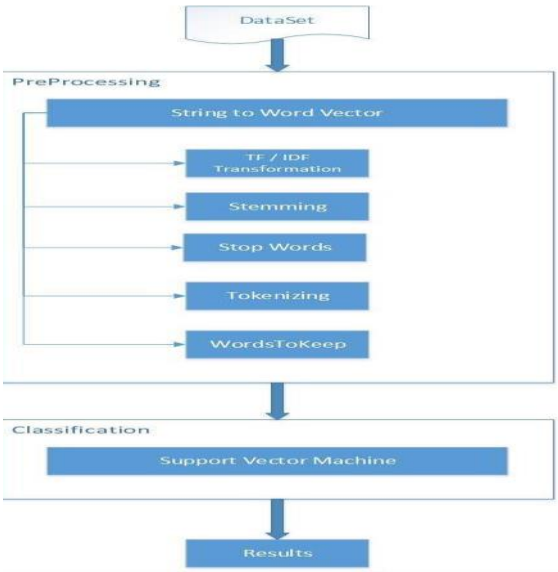



Fig.2. Sentiment Analysis Framework (SAF)

## C. Pre-Processing

It is the most important phase of our framework., in which selected dataset is normalized and get ready for the classification algorithm. In this phase, Strings are converted into vectors for the classification process. Following subtasks are performed in this phase.

### 1- Term Frequency-Inverse Document Frequency (TF-IDF):

TF-IDF provides useful and important information in the pre-processing phase. It typically evaluates the frequency of useful words, which eventually make the sentiment detection process easy. Frequency of terms plays an important role in the identification of important information as explained by [1]. For example, frequently appearing words in a text document can be ‘Good', ‘Bad', ‘Happy' or ‘Sad' etc. Identification and frequency of these words can play a vital role in the process of Opinion Mining. Term Frequency(TF) is the number of occurrence for a term in a given document. Following equation can be used to calculate it:

$$W_d(t) = TD(t, d) \qquad (1)$$

Where TD corresponds to the frequency of term t in a given document d. TF-IDF contains the inverse document frequency (IDF), that reverts higher weight-age for rare conditions while lower-weight age for common conditions as explained by [29].

In Weka, TF & IDF transformations are available along with other filters as shown in Fig. 3. below:

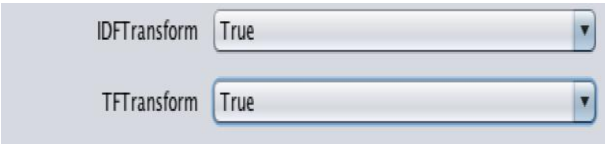



Fig.3. TF and IDF Transform

### 2- Stemming

The way toward Stemming is extremely valuable in numerous regions of computational etymology and data recovery as it decreases all words with a similar stem/base to a typical structure [30], for instance, the word 'working' will be stemmed into 'work, etc. Word Stemming is one of the basic highlights of pre-processing in content mining [31]–[35]. In this examination, "IterativeLovinsStemmer" is chosen in WEKA as the word stemmer in the pre-processing stage as appeared in Fig 4. It depends on the LovinsAlgortihm which was the first Stemming calculation by Lovins JB in 1968[36].

### 3- MultiStopWords

The Concept of stop words was initially presented by [37]. These are regular high-frequency words like "A", "the", "of", "and", "an". This data is

Superfluous and does not influence the exhibition of classification along these lines; it must be expelled. There are a few techniques accessible for stop word expulsion as clarified by [30], [31], [33], [38], [39]. "MultiStopwords" was chosen (Fig 4) for stop words model for the pre-processing stage in Weka.

### 4- N-GramTokenizer

"N-GramTokenizer" was chosen as the Tokenizer in Weka (Fig 4) for pre-processing of data. It first breaks the content into words at whatever point one of the recorded determined characters is distinguished in it. A short time later, it transmits N-Grams of each expression of the predefined length.

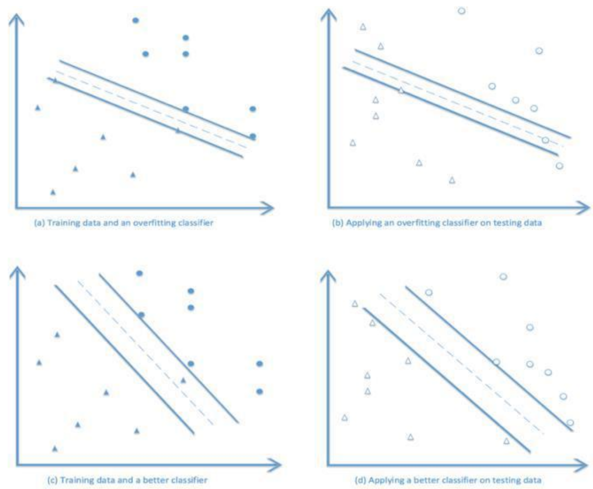

Fig.4. Stemmer, Stopwords, Tokenizer, and Wordstokeep

### 5- WordstoKeepN

1000 words were kept in the "words to keep" parameter to limit results inside a restricted measure of time. In the wake of applying these parameters as appeared in fig 4, the pre-processing on each of the three datasets were done and after that, the prepared datasets were sent to the classifier.

### D. Classification

In supervised machine learning approach, first, the calculation needs to get prepared with pre-characterized data (preparing data) with which it makes rules for classification and afterward based on these principles it arranges the info data (test data). For execution analysis of any supervised machine learning calculation, pre-ordered data is given as test data and after that, the aftereffects of the calculation can be contrasted and this pre-named data. A similar methodology is utilized in this examination to break down the presentation of the proposed network seek strategy. Pre-named datasets are acquired from social gatherings: Twitter and IMDB. For classification, Support Vector Machine (SVM) with network inquiry and K-overlay cross-approval procedure is utilized. Framework Search is fundamentally a model for hyperparameter enhancement. Hyperparameter tuning is a significant assignment in SVM to separate increasingly exact outcomes [30]-[33]. In Grid-Search, various models having diverse parameter esteems are prepared and afterward assessed utilizing cross-approval. For an RBF portion, there are two parameters: C and Y. It can't be discovered ahead of time what estimations of C and Y are most appropriate for a given issue, so an improved model is required which can distinguish the perfect pair of qualities for these parameters to accomplish the greatest exactness. The procedure of 10-k cross-approval is performed on each model of C and Y and the pair with ideal outcomes are chosen. Cross-approval is a strategy used to test various models under a specific classifier with the subset of information data as clarified by [35]. For K-overlap cross-approval, the preparation data is first isolated into k subsets of a similar size. One subset is tried utilizing the classifier on the rest of the k-1 subsets. The cross-approval system can prevent the overfitting issue [34], [36], a parallel classification issue is appeared in Fig. 2 to represent this issue. Filled circles and triangles are the preparation data while empty circles and triangles are the trying data. The testing exactness of the classifier in Fig. 2(a) and (b) isn't great as it overfits the preparation data. Then again, the classifier in Fig. 2(c) and (d) does not overfit the preparation data and gives better exactness with cross-approval.




Three distinctive datasets are utilized for classification to especially watch that whether the exhibition is dataset and proportion (preparing data: test data) subordinate or not? Three unique proportions are utilized for preparing data and test data (preparing data: test data): 1) 70:30, 2) 50:50 and 3) 30:70.

# IV. RESULTS ANALYSIS

The This area centers around the near analysis of SVM execution. For examination, three assessment parameters are utilized in this investigation: Precision, Recall and F-Measure. The precision can be calculated using TP and FP rate as shown below:

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP})$$

TP used for the sentences, which are correctly classified, and FP is for sentences, which are wrongly classified.

Recall can be calculated as shown below:
The review can be determined as demonstrated as follows:

$$\text{Review} = \text{TP}/(\text{TP} + \text{FN})$$

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

### A. Results with First Dataset

First dataset is taken from [25] and contains the tweets regarding four particular words: 'Apple', 'Google', 'Microsoft' and 'Twitter'. Three proportions of training-data and test-data (training data: test data) are used for the classification of each dataset. The experimental results show that with the 70:30 (ratio) the average Precision, Recall and F-Measure is 70.4%, 70.3% and 56.3% respectively. With 50:50, the average Precision, Recall and F-Measure is 68.1%, 67.7% and 67.9% respectively. Moreover, with the 30:70 the average Precision, Recall and F-Measure is 65.0%, 64.6% and 64.8% respectively.

Table 2. Ratio wise Precision, Recall and F-Measure for First Dataset

| Distribution | Class | Precision | Recall | F-Measure |
|---|---|---|---|---|
| 70% - 30% | Negative | 0.5 | 0.569 | 0.532 |
| | Positive | 0.412 | 0.377 | 0.394 |
| | Neutral | 0.726 | 0.717 | 0.721 |
| | Irrelevant | 0.836 | 0.833 | 0.835 |
| | Average | 0.704 | 0.703 | 0.563 |
| 50% - 50% | Negative | 0.434 | 0.505 | 0.467 |
| | Positive | 0.373 | 0.353 | 0.363 |
| | Neutral | 0.706 | 0.702 | 0.704 |
| | Irrelevant | 0.827 | 0.8 | 0.813 |
| | Average | 0.681 | 0.677 | 0.679 |
| 30% - 70% | Negative | 0.367 | 0.416 | 0.39 |
| | Positive | 0.322 | 0.312 | 0.317 |
| | Neutral | 0.691 | 0.691 | 0.685 |
| | Irrelevant | 0.794 | 0.794 | 0.789 |
| | Average | 0.65 | 0.646 | 0.648 |

These results are arranged in Table 2 and change of trend with change of proportions is shown with graph (Fig 5).

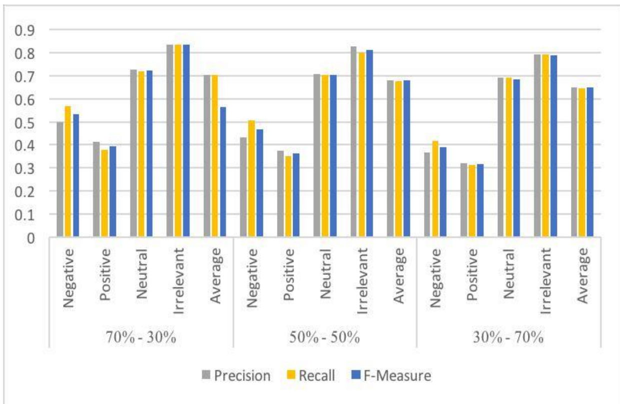



Fig.5. Precision, Recall and F-measure

The results show that the ratio 70:30 performed the best for Precision and Recall in this dataset at average while the ratio 50:50 performed better for F-Measure on average.

### B. Results with Second Dataset

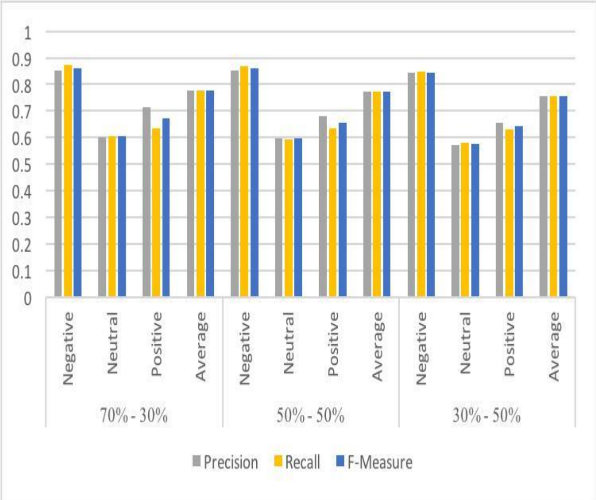
Second dataset is taken from [26] and contains the tweets regarding major US airlines. According to the experimental results with (ratio) 70:30 the average Precision, Recall and F-Measure is 77.6%, 77.8% and 77.6% respectively. With 50:50 the average Precision, Recall and F-Measure is 77.2%, 77.4% and 77.3% respectively. And for the 30:70 the average Precision, Recall and F-Measure was 75.6%, 75.6% and 75.6% respectively.

Table 3. Ratio wise Precision, Recall and F-Measure for Second Dataset

| Distribution | Class | Precision | Recall | F-Measure |
|---|---|---|---|---|
| 70% - 30% | Negative | 0.851 | 0.874 | 0.862 |
| | Neutral | 0.603 | 0.606 | 0.604 |
| | Positive | 0.713 | 0.633 | 0.671 |
| | Average | 0.776 | 0.778 | 0.776 |
| 50% - 50% | Negative | 0.851 | 0.869 | 0.86 |
| | Neutral | 0.599 | 0.593 | 0.596 |

| | | | | |
|---|---|---|---|---|
| | Positive | 0.682 | 0.635 | 0.657 |
| | Average | 0.772 | 0.774 | 0.773 |
| 30% - 50% | Negative | 0.842 | 0.846 | 0.844 |
| | Neutral | 0.572 | 0.579 | 0.575 |
| | Positive | 0.656 | 0.631 | 0.643 |
| | Average | 0.756 | 0.756 | 0.756 |

Fig.6. Precision, Recall and F-measure




Results are presented in Table 3 and reflection of trend changing according to proportions is presented in graph in Fig. 6. The results show that the ratio 70:30 out performed in Precision, Re-call and F-Measure on average.

*C. Results with Third Dataset*

Third dataset was taken from [27] and contains the IMDB reviews. The experimental results showed that for the ratio 70:30 the average Precision, Recall and F-Measure was 78.8%, 78.8% and 78.8% respectively. For

| Distribution | Class | Precision | Recall | F-Measure |
|---|---|---|---|---|
| 70% - 30% | Negative | 0.793 | 0.79 | 0.791 |
| | Positive | 0.784 | 0.786 | 0.785 |
| | Average | 0.788 | 0.788 | 0.788 |
| 50% - 50% | Negative | 0.803 | 0.803 | 0.803 |
| | Positive | 0.805 | 0.805 | 0.805 |
| | Average | 0.804 | 0.804 | 0.804 |
| 30% - 70% | Negative | 0.793 | 0.761 | 0.776 |
| | Positive | 0.768 | 0.799 | 0.783 |
| | Average | 0.78 | 0.78 | 0.78 |

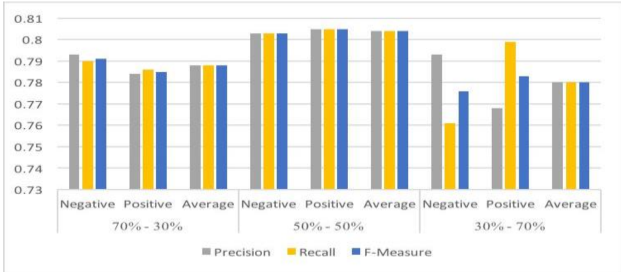



Fig.7. Precision, Recall and F-measure

## CONCLUSION

In this exploration, we have broken down the exhibition of Support Vector Machines (SVM) for polarity detection in Weka condition. The SVM method is connected to three diverse pre-marked datasets. Two datasets are taken from Twitter and one dataset is taken from IMDB Movie Reviews. In addition, Sentiment Analysis Framework is proposed in this investigation for the successful and smooth technique of polarity detection. The proposed system comprises of four stages: Data set, Preprocessing, Classification, and Results. Preprocessing is the most significant stage and further comprises of five stages including TF-IDF, Stemming, Stop Words, Tokenizing and WordstoKeep. For the classification of each dataset, three proportions of Training Data and Test Data are utilized: 70:30, 50:50 and 30:70. The proportion 70:30 with First Dataset performed better in precision and review while 50:50 performed better in F-Measure. For the Second dataset,70:30 beat the other two. For the Third dataset, the 50:50 performed normally. We have reasoned that the presentation of SVM relies on dataset just as on the proportion of Training and Test Data. Results are masterminded in forbidden and in graphical structures. This examination can be utilized as the benchmark for further relative investigations of other machine learning calculations by utilizing extraordinary and huge datasets.

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