"A Hybrid Approach to Sentiment Analysis: Combining Rule-Based and Machine Learning Techniques"

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ABSTRACT:

The Sentimental Analysis method is frequently utilized to assess user thoughts, sentiments, and text subjectivity. Sentiment Analysis, also known as Opinion Mining, entails the thorough evaluation of emotions conveyed by individuals. The websites function as an effective medium for collecting client feedback derived from historical data. The existing methods employing sentiment analysis have demonstrated ineffectiveness. A new hybrid framework has been established, integrating three classifiers: SVM, logistic regression, and Random Forest. The hybrid model functions as a proficient classifier that improves classification results by user feedback or historical data. The proposed model has been effectively applied and assessed against current methodologies utilizing several performance criteria, including as accuracy, precision, and recall.

KEYWORDS: SVM, Hybrid Classification, Sentiment analysis, ML, MLT

1. INTRODUCTION

Data mining is a technology that retrieves information from extensive datasets. This technology use advanced data analytic methods to reveal previously unrecognized, legitimate occurrences and relationships within extensive databases. Frequently employed instruments encompass statistical models, computational methodologies in statistics, and machine learning algorithms. Consequently, data mining involves the acquisition and administration of data, in addition to analysis and prediction. This technique aims to discern lawful, innovative, possibly profitable, and comprehensible correlations and patterns within the existing data [1].The methodology employed to discern important data patterns is known by multiple designations. Mathematicians, database researchers, and commercial entities initially adopted the phrase "data mining." KDD involves a systematic methodology for deriving meaningful insights from data. Data mining is a crucial stage in this comprehensive process. The key duties in this methodology encompass data preparation, selection, and cleansing, ensuring a comprehensive grasp of the outputs linked to the data mining technique. Data mining enables the discovery of useful insights. Data mining signifies an evolution of conventional techniques. Data mining comprises techniques sourced from other disciplines.

2. SA refers to the analytical assessment of a person's beliefs, behaviors, and attitudes around a particular object. The item may represent individuals, events, or subjects. These subjects are generally included in assessments. Opinion Mining (OM) entails the extraction and analysis of individuals' sentiments regarding a specific object. Conversely, Sentiment Analysis (SA) first determines the sentiment conveyed in a text and then examines it [2]. Consequently, sentiment analysis aims to find concepts, discern the attitudes expressed by individuals, and subsequently classify these sentiments based on polarity. Sentiment analysis comprises three principal classification levels. These are categorized as document-level, sentence-level, and aspect-level sentiment analysis. The fundamental objective of the initial method is to categorize ideas that express two types of sentiments: positive or negative. It regards the entire article as a fundamental unit of information. The main aim of sentence-level analysis is to categorize the sentiments conveyed in each sentence. This analysis first offers insights into the subjective or objective nature of a statement. This method determines the positive or negative mood expressed in a subjective remark. The principal objective of aspect-level sentiment analysis is to categorize sentiment based on particular attributes of an entity [3]. The preliminary phase of this sentiment analysis involves the identification of entities and their characteristics. Individuals may have differing views about the attributes of similar objects. Sentiment classification techniques are often categorized into machine learning, lexicon-based, and hybrid methodologies. The machine learning approach incorporates significant algorithms and utilizes linguistic features. The subsequent lexicon method utilizes a sentiment lexicon that consists of a compilation of recognized and pre-existing opinionated phrases. The lexicon-based approach can be further categorized into dictionary and corpus-based techniques. These methods utilize statistical techniques to ascertain sentiment polarity. The hybrid approach integrates both techniques. This method is extensively employed with sentiment lexicons. Sentiment lexicons are essential in almost all techniques. Text classification employing machine learning methods can be generally categorized into two kinds. The primary category of supervised algorithms utilizes a significant amount of labeled training documents. Alternative strategies are employed when these designated training documents are not easily discernible. Naive Bayes is the simplest simplistic and one of the most extensively employed classification methods. This classifier assesses the posterior class probability by analyzing the distribution of words inside a document. The classifier utilizes Bag of Words for feature extraction. This feature extraction method ignores the placement of words inside the page. This classifier employs Bayes Theorem to assess the likelihood that a specific feature set is associated with a particular label. The Maximum Entropy Classifier transforms labeled feature sets into vectors by encoding. This encoded vector is employed to compute weights for each characteristic. These weights are employed to determine the most likely label for a set of features. This categorization model is represented by a resource of X{weights} [5]. This is employed for integrating the characteristics of a feature set using an X{encoding}. The encoding associates the C {(feature set, label)} pair with a vector. The main objective of the SVM classifier is to identify linear separators in the search space that effectively differentiate among various classes. Text data are particularly appropriate for SVM due to their sparse characteristics, wherein certain features may be extraneous; yet, they generally display correlations and are often classified into discrete categories linearly. The lexicon-based approach aims to identify the opinion lexicon. The opinion lexicon is employed for the examination of textual content. This methodology is further classified into dictionary-based and corpus-based methodologies [6]. The first phase entails finding subjective phrases, subsequently utilizing the dictionary to explore their synonyms and antonyms. This method is primarily limited by its incapacity to recognize opinionated phrases that are relevant to specific domains and contexts. The second strategy assists in resolving the issue of recognizing opinionated words with context-dependent orientations. This method utilizes syntactic patterns derived from a core list of opinionated phrases to detect supplementary opinionated words inside extensive datasets.

LITERATURE REVIEW

Rincy Jose, et.al (2016) devised a new scheme for robotically classifying the sentiment of tweets [8]. In this approach, ML models and Lexicon-based approach were utilized together. SentiWordNet classifier, NB classifiers and HMM classifiers had applied in this technique. After achieving the results of reviews from these classifiers, the negativity and positivity of each tweet was determined on the basis of majority voting principle. The political sentiments had been found from the real time tweets by utilizing these sentiment classifiers. This ensemble technique of classifiers helped to acquire an enhanced exactness in sentiment analysis. High accuracy had been achieved by using negation handling and word sense disambiguation of this method.

Minu Choudhary et al. (2018) gathered reviews from Twitter, a prominent social media network [7]. A total of 5,000 reviews were gathered from several smartphone brands. The Lexicon-based method was employed for the sentiment analysis of these reviews. A graph was created to illustrate the outcomes of sentiment analysis. This graph assisted buyers in making decisions on the purchase of new mobile phones, while sellers utilised it to improve their company operations. Diverse machine learning algorithms were employed in the trials for the classification of reviews for future study. The machines provided a more precise assessment of the goods.

Vallikannu Ramanathan et al. (2019) proposed an innovative method for sentiment analysis grounded in common knowledge [9]. A tourist ontology for Oman based on Concept Net has been developed using this method. Initially, the POS was employed to discern the entities extracted from the tweets. In the domain-specific ontology, these elements were juxtaposed with the idea. The feelings of the extracted entities were further analysed using a mutual sentiment lexicon technique. The semantic orientations of explicit attributes and the domain have finally been integrated. To enhance the performance of SA, the conceptual semantics were integrated as an attribute with the machine learning method.

Sonia Saini, et.al (2019) recommended an open source technique [11]. In this approach, the tweets were collected from the Twitter API. These tweets were pre-processed, analysed and visualized by utilizing R programming. It was a statistical tool that was applied for the sentimental analysis of tweets. SA was done on the basis of the text data that was retrieve from the streamed web. The perceptions of the people were classified according to the eight different categories of the feelings. The analysis of sentiments was also based on the two unique sentiments: positive and negative.

Zahra Rezaei, et.al (2017) studied that the messages on the Twitter were continually generated and they were reached to the destination at high speed [10]. These messages had followed the data stream model. Therefore, the algorithms were utilized to foresee sentiment on Twitter under limited and real time. For this, the most well-liked tool in mining data streams that was known as Hoeffding tree algorithm was utilized. By this algorithm, the smallest number of instances had been found that were required to select a splitting feature in a node. In the Hoeffding tree algorithm, MacDiarmid's bound was replaced. That was why, McDiarmid tree algorithm had been applied in this paper. The accuracy acquired on Twitter for sentiment analysis from the McDiarmid tree was similar to that of Hoeffding tree and the processing time of the former was reduced noticeably.

In their model, Sahar A. El Rahman et al. (2019) used actual data retrieved from Twitter to do sentiment analysis [12]. The data collected from Twitter was inherently unstructured, making sentiment analysis a challenging task. However, compared to earlier approaches, the suggested model was unique. This approach is a hybrid of supervised and unsupervised learning techniques. Two individuals were studied for this data set. We chose two fast food chains—McDonald's and KFC—to show how popular each is. The outcome of these models was examined using various testing metrics. When tested with texts mined directly from Twitter, the provided model functioned admirably.

3. RESEARCH METHODOLOGY

The methodical system for projected method is elucidated in the figure 1 where both N-gram and KNN approaches are exploited.

A. Dataset

This work generates two categories of information samples physically. One of these samples is utilized for training, while the other is designated for testing. The training sample exhibits an X:Y relationship. X denotes a viable assessment remark, whereas Y evaluates a favorable or unfavorable statement. Upon acquiring comments from many websites, the testing set is established. The tagging of a comment is performed manually to identify negative or positive test samples.

B. Data Pre-processing

This study employs three distinct pre-processing methods: stemming, fault alteration, and discontinuation statement deletion. The initial method of stemming is to identify a foundational sentiment. This method eliminates suffixes and several associated terms. This method can markedly decrease energy and time expenditure. It is important to establish a fault modification strategy owing to the restricted application of grammatical standards, punctuation, and spelling.

C. Lexical Analysis of Sentences

A sentence often encompasses two categories of sentiments: positive or negative. Additionally, several inquiries submitted by users devoid of emotion exemplify objective statements. To minimize the review size, sentences may be separated to reduce the overall appraisal volume. The initial phase of a compiler is lexical analysis. Enhanced source code articulated as sentences by lexicon pre-processors is employed for this objective. The lexical analyzer is tasked with transforming a raw byte or a sequence of input characters from the source file into a stream of tokens. To do this, the input is segmented into several components, and superfluous elements are removed. The lexical analyzer generates an error upon encountering an illegal token. This provision significantly simplifies the process of consecutive syntactical analysis. In other instances, whitespace and comments may occur anywhere. Lexical analysis seeks to categorize input tokens into several kinds, such as opening brackets, keywords, integers, etc. The lexical step provides an additional benefit by reducing input size by up to 80%. A lexer may regard the primary layer of a coherent lexical perspective on the input dialect. The lexical and syntactic analyzers operate in close conjunction. The lexical analyzer, upon reading characters from the source code, validates for legitimate tokens. Subsequently, it transmits data upon request from the syntax analyzer.

D. Extraction of Features

When features of a sample are analyzed, key questions regarding the opinion study emerge. The depiction of an entity characteristic through a noun is pervasive. We employ POS tagging to identify and extract all nouns in order to recognize all attributes. Feature extraction entails condensing the actual feature space into a more succinct representation. A new compressed space is established without the elimination of any actual properties; all properties are transformed. A condensed set of representations substitutes for the genuine features. This indicates an inability to process the input data due to its substantial bulk. This is the rationale for transforming the data into a new set of features with a diminished quantity of features. The fundamental element of a feature is referred to as a text feature. Feature extraction is a technique for picking a subset of features to reduce the feature space. In feature retrieval, we eliminate unnecessary characteristics. This procedure enhances both the accuracy rate and execution time of the learning approach. Selecting only a portion of the document can create the appearance of the original text. Weight computation is synonymous with text feature extraction.

E. Hybrid Classifier

The application of a hybrid classifier technique facilitates the categorization of data into distinct classifications. The integration of support vector machines (SVMs), logistic regression (LR), and random forests (RF) produces a hybrid classifier. Decision trees are frequently the preferred method for categorization and prediction. Decision trees are organized in a manner akin to trees. Each internal node in this configuration signifies a feature evaluation. All nodes in this tree represent the tested outcomes [13]. Every leaf node is assigned a class identification. This node is referred to as a termination node. A feature value test is employed to divide the source set into subgroups for tree learning. All generated subgroups undergo this technique iteratively. Recursive partitioning delineates this process. At the conclusion of the recursion, either the subset at a node has equalized the value of the target variable, or partitioning ceases to enhance the predictions. Generating this classifier requires no prior knowledge of the domain or parameter configuration. This classifier facilitates knowledge discovery analysis. This classifier can effectively manage the substantial volume of data. In the majority of instances, the outcomes generated by this classifier are accurate. These models are generally characterized by a separating hyperplane. This algorithm generates the optimal hyperplane when provided with labeled training data. New patterns are classified utilizing this hyperplane. A support vector machine (SVM) model represents patterns as spatial points, delineating various classes by establishing a clear separation between them. The classifier is predicated on the notion that a (natural) class's function is to generate predictions concerning the feature values of its components. Patterns are classified into categories according to the values of their attributes. Natural classes is the prevalent designation for these categories of classes. A Bayesian classifier use an agent's understanding of the class to anticipate the values of other attributes. Conversely, Bayes' theorem can be employed to infer the originating class of the attribute values. This classification technique use a learning agent to construct a probabilistic model incorporating features. This model facilitates the categorization prediction of a new pattern. The results of all classifiers are aggregated using the voting method in the final output. All classifiers are assigned weights when employing the voting procedure. The precision of sentiment analysis may fluctuate based on the specified weights.

The distances from the origin of the hyper-planes of the support vectors are:

$$d_{+} = \frac{|1-b|}{\|w\|^2}$$

The distance between two planes is:

$$d_{-} = \frac{|1+b|}{\|w\|^2}$$

Linear regression:

$$Y = b_0 + b_1 \times x_1 + b_2 \times x_2 \dots \dots . + b_k \times x_k$$

$$Sigmoid\ function: p = \frac{1}{1+e^{-Y}}$$

Result written below can be achieved by inserting Y in sigmoid function:

$$\text{In}\left(\frac{P}{1-P}\right) = b_0 + b_1 \times x_1 + b_2 \times x_2 \dots \dots . + b_k \times x_k$$

This work uses RF classifier for resolving regression issues. Here, MSE is used to know the branching of data from each node.

$$MSE = \frac{1}{N}\sum_{i=1}^{N} (f_i - y_i)^2$$

Here, N corresponds to the number of points. f_i Is the value returned by the model and y_i is the actual value for data point i

By applying Random Forests on the basis of classification data, the Gini index, or the formula is considered for determining the no, of nodes on a decision tree edge.

$$Gini = 1 - \sum_{i=1}^{C} (p_i)^2$$

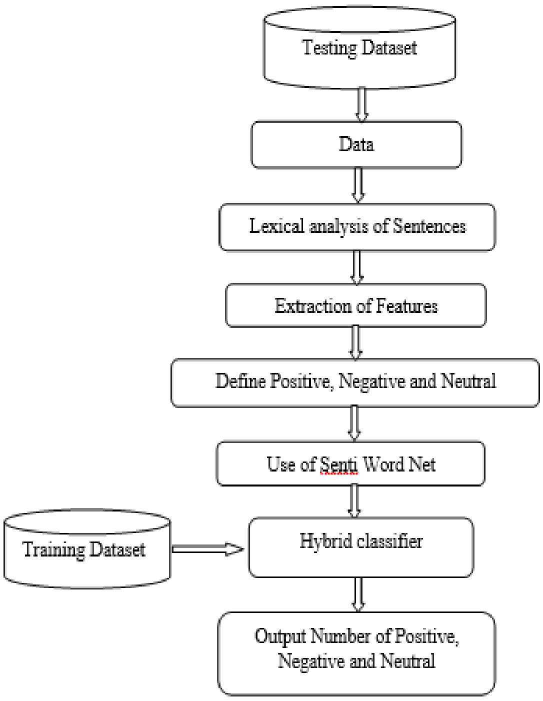

Fig. 1 Proposed Flowchart

4. RESULT AND DISCUSSION

The focus of this work is on SA (sentiment analysis). This work performs comparison between the proposed and SVM approach. In order to do so, thus work makes use of two dissimilar training and test sets. The outcomes are compared with regard to execution time and accuracy.

Table 1: Accuracy Analysis

Test-Training Ratio	SVM Classifier	Hybrid Classifier
10-90	83 percent	92 percent
20-80	82.5 percent	93.2 percent
30-70	84 percent	94 percent
40-60	82.6 percent	94. percent

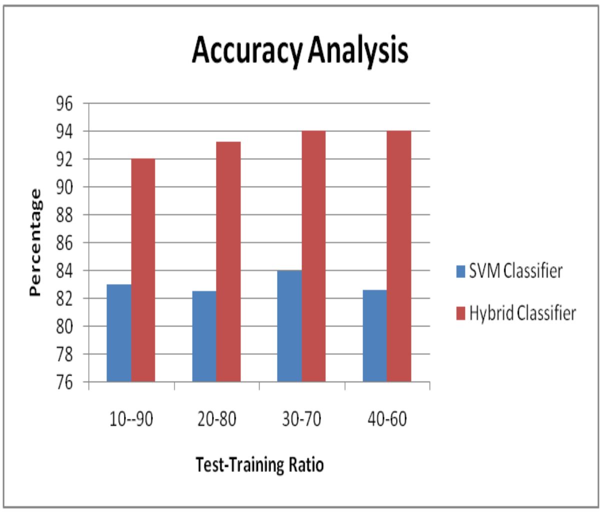

Fig. 2 Accuracy Analysis

Figure 2 shows accuracy-based comparison between new algorithm and former SVM algorithm. The accuracy of proposed algorithmic approach is higher than existing algorithmic approach for sentiment analysis. The results of accuracy are analysed on different sets of training and testing. The test and training sets are 10:90, 20:80, 30:70 and 40:60. The accuracy which is achieved on defined ratios is 92,93,94,94 by proposed method respectively. The proposed method achieved approx 10 percent more accuracy as compared to SVM classifier.

Table 2: Precision Analysis

Test-Training Ratio	SVM Classifier	Hybrid Classifier
10-90	83.2 percent	92.1 percent
20-80	82.3 percent	93.1 percent
30-70	84.1 percent	94 percent
40-60	82.6 percent	94. percent

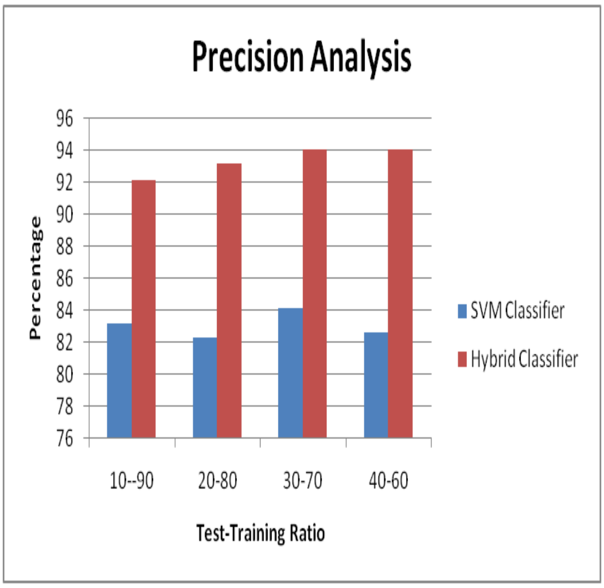

Fig. 3 Precision Analysis

Figure 3 shows precision-based comparison between new algorithm and former SVM algorithm. The precision of proposed algorithmic approach is higher than existing algorithmic approach for sentiment analysis. for sentiment analysis, the test and training sets are 10:90, 20:80, 30:70 and 40:60. The precision which is achieved on defined ratios is 92,93,94,94 by proposed method respectively. The proposed method achieved approx 10 percent more precision as compared to SVM classifier.

Table 3: Recall Analysis

Test-Training Ratio	SVM Classifier	Hybrid Classifier
10-90	83.2 percent	92.1 percent
20-80	82.3 percent	93.1 percent
30-70	84.1 percent	94 percent
40-60	82.6 percent	94. percent

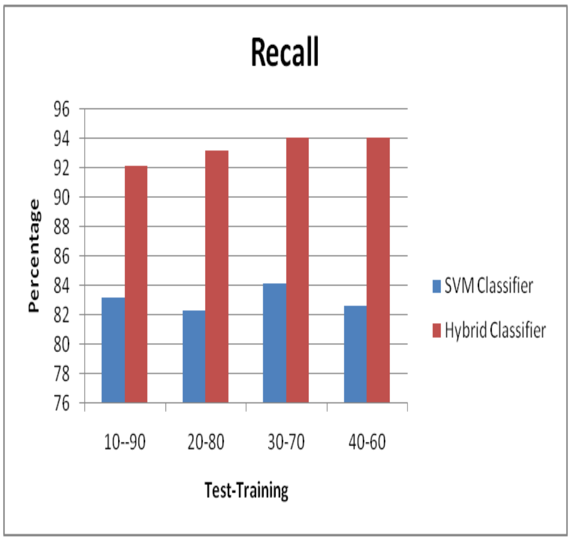

Fig. 4 Recall Analysis

Figure 4 shows recall-based comparison between new algorithm and former SVM algorithm. The recall value of proposed algorithmic approach is higher than existing algorithmic approach for sentiment analysis. The test and training sets are 10:90, 20:80, 30:70 and 40:60. The recall which is achieved on defined ratios is 92,93,94,94 by proposed method respectively. The proposed method achieved approx 10 percent more recall than SVM.

5. CONCLUSION

The results of this study show that sentiment analysis is used to assess the feelings that are present in the input data. There are several steps involved in the sentiment analysis. This research creates a hybrid method for analyzing sentiment. The new technique is assessed according to its accuracy and execution. The performance is assessed by using a variety of training and testing ratios. When compared to its equivalent, the new technique shows improved accuracy and a shorter execution time.

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