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A Hybrid Adaptive Neuro-Fuzzy Interface and Support Vector Machine Based Sentiment Analysis on Political Twitter Data

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Abstract: Twitter is a microblogging site where clients read and compose short messages on different points each day. Political investigation using social media is getting the consideration of numerous scientists to understand the general assessment and pattern, particularly at the time of elections. In this paper, a proficient approach with respect to fuzzy rules to dissect the general assessment and further anticipated poll results. The system contains mainly three modules in particular Data extraction, Pre-processing and characterization of sentiment. The initial two stages have undertakings, namely social media information extraction and data pre-processing in order to, expel all Uniform Resource Locator (URL) frame separated tweet. The last stage is a grouping stage where a strategy called Adaptive Neuro-Fuzzy Inference System (ANFIS) where the fuzzy based ontology is designed by actualizing Non-Linear Support Vector Machine (SVM) classifier analysis to improve the fuzzy principles. The result showed that the ANFIS- NonLinearSVM based Sentiment analysis of social network data is less complex and gives the high rate of accuracy compared to the existing methodologies.

Keywords: Twitter, Adaptive neuro-fuzzy inference system, Support vector machine, Political analysis, Social media.

1. Introduction

The web is one of the fastest developing field and the general population are frequently communicating, talking about and sharing data through the web o some topic. In this way, the web is a huge piece of human life. The data covers by the web are a broad scope of territories, for example, scholarly data, reviews, social media, opinions about market products, or remarks about social issues, and so forth. This data encourages individuals to think and settle on a choice on numerous things. The greater part of individuals dependably tunes in to others sentiment before taking an ultimate choice. The data which are gathered normally broke down to decide the supposition of the data, for example, negative assumption or positive conclusion. For the most part, supposition refers to feelings, state of mind, emotions, and assessment. The main goal of the sentiment analysis is to repeatedly perceive sentences by evaluative significance instead of, sentences are arranged by their division as either positive, negative or neutral. On the web, people consistently express their estimations over the web through electronic long range interpersonal communication, sites, rating, and reviews. Emotion examination is used to find the point of view of people [1, 2]. More often Sentiment examination incorporates three levels, in particular sentence level, document level, and perspective level [3]. Document level sentiment classification focuses around grouping the whole report as positive or negative. Sentiment scientific classification in sentence level thinks about the division of client's sentences in a record. Perspective level order perceives the different parts of the archives in a corpus and each record extremity is assessed [4, 5]. The informal communication locales like Twitter is the stage for the general population to raise their perspectives on different points and delivers a billion of kilobytes of information every day [6].

To be particular, the remarks about items in tweets, are well worth mining. Merchants can get the purchaser's remarks progressively and afterward update their own items to be more aggressive in the commercial market. Purchasers likewise can get other's involvement through these remarks to enable them to decide on whether to purchase an item. The publicizing organizations and entrepreneurs much of the time use sentiment analysis to decide systems of new business [7]. Twitter sentiment assessment expects to group the positive and negative notion polarity classes partitioned into subclasses in which the erroneous outcomes tend to diminish remarkably. Tweets are normally made out of incomplete, noisy and ineffectively organized sentences, irregular articulations, irregular form words and non-lexicon terms. Before feature selection, a progression of pre-preparing (e.g., expelling stop words, evacuating URLs, supplanting invalidations) are connected to lessen the measure of emotion in the tweets [8-9]. The writings utilized in Twitter are called tweets, which are short messages of a most extreme of 140 characters and a dialect that does not have any limitation on the frame and substance. In any case, because of the casual dialect utilized in Twitter and the impediment as far as characters (i.e., 140 characters for each tweet), understanding the feelings of clients and performing such examination are very troublesome [10, 11]. In twitter, it is difficult to isolate noteworthy data from an immense number of tweets posted every hour. Consequently, sentimental standards are used in printed data sources. Sentimental standards have a few helpful applications like mining audit portrayal information from client survey to perceive the causality between assorted highlights of items. Policy developers may likewise utilize sentimental standards for better basic leadership [12, 13].

Although numerous extremely accurate strategies as of now exist to analyze and extract significant learning from organized information the task of extricating valuable data from unstructured information still poses some major difficulties. In this work, a framework for tending to the undertaking of political propensity recognition of Twitter clients in view of sentiment analysis procedures. For every client, we gather every one of their tweets and we remove every one of the substances identified with the political subject. The framework comprises of principally three modules, for example, information extraction, pre-preparing and sentiment characterization. The initial two stages undergo two stages, namely social network information extraction and information pre-handling in order to expel all URL forms in the tweet. At that point, a strategy where the fuzzy based ontology is composed by joining SVM grouping calculation to select the fuzzy principles that are being created for ontology generation. The rest of this paper is organized as follows, Section 2 presents background with advances in the state of the art related to sentiment analysis, concentrating on social networks. In Section 3 to enhance the efficiency of information in social network the proposed hybrid adaptive Neuro-fuzzy inference and SVM algorithm concentrates on getting the emotion of a message. Segment 4 demonstrates an assessment of the proposed hybrid adaptive Neuro-fuzzy inference and SVM algorithm. At last, Section 5 describes the conclusions and future work to be accomplished.

2. Related works

Along with governance, Twitter sentiment analysis is additionally utilized in the immense range of zones identified with governance and open trust running from anticipating re-sentiment against government arrangements to foreseeing general election results. Different models have been produced that attempted to understand the client's conduct and retweeting on Twitter. Concerning the utilization of Twitter in political issues, specialists have analyzed the ways by which Twitter impacts in correspondence to standard news and news-casting. This area of research revealed that in the ongoing process of research social media, specifically Twitter, is assumed as an essential part of predominant media as a news source.

D. Liu and L. Lei, [14] examined Hillary Clinton's and Donald Trump's addresses during the 2016 presidential election to recognize about their discussed topics assessment and techniques by utilizing machine-based strategies. The machine-based automatic investigations were additionally supplemented by a subjective examination of the discourse information persuaded by the best topical terms recognized by the automatic examinations. The consequences of the analysis uncovered that Trump's addresses were fundamentally more negative than Clinton's. The results of this assessment may help clarify Trump's victory in spite of the fundamentally more negative notion in his discourse. This strategy helps in dissecting huge datasets automatically and adequately found the data of enthusiasm, something that is impossible physically. These outcomes additionally uncovered the gain of an unmistakable and precise comprehension of the applicants' topics, the machine-based programmed investigation ought to be supplemented by a nearby subjective examination of the information. Without such close subjective investigation, the machine-based automatic examination may miss out some critical data.

S.S. Koc, M. Özer, I.H. Toroslu, H. Davulcu, and J. Jordan [15] executed a strategy to produce co-clusters in three measurements at the same time. In this issue, from a given marked 3-partite chart, clusters with the highest positive named edge, and low negative named edge thickness were resolved which conceivably had basic nodes. The approach additionally displayed a greedy heuristic answer for this issue with the adequacy of strategy which has been demonstrated utilizing both process and genuine datasets. The inspiration was to find clusters of government officials, issues and the sentimental words politicians used to express their emotions on these issues in their tweets. So as to assess the nature of the clusters produced from a true analysis, the technique majorly utilized interior assessment measurements. Yet, the execution of the approach will mostly rely on both the assessment measurements, for example, external assessment by acquiring remarks from the domain specialists, for example, political researchers, about the clusters produced.

S. Rill, D. Reinel, J. Scheidt, and R.V. Zicari [16] built up a framework called PoliTwi to distinguish developing political subjects (Top Topics) in Twitter sooner than other standard data channels. The outcomes showed that new points showing up in Twitter can be distinguished directly after their event. The outcomes observed that the subjects arisen before in Twitter than in Google Trends. At long last, the approach indicated how these themes were utilized to extend existing learning bases which were required for concept level sentiment examination. For this, the system used unique Twitter hashtags, called sentiment hashtags, utilized by the German people group during the parliamentary race. The issues looked by the strategy was a misuse of extra meta data stored with each tweet, e.g., the Geo-data, to inspect the spatial circulation of the tweets.

K. Singhal, B. Agrawal, and N. Mittal [17] executed a novel approach according to semantics and context-aware standards to identify the general supposition and further foresee election results. This study was unsupervised without any earlier preparation of dataset. By predicting the outcomes has persuaded that there was an incredible breadth in investigating Indian political twitter information and considering its sentiment alone could result in giving a general thought regarding the election results. The trial results demonstrated the adequacy of the proposed rules in deciding the estimation of the political tweets over existing strategies. The strategy spent an additional time because of the fact that the examination of tweets on the election was done physically containing casual dialects.

A. Ceron, L. Curini, and S.M. Iacus [18] applied the administered technique proposed by Hopkins and King to analyze the motivation of voting of Twitter clients in the United States and Italy. This system displayed two essential points contrasted with customarily utilized choices for a better understanding of the writings and more effective outcomes. The examination demonstrated a capacity of Twitter to "nowcast" and in addition to figure appointive outcomes. The dissimilarities were clearly decisive for investigating the impact of outcomes and for controlling the probability of a technique for various distinctive reasons clarified accordingly and seems to progressively better when contrasted with other existing strategies. At last, despite of the fact that the social media users, was not still constantly illustrative of one nation's citizenry, there were still a few questions about whether such predisposition could influence the prescient abilities of social media examination.

U. Yaqub, S.A. Chun, V. Atluri, and J. Vaidya [19] investigated the political short messages to assess how precisely Twitter represent the general conclusion and genuine occasions of significance related to the elections. They additionally broke down the conduct of over a million particular Twitter clients to distinguish whether the stage was utilized to impart unique opinions and to connect with different clients or whether couple of sentiments were rehashed again and again with little between client discourse. At last, the approach attempted to evaluate the sentiments of tweets by the two politicians and their effect on the election related talk on Twitter. The significance was the finding that sentiments and themes communicated on Twitter can be a decent intermediary for popular sentiment and imperative election related occasions. They have found that Donald Trump offered a more hopeful and positive battle message than Hillary Clinton and delighted in better emotion during his message’s response rendered by Twitter users. The confinement of this investigation was the absence of a topic sentiment model. In spite of the fact that the strategy had analyzed as often as possible about themes which talked during the elections, we have not assessed their effect regarding the conclusion of the election related dialog on Twitter.

The proposed approach of ANFIS-NonLinear

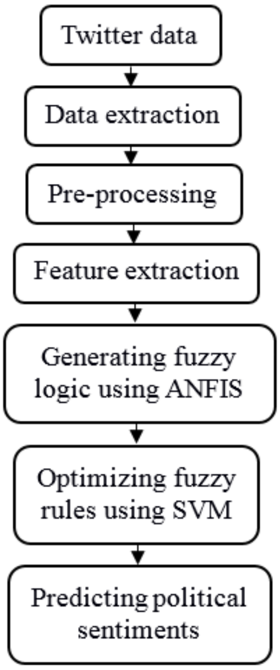

Figure. 1 The block diagram of the proposed method

SVM is implemented for detecting the public opinions about the election to overcome the above issues faced by several methodologies.

3. Proposed work

With a specific end goal to understand whether the action on Twitter can serve as an analyzer of the election result, this research looks at two viewpoints. To start with, the proposed scheme analyzes the opinion about the political parties on Twitter with the election result. Second, we break down whether tweets can illuminate us about the ideological ties amongst parties and potential political coalitions after the election. The proposed method considers the major part which manages the tweets extraction and sentiment classification to fuse semantics notion examination. The basic diagram of the proposed structure is clarified in the accompanying Fig. 1. This framework used to quantify political estimation. The framework comprises of primarily three modules. They are Data extraction, Pre-handling, Sentiment characterization. The next section explains in detail about these three modules.

3.1 Data extraction

The main stage is to assemble the ontology method by utilizing the information extricated from the online networking platform, Twitter. The tweets are gathered by utilizing the Twitter Streaming API and put away in a raw database. The Twitter Streaming API incorporates a few restrictions in terms of the quantity of keywords and in addition the most extreme number of results. During the venture, these impediments were achieved, therefore having no impact on the outcomes. For each tweet, an arrangement of meta-data is accessible from the Twitter Streaming API, e.g., the clients' dialect or area. This meta data is also stored in the database and can be utilized for assisting examination or expansions of the framework.

3.2 Pre-processing

The second stage is to pre-handling the extricated information and recovers corresponding contents of tweets from the negative sentiments related to a tweet utilizing a formerly assembled ontology demonstrate. In this module, different pre-preparing steps are performed. The steps incorporate Source analyzer, Hashtag analyzer, Sentiment Hashtag analyzer and Emoticon analyzer.

3.2.1. Source analyser

The source analyzer is most encouraging mechanism for differentiating new points from client composed tweets in twitter. In the best case, an onlooker reports a new point by means of Twitter and different clients retweet or remark on this theme. There are naturally created tweets that we need to reject in the Source Analyzer, as these tweets frequently refer to an online article.

3.2.2. Hashtag/ Sentiment hashtag analyser

The Hashtag Analyzer removes all hashtags contained in the tweets. These hashtags are the reason for the subject location. The Sentiment Hashtag Analyzer denotes all sentiment hashtags contained in the tweets. In the dataset, around 100 diverse sentiments hashtags in 171,000 tweets can be found.

3.2.3. Emoticon analyser

The Emoticon Analyzer removes data about emoticons within the tweets, regularly observed as markers for the nearness of incongruity in such messages. This data isn't yet abused for this examination. It will be utilized in a later expansion of the framework. The consequences of the pre-handling are stored in the Analyze-DB, which are the reason for the subject location later on.

3.3 Feature extraction

After pre-processing the twitter data, unigram and bigram models are used for feature extraction.

The unigram model helps to select individual words from the pre-processed data and the bigram model extracts a pair of words from the pre-processed data. The unigram model is defined as the proportional context word, which is calculated by using the Eq. (1).

$$p(wd_i|wd_0 \dots\dots wd_{i-1}) \approx p(wd_i) \quad (1)$$

Eq. (2) helps in calculating the unigram property of the tweet by analysing each word. The bigram model adds one more word of context and it is defined as follows,

$$p(wd_i|wd_0 \dots\dots wd_{i-1}) \approx p(wd_i|wd_{i-1}) \quad (2)$$

Where, p is represented as the part of speech of unigram/bigram model and wd is denoted as the context of word with $i = 0,1,2,3, \dots N$.

3.4 Sentiment classification

The sentiment classification depends on Adaptive Neuro-Fuzzy Inference System (ANFIS) which relies upon the fuzzy rationale. At that point, SVM classifier is utilized for advancing the fuzzy rules that are being produced for generating ontology.

3.4.1. Adaptive neuro-fuzzy inference system

ANFIS is one of the neuro-fuzzy model, which has the advantages of both neural systems and fuzzy rule. In this exploration work, ANFIS classifier is proposed to productively break down the twitter information. Let consider, ANFIS show comprises of two sources of input positive and negative keywords in tweet specifically $x \, and \, y$ and one output$f$. In ANFIS function, information factors are also called as versatile (adaptive) nodes. The membership function for the versatile nodes is characterized by Eq. (3) and (4),

$$F_{1i} = \mu_{U_i(x),i=1,2} \quad (3)$$

$$F_{2i} = \mu_{V_i(y),i=1,2} \quad (4)$$

Where F_{1i} and F_{2i} have indicated the fuzzy membership grades, U_i and V_i show the fuzzy sets. The μU_i and μV_i represents the fuzzy membership functions and these are varies from 0 to 1 as follows in Eq. (5).

$$\mu U_i(x) = \frac{1}{1+\left|\frac{x-w_i}{u_i}\right|^{2v_i}} \quad (5)$$

Whereas, u_i , v_i and w_i represents the membership functions on linguistic labels. This parameter is additionally named as non-linear parameters. The following multiplication layer comprises of settled nodes and this layer duplicates the input tests and registers the item. The multiplication work is characterized by Eq. (6),

$$wt_i = \mu U_i(x) \times \mu V_i(y), i = 1,2 \quad (6)$$

Where, w is the multiplication layer, U and V are fuzzy sets.

The summation layer consists of fixed nodes and this layer computes the sum of all rules firing strengths. The summation function is defined by Eq. (7).

$$\grave{wt}_i = \frac{wt_i}{wt_1+wt_2}, i = 1,2 \quad (7)$$

The functional layer consists of adaptive nodes. This layer computes the first order polynomial features. The functional layer is defined by Eq. (8)

$$\grave{wt}_i f_i = \grave{wt}_i(p_i x + q_i y + r_i), i = 1,2 \quad (8)$$

Where, $\grave{wt}_i$ represents the computation in summation layer and p_i , q_i , r_i indicates the first order polynomial features. At last, in the final layer comprises of the single node. This layer registers the summation of all the information parameters processed at different stages. The output layer is characterized by Eq. (9),

$$f = \grave{wt}_i f_i = \frac{\sum_i wt_i f_i}{\sum_i wt_i}, i = 1,2 \quad (9)$$

A classification of principles has been depicted for a fuzzy rule where it yields the product endeavors in reference to the properties fuzzy logic as a representation of the sentiment analysis. The product endeavors are gathered into various standards depends on the parameters and in our technique we use SVM classification process for choosing the fuzzy guidelines to perform consistent fuzzy activities ideally with respect to the idea of tweet.

3.4.2. Support vector machine

In general, SVM empowers a proficient method for separating the features and an arrangement of principles to perform grouping. SVM is a discriminative approach represented by a different hyperplane. The objective of SVM is to prepare the fuzzy guidelines by using prepared information and produce an ideal fuzzy administer to break down the conclusion of a relating tweet [20]. The SVM principally arranged into Linear SVM (i.e. Linearly Separable Case and Linear Non Separable Case) and Non-Linear SVM. A characteristic method to enhance the division between two data classes comprises in generalizing the linear strategies to the classification of non-linear discriminant capacities. To outline information through a legitimate non-linear change $\Phi(.)$into a higher dimensional feature space $\Phi(X) \in \Re^{d'} (d' > d)$, where a partition between the two classes can be looked by methods for an ideal hyperplane characterized by an ordinary vector $w \in \Re^{d'}$and a bias$b \in \Re$. In the choice of fuzzy control, the ideal decision rule to recognize the assumption, it takes care of a double issue for the linearly detachable case by replacing the inner items in the first space $(X_i \cdot X_j)$with inner products of twitter raw data in the transformed space $[\Phi(X_i) \cdot \Phi(X_j)]$. Now, the principle issue comprises of the explicit calculation of $\Phi(X)$, which can demonstrate costly and again unfeasible. The kernel strategy gives an exquisite and viable method for managing this issue. Consider a kernel work that fulfils the condition expressed in Mercer's hypothesis in order to compare to some sort of internal result of twitter information in the transformed (higher) dimensional feature space explained in Eq. (10).

$$K(X_i, X) = \Phi(X_i) \cdot \Phi(X) \tag{10}$$

Where K is a kernel function of SVM. This kind of kernel function allows to simplify the solution of the dual problem considerably, since it avoids the computation of the inner products in the transformed space$[\Phi(X_i) \cdot \Phi(X_j)]$, The final result is a fuzzy rule in form of discriminant function $f(X)$ conveniently expressed as a function of the data in the original (lower) dimensional feature space in Eq. (11),

$$f(X) = \sum_{i \epsilon S} \alpha_i \,, y_i K(X_i, X) + b \tag{11}$$

Where, $\propto_i$ is represented as a Lagrangian values in that i indicates$i = 1,2,..,N$. y_i is a hyperplane values of SVM, $K(X_i, X)$ is a kernal function of higher dimensional feature space and b is constant.

The state of the discriminant work relies upon the sort of kernel capacities received. Kernel capacities and their advantage points enable the client to utilize an ideal classifier that clearly has no specific portrayal of fixed dimensional vector space. In this work, the information from the ANFIS having the obliged number of attributes are given to the Non-Linear SVM classifier to select the ideal standards to the fuzzy logic framework.

4. Experimental result

The primary objective of this work was to propose an assessment approach for sentiment analysis of twitter information about political issues. In this section, we investigated and showed the exploratory outcomes and assessment measurements to test the execution and viability of the proposed ANFIS-NonLinearSVM approach.

4.1 Result analysis

The information was gathered from the Twitter accounts for assessment of sentiment. The tweets were gathered in the light of the political issues. The experimental setup was completed utilizing the working platform of Python and the outcomes were compared with some current works to assess the proposed strategy. The outcomes acquired through ANFIS-SVM, ANFIS-LinearSVM, and ANFIS-NonLinearSVM were analyzed by their relative exhibitions on three parameters specifically accuracy, precision and recall.

4.1.1. Accuracy

Accuracy is represented as the exactness of a particular methodology in terms of how much proposition is correctly identified from the total test samples. The accuracy performance evaluation of a system is denoted in the Eq. (12).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{12}$$

Where TP is represented as true positive, FP is described as false positive, TN is stated as true negative and FN is stated as the false negative. Table 1 shows the performance measure of ANFIS-SVM, ANFIS-LinearSVM, and ANFIS-NonLinearSVM in terms of accuracy.

Table 1. Comparison of Accuracy

Methods	Accuracy
ANFIS-SVM	86
ANFIS-LinearSVM	87.9
ANFIS-NonLinearSVM	90.43

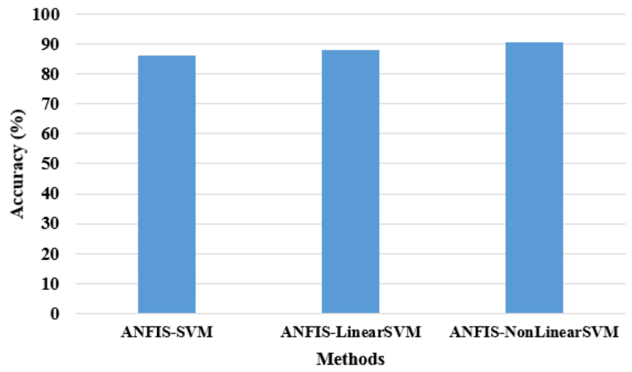

Figure. 2 Performance of accuracy

Fig. 2 shows a comprehensive view of the accuracy of the three existing supervised learning techniques with the proposed ANFIS-NonLinearSVM.

4.1.2. Precision

The precision of a system represents the exact identification of a particular class or subject from the total test samples of that corresponding class. In this work, precision values are taken as positive and negative precision values in the proposed ANFIS-NonLinearSVM approach. Precision positive (p) and Precision negative (n) are precision ratio and are computed as in Eq. (13) and Eq. (14):

$$Precision(p) = \frac{TP}{TP+FP} \tag{13}$$

$$Precision(n) = \frac{Tn}{Tn+Fn} \tag{14}$$

Table 2 shows the performance measure of ANFIS-SVM, ANFIS-LinearSVM, and ANFIS-NonLinearSVM in terms of precision.

Fig. 3 shows a comprehensive view of precision of the three existing supervised learning techniques with the proposed ANFIS-NonLinearSVM.

Table 2. Precision comparison

Methods	Precision	
	Positive value (p)	**Negative value (v)**
ANFIS-SVM	85	70
ANFIS-LinearSVM	81	79.7
ANFIS-NonLinearSVM	89	89.6

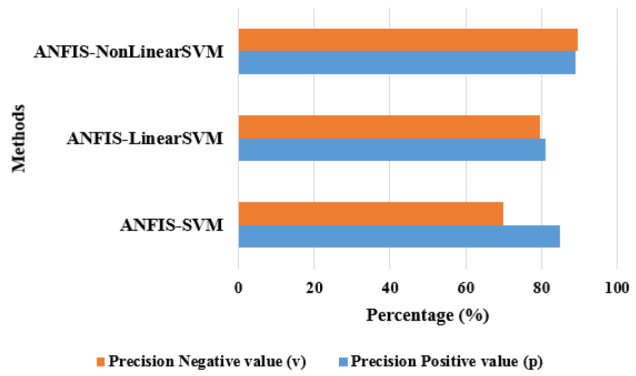

Figure. 3 Compression of Precision values

4.1.1. Recall

There are two values for recall such as the positive and negative value in the ANFIS-NonLinearSVM method. Recall positive (p) and Recall negative (n) is recalling ratio and are computed as in Eq. (15) and Eq. (16):

$$Recall(p) = \frac{TP}{TP+Fn} \tag{15}$$

$$Recall(n) = \frac{Tn}{Tn+Fp} \tag{16}$$

Table 3 shows the performance measure of ANFIS-SVM, ANFIS-LinearSVM, and ANFIS-NonLinearSVM in terms of recall.

Table 3. Compare the values of recall

Methods	Recall	
	Positive value (p)	**Negative value (v)**
ANFIS-SVM	74.5	70
ANFIS-LinearSVM	79	84
ANFIS-NonLinearSVM	90.2	89.6

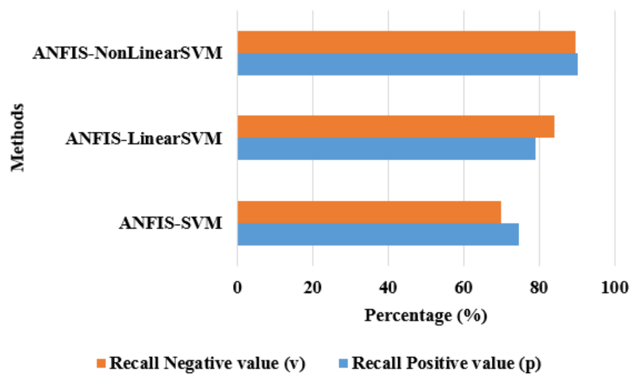

Figure. 4 Recall values for the proposed method with existing method

Fig. 4 shows a comprehensive view of recall of the three existing supervised learning techniques with the proposed ANFIS-NonLinearSVM. From the above outcomes, the approach expressed that the accuracy of ANFIS-NonLinearSVM is better than each of the existing strategies. In addition, the assessment results for positive and negative sentiments on precision and recall are figured in view of both accurately distinguished positive and negative opinions on the elements. From the tables, the graph results showed that ANFIS-SVM and ANFIS-LinearSVM perform inadequately in all measurements. The ANFIS-NonLinearSVM performs better by considering about the qualities of Twitter information.

4.2 Comparative analysis

O.A.M. Ghaleb, and A.S. Vijendran, [21] improved sentiment analysis using senti-strength for achieving more accurate sentiment labeling. Here, twitter sentiment was enhanced by using semantic role labeling, which extracts semantic arguments and roles. Respectively, kullback-leibler divergence used for labeling the sentiments based on the extracted roles. The developed approach almost achieved 85% of accuracy in twitter sentiment classification.

Additionally, M. Trupthi, S. Pabboju, and G. Narsimha, [22] developed a new system for classifying and identifying sentiments or opinions expressed by people in their tweets. Initially, an effective topic modelling methodology: latent dirichlet allocation was implemented for extracting the keywords and identifying the concerned topics. The extracted key words were utilized for twitter sentiment analysis using possibilistic fuzzy c-means. The developed clustering method finds the optimal clustering heads from the sentimental contents of twitter-sandersapple2 database. The acquired results were obtained in two forms such as positive and negative. In this research study, the developed methodology achieved 87% of accuracy in classification. Compared to these existing approaches, the proposed work achieved 90% of classification accuracy that was higher than the existing works.

5. Conclusion

Social media presently assume as a critical part in political electoral campaigns. The fast spread of data through different stages of people, for example, Twitter has empowered politicians to communicate their message to a wide group of onlookers. In this paper, a fuzzy based approach for sentiment examination of negative feelings from social network content is proposed. This framework used to quantify political assessment. The framework comprises of three modules such as Data extraction, Pre-processing, Sentiment classification. On the classification stage, a technique ANFIS-NonLinearSVM is planned by executing SVM classification algorithm to optimize the fuzzy rules. The exploratory outcomes demonstrate that the proposed technique significantly enhances the recall and accuracy. Moreover, it outperforms the necessities to process as an effective sentiment analyzer for social network data. The experimental results demonstrated that the proposed method almost achieved 90% of accuracy, precision and recall measures achieved nearly 89.7% in both positive and negative ratings. The outcome additionally got by ANFIS-NonLinearSVM based sentiment analysis of negative feelings from social networks has reduced complexity and gives the best level of accuracy when compared to the existing techniques. Also, the adequacy of the proposed ANFIS-NonLinearSVM strategy is recognized in deciding the assumption of the political tweets. In the future, an effective sentiment polarity estimator for the tweets to improve the analysis of proposed method can be enhanced.

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