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A smart recommender model based on learning method for sentiment classification

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Abstract
The problem of classifying the text is not only the topic since it contains the sentiment. Large amount of information are availed but determining the positive and negative thoughts is a major task. The existing method uses various classification technique and machine learning techniques for data processing. Naïve Bayes, entropy classification, linear regression, etc., are the existing algorithm. These algorithms are not performing well with time-consuming analysis. The proposed method uses the Structured Support Vector Machine Learning Algorithm for classification. Here the multifaceted text classification dataset is taken for the analysis. This proposed research work recognizes the favorable and unfavorable sentiments towards specific subjects. The techniques for giving the sentences and terms in a document their semantic significance so they can be used more effectively than existing possibilities. Based on the sentiment keyword from the user review, we can rank the positive and negative weights. By this application, the user will get to know which is best and suitable related to their requirement since they can access their requirement in efficient way. Entire survey should be model in MATLAB 2018a suite. The accuracy of this proposed analysis been increased when compared to the existing analysis.

Keywords Sentiment analysis · Structured support vector machine · Recommendation system · Feature extraction and optimum feature selection

1 Introduction

Sentiment analysis and opinion mining are relatively a new research field in which a lot of room for doing a research. In social networks, sentiment analysis and opinion mining finds the solution to categorize user's opinions. The online social networks such as Twitter,

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YouTube and Facebook consist of more users and they share views about any common social issue, or product [1–3]. Sentiment analysis is the process of analyzing the unstructured text based on analytical process. The analytical process is used to extract the individual information from an unstructured text. Unstructured means which has the information of rumors or gossips. It represents the results in three formats which are shown in Fig. 3

In recent pandemic days opinion mining plays a vital role for obtaining a current situation of the society. In many applications are used sentiment analyses to get the feedback of purchasing product, advertisement, and so on [4–6] Existing researches has difficulties in terms of scalability, model resilience over time, and massive dataset management. These issues impede performance in real-world applications, needing more efficient algorithms and frameworks to efficiently address dynamic environmental and data unpredictability.

Structure of sentiment review is an important factor for assuming the category of reviews. Sentiments are defined as three structures such as structure, semi-structure and unstructured.

- **Structured—**Sentiments are present in the structured format at formal reviews, because which are written by professionals and the sentiments are about scientific issues.
- **Semi-structured—**Semi-structured format review is present between structured and unstructured formats, because the writer denotes the both the advantages and disadvantages of the content.
- **Unstructured**—Online social network has collective number of social media such as Youtube**,** Facebook and Twitter, which is shown in Fig. 1. Online social media is most useful to business and other customer based service [7, 8].
- **Youtube—**First we see about Youtube. It is most popular social media with millions of users. The purpose of youtube is to watch and share videos with everyone over the internet; in addition youtube allows users to share and comment on that video. Individual person can create a channel and upload their videos. The users can subscribe the channel if they like. It is one of the ways to earn money. Sentiment analysis of youtube comments is a challenging task.
- **Facebook—**Facebook is one of the social media which is used to communicate with others over the internet. In addition facebook can be accessed from personal devices such as mobile phone, laptop, and tablets. The facebook user can post photos, videos and multimedia about personal details or others. It is very useful to other humans who want to know about the details of the product or videos.
- **Twitter—**Twitter is a widely used social network in which everyone around the globe share the information known as tweets and post feedback comments for the corresponding information. Twitter.com is a famous micro blogging website. Each

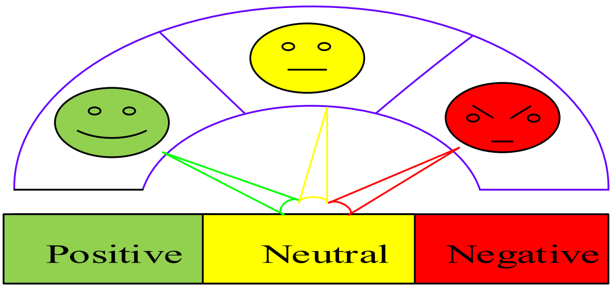


Fig. 1 Sentiment classes

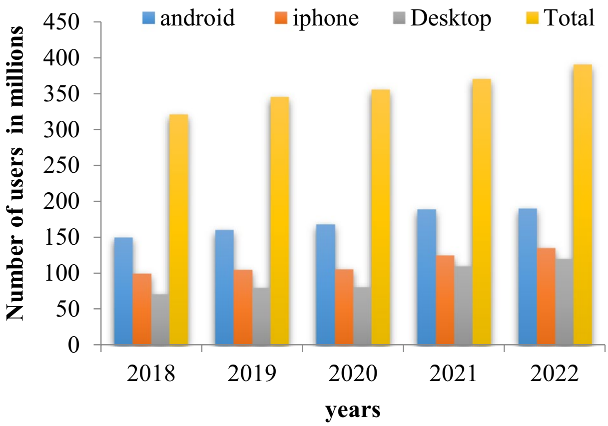


Fig. 2 Twitter users

tweet length is must be within 140 characters. Tweets are used to express the emotions of the particular information. These tweets are collected from twitter API [9–11].

Figure 2 represents the classification of twitter traffic based on the devices used for accessing the twitter. It is clear that the number of users accessing twitter increases exponentially each year in terms of millions. The categories of classification of devices are android, iPhone and desktop (Fig. 3).

- **Twitter API—**The twitter API allows read and write twitter data. Twitter API has a set of URLs which takes parameters. The URLs used to access many features of twitter, such as tweet posting and tweet finding. An open source library called Tweepy is hosted from web-based software called Github and enables users to interact with the Twitter platform and make use of its API. This dataset is determined from Natural Language Toolkit (NLTK). Twitter API has 10,000 tweets. Twitter present two types of APIs for extracting the tweets like search (API) and Streaming (API).
- **Search API –** It dumps all the old tweets. Training dataset is built for Sentiment Classification.
- **Streaming API—**It is used to dump live sentiments. Streaming API is used to display the current results.

Twitter is a popular microblogging website, which has five hundred million daily tweets generated and two hundred million subscribers. Based on the tweets customers can know about the product review, service review and attitude of the political leaders [12–15]. The length of the data is very small. Sentiment analysis denotes the corresponding tweets are positive or negative. Many users/celebrities/political leaders are used twitter so twitter sentiment analysis is more important than other social networks is shown in fig. 3.

In order to discard needless information, the following criteria were taken into account as follows,

- Eliminate re-tweets (if any tweet which contains the string)

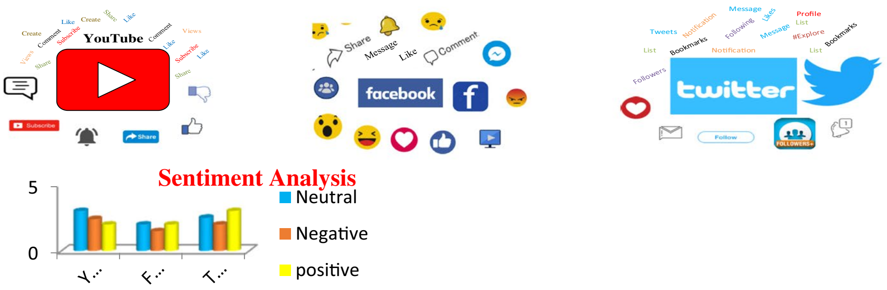


Fig. 3 Sentiment analysis in online social networks

- Eliminate annoying English tweets (other languages tweet must be translated to English and remove stopping words, and any other single characters)
- Eliminate redundant tweets (When two tweets are looking similar, then that are removed from the data collected) [16, 17].
- Eliminate punctuation marks and special characters
- **Grammatically incorrect words—**Grammatical errors introduce challenges in sentiment analysis because the user comment has many errors. Consideration of grammatical error improves the performance of the sentiment classification and recommendation [18].
- **Handling noise and dynamism—**Social media has large amount of data which has noise, unstructured and dynamic in nature [19].
- **Use of abbreviation—**User used abbreviations to reduce the characters but abbreviations are not mention properly which makes difficulty in sentiment analysis [20].
- **Lingoes and slangs—**Lingoes and slangs is one of the main challenges because users are located in many places and post their reviews in many languages [21–23].

Figure 4 illustrates the methods for sentiment analysis which are classified into two classes as machine learning techniques and lexicon based techniques. This research shows a novel method for sentiment inspection based on the recommendation model by means of machine learning techniques. The proposed recommendation system has issues in effectively integrating multiple machine learning algorithms, providing robust multi-class sentiment categorization, and efficiently scaling to accommodate enormous amounts of social media data. Addressing these issues is critical for improving performance in practical social media applications. The proposed method addresses these issues by incorporating comprehensive preprocessing techniques, optimal feature selection with bi-objective optimization to reduce redundant information, and a Structured SVM algorithm that effectively categorizes tweets into nuanced sentiment classes, thereby improving overall classification accuracy and robustness to linguistic complexities in Twitter information (Fig. 5).

The remainder of this topic is organized as follows: The sentiment analyzed recommendation model is explained in Section 2. The relevant works in the domains of recommendation systems and sentiment analysis are covered in Section 3. The suggested system model is covered in full in Section 4. Both the testing outcomes and discussion of the outcomes are covered in Section 5. The proposed method's conclusion and future directions are depicted in Section 6.

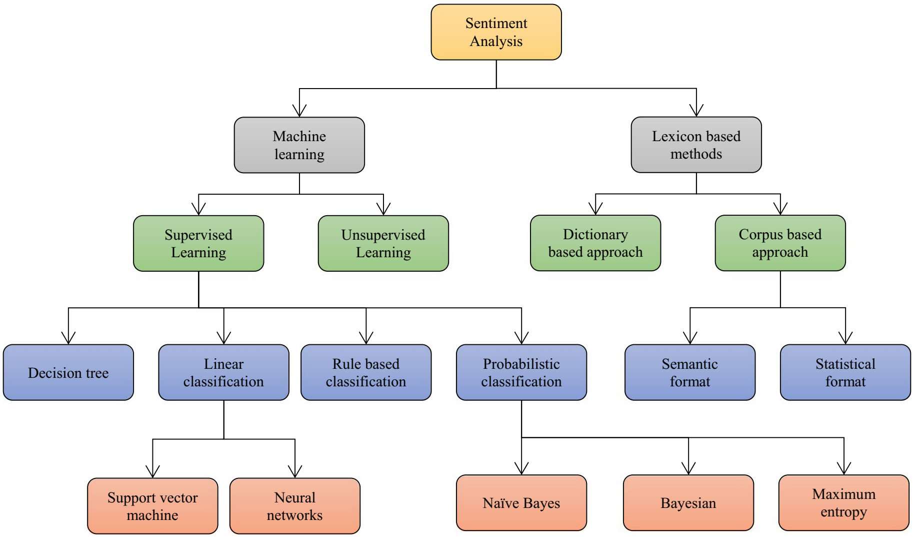


Fig. 4 Sentiment analysis approaches

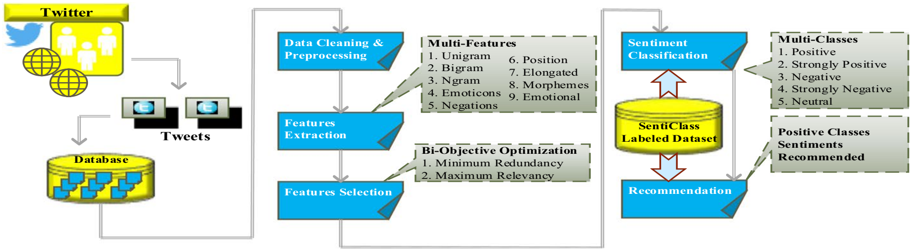


Fig. 5 Proposed frameworks

2 Related work

Gaussian process dynamic Bayesian network was constructed to represent the dynamic interaction of the sentiment topic on social media [24]. The proposed system used dynamic Bayesian network to model the time series of the sentiment topic with respect to the sentiments and it learns dependency relation between them. Markov chain based montecarlo mechanism is used to create a parent set, which is used to analyze the sentiments for every word in a dataset. Bayesian network has some challenges for managing massive amount of data, hence it decrease the performance of the sentiment analysis. Sentiment analysis for the social media applications were considered in [25] by using machine learning algorithms. There are two machine learning algorithms were utilized in this paper as Random Forest, Decision Tree and Naïve Bayes algorithm. These algorithms do not sufficient for multi-class based classification and also does not support for large amounts of data.

In paper [26] author used refined neutrophic set based sentiment analysis. Social media comments are used for sentiment analysis. Multi refined Neutrosophic method is used for feature extraction process. The Neutrosophic data includes 3 types information with five classes 2 for positive, 2 for negative and 3 for neutral. The positive class is classified into strongly positive and positive. Negative class is defined as negative and strongly negative. Intermediate class is divided into positive intermediate, negative intermediate and intermediate. 3 neutrosophic dataset are used to analyze the twitter sentiments which are SVNS, TRINS and MRNS.

The study [27] recommends using ML, Deep learning, and time series algorithm used for smart farming to improve agricultural sustainability. Its goal is to improve procedures such as crop preference, yield estimation, and suitability for soil categorization. Using these AI tools, the project hopes to estimate crop productivity and offer data-driven agriculture suggestions, ultimately addressing food shortage concerns caused by the expanding population. The study [28] recommends using machine learning operations (MLOps) for smart farming to assure the correctness and dependability of machine learning models in production. The study's goal is to keep these models correct despite changes in environmental conditions or soil qualities. This solution solves the difficulty of model performance degradation over time, ensuring long-term and effective smart farming operations.

The paper [29] proposes densely knowledge-aware network (DKN) for improving multivariate time series classification using deep learning. DKN employs a residual multihead convolutional network for collecting local data patterns, transformer-based network for extracting global data patterns. It also employs densely dual self-distillation to improve representation of understanding from the data through the extraction of rich correlations and regularization. Experiments show that DKN beats numerous cutting-edge MTSC algorithms, yielding superior classification performance.

The work [30] suggests CapMatch, a semi-supervised contrastive capsule transformer approach with characteristic-based knowledge distillation (KD), for identification of human activity which is wearable CapMatch employs pseudolabeling, contrastive learning, and feature-based KD to extract rich representations from both supervised and unsupervised learning. It features a capsule transformer network for detecting local and global trends in HAR data. CapMatch beats cutting-edge algorithms on HAR datasets, reaching high F1 values while having less labeled data.

This research [31] offers PCapN, a dual-network feature extractor for multivariate time series classification, which combines a local feature network and a global relation network to capture both local and global data patterns. A lightweight version, LCapN, is optimized for mobile device deployment. The study also discusses DTCM, a deep transformer capsule mutual distillation method for transferring knowledge from PCapN to LCapN. On the UEA2018 datasets, the experimental results show that PCapN and DTCM work exceptionally well.

This paper [32] introduces the Self-BiDecKD approach for time series classification which improves by promoting cooperation in learning between low- and high-level conceptual knowledge and model performances via bidirectional decoupled knowledge distillation. Unlike other self-distillation algorithms, Self-BiDecKD generates knowledge distillation pairs between lower-level block outputs and the output layer. This method extracts rich representations from data and outperforms numerous self-distillation algorithms, with the lowest average rank score on UCR2018 datasets.

These problems are undertaking in this thesis and the main objectives of this study are follows:

- To create and manage tweets corpus for contextual opinions and sentiments.
- To bring high quality sentiment analysis and recommendation using machine learning classifiers for analyzing the Twitter users.

- To achieve high recommendation accuracy detects trends based on comments, discussions and contextual reviews.
- To establish a recommendation system to provide desired & customized services to the requested users.
- To investigate the performance of the sentiment analysis and recommendation system using metrics as Accuracy, Precision, Recall, F-Score, Computational Time and Recommendation Accuracy.

3 Proposed work

The proposed sentiment analysis framework consists of five phases which are shown in Fig. 5.

- **Data cleaning—**Data cleaning process is used to diminish the uncertainty tweets from the twitter dataset. It removes the URL, user name, punctuation marks and spell correction for twitter sentiment analysis.
- **Preprocessing—**Preprocessing is used to enhance the accuracy of the feature extraction. Tokenization, POS tagging, stop word removal, stemming, lemmatization, slang correction, acronym expansion, and split attached wording are among the data preprocessing operations which are carried out.
- **Feature extraction—**The features are extracted from given tweets. Feature extraction is used for enhancing the accuracy of the sentiment classification. Features: hashtag, unigram, standardized word, slang, emotional, semantic, and syntactic and negation feature [33].
- **Feature selection—**Feature selection is used to select an optimal feature. The proposed system used optimum feature selection approach for choosing characteristics; it chooses the characteristic that is most suitable.
- **Classification—**Classification is done by using Structured SVM algorithm. Sentiments are classified into 5 types which are positive, strong positive, negative, strong negative and finally neutral. The algorithm focuses on splitting the sentiments into five classes as accuracy, precision, recall, error rate and f-score [34].

3.1 Database description

Each object presented in the given dataset have 5 tuples:

- Tweet identifier (tweet id)
- Timestamp (tweet date)
- User identifier (mention the tweet poster)
- Tweet message (message of tweet)
- GeoTag identifier (user location)

3.2 Cleaning and preprocessing

In first stage, URLs are removed, tags are removed, and irrelevant messages are removed.

- **Tokenization—**Tokenization means split the documents into a series of tokens. The twitter message consist noise or unrelated messages, hence that messages are need to remove for improving classification performance.
- **POS tagging—**PoS tagging is a crucial to build the lemmatizer, which is used to find the parts of speech for each word in a tweets.

  Example:

  The first congestion free day that was held on October 9 was a success

  Determiner-The, a
  Adjective—first congestion free
  Noun- day, success
  Pronoun- that
  Auxiliary—was
  Verb- held, was
  Ad position—on
  Proper noun—October
  Numeral -9

- **Phrase removal—**Phrase removal is the important step which is run previously to stop word removal to analyze the twitter messages**.**

  Example:

  I dropped out of science because it was too difficult

  After removed phrase verb and stop word the sentence becomes Science difficult. This sentence gives a negative sentiment.

- **Stop word removal—**In this process is used to eliminate the stop words, which are previously defined. Stop words are not necessary for sentiment classifications.

  Example:

  Is it an imaginary #WaronWomen when Wisconsin's #GOP governor & legislative repeal the state's equal pay law?

  After removed stop words: Imagery WaronWomen Wisconsin's GOP governor legislative state equal pay law

- **Morphemes—**This method is used to eliminate the bad stemming, which means it represent the small units of meaning. Morphemes method gives a meaningful word that cannot be dividing into small meaningful parts.

  Example:

  The Honda service is not bad. After finding the root word becomes "bad". It denotes negative response, but the original meaning is positive "not bad", thus will leads to worst sentiment classification.
- **Stemming—**Stemming is used to remove the affixes from the base word, its find the stem word from the base word, which gives the proper meaning with short length.

  Example:

Considered
Considering -----------→ Consider
Consideration

3.3 Feature extraction

It is and efficient approach for selecting necessary features, and removes the large amount of words which are not necessary for sentiment analysis. It is also used to remove the noise from the message and provide better classification for tweets. The following features are extracted for twitter sentiment analysis. Table 1 describes the types of features.

- **Unigram Feature—**It is a special type of feature which is extract the features in word by word to construct the dictionary based on user defined parameter. Unigram has used

Table 1 Negation feature and its categories

Negation categories	Negations
Syntactic	No
	Not
	Never
	None
	Nobody
	Rather
	Wasn't
	Can't
	Didn't
	Weren't
	Mustn't
	Couldn't
	Wouldn't
	Shouldn't
Diminisher	Hardly
	Less
	Little
	Scarcely
	Seldom
	Rarely
Morphological	Prefixes
	Im,Ir, De
	Dis,Un,Non
	Suffixes
	Less,Able,ment

a fundamental feature for twitter sentiment analysis in machine learning. Word net is used for collecting unigram features.

- **Bigram feature—**Bigram feature takes a series of words in a message, for eg, if n = 2, this represents The two different terms which is also called as bigram.
- N **gram feature—**N gram feature is used to extract each word in message. It takes sequence of n words. The trigram and four gram features are also called as n gram feature.
- **Emoticons feature—**This feature is used to calculate the number of features such as positive, negative, neutral. The person who do not show accurate emotions which is known as neutral message, the person who used the emoticons like happy, jokes, which is known as positive message.
- **Negations feature—**In this type of features are affects the sentiments of another words in a twitter message. Example no, can't should not, would not, could not, may not, do not. These negations are categorizes into three sections which are shown in Table 1.
- **Position feature—**In twitter one user location is affects by other user locations, this problem is solved by position feature extraction, and also it is used to improve the performance of classification.
- **Elongated feature—**This feature is used to extract the elongated word (veryyyy, happyy). This feature extraction is used for improving the performance of sentiment classification.
- **Morphemes feature—**Morpheme consist the smallest amount of language which can convey the full meaning. Morphemes include two slices such as stems and affixes. Stem represent the full meaning in a small word. Affixes given a new word when attach the stem word.
- **Emotional feature—**It is used to extract the emotional features from the twitter messages, which includes ratings, positive and negative emotions, sentiment words and applauses, therefore emotional feature need to extract many features.

3.4 Utilizing Bi-objective optimization for feature selection

The feature selection is considered as the essential process for sentiment analysis which reduces the count of features that is shown in Fig. 6. It is used to eliminate the irrelevant and unwanted features for selecting optimal features in a twitter message. In this proposed work follows bi objective optimization process. It has two functions such as relevancy and redundancy it follows optimum feature selection method for feature selection. The optimum feature selection method is quicker and more flexible which is considered as essential to all the features for performing classification process. Based on redundancy and relevance, this technique provides a restricted number of features [35–37]. The highest dependence between characteristics and is found using the optimal feature selection approach and

$$MI\,(\mathrm{X},\mathrm{Y}) = \sum y \in Y \sum x\epsilon XP((x,y)\ \log\ (\mathrm{p}(x,y)/\mathrm{p}(x)\mathrm{p}(y))) \tag{1}$$

The combined probability and margin probability among two features are denoted by the symbols P(x, y), p(x), and p(y). In a highly demanded space, generate maximal reliance is doubtful to solve the procedure. Maximum relevance is measured by using the following formula

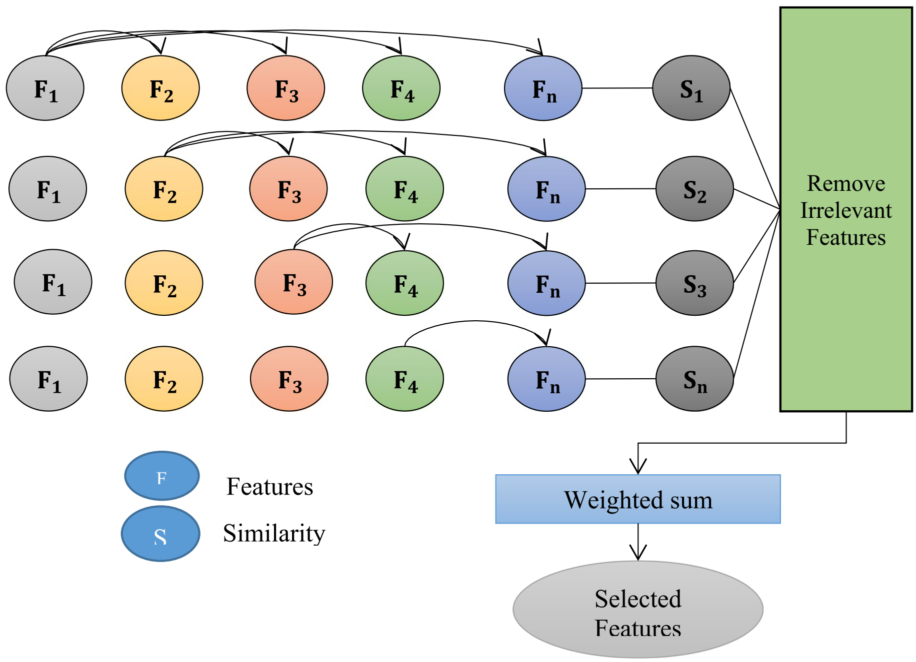


Fig. 6 Feature selection process

$$\max D(F, C);D = \frac{1}{|X|}\sum_{F_i \in F} MI(F_i;C \tag{2}$$

where, MI denotes Mutual information. Maximum dependency is finding by used MI, which represents the exchange of data among the quantity of characteristics and classes Select features based on the maximum relevance parameter, which gives a huge quantitiy of redundancy. Therefore Minimum reduncdancy is find by using following formula

$$\min R(F);F = \frac{1}{|F|}\sum_{F_i F_j \in F} MI(F_i, F_j) \tag{3}$$

$$\max F_{i \notin S}\left[MI\left(F_i, C\right) - \frac{1}{|S|}\sum_{F_j \in S} MI(F_j;F_i \right) \tag{4}$$

where, min R(F) represents Minimum redundancy. MI (Fi, Fj)- Represent mutual information between feature i and feature j. The measurement of maximum relevancy and minimum redundancy has highest computation cost. Mutual information computation also performed between the features and classes. Therefore the proposed system used a greedy algorithm to the optimum feature selection method parameter. This algorithm is used to select the minimum nunmber of features, which follows the rank approach.

Classification It is a crucial process in twitter sentiment analysis. It is called as multiclass SVM. The proposed system used multiclass SVM for sentiment classification, because it performs one against one SVM. Consider M number of class problems and N number of training samples (X_1, Y1) to ($X_{N,}$ YN). $x_i \in D^m$ represents m dimensional feature vector. $yi \in \{1, 2\ldots\ldots\ldots\ldots.M\}$ – class label. Figure 7 represent the flow of Structured SVM mechanism which includes five class such as positive, negative, strongly positive, strongly negative, and neutral. When employing four class classifiers, it is necessary to take into account the two binary SVM classifiers, namely SVM 2, SVM 2, SVM 3, and SVM 4. The classifiers that produce the best results are those whose class labels accurately anticipate the outcome for the given input feature vector.

For every class, there are m binary SVM classifiers in a structured SVM. To separate a class from others, utilize each SVM classifier.The multi classifier results are proposed, which is based on highest values of the SVM classifiers. The proposed Structured SVM mechanism is trained with training samples which includes both positive and negative labels for the i^th class of the SVM. The i^th class of the SVM is used to solve the problems of decision function which is defined as follows,

$$\mathfrak{f}_{i(x)} = (x) + bi \tag{5}$$

Here, $\mathfrak{w}$- represents weight vector and b-denotes Bias term.(x)- represents feature space point.

$$\begin{gathered} Minimize \rightarrow (\mathfrak{w},) = 12\|\mathfrak{w}i\|2 + C\sum \mathfrak{E}jiNi = 1 \\ Subjectto \rightarrow \widetilde{y}j((x)+) \geq 1 - \mathfrak{E}ji, \mathfrak{E}ji \geq 0 \\ \widetilde{y}j \rightarrow 1 \rightarrow Ifyj = iand\widetilde{y}j \rightarrow -1 \rightarrow otherwise \end{gathered} \tag{6}$$

The classification process sample is denoted as x which is classified into class i* whose fi*, it generates the highest value.

$$i * argmaxi = 1{,}2, ..M\mathfrak{f}i(x) = argmaxi = 1{,}2, ..(\mathfrak{w}iT\phi(x) + bi) \tag{7}$$

The proposed SVM mechanism used to predict the score of sentiments, for that SentiWordNet mechanism is used. This mechanism provides accurate sentiment classification of the

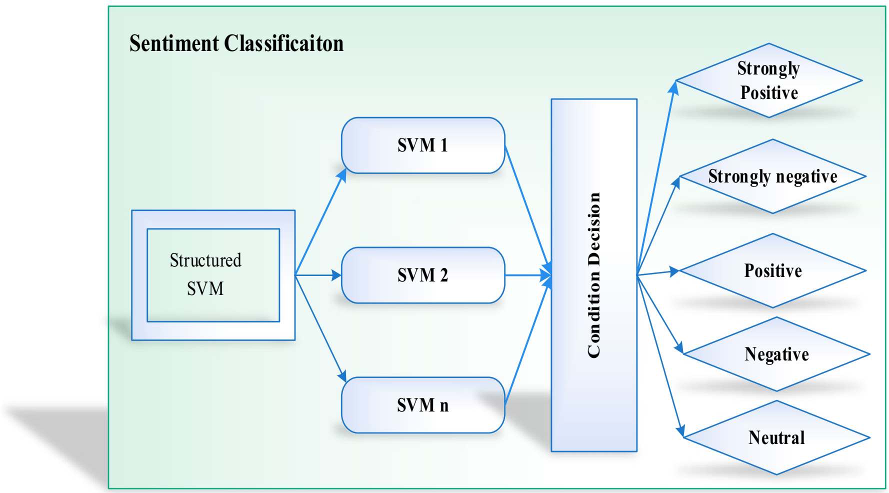


Fig. 7 Sentiment classification

given tweets. The sentiment score is calculated by using the given formula, *sc* (f_k) represent the sentiment score of feature (k).

$$(f) = \sum \mathrm{k}^{\mathrm{n}} = 0, \mathrm{S_c}\left(\mathrm{f_k}\right)/\mathrm{n}$$

4 Experimental results and discussion

This research employed three benchmark datasets often used in “time series classification”: “UCR Time Series Classification Archive” 2018, which comprises datasets such as ECG200, GunPoint, and FordA. These datasets were preprocessed to deal with missing values and standardized for uniformity. The evaluation criteria comprise of the “F1-score, recall, classification accuracy, and precision”, which offer a thorough evaluation of the model’s performance.The performance requirements were predicated on achieving high accuracy and robustness across various datasets and circumstances. The entire model construction was carried out using the MATLAB 2018a suite, which ensured compatibility and leveraged its extensive analytical capabilities.

4.1 Accuracy

It measures the accuracy the of the sentiment classification. It is used to estimate the accurate ratio of the model for overall process. The calculation of accuracy is defined as below

$$Accuracy = \frac{TN + TP}{TP + FP + FN + TN} \tag{8}$$

- TN – “True Negative”
- TP – “True Positive”
- FP—“False Positive”
- FN – “False Negative”

4.2 Precision

Each section of the tweets, which is correctly classfied into given sentiments.The precision calculation is defined as follows,

$$Precision = \frac{TP}{TP + FP} \tag{9}$$

4.3 Recall

Recall mentioned the tweets ratio that is representing the corrected classification of given sentiment classes. Recall is measured by using the following formula,

$$Recall = \frac{TP}{TP + FN} \tag{10}$$

4.4 F-measure

It is employed to assess the sentiment classification's effectiveness. The formula for the f-measure is stated as follows and is used to calculate integration with precision, recall.

$$F_{\beta} = \left(1 + \beta^2\right) \times \frac{precision \times recall}{\beta^2 \times precision + recall} \tag{11}$$

Where,

βrepresentsPrecisionweight In proposed hybrid machine learning approach set a value of β is equal to one which is known as harmonic mean with respect to the precision and the recall. The use of rewritten formula of F-measure is defined as follows,

$$F_{0.5} = 2 \times \frac{precision \times recall}{precision + recall} \tag{12}$$

4.5 Error rate

This is used to evaluate the accuracy of using sentiment classifiers. The value of error rate is equals to one – accuracy rate.

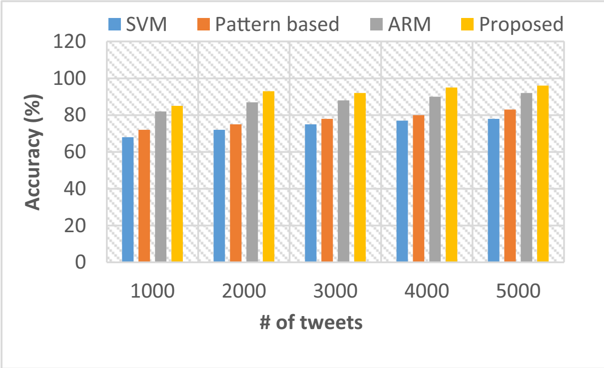
$$\text{Error rate} = 1 - \text{Accuracy rate} \tag{13}$$

Compute the precision, recall, f-measure, accuracy, and error rate first. Then, the outcome of hybrid machine learning approach are compared to the existing work such as SVM, Patten based multiclass and ARM. SVM, multi class classification, supervised and unsupervised classification approaches. Table 2 represents the comparison between proposed system and existing system includes the performance metrics called precision, recall, accuracy, F-measure and error rate.

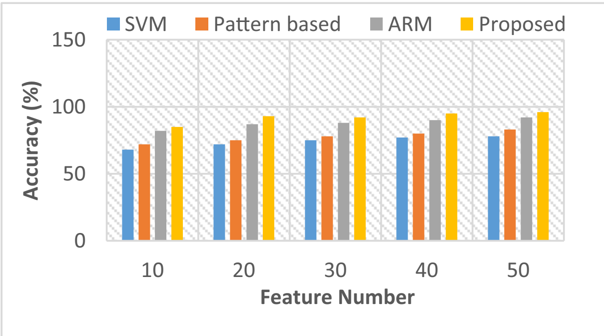
To calculate the accuracy of every algorithm, that the proposed system counts the total amount of tweets. The percentage of accuracy is calculated by using the amount of tweets tagged, which is similar to evaluate the sentiment results for tweets. The Fig. 8 (a) and (b) explained that how the proposed hybrid machine learning approach will perform when compared to other classifiers. The above techniques (SVM, multiclass, supervised, and unsupervised) have an impact on how attitudes on Twitter are classified. The precompiled classic stop list employed in the SVM approach gives the classification a bad impression. Method Pattern based used to perform multiclass classification by using SVM but this method has an over fitting problem. To avoid this problem proposed system used hybrid machine learning approach. It keeps only the attribute determination for a given value of

Table 2 Outcome of H-MLA vs. previous method

Classifiers	Precision	Recall	Accuracy	F-measure	Error rate
SVM	84.15%	89.76%	88.13%	88.63%	17.81%
Pattern based	69.7%	70.1%	70.1%	69.9%	29.12%
ARM	84.4%	83.1%	83%	83.8%	17%
Structured SVM	88.12%	89.96%	89%	89.03%	11%



(a) Accuracy results

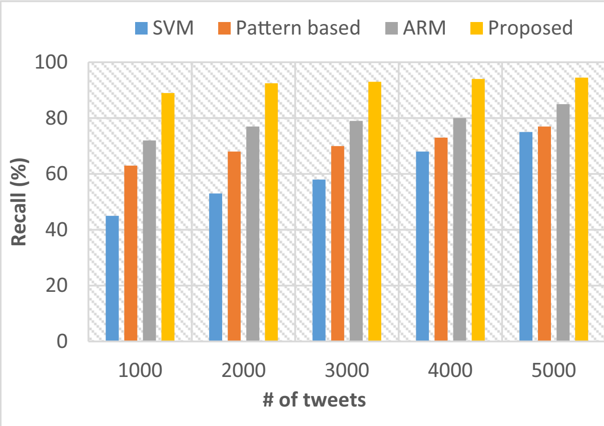


(b) Accuracy results

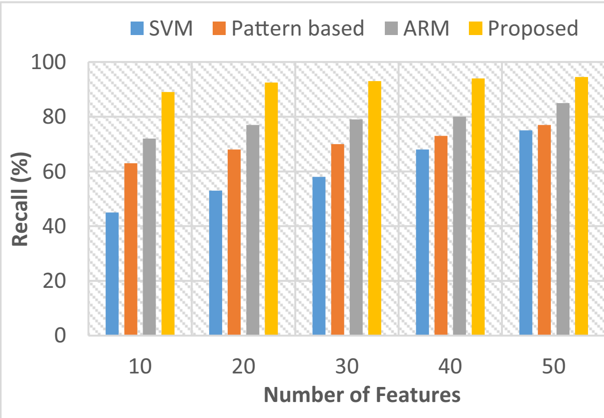
Fig. 8 **a** Accuracy results. **b** Accuracy results

normalization and kernel attributes. The kernel selection is a quite sensitive process which has over fitting model selection attribute. Method ARM used two machine learning algorithms such as supervised and unsupervised for sentiment classification. These two learning algorithms have a challenge in being noise. The proposed method obtained a best performance for reducing feature space and classification maintenance. The proposed system used preprocessing steps to increase the accuracy of classification. Proposed hybrid machine learning approach used only selected features; hence it achieves 89% of accuracy.

It is important to remember that recall stated the proportion of all the models in a given class that were properly classified. Eg. If nine thousand twitter messages are present in positive class and eight thousand messages are correct. The database has ten thousand twitter messages that are positive, therefore recalling of the positive class is the same as the zero point eight (0.8) that represent by 8000/10000. The Fig. 9 (a) and (b) shows the recall results for hybrid machine learning approach, SVM, multi class SVM, supervised and unsupervised learning classifications. Existing machine learning algorithms are generally obtained the background terms but it ignores the usage of sentiment data. This problem will be moderate when the hybrid ML approach learns using feature sentiments; in addition it is used to extract the selected features. The proposed system used structured SVM for sentiment classification. The proposed method achieves 89.96% recall which is used only selected features.



(a) Recall Results

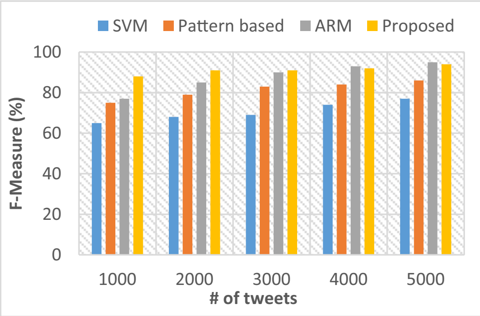


(b) Recall Results

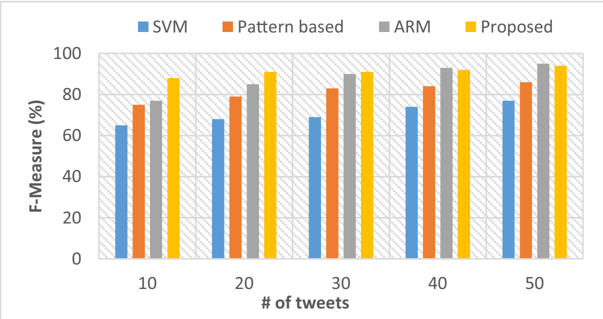
Fig. 9 **a** Recall results. **b** Recall results

Precision mentioned the proportion of properly classified models for a single class within the entire models that are classified. Eg. if nine thousand twitter messages are classified into positive class and eight thousand is correct and dataset has ten thousand twitter message. If is positive, then the 8000/9000 symbol represents the precision for the positive class, which is 0.89. The proposed hybrid machine learning approach and structured SVM method used enriched feature selection method for selecting the features hence it give 88.12% precision. The method of SVM classification gives high precision (87.15%), but multiclass SVM gives a precision of 69.7%. The supervised and unsupervised learning gives poor performance. Figure 9 (a) and (b) represents the comparison between the existing method such as SVM, pattern based, ARM and proposed method.

It is among the more effective techniques for assessing sentiment classification measurement. The harmonic mean of location and recall defines the conventional f-measure. Every kind of classifier in sentiment classification offers a unique set of f-measures to determine classification. The Fig. 10 (a) and (b) shows the results of f-measure for the proposed



(a) F-measure Results



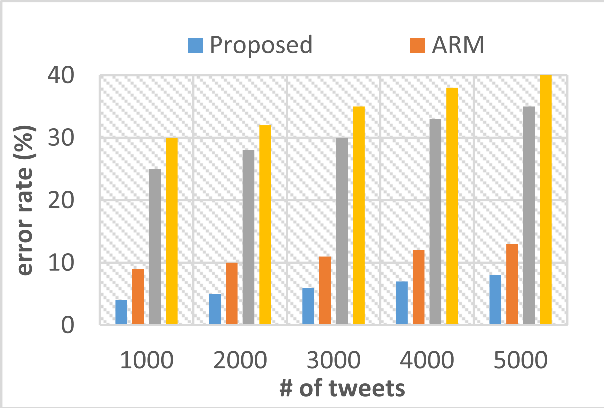
(b) F-measure Results

Fig. 10 **a** F-measure results. **b** F-measure results

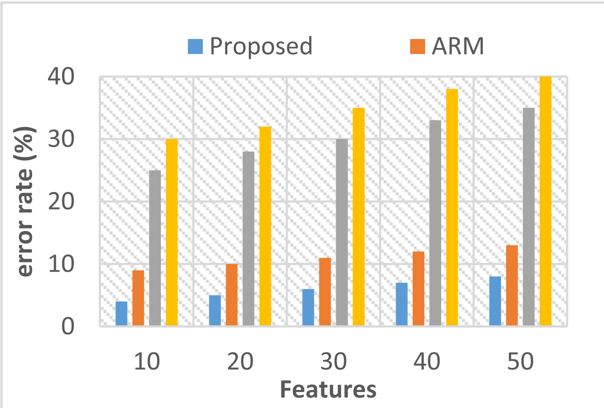
hybrid machine learning approach. It also represents the comparative performance of other machine learning algorithms which are used in previous experiments. The proposed hybrid machine learning algorithms gives a better performance for sentiment classification.

It represents the amount of misclassified tweets for individual type. For example if the accuracy is 88% then the errors will be defriend as 1.0 – 88% = 12%. The suggested effort solely aims to lower the particular sentiment type's mistake rate. If the is high for the sentiment classifier it will be denotes inaccurate classifier. These errors are rectified by using large amount of preprocessing steps. Fig. 11 (a). Describe the error rate comparison between the existing and proposed system. It shows the better performance for error rate. The proposed system error rate is compared to other machine learning classification algorithms for sentiment classification. The Fig. 11 (b). shows the error rate of the proposed hybrid machine learning algorithm with reference to other three classification approaches. The proposed method achieves the accurate result for both training and testing dataset, which represents it, has better sentiment classification.

The above experimental settings provide better results for proposed hybrid machine learning approach, which is based on feature extraction and feature selection. In addition to improving accuracy and resilience, the proposed sentiment analysis framework includes processing efficiency. By using bi-objective optimization for feature selection, the strategy reduces the computing complexity of processing large-scale Twitter datasets. This method systematically decreases the number of features while maximizing relevance and minimizing redundancy, hence optimizing overall computing load during both training and



(a) Error rate results



(b) Error rate results

Fig. 11 **a** Error rate results. **b** Error rate results

inference stages. Furthermore, using a Structured SVM classifier allows for efficient multi-class classification while retaining computational feasibility without sacrificing sentiment analysis accuracy.

5 Conclusion

Twitter sentiment analysis faces many difficulties because of some unique characteristics of twitter. Large amount of preprocessing steps and feature selection techniques are used to solve these problems, in addition it increase the performance. The proposed system used hybrid machine learning approach for twitter sentiment classification, which classifies the sentiment into five different types. The proposed approach extracts nine features for sentiment classification. For feature selection, optimum feature selection method is used to reduce the amount of features. Structured SVM is used to improve the accuracy of training datasets. The proposed method conducts statistical analysis and obtains the results in better potential. Accuracy is measured in the term of percentage for twitter sentiment analysis. In future, real-time recommendation model is proposed for the sentiment analysis using lightweight deep learning techniques. The proposed approach has drawbacks, including its current reliance on structured time series data, which may not completely accept unstructured or irregularly sampled datasets used in real-world applications. Future research might look into improving scalability to handle larger datasets more efficiently, as well as incorporating more complex anomaly detection techniques to improve robustness in outlier identification and handling. Furthermore, expanding the system's ability to dynamically adapt to changing data patterns and integrating with real-time streaming analytics would increase its practical utility and relevance in dynamic situations.

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Data Availability Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

Declarations

Ethics Approval and Consent to Participate No participation of humans takes place in this implementation process.

Human and Animal Rights No violation of Human and Animal Rights is involved.

Conflict of Interest Conflict of Interest is not applicable in this work.

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