Benchmarking Machine Learning for Sentimental Analysis of Climate Change Tweets in Social Internet of Things

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Abstract

Climate change has become one of the most critical problems threatening our world, gaining increased attention in either academia or industry. Climate change has been demonstrated as the major barrier in the way of sustainable development strategy in the 2030 Agenda. Nowadays, the Social Internet of Things (SIoT) has paved new ways for public deliberations and has transformed the communication of global issues such as climate change. Thus, sentiment analysis of SIoT media streams can offer great help in improving the mitigation and adaptation to climate change. Machine learning (ML) is demonstrating great success in a wide range of SIoT applications. However, training ML algorithms for sentimental analysis of climate change is notoriously hard as it suffers from feature engineering issues, information squashing, unbalancing, and curse-of-dimensionality, which bounds their possible power for modeling social awareness of climate change. Besides, the absence of a standard benchmark with reasonable and dependable experimentations brings a practically intractable difficulty to the evaluation of the efficiency of new solutions. In this regard, this study introduces the first reasonable and reproducible benchmark devoted to evaluating the potential of ML algorithms in identifying users' opinions about climate change. Moreover, a novel taxonomy is presented for categorizing the existing ML algorithms, exploring their optimal hyperparameter, and unifying their elementary settings. Inclusive experiments are then performed on real Twitter data with different families of ML algorithms. To promote further study, a detailed analysis is provided for the state of the field to uncover the open research challenges and promising future directions.

Keywords: Machine Learning; Climate Change; Sentimental Analysis; Benchmark

1. Introduction

Climate change and related actions have turned out to be one of the global problems gaining increased attention. Climate change, a global geophysical phenomenon, has been a source of stress for humankind for a long time. An ever-increasing concentration of greenhouse gases in the atmosphere is to blame for the escalating temperatures, rising sea levels, acidification of the ocean, and intensification of severe weather. Human activity is frequently blamed, but public opinion seems to be split [1]. Both the public and government must work together to raise awareness about climate change and its modern incarnation, global warming. Finding out what people think about climate change and global warming is crucial, thereby the people's views on climate change must be better understood, and the DPSIR cycle must be made clearer to the community, for policy and decision-makers to be able to successfully address the issue. Given the scope of the issue at hand, it is challenging to apply conventional methods of measuring popular sentiment, such as surveys, when it comes to climate change [2].

In view of this, social involvement in public deliberation has amplified considerably through the publication of numerous newspapers, research studies, or information posted in more casual different **Social Internet of Things (SIoT)**. Today, **SIoT** media is being regarded as a valued source of information participating in the deliberation of

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existing climate change issues, whereby humans from a variety of countries, experiences, and preferences share their sentiments and thoughts. The increased popularity of **SIoT** media has come up with many **SIoT** platforms such as Facebook, Instagram, Flickr, Twitter, etc. A growing body of research indicates that **SIoT** media might be a helpful resource for understanding how people feel about climate change [3]. Twitter is one of the most well-known **SIoT** media sites because anyone may post short messages (called "tweets")—up to 280 characters in length—about anything they like. Twitter is used by researchers and **SIoT** scientists to glean insights into public opinion and perception by mining the platform for hidden patterns and trends in language. Finding data from many external sources, merging them, and using them is also simpler than before [4].

When discussing a topic of political, commercial, social, or any other kind, public opinion is a measure of how the majority of people feel and what they hope to see happen [5]. Every company that cares about the success of its brands, goods, and reputation needs access to the most recent data available on consumer preferences and attitudes. And it helps companies figure out which leisure, health, and lifestyle fads will bring in the most cash. Astute use of this information in the development of a product or service gives companies a leg up in the marketplace. Governments need to keep tabs on public opinion to spot radicalism and anticipate and react to possibly awkward trends and occurrences, as these factors are often the basis for political decisions. Expressions of radicalization, if left unchecked, have been recognized to be predictive factors of intense occurrences, like the online declarations published by gunmen who later use them to do a radical acts of violence. In the most extreme cases, such sentiments can lead to civil disobedience or even rioting [6]. Governments would benefit greatly from real-time monitoring and analysis of popular opinion because this would provide a solid foundation for decision-making and aid in the prediction, correction, and prevention of undesirable events, such as by highlighting areas where pressure is mounting or where intervention is required. As a result, keeping tabs on public sentiment is seen as a useful strategy for disaster prevention, stopping violence before it starts, and keeping the peace [2].

Attempts to gather and analyze public opinion are fraught with complications. The overwhelming quantity of data that needs to be evaluated, the complexity of gathering and processing data, and the wide variety of sources that need to be tracked all contribute to this difficulty. Discussions and arbitrary surveys are frequently used tools for measuring international perception. Nevertheless, there are limitations to using either technique to gather national sentiment, including small sample size, the possibility of bias in the questions asked, and an absence of accountability in the data collection process. Further, data gathering and analysis using these techniques are time-consuming, labor-intensive, and costly. Massive amounts of user-generated content from ever-expanding **SIoT** media platforms, when properly mined and analyzed, can shed light on the general public's perspective on current events and supplement traditional research methods like questionnaires and interviews [7]. The research community is still debating the optimal method for achieving this goal. One way to get a quick and reliable read on public sentiment is to conduct sentiment analysis on **SIoT** posts from influential people.

In this regard, machine learning (ML) is an active field of AI that has been revolutionizing the field of natural language processing (NLP) and **SIoT** network analysis in recent years, however, the ability of ML to interpret and analyze climate-related **SIoT** streams is still an open research question. Thus, this study presents the author's attempt to answer that question from both theoretical as well as practical standpoints. With the increased threats of climate change issues, social awareness and social adaption turning to be essential factors to help inform society about the criticality of the issues and the role of humans to solve these issues. As a matter of the fact, most **SIoT** networks have an indispensable role in interpreting and changing the opinion and awareness of people and societies toward specific matters.

In line with the evolving interest in climate change issues especially over **SIoT** networks, this work contributes to the body of knowledge as follows:

- To the best of the authors' knowledge, this study presents the first fair ML benchmark that methodically explores the implementation details and development philosophy of state-of-the-art ML algorithms for classifying social opinions about climate change using Twitter data.
- This study presents a new taxonomy for categorizing the existing ML algorithms into different families by analytically reviewing the main characteristics and potentials for classifying and analyzing the textual sentiments toward climate change in Twitter data
- The experimental findings can be found in Tables 1-3. In some way inappropriately, the hyperparameter settings of ML algorithms are highly conflictingly implemented making

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it challenging to draw any reasonable conclusion. To this end, this work cautiously scrutinizes these sensitive hyperparameters and stochastically selects the optimal one to lays the basis for a reasonable and re-producible benchmark of implementing ML algorithms for analyzing climate change sentiments.

- By the end, this study settles a road map for applying ML for analyzing and mining **SIoT** streams to improve the social awareness of climate changes issues, mitigation efforts, and adaptation strategies.

The remainder of this study is planned as follows: Section 2 reviews the literature study of ML for climate change. Section 3 presents a taxonomized overview of ML algorithms for sentimental analysis. Following, the experimental details of evaluating the ML algorithms, the results, and the findings are described in section 4. Section 5 summarizes the open research challenges and the promising future directions. Finally, section 6 concludes this work.

2. Materials and Case Study

The discussion in this section provides a detailed description of the dataset used as a case study in our experiments, the relevant data preprocessing, and the essential exploratory analysis applied in our work.

2.1. Twitter Dataset

This work uses Twitter sentiment data to examine and analyze the sentiment of the public audience about the topic problem of climate change. The matter of climate change has indeed been actively addressed by users, social influencers, organizations, and significant figures on **SIoT** networks, eliciting important reactions from their respective fan bases because of the topic's possible effects on the survival of humanity. This is why we decided to use Twitter data as a case study in our study of sentiment tracking and analysis. however, it is worth mentioning that our benchmark may be applied to the study of any textual content from any **SIoT** platform, not only Twitter. The Twitter data was collected by aggregating the tweets relating to climate change in the time frame between Apr 27, 2015, and Feb 21, 2018. The acquisition of tweets ended up with 43943 tweets, each was labeled as belonging to one of three classes namely Pro (Supporting), Anti (Denying), and (Neutral). The class distribution of the data is given as shown in Table I.

Table 1: summary of the distribution of tweets across the different classes

Class Name	Train set	Test set	Total
News	7,421	1,855	9,276
Pro	18,370	4,592	22,962
Anti	3192	798	3,990
Neutral	6,172	1,543	7,715
Total	43,943	8,788	43,943

2.2. Data Preparation

Given the description of the Twitter dataset, this section starts by describing the preprocessing operations applied to prepare the dataset before feeding it to ML algorithms. These operations are briefly described as follows:

- **Lower Case Conversion**: At this stage, it is important to emphasize changing all of the text to lowercase. If we do not convert words like CLIMATE, climate, and Climate to lowercase, we are considering all of these words as though they are entirely separate words. After lowering the case of each word, the three words are combined into a single term that is referred to be the climate.
- **Removing Stopwords:** As the first step in this text preparation procedure, it is preferable to conduct the text in lowercase. Because if we are going to get rid of stop words, every word must be written in lowercase letters. For instance, there are very few sentences that begin with the word "The," and if we do not do the lower casing technique before the technique in question, we will not be able to get rid of all of the stop words. The second scenario involves determining the count of occurrences of a particular frequency.
- **Removing HTML tags:** This is a very important step in the preprocessing phase. When we harvest or "scrape" data from multiple websites, there is a good likelihood that some of our text data will contain HTML tags. This is a rather regular occurrence. These HTML tags do not provide us with any information that is useful to us. Therefore, removing them from our text data is the best option.

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- **Spelling correction:** When working with things like tweets, comments, and so on, one of the most crucial preprocessing techniques to use is spelling correction. Because we can recognize words that have been spelled incorrectly in specific sections of the text. The words that were spelled incorrectly need to be changed to their correct spellings. By utilizing two different Python libraries—pyspellchecker and autocorrect—we will be able to check for misspelled words and substitute them with the proper spelling of those terms.
- **Chat conversion**: If we work with chat conversions, or if our issue statement requires us to analyze chat conversions, then this is yet another preprocessing technique that is necessary. We are going to have to deal with the short form. People tend to utilize abbreviated forms of terms in their talking conversations because of how much easier they are to understand.
- **Expanding contractions**: Contractions are words or word combinations that are generated by omitting a few letters and substituting those letters with an apostrophe. This process creates a shorter version of the original term. We extract contractions from the text and match them with the corresponding contraction map words. In the event that we have not already carried out a method of converting upper case letters to lower case, we are required to use the initial character to represent the final product of the contraction. "Doesn't" like "Does not"
- Stemming: The process of reducing words to their fundamental form, also known as their root form, by deleting a few suffix characters is known as stemming. The process of normalizing the text is known as stemming. Porter stemming is by far the most popular choice among the numerous different stemming algorithms that are now available.
- **Lemmatization:** The purpose of using lemmatization is comparable to that of the stemming approach, which is to simplify inflected words to their root words, also known as base words. On the other hand, the lemmatization procedure is not the same as the method described above. Lemmatization is not limited to just removing the characters of a suffix; rather, it draws on lexical knowledge bases to generate the original words. In contrast to stemming, lemmatization generally results in a valid word being produced as the end product.
- **Converting Emojis to the word:** Emojis are essentially miniature images. Emojis and emoticons allow users to convey exactly how they are feeling at any given moment. We are able to communicate these with anyone, wherever in the world. It is necessary to convert the text of any emojis into words to do opinion mining.
- **Removing of Punctuations or Special Characters**: Punctuations or special characters are all characters except digits and alphabets. A list of all available special characters are [!"#$%&'()*+,-./:;<=>?@[\]^_`{|}~]. This is better to remove or convert emoticons before removing punctuations or special characters.
- **Others**: removing white spaces, rare words, single characters,

2.3. Exploratory Analysis

Exploratory data analysis is one of the most vital steps in the workflow of any machine learning process, and natural language processing is no exception. In this section, we will talk about and put into practice nearly all of the most important methods that you can employ in order to comprehend the text data you have. The analysis of word frequency is a crucial step in gaining an understanding of the terms that appear most frequently in the dataset. The removal of

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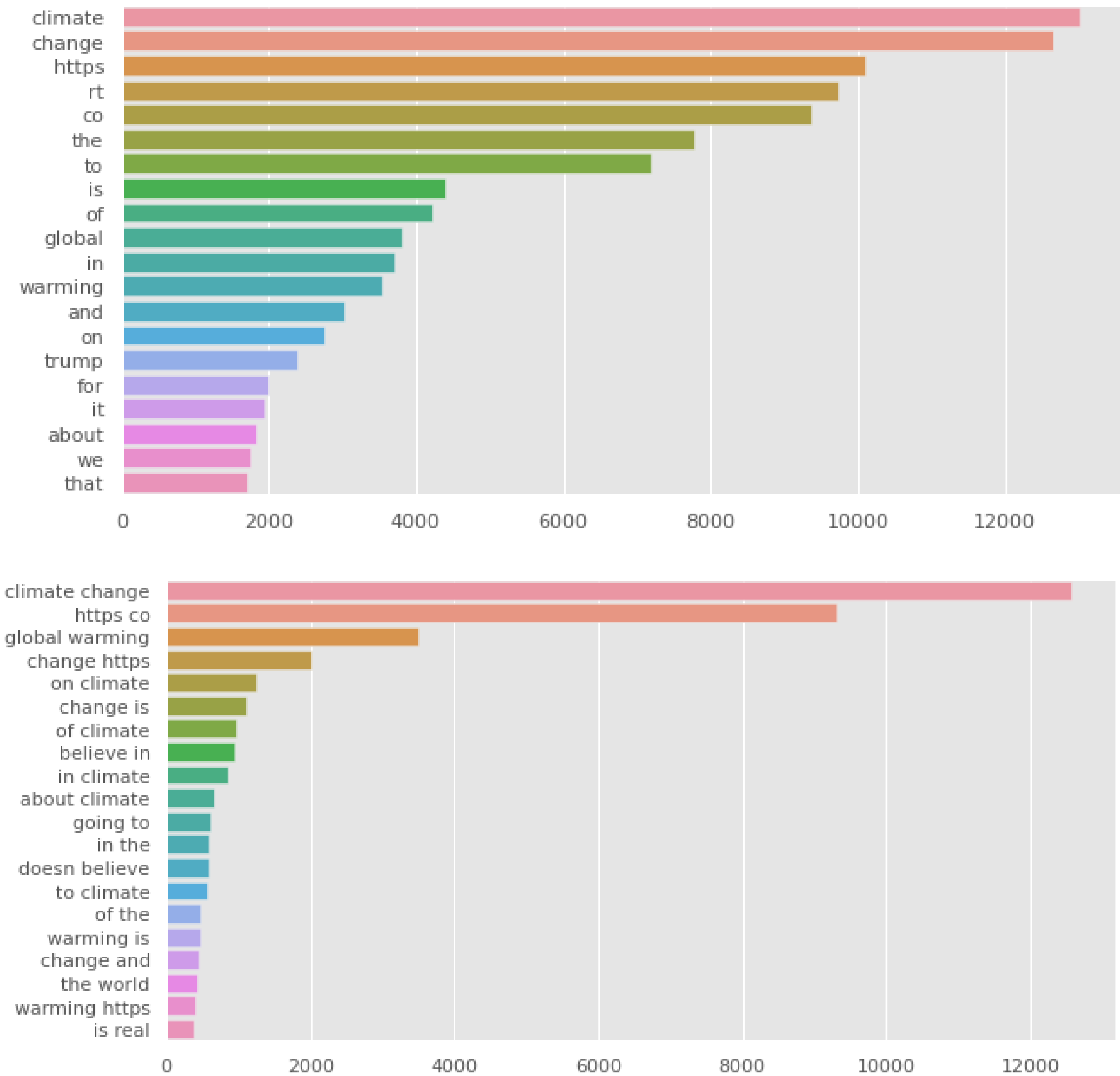

Figure 1: Illustration of word frequency analysis for unigram (upper part) or bigram (low part)

stopwords is a necessary step in word frequency analysis because these words are the most frequent in the text. Once the stopwords have been counted, the analysis can move on to determining which words are used most frequently. Figure 1 presents a histogram of word frequency analysis, in which the term "climate change" is the most frequent term. A word cloud is an effective way to display text data. The frequency with which a word appears in the word cloud is represented by its size as well as the color it is displayed in (see Figure 2).

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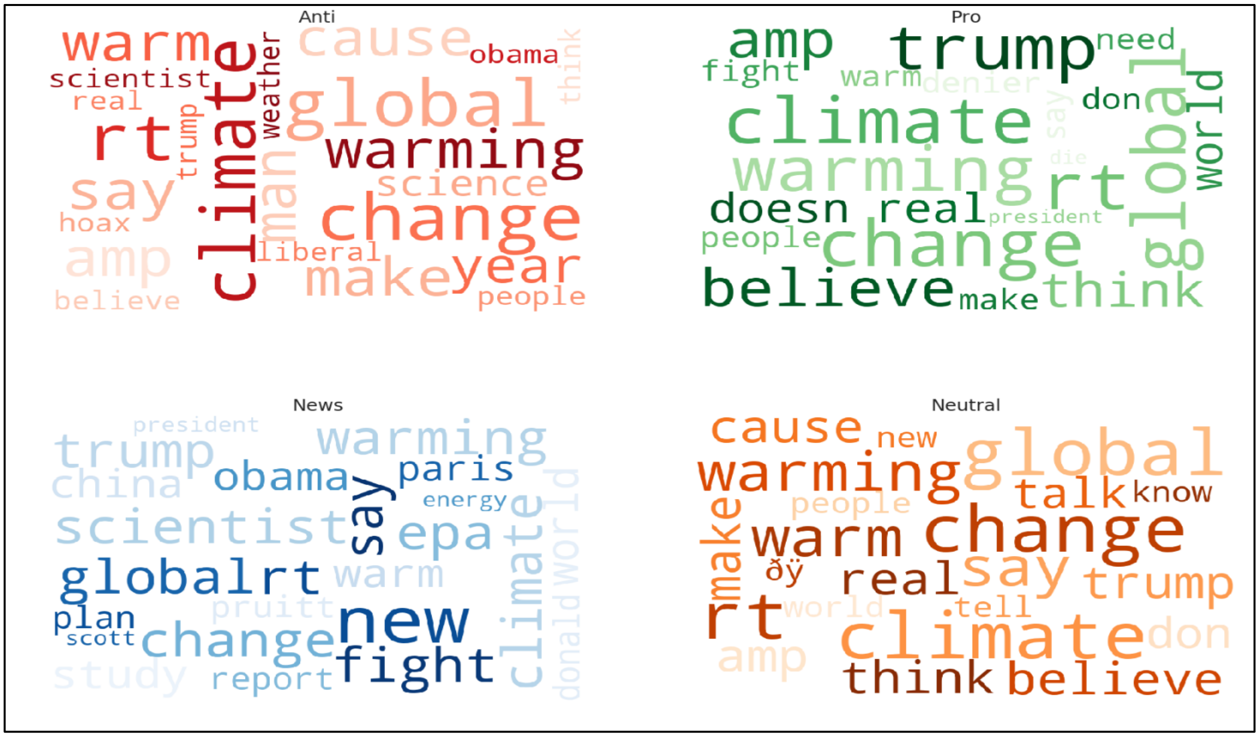

Figure 2: Illustration of the word cloud for each class.

3. Overview of ML algorithms

4.1. Levels of Sentiment Analysis

The methods of sentiment analysis can be categorized into different categories according to the level at which it was performed, which include sentence-based, phrase-based, document-based, and aspect-based. Figure 3 shows the interrelation between different levels of sentiment analysis [8], [9], [10].

Sentence-based sentiment analysis: At this stage of processing, the polarity of each sentence is determined. When a paper has a wide variety of feelings, this is an invaluable tool. This tier of categorization is linked to the practice of subjective categorization. Identical techniques used at the document level will be applied to identify the polarity of individual sentences, but more data and computing power will be available for training and analysis. Each sentence's polarities can be used independently or as part of a whole to reveal the article's mood. As useful as document-level sentiment analysis can be, there are times when it falls short. Finding subjectivity statements has been the focus of

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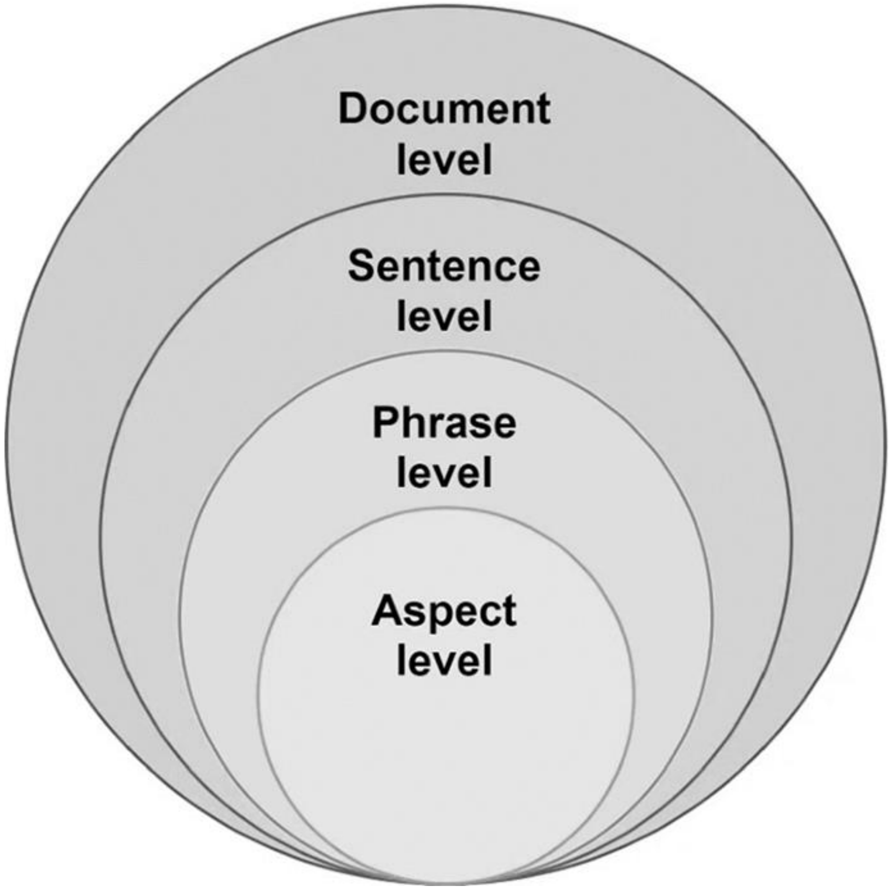

Figure 3. Illustration of levels of sentiment analysis for climate change tweets

prior work at the sentence level. Nevertheless, more interesting responsibilities, such as those involving ambiguous assertions or contingent expressions. Sentiment analysis at the sentence level is essential in such a situation [11]–[13].

Phrase-based sentiment analysis: Sentiment analysis can also be done, which entails phrase-level opinion mining followed by a classification of the findings. There may be single or multiple meanings attached to each word. It's possible that these are insightful critiques of a variety of lines, but in this case, it's clear that only one feature is being discussed. There has been a rise in the quantity of research into this topic in recent years. Since a document may include both pro and con comments, examination at the sentence level is preferable. Research at the document level seeks to label the entire piece as positively or negatively biased, while research at the level of the sentence examines the text of single sentences. Language's most basic unit is the term, and the level of objectivity in a given sentence or document is proportionate to the polarity of the term utilized therein. Subjective sentences are more likely to contain adjectives than objective ones. A person's demographic aspects, such as gender and age, in addition to their ambitions, social standing, personality, and other psychological and social characteristics are all reflected in the phrase that has been selected to convey anything. This means that the phrase can be used as a foundation for classifying the sentiment of texts [11], [14]–[17].

Document-based sentiment analysis: An entire manuscript is analyzed for its emotional tone, and then assigned a single polarity. In practice, sentiment classification of this kind is rarely employed. To utilize it, you can label the chapters or pages of a book as either positive, negative, or neutral. The document can now be classified using either supervised or unsupervised learning techniques. The two biggest problems in document-based sentiment can be categorized as cross-domain and cross-language sentiment analysis. Evidence shows that domain-based sentiment classification can be remarkably accurate while yet being substantially domain-sensitive. The feature vector in such tasks is a constrained collection of words unique to the given domain [16], [18]–[20].

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Aspect-based sentiment analysis: Analyzing how someone feels can be done at the aspect level in sentiment analysis. Considering that each sentence may have many different components, aspect-level sentiment classification is more accurate. Keen attention to detail to all of the components employed in the sentence and assigning polarity to each component; after doing so, overall sentiment is computed for the sentence overall [8], [10], [14], [19], [21].

4.2. **Taxonomy of ML algorithms for Climate Change**

When it comes to studying climate change sentiment analysis, three distinct categories of methods are available, specifically lexicon-dependent approaches, ML approaches, and hybrid techniques.

lexicon-dependent approaches: Utilizing sentiment lexicons as a means of categorizing polarity is one of the key methods that are utilized in sentiment analysis. A sentiment lexicon is a collection of words or phrases that have been assigned scores. These scores are going to be utilized in the process of calculating the overall polarisation or cooperative sentiment direction of the sentiment task. Sentiment lexicons can be produced in one of four ways: manual process programming the attitude of the lexical items; conducting an investigation of the semantic relatedness between a collection of word embeddings from an established sentiment lexicon; adjusting the sentiment analysis from one particular domain to another by domain adaptation; or making use of stochastic models, such as ML classifiers, to recognize sentiment-bearing words. SentiWordNet and MPQA are two examples of lexicons of feelings that already exist and are used quite regularly.

ML approaches: The three forms that make up the machine learning-based methods are unsupervised learning, which examines the words contained within the documents, frequent words grouping, which results in the formation of multiple groups that have been indicated by the investigators, and supervised learning, which analyses the words contained within the documents. Even during the training of the learner, semi-supervised learning makes use of both unlabeled data and a limited quantity of labeled data. The unlabeled data are used to extract significant characteristics, whereas the labeled data are utilized to fine-tune the outcome of the classification model. The third type, known as supervised learning, will be the focus of this research project. There have been a lot of studies that have been done to enhance methodologies for sentiment classification, and one of the methods that have been used is supervised machine learning learners. This method is characterized by the utilization of labeled data as features for training sessions and ml algorithms to generate the desired output [36]. After that, using the classification algorithm to predict the sentiment polarity of the unlabeled data is a viable option. It has been demonstrated through a plethora of research that supervised learning surpassed both semi-supervised and unsupervised learning in several facets. Despite this fact, one of the biggest weaknesses of this method is the necessity for a significant number of labeled data to be used during the training phase. This may be ineffective if the data have to be labeled individually by living beings.

4. Experimental Settings

This section first argues the experimental configurations of the intended benchmark studies, then, the experimental results of ML algorithms are tabulated and discussed to generate valuable insights and remarks.

4.1. Performance Metrics

To assess the performance of the image recognition model, five popular evaluation metrics are used and defined as follows:

$$Accuracy\ (A) = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \tag{1}$$

$$Precision\ (P) = \frac{TP}{TP + FP} \times 100 \tag{2}$$

$$Recall\ (R) = \frac{TP}{TP + FN} \times 100 \tag{3}$$

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$$F1 - measure\ (F1) = 2 * \frac{P * R}{P + R} \quad (4)$$

where FN, FP, TN, and TP represent the false negative, false positive, true negative, and true positive, respectively.

4.2. Hyper-parameters

To facilitate the reproducibility of the abovementioned methods in our benchmark, this section presents the hyper-parameters of each ML algorithm, according to which, the best experimental results are calculated. To evade the non-optimality of manual hyperparameters, Tree-structured Parzen Estimator (TPE) algorithm is adopted for hyperparameter optimization [22]–[26]. The optimized hyperparameters of each ML algorithm and the corresponding search domain are summarized. The optimization process is performed based on 3-fold cross-validation experiments to evade the overfitting problems regarding the fitness function, whilst the maximum number of iterations is set to 25.**Implementation Setups**

The development of all ML algorithms is performed using Python 3.8.1. programming language running on a Toshiba workstation that has a Windows 10 32 OS, and is outfitted with a CPU of Intel (R) Xeon (R) CPU E5-2670 0@ 2.60GHz, and 256 GB RAM. SK-learn Library is used to develop most of ML algorithms.

4.3. Experimental Results

A. Comparative Results

In order to assess and analyze the ML for sentimental analysis from climate change data, we fairly benchmark state-of-the-art ML models (Logistic regression, Naive's Bayes Classifier, Support Vector Machine Classifier, XGBoost Classifier, Gradient Boosting (GB) Classifier, Decision Tree (DT) Classifier, Random Forest (RF) Classifier, KNeighborsClassifier, LIGHTGBM Classifier, MLP classifier) on the dataset that was previously mentioned. The results of the experiments are presented in Table 2 below for the various models. We report the performance of each of these methods using the performance metrics that were discussed earlier in this paragraph. To further understand the classification performance of the proposed ML models at class level, the confusion matrix of each model is presented in Figure 4.

Table 2: The classification performance of different ML algorithms on the climate change datasets.

ML algorithm	Accuracy	Precision	Recall	F1-score	AUC
Logistic regression	69.35±6.89	67.82±3.84	60.33±9.06	61.33±5.40	73.65±4.87
Naive's Bayes Classifier	66.92±2.08	63.34±18.91	60.42±8.53	61.67±11.75	73.84±13.40
Support Vector Machine Classifier	70.23±18.30	68.71±14.11	60.31±10.87	63.19±12.28	73.25±18.35
XGBoost Classifier	69.47±4.78	66.45±3.06	61.12±12.64	63.88±4.93	74.21±15.98
Gradient Boosting Classifier	55.18±19.37	52.23± 11.95	36.74±5.65	36.37±7.67	57.29±15.81
Decision Tree Classifier	69.95±4.84	67.14± 5.83	62.32±2.84	64.41±3.82	74.35±15.79
Random Forest Classifier	69.20±10.01	66.77± 10.53	60.71±17.25	62.67±13.08	73.49±8.47
KNeighborsClassifier	66.79±3.74	60.33± 16.16	62.54±11.19	61.51±13.22	74.25±17.29
LIGHTGBM Classifier	69.90±13.39	65.21± 3.65	63.32±7.82	64.21±4.98	75.25±5.98
MLP classifier	63.08±1.86	45.34± 6.90	46.41±12.87	44.34±8.98	65.34±5.19

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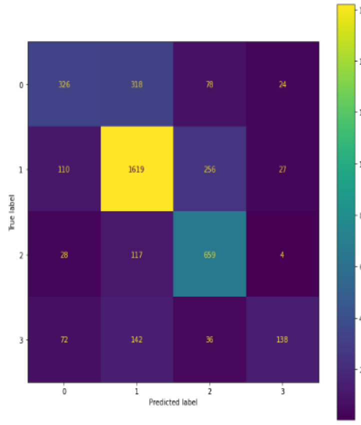
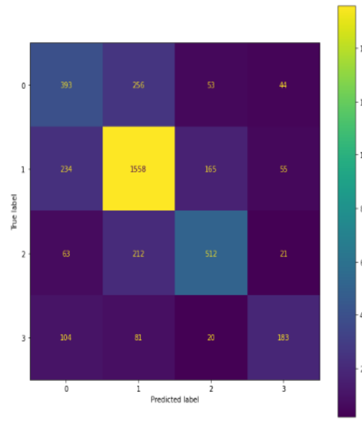
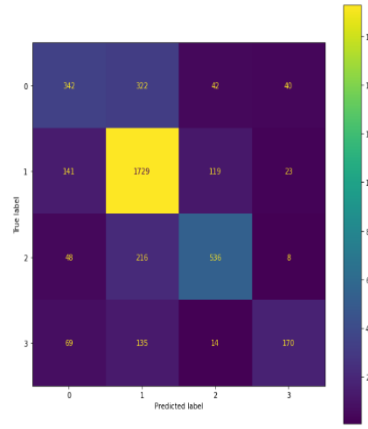


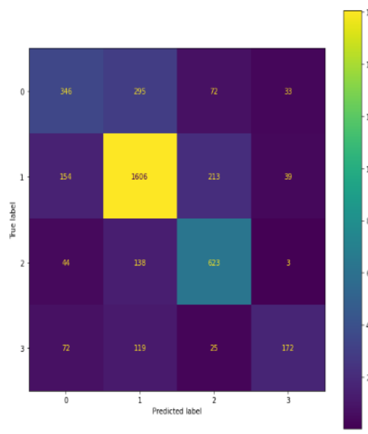
Logistic regression



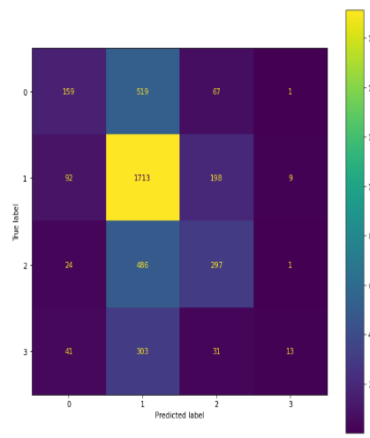
Naive's Bayes



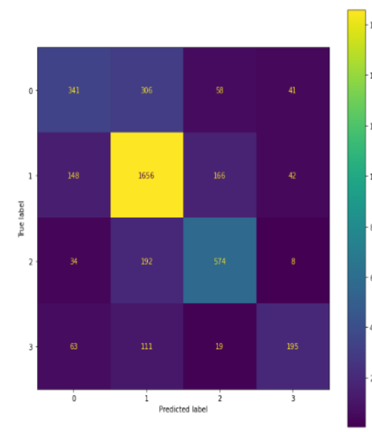
Support Vector Machine



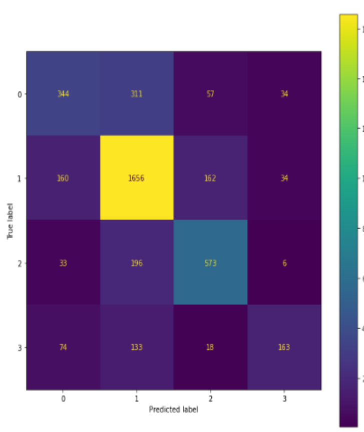
XGBoost



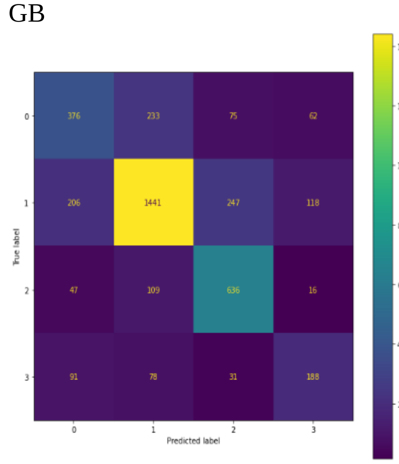
GB



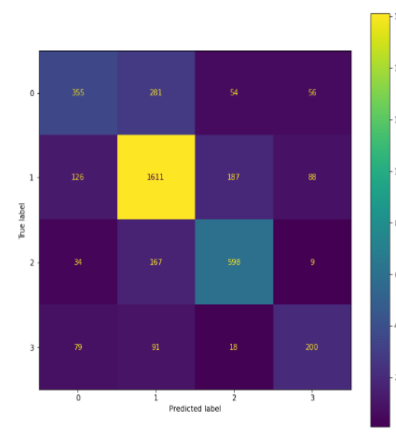
DT



RF



KNeighbors



LIGHTGBM

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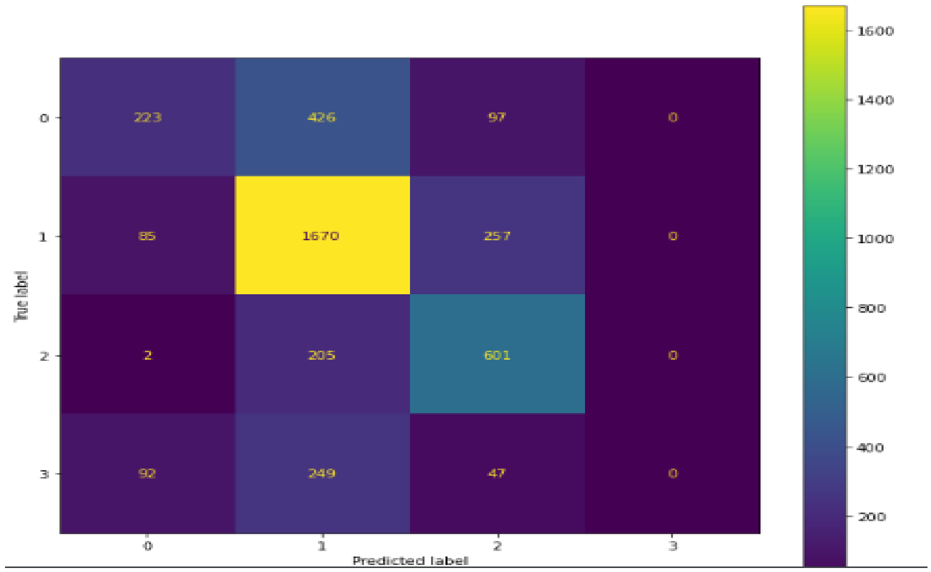


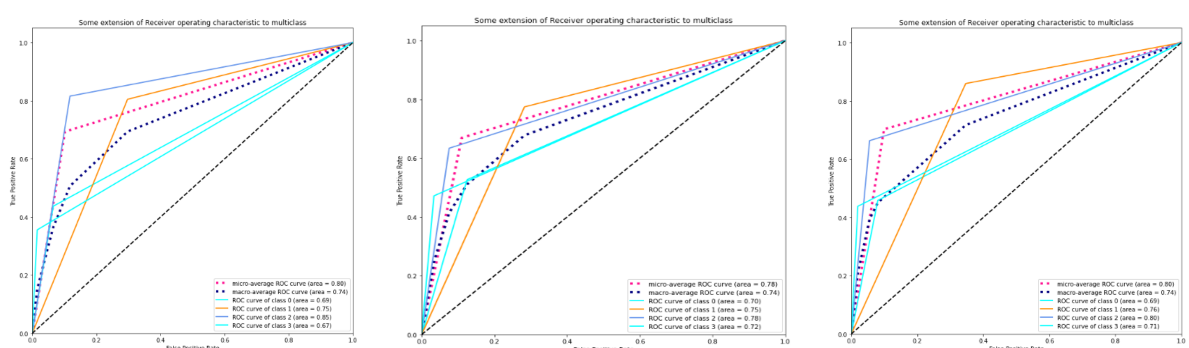
MLP classifier

Figure. 4: Comparison of confusion matrixes of different ML classifiers (test set).

B. ROC Analysis

Accuracy and the area under the curve (AUC) in a receiver operating characteristic (ROC) plot are two crucial and frequently used indicators of the effectiveness of discrete diagnostics and models. On the ROC curve of a model, accuracy is determined at one operational point or determination criterion, whereas AUC measures all operating points. However, all performance measurements at a single observation point are overly specialized since they rely on a particular set of misclassification costs that represent a single or typical patient and omit data on surrounding locations where performance may occur immediately. On the contrary side, all performance metrics across all operational points, or global metrics, are overly broad. AUC is favored over accuracy, a generic metric, however, AUC is critiqued for including operation conditions that are not practical and for not revealing the effectiveness distribution throughout the ROC curve.

ROC charts are designed to display the success distribution for additional studies. ROC analysis is frequently used to determine the best ROC point or threshold, examine where dominance changes when ROC curves intersect or observe the general domination or ranking of learners. Therefore, this illustration of ROC curves of state-of-the-art ML models is introduced in the Figure. 5. As shown, the performance of the model varies for each class reflecting the low stability of the model.



Logistic regression Naive's Bayes Classifier Support Vector Machine Classifier

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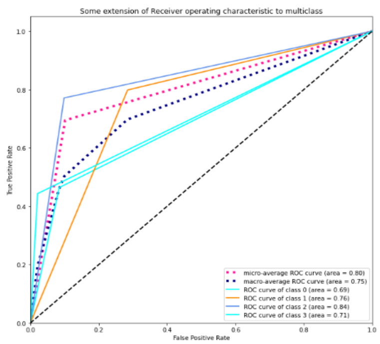
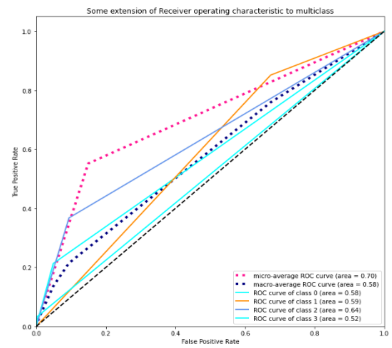


XGBoost



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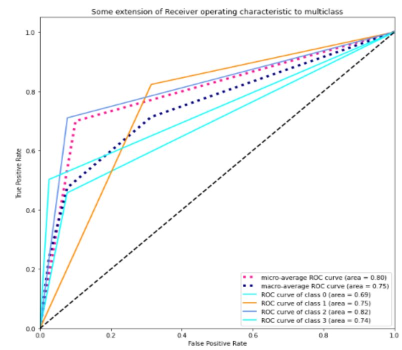
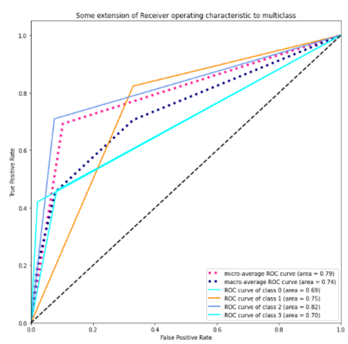
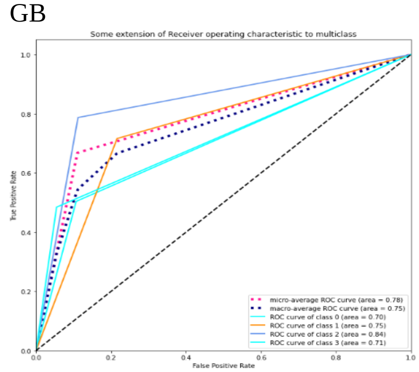


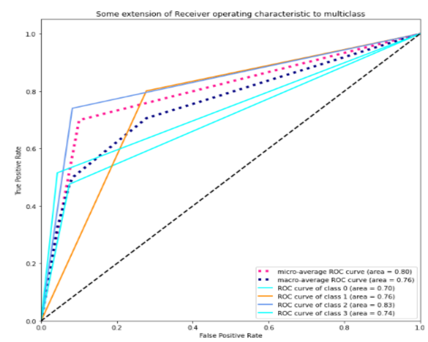
DT



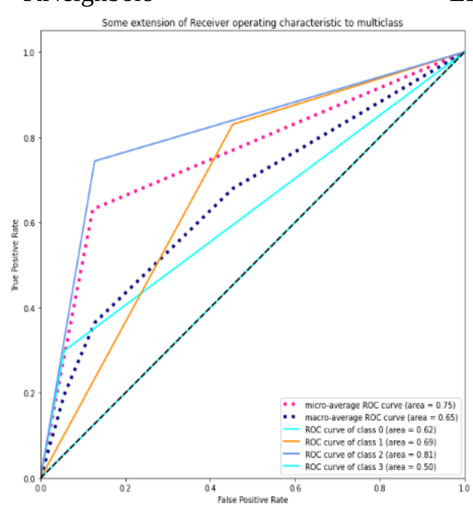
Random Forest



KNeighbors



LIGHTGBM Classifier



MLP classifier

Figure 5: Comparison of receiving operator characteristic curve for different ML classifiers (test set).

5. Conclusion

Machine Learning algorithms are key enablers for efficient and effective analysis of the sentiments regarding climate change across different **SIoT** platforms. This work settles the entry point for intelligent analysis of the social impact of climate change by developing a standardized benchmark of ML algorithms with reasonable and dependable experimental conformations to promote further research in this field. This includes holistic and taxonomic investigation of legacy and modern ML algorithms. The experimental findings show highlighted many robust training tricks and found new state-of-the-art performance. This work provides the ML research community with a compact, reasonable, and applied evaluation fundamental by offering robust baselines for ML-based sentiment analysis for climate change.

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