# Hate Speech Detection with Hateful and Offensive Expressions on Twitter using various Machine Learning Techniques

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*Abstract— A lethal online substance has turned into a noteworthy issue in this day and age because of an exponential increment in the utilization of the web by individuals of various societies and instructive foundation. Separating hate speech and offensive language is a key test in the programmed detection of dangerous content substance. In this paper, we propose a way to deal with naturally order tweets on Twitter into three classes: hateful, offensive and clean. Utilizing Twitter dataset, In this paper, we propose a way to deal with distinguish hate expressions on Twitter. Our methodology depends on unigrams and examples that are consequently collected from the preparation set. These examples and unigrams are later utilized, among others, as highlights to prepare a machine learning calculation. Our analyses on a test set made out of 2 010 tweets demonstrate that our methodology achieves an exactness equivalent to 87.4% on identifying whether a tweet is offensive or not (twofold classification), and precision equivalent to 78.4% on distinguishing whether a tweet is hateful, offensive or clean (ternary classification).*

*KEY WORDS—Twitter, Hate Speech, Machine Learning, Sentiment Analysis.*

## 1. INTRODUCTION

THIS In the previous 10 years, we have seen exponential development in the number of individuals utilizing on the web gatherings and interpersonal organizations. Like clockwork, there are 510,000 remarks produced on Facebook [1] and around 350,000 tweets created on Twitter[2].

The individuals collaborating on these gatherings or informal organizations originate from various societies and instructive foundations. On occasion, the distinction in feelings prompts verbal strikes. In addition, unchecked the right to speak freely over the web and the veil of obscurity that the web gives instigate individuals to utilize racists slurs or defamatory terms. This can bring down the confidence of individuals, promoting psychological sickness and a negative effect on society all in all. Besides, lethal language can take different structures, for example, cyberbullying, which was one of the significant explanations for suicide [3]. This issue has appeared to be progressively vital in the most recent decade and identifying or expelling such substance

physically from the web is a monotonous undertaking. So there is a requirement for formulating a mechanized model

That can identify such lethal substance on the web.So as to handle this issue, right off the bat, we should most likely characterize lethal language. We comprehensively isolate lethal language into two classifications: hate speech and offensive language. A comparative methodology was utilized in the examinations [4] and [5]. As per Wikipedia, hate speech is characterized as "any speech that assaults an individual or gathering based on qualities, for example, race, religion, ethnic starting point, national beginning, sex, handicap, sexual introduction, or sex personality." We characterize offensive language as the content which utilizes harsh slurs or deprecatory terms.

To conquer this commotion and the non-unwavering quality of data, we propose in this work a proficient method to recognize both offensive posts and hate speeches on Twitter. Our methodology depends on composing designs, and unigrams alongside sentimental highlights to play out the detection. The rest of this paper is organized as pursues: in Section 2 we present our inspirations and portray a portion of the related work. In Section 3 we formally characterize the point of our work and depict in detail our proposed strategy for hate speech detection and how includes are extricated.

## I. Related Work

The analysis The analysis of abstract language on OSN has been profoundly considered and connected on various fields differing from sentiment analysis [10] [11] [12] to mockery detection [6] [7] or detection of gossipy tidbits [13] and so forth. In any case, moderately fewer works (contrasted with the previously mentioned subjects) have been routed to the hate speech detection. A portion of these works focused on sentences on the internet, for example, crafted by Warner et al. [5] and Djuric et al. [14]. The primary work achieved a precision of classification equivalent to 94% with an F 1 score equivalent to 63.75% in the assignment of parallel classification, and the second achieved an exactness equivalent to 80%.

Gitari et al. [15] extricated sentences from some real "hate destinations" in the United States. They commented on every one of the sentences into one of three classes: "emphatically hateful (SH)", "pitifully hateful (WH)", and "non-hateful (NH)". They utilized semantic highlights and syntactic examples highlights, run the classification on a test

set and got an F1-score equivalent to 65.12%.

Nobata et al. [16] utilized dictionary highlights, n-gram highlights, phonetic highlights, syntactic highlights, prepared highlights, "word2vec" highlights and "comment2vec" highlights to play out the classification undertaking into two classes, and acquired a precision equivalent to 90%.

By the by, some different works focused on the detection of hateful sentences on Twitter. Kwok et al. [17] focused on the detection of hateful tweets against dark individuals. They utilized unigram highlights which gave a precision equivalent to 76% for the assignment of twofold classification. Clearly, the attention on the hate speech toward a particular sexual orientation, ethnic gathering, race or different makes the collected unigrams identified with that particular gathering. In this manner, the assembled word reference of unigrams can't be reused to recognize hate speech towards different gatherings with similar proficiency. Burnap et al. [3] utilized composed conditions (i.e., the connection between words) alongside the sack of words (BoW) highlights to recognize hate speech expressions from clean speech ones.

## II. PROPOSAL METHODOLOGY

In the event that you are utilizing Word, Given a lot of Tweets, the point of this work is to characterize every one of them into one of three classes which are:

**Clean**: this class comprises of tweets which are impartial, non-offensive and present no hate speech.

**Offensive**: this class contains tweets that are offensive, however, don't present any hate or segregative/bigot speeches

**Hateful:** this class incorporates tweets which are offensive, and present hate, supremacist and segregative words, and expressions.

We use machine learning to play out the classification: we separate a lot of highlights from each tweet, we allude to a preparation set and play out the classification.

### 3.1 Data

For this work, we have collected and consolidated 3 different datasets:

A first data set freely accessible on Crowdflower2: this data set contains in excess of 14 000 tweets that have been physically characterized into one of the accompanying classes: "Hateful", "Offensive" and "Clean". Every one of the tweets on this data set has been physically clarified by three individuals.

A second data set openly accessible additionally on Crowd-flower3: which has been utilized beforehand in [19] and which has likewise been physically explained into one of the three classes: "Hateful", "Offensive" and "Not one or the other", the last alluding to the "Spotless" class referenced already.

A third data set, which has been distributed in github4 and utilized in the work [18]: Tweets on this data set are arranged into one of the accompanying three classes: "Sexism", "Prejudice" and "Not one or the other". The initial two ("Sexism", "Bigotry") alluding to explicit types of hate speech, they have been incorporated as a piece of the class "Hateful", while the tweets of the class "Not one or the other" have been disposed of in light of the fact that there is no sign whether they are spotless or offensive (a few tweets were physically checked, and they have been distinguished as having a place with the two classes).

As expressed over, the three data sets were consolidated to make a greater data set, that we split as we will depict later in this area.

To play out the assignment of classification, the data set is part into three subsets as pursues:

**A preparation set:** this set contains 21 000 tweets, circulated equally among the three classes (i.e., "Clean", "Offensive" and "Hateful"): each class has 7 000 tweets. This set will be alluded to as the "preparation set" in whatever is left of this work.

**A test set:** this set contains 2 010 tweets: each class has 670 tweets. This set will be alluded to as the "test set" and will be utilized to upgrade our proposed methodology.

**An approval set**: this set contains 2 010 tweets: each class has 670 tweets. This set will be alluded to as the "approval set" and will be utilized to assess our proposed methodology.

To get a reasonable outcome, we utilize a similar number of tweets for each set. Given that the number of tweets in "Hateful" class was 8 340 and it is the least among the three classes, we set the quantity of preparing tweets for each class to 7 000 tweets, that of the test tweets to 670 tweets and that of the approval tweets to 670.

### 3.2 Data Pre-Processer

In this segment, we quickly depict how the tweets were preprocessed. Fig 1 demonstrates the diverse advances done amid this stage.

In an initial step, we tidy up the

tweets. This incorporates the evacuation of URLs (which beginning either with "HTTP://" or "https://") and labels (i.e., "@user") insignificant expressions (words written in dialects that are not bolstered by ANSI coding). This is on the grounds that these don't include any data whether the tweet may express hate or not. Specifically, for the instance of labels, if the connection between the creator of the tweet and the individual labeled is known, this data may be profitable. In any case, since no foundation is given in regards to the creator and the labeled individual, we trust that the utilization of labels isn't helpful for our work.

The second step comprises of the tokenization, Part-of-Speech (PoS) Tagging, and the lemmatization (utilizing both

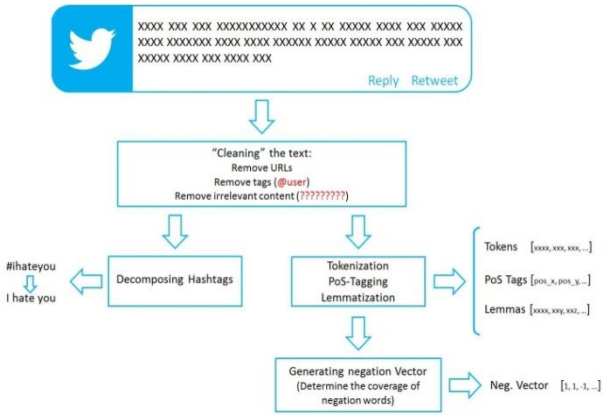


Fig. 1: Pre-processing phases of the tweets

Tokens and PoS labels) of various words. For this purpose, we utilized OpenNLP5 to play out the Natural Language Processing (NLP) errands of tokenization and lemmatization. Nonetheless, to play out the Part-of-Speech (PoS) labeling, we depend on Gate Twitter PoS Tagger [20]. This is on the grounds that OpenNLP presents poor exhibitions on PoS labeling of casual and uproarious messages, for example, tweets.

Subsequently, we produce what we qualify as refutation vector: we identify the situation of invalidation words (e.g., "not", "never", and so forth.) and distinguish the inclusion of these words. The methodology we utilized is very straightforward and motivated from crafted by Das et al. [21]: essentially, an invalidation word covers every one of the words that tail it until the following accentuation mark or the event of a differentiation word (e.g., "yet", "notwithstanding", and so forth). Words secured by a nullification word are given an invalidation score equivalent to 1 while whatever remains of the words will be given a score equivalent to 1. This will be utilized later on the check of positive and negative words: a positive word (negative word) having a refutation score equivalent to 1 will be considered as a negative word (positive word), and it is credited the inverse of its unique score (This will be clarified in the following subsection).

On a different advance, we

extricate all the hashtags, and utilize a little apparatus we formed to deteriorate it into the words that make it (e.g., the hashtag "#ihateyou" will give the articulation "I hate you") and are kept aside to be utilized when required.

### 3.3 Features Extraction

In this subsection, we depict how includes are extricated from the tweets, and which we will utilize later to play out the classification. Be that as it may, we initially clarify the decision of our arrangements of highlights.

Hate is essentially a sentiment among others, a negative sentiment to be exact. Subsequently, we trust that depending on sentiment extremity of the tweet is a critical marker of regardless of whether it tends to be a potential hateful tweet.

What's more, accentuation checks and utilization of all-uppercase words can essentially change the significance of the tweet, or make unequivocal some goal covered up in content. Subsequently, such highlights should be removed alongside sentiment highlights to distinguish hate.

Nonetheless, hate shows fundamentally on the words and expressions an individual employee. Hence, the substance of the words itself is significantly more critical than the previously mentioned highlights. For this, we extricate from the preparation set, practically, a lot of words (to which we allude as unigrams) and expressions (to which we allude as examples), that are well on the way to be identified with hate and use them as additional highlights for hate detection.

As clarified at an opportune time this work (Section 2.1), in contrast to sentiment analysis, it isn't extremely helpful to depend just on the sentiment extremity of the words to recognize hate speech: not exclusively do the words' implications change as indicated by the specific situation yet in addition hate speech has distinctive appearances. Examples, in such cases, are valuable to recognize longer hateful articulation. In this way, we extricate designs alluding to words, just as a feature of speech labels, to ensure that we don't get select examples that apply to without a doubt, unmistakable circumstances, yet broad ones that reflect hate paying little mind to the substance. As it were, we ensure that an articulation extricated that demonstrates hate, is a general one that applies to various settings of hate. This will be explained later on this work, when we set a few parameters to ensure that a specific articulation happens enough occasions in a given class (i.e., it isn't explicit to a solitary case or situation) and does not

happen in alternate classes (i.e., it's anything but a general articulation that has nothing to do with that class).

To close, basically, 4 sets of highlights are removed which we qualify as "sentiment-based highlights", "semantic highlights", "unigram highlights", and "example highlights". By consolidating these sets, we trust it is conceivable to distinguish hate speech: "sentiment highlights" enable us to extricate the extremity of the tweet, an exceptionally basic segment of hate speech (given that hateful speeches are for the most part negative ones). "Semantic highlights" enable us to locate any stressed articulation. "Unigram highlights" enable us to distinguish any express type of hate speech, while designs permit the ID of any more or certain types of hate speech. In whatever remains of this subsection, we depict how these highlights are separated.

### *3.3.1 Sentiment-based Features*

Despite the fact that thSe assignment of detection of hate speech varies radically from that of sentiment analysis and extremity detection, regardless it bodes well to utilize sentiment-based highlights as the most fundamental highlights that permit the detection of hate speech. This is on the grounds that hate speech is well on the way to be available in a "negative" tweet, as opposed to a "positive" one.

Thusly, we first concentrate includes that would decide if a tweet is sure, negative or impartial. As referenced over, the detection of the extremity in itself isn't the motivation behind this work, yet an additional progression to encourage the principle assignment which is the detection of hate speech.

In this way, from each tweet t, we extricate the accompanying highlights: the all-out score of positive words (P W ), the complete score of negative words (N W ), the proportion of passionate (positive and negative) words

($t$) defined as: ($t$) =pw nw; ($t$) is set to 0 if the

$PW + NW$

the tweet has no emotional words,

The number of positive slang words, the number of negative slang words, the number of positive feelings, the number of negative feelings, the number of positive hashtags, the number of negative hashtags.

The all-out score of positive words and that of negative words are extricated utilizing SentiStrength6, an apparatus that at-tributes sentiment scores to sentences just as the expressions of which it is

formed. The scores go from - 5 to - 1 for negative words, and from 1 to 5 for positive words. Given a tweet t, we check the aggregate of the scores of individual words that have a positive extremity and credit the acquired total to the main highlights; and we do likewise for the negative words and trait the total estimation of the got whole to the second highlights (i.e., the two highlights take positive qualities).

To distinguish the extremity of emojis and slang words, we depend on two physically manufactured lexicons containing the emojis/slang words alongside their extremity. With respect to Hashtags, we built up our very own instrument that parts a hashtag into the words that create it and utilized SentiStrength scores to settle on its extremity.

Sentiment-related highlights are great pointers of regardless of whether a content is negative. As referenced over, negative content is destined to introduce hate speech. In any case, not every single negative content do. Along these lines, more highlights should be removed for detection of hate speech.

### *3.3.2 Semantic features*

Semantic highlights are ones that depict how a web client utilizes accentuation, uppercase words, and additions, and so forth. In spite of the fact that hate speech on informal communities and microblogging sites don't have a particular and regular utilization of accentuation or work of capitalization, sometimes, a portion of these mirrors a type of isolation or others, for example, the accompanying precedent:

"For what reason don't you basically return to YOUR COUNTRY and abandon us in harmony?"

The tweet is clearly offensive and demonstrates some hate, be that as it may, there is no express utilization of hate words, or any sentimental word (aside from "harmony" which is clearly a positive word.).

In this way, we trust that accentuation highlights, including the capitalization, the presence of inquiry and outcry marks, and so forth help to identify hateful speech, and they can't be essentially disposed of. In our work, we make utilization of the accompanying highlights:

The quantity of outcry denotes, the quantity of question marks,

the number of full stop marks,

the quantity of all-uppercase words, the number of statements,
the number of interpositions,
the quantity of chuckling expressions, the number of words in the tweet.

### *3.3.3 Unigram features*

Unigram highlights are basically unigrams collected from the preparation set practically and are utilized each as a free component which can take one of two qualities: "genuine" and "false".

All unigrams that have a grammatical feature (PoS) tag of a thing, an action word, descriptor or verb modifier are removed from the preparation set and put away in three unique records (one rundown for each class) alongside their number of events in the comparing class. We keep just words that happen no less than a moment (a limit that speaks to the negligible number of events of unigrams to be considered).

Given a word w that showed up in one of the three records (for accommodation we call it C1), we measure two proportions we allude to as 12 and 13 characterized as pursues:

$$\rho 12(\omega) = \frac{\mathrm{N1}(\omega)}{N2(\omega)} \quad (1)$$

$$\rho 13(\omega) = \frac{\mathrm{N1}(\omega)}{N3(\omega)} \quad (2)$$

where Ni(w) is the number of events of the word in class I. On the off chance that the denominator of the proportion is 0, the esteem is set to 2.

This is improved the situation every one of the expressions of the three classes that fulfill the condition referenced above with respect to the number of events. We keep just words that fulfill a second condition characterized as pursues:

$$P_{ij}(w) \geq Th_u$$

where The is a limit we set for the proportions, that should be tuned to amplify the precision.

As referenced over, every one of the subsequent words will be utilized as an interesting component: for a word w, in each tweet, we check whether it is utilized or not. In the event that the tweet contains the word, the estimation of the comparing highlight is set to "genuine", else, it is set to "false".ta

Given the ideal estimations of the two parameters moment and T hu (we will portray the enhancement procedure of the distinctive parameters later in this area), the most happening best words separated from the tweets of the class, "hateful" are given in Fig. 2 "offensive"

While the vast majority of the utilized words from the two classes are simply broad words that individuals use while annoying or disparaging somebody, some of them have a supremacist substance or substance that alludes to a particular sexual orientation, ethnic gathering or others (e.g., "Muslims', "Islamic", "faggot", "spic" and so on.). We trust that utilizing a greater preparing set, we can utilize the methodology we proposed above for "unigram-highlights" to assemble a lexicon of hate-related words that can be utilized for future works.

Altogether, we extricated 1 373 words. Thusly, 1 373 unigram highlights are characterized.

### *3.3.4 Pattern Features*

Example highlights are separated a similar way we extricate unigrams: anyway before we depict how design highlights are ascribed to their qualities and are removed from the preparation set, we initially present an example in our unique circumstance.


Fig.2: Hateful Class Top Words

In an initial step, we isolate the expressions of a tweet into two gatherings dependent on regardless of whether they can be sentimental into two classifications: a classification "SW" (i.e., sentimental word) and a class "NSW" (i.e., non-sentimental word). Words that can be sentimental are just things, action words, descriptor, and intensifiers. In this manner, any word in the tweet that has a PoS that alludes to a thing, action word, modifier or verb modifier is qualified as having a place with "SW". A word that has another PoS tag is qualified as having a place with "NSW".

An example is separated from a tweet as pursues: for each word, in the event that it has a place with "SW", it is supplanted by

Its improved PoS tag as depicted in TABLE 1 alongside its extremity. For instance, "defeatist" will be supplanted by the articulation "Negative ADJECTIVE". Something else, if the word has a place with "NSW" it is basically supplanted by its rearranged PoS tag as portrayed in TABLE 1

The subsequent vectors removed from various tweets have distinctive lengths, in this manner, we characterize an example as a vector of sequential words having a

settled length L where L is a parameter to upgrade. In the event that a tweet has more than L words, we separate every single imaginable example. On the off chance that it has fewer words than L, it is essentially disposed of.

| Pos Tags | Simplified Tags |
|---|---|
| NN,NNS,NNP,NNPS | NOUN |
| VB,VBD,VBG,VBN, VBP,VBZ | VERB |
| RB,RBR,RBS | ADVERB |
| JJ,JJR,JJS | ADJECTIVE |
| CC | COORDCONJUNCTION |
| CD | CARDINAL |
| DT | DETERMINER |
| EX | EXITTHERE |
| FW | FOREIGNWORD |
| IN | PREPOSITION |
| LS | LISTMARKER |
| MD | MODAL |
| PDT | PREDETERMINER |
| POS | POSSESSIVEEND |
| PRP,PRPS | PRONOUN |
| RP | PARTICLE |
| SYM | SYMBOL |
| TO | TO |
| UH | INTERJECTION |
| WDT,WP,WPS,WRB | WHDETERMINER |
| Punctuation marks | . |

TABLE 1: List of pos Tags and their Corresponding Simplified Tags

We extricate diverse examples as portrayed from the preparation set and spare them in three distinct records alongside their number of events. We sift through the ones that seem not exactly minpocc. Thereafter, given an example p that showed up in one of the three records

(we call it C1), we measure two proportions we allude to as 12 and 13 characterized as pursues:

$$P12(p) = \frac{N_1(p)}{N_2(p)} \quad (4)$$

$$P13(p) = \frac{N_1(p)}{N_3(p)} \quad (5)$$

where Ni(p) is the number of events of the example p in class I. In the event that the denominator of the proportion is 0, the esteem is set to 2.

Just examples that fulfill the condition

$$Pij(P) \geq Th_p \quad (6)$$

are kept, where T hp is a limit we characterize and tune. Utilizing the ideal estimations of the two parameters minpocc and T hp, 1875 examples highlights are extricated altogether. Given an example p, the relating highlight is credited to numeric esteem estimating the likeness of the tweet to that design. Accordingly, given a tweet t and an example p, we characterize the accompanying likeness work [6]:

### 3.4 Parameters Optimization

The proposed sets of highlights present diverse parameters that should be enhanced to get the most extreme exactness of classification. The parameters to be upgraded are the accompanying: the insignificant event of words minute the word proportions edge T hu

- the negligible event of examples minpocc the example proportions edge T hp

- the design length L the coefficient

To tune these parameters, each time we fix every one of the parameters with the exception of one and search for its ideal esteem. In this manner, to decide the best estimation of the parameter minuocc, we set the estimations of the diverse parameters as pursues:

- $Th_u = Th_p = 1.4$,
- $Min^p_{occ} = 3$,
- $L = 7$
- $\alpha = 0.1$

as follows:

The decision of these qualities depended on a before set of a trial in which we attempted to restrain the interims of the estimations of the parameters: we ran our investigations on every group of highlights freely utilizing the estimations of comparative parameters that we presented in a past work [6]. At that point, we balanced the highlights to get the present qualities.

We attempt distinctive estimations of the parameter minuocc. The outcomes are given in Fig. 2. The ideal esteem was gotten for minuocc = 9.

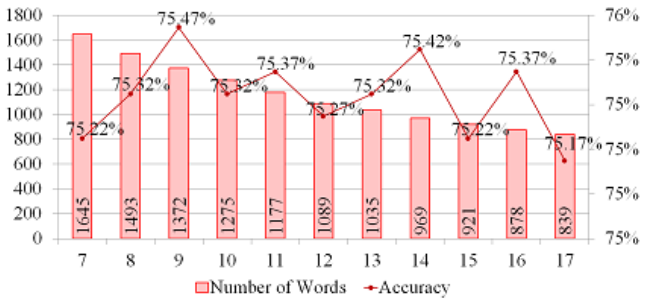

Fig. 2: Classification accuracy (right axis) and number of

words collected (left axis) for different values of the parameter minuocc

We at that point keep the estimations of the distinctive parameters as

they are, set minuocc to 9, and change the parameter T hu. Distinctive qualities from 1.1 to 2 have been checked, and Fig. 6: Classification exactness (right hub) and the number of examples collected (left pivot) for various estimations of the parameter L ideal esteem was acquired for T hu = 1:4 as appeared in Fig.3

. . Altogether, 1 373 words are collected.

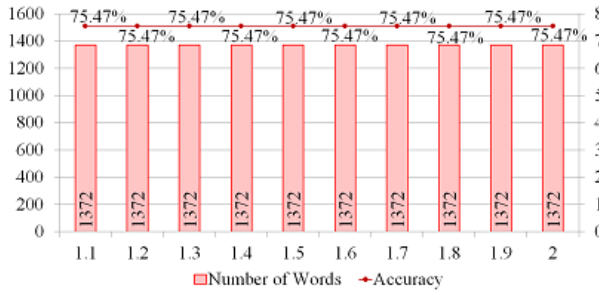


Fig. 3: Classification accuracy (right axis) and number of

words collected (left axis) for different values of the parameter T hu

To decide the best length of examples (i.e., L), we set the estimations of the parameters identified with unigram highlights to their ideal To decide the best length of examples (i.e., L), we set the estimations of the parameters identified with unigram highlights to their ideal qualities and attempt diverse estimations of

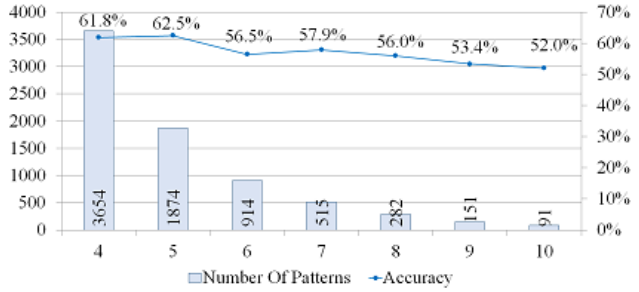


Fig. 4: Classification accuracy (right axis) and the number of patterns collected (left axis) for different values of the parameter L

we kept alternate parameters as we set them at first. The ideal esteem was gotten for L = 5, and the complete number of examples acquired is 1 875.

We continue a similar method to get the ideal estimations of minpocc and T hp. The ideal estimations of the parameters are 7 and 1:3 1:9 (in whatever is left of this work the esteem 1.4 is considered) separately as appeared in Figs. 5 and 6.

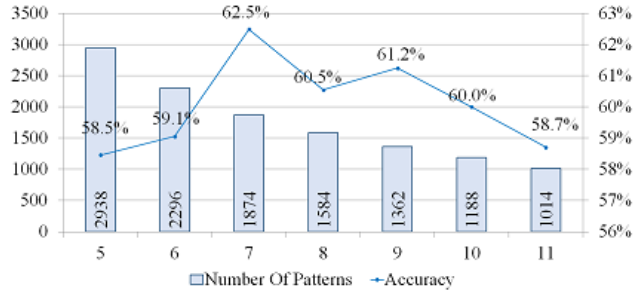


Fig. 5: Classification accuracy (right axis) and number ofpatterns collected (left axis) for different values of the parameter minpocc

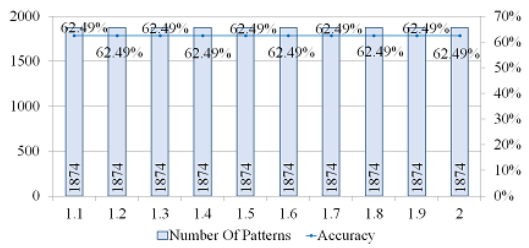


Fig. 6: Classification accuracy (right axis) and number ofpatterns collected (left axis) for different values of the parameter T hp

We at last set the estimations of the four parameters to their ideal and attempted distinctive estimations of. The got outcomes Fig. 8: Classification exactness (right pivot) and number of examples collected (left hub) for various estimations of the parameter T hp

| | *TP Rate* | *FP Rate* | *Prec.* | *Recall* | *F1-Score* |
|---|---|---|---|---|---|
| *Rand.Forest* | *0.592* | *0.204* | *0.605* | *0.592* | *0.589* |
| *SVM* | *0.57* | *0.276* | *0.643* | *0.57* | *0.599* |
| *j48graft* | *0.784* | *0.108* | *0.794* | *0.784* | *0.784* |

TABLE 2: Accuracy, Precision, Recall and F1-Score of Classification Using Different Classifiers

$$\begin{cases} Min^{u}_{occ} = 9, \\ Th_{u} = 1.4, \\ Min^{n}_{occ} = 7, \\ Th_{p} = 1.4, \\ L = 5, \end{cases}$$

Did not very much (remembering ought to have low esteem). The ideal estimation of this parameter is equivalent to 0.01. Hence, for whatever is left of this work, we considered the main case and keep the estimations of the parameters as pursues:

## Conclusion

In this work, we proposed another technique to recognize hate speech on Twitter. Our proposed methodology consequently distinguishes hate speech designs and most basic unigrams and utilize these alongside sentimental and semantic highlights to order tweets into hateful, offensive and clean. Our proposed methodology achieves a precision equivalent to 87.4% for the double classification of tweets into offensive and non-offensive, and exactness equivalent to 78.4% for the ternary classification of tweets into, hateful, offensive and clean. In future work, we will endeavor to fabricate a more extravagant word reference of hate speech designs that can be utilized, alongside a unigram lexicon, to recognize hateful and offensive online writings. We will make a quantitive investigation of the nearness of hate speech among the diverse sexual orientations, age gatherings, and areas, and so forth.

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