Machine Learning for the Detection of Suicide Related Text Communication on Social Media Using Prism Algorithm

Andanapalli Pavani
PG scholar, Department of Information Technology
SRKR Engineering College, Bhimavaram, West Godavari (Dist), Andhra Pradesh, India

Dr.I.Hemalatha
Associate Professor, Department of Information Technology
SRKR Engineering College, Bhimavaram, West Godavari (Dist), Andhra Pradesh, India

Abstract- Machine learning is a part of artificial intelligence that gives systems which can naturally detect and use patterns for prediction from information. The use of machine learning has spread quickly in the most recent decade particularly in computer science, as it has been connected to different and different regions, for example, fraud detection, dignified structure, and we look and recommender systems. Raw Data yet important client information is continuously being generated on Twitter stages. This information is, be that as it may, increasingly important when they are mined using distinctive methodologies, for example, machine learning techniques. Also, this client generated information can be used to possibly spare lives particularly of vulnerable social media clients, as a few investigations did have demonstrated the correlation between Twitter and suicide. In this examination, we go for contributing to the examination relating to suicide communication on Twitter. We quantified the execution of two machine learning calculations: Prism, ELM classifier in suicide-related content from Twitter.

Keywords – Text classification, Machine Learning, Prism, ELM, Suicide Text.

I. INTRODUCTION

A social network is a sort of social media platform which gives an online help that empower users to speak with one another [1], for example, Face book and Twitter. These platforms have given some advantage to the society just as represent some danger to weak web users who are at potential risk of hurting themselves because of information they get, for example, the spread of suicidal ideation [2]. A few investigations have demonstrated the relationship between social media and suicidal behavior [3, 5] and according to the World Health Organization, bunches are additionally the majority of users on Tweeter [8, 9]. All things considered, this has prompted some developing concerns [6, 10, 11] about the effect or impact of Tweeter on these weak users. Nonetheless, whenever handled correctly, these platforms have bountiful information with respect to individuals. Every day lives and behaviors, which can be utilized to examine and understand suicide and conceivably intercede [3]. According to [2], so as to help Tweeter users who are suicidal, it is important to understand the communication of suicidal ideation. Studies, for example, [2, 6, 12] have indicated that it is more likely for a person to search for nonprofessional support through social media rather than proficient support because of concerns with respect to social shame. Therefore, this examination is meant to add to the continuous exploration on suicide in Tweeter by leading a benchmark trial to gauge the performance of famous machine classifiers in recognizing suicide related and no suicide related communication. Additionally, we attempt information control to draw various forms of preparing information and research the effect of information control on the performance.

Machine learning is a part of computerized reasoning that gives techniques which can naturally recognize and utilize designs for forecast from information [1, 3]. According to [3], the utilization of machine learning has spread quickly in the most recent decade particularly in software engineering, as it has been applied to different and assorted territories, for example, fraud detection, drug design, and web search and recommender frameworks Furthermore, one of the most well known errands in machine learning is classification [3, 5], where the category of an inconspicuous case is judged. Therefore in this investigation we are applying the ELM algorithm on short text identifying with suicide communications on Tweeter information to quantify its classification performance against one well known machine learning algorithms: Prism.

II. Related work

Text classification or sentiment classification [13] has been applied to various texts including tweets, and in general, it is a very much examined field [13, 16]. Nonetheless, reads on text classification for suicide related communication are still in its outset stage in that capacity, the examination around there is restricted. Some other related works have been done with respect to suicidal communication utilizing different strategies than text classification (measurable investigation). For instance, [3, 5] found a correlation between suicidal behavior and twitter, in this way raising concerns with respect to human safety and building a platform for additional investigations to be completed so as to support weak users. The authors in [17] made word arrangements of suicide related points and feelings their examinations planned for ordering tweets into risky and non risky language utilizing machine learning. They acquired a precision of around 63 percent. The work in [3] showed that users at risk of suicide might be recognized utilizing Tweeter. They concentrated on the United States and distinguished suicide related risk factors from Twitter discussions they found a solid correlation between the Twitter information and the geographic suicide rates. The consequence of their investigations demonstrated the proportions of suicide related tweets per state, with Midwestern and western states having a higher proportion than different states. Furthermore, [4] analyzed the potential of twitter in predicting suicide at populace level. They created and approved forecast models, and their outcomes recommended including twitter information when surveilling patterns and procedures for avoidance that identifies with suicide.

In any case, supposedly, the investigation that is generally related to the point of our examination is [2]. They estimated the performance of machine classifiers in ordering suicide related text from Twitter by separating text utilizing lexical terms and names of expired (suicide) as search key terms. The aftereffect of their gauge test gave a F proportion of 0.702. This outcome was additionally improved by building and applying a group classifier which accomplished an improve F proportion of 0.728. In this paper we expand on the work in [2] to additionally examine the detection of suicide related communication. Numerous explorations identifying with the use of machine learning techniques has been done in different territories, for example, Finance [10], Medicine [11, 13], Safety [14] and Economical problems [15] to give some examples. In any case, research identifying with ELM learning algorithm is restricted; therefore research for its application to short informal text is practically nonexistent.

III. Problem statement

In the current framework, the framework actualized to comprehend the network and correspondence attributes of Twitter clients who post content therefore arranged by human annotators as containing conceivable self- destructive expectation or considering, normally alluded to as self-destructive ideation. The framework accomplishes this comprehension by breaking down the attributes of their informal organizations. Beginning from a lot of human commented on Tweets we recovered the creators' supporters and companions' records, and distinguished clients who re tweeted the self-destructive substance. We along these lines manufactured the interpersonal organization charts

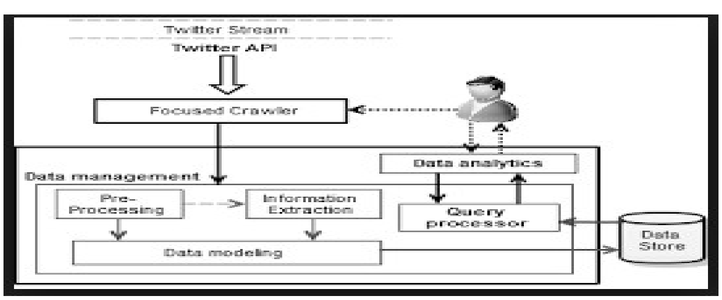

Figure 1. System Architecture

IV. TEXT CLASSIFICATION AND EVALUATION

Classification is among the most mainstream machine learning tasks by and by and it has been applied to various regions including sentiment investigation. Moreover, they expressed that classification can be particular into two: the binary classification, which contains two (classes) for data instances and multi class classification, which contains multiple classifications of instances.

Consequently, in our examination, we sorted out the data into two datasets for binary and multi-class classification. The binary dataset comprises of the Suicide and Flippant classes, while the multi-class dataset contains the Suicide, Flippant and Non-Suicide classes. The Non-suicide class involves all the classes that are not identified with self-destructive ideation or have any careless reference to suicide (for example Suicide or Flippant). Along these lines, the class's crusade, uphold dedication, reports and other, all have a place with the non-suicide class in this specific case. The two datasets and the instances distribution, where Raw are the crude instances before pre-handling and prepared are the instances after pre-preparing.

4.1. Data Collection and Annotation-

For the data assortment and explanation, we gathered tweets utilizing lexicon terms from known suicide sites to gather data that contain suicidal ideation, and additionally names of expired as search keywords to gather tweets that are associated with suicide. An aggregate of 8,000 tweets were gathered and spitted into three datasets and classified into two classifications by master human annotators. Online content that makes reference to suicide or contains signs of suicidal considerations can introduce itself in numerous structures, and not every last bit of it is pertinent for avoidance purposes. Initial, a book is decided on its significance utilizing a clinical meaning of suicide. It can either coordinate the definition, notice suicide in an unexpected way (in overstatements or in non-clinical faculties, for example suicide fear based oppression), or be disconnected. Just messages that coordinate the definition are clarified further.

4.2. Preprocessing –

Tweeter data are boisterous [2]. Diminishing this noise will improve the nature of data and the presentation of classifiers. Consequently, there is a need to clean the content (tweets) to set it up for classification; this cycle is known as pre-preparing. We followed built up techniques [2] and eliminated all the tweets that have under 75% annotator understanding score. A sum of 936 instances was eliminated, leaving 1064 instances.

Writings were additionally changed utilizing standard preprocessing methods that are generally utilized in text mining [2] for example the expulsion of URLs, stop words and non-ASCII characters, case conversion, stemming (to diminish repetition) and POS (Part of Speech) tagging. Besides, the Bag of Words (BOW) and the Inverse Document Frequency (IDF) portrayals were applied. BOW center around words as opposed to context, it regards a book as an assortment of words and overlooks the syntactic and semantic data . IDF gives more weight to the less regular or uncommon terms while the continuous terms are probably going to weigh less . In this way, a document vector was made for every one of the terms in the document utilizing the IDF as a vector value for example for every remarkable document or term taken care of words, one info table section was made and every one of this term segments was appointed a value dependent on the IDF. This brought about the extraction of 2393 terms.

4.3. Feature preparation –

We utilized the text of the tweets so as to train and test a number of machine classifiers to identify suicidal ideation and differentiate among this and other types of suicide related communication, including references to suicide. Features sets were derived from the text as follows:

Features representing lexical characteristics of the sentences utilized, for example, the Parts of Speech (POS), and other language structural features, for example, the most frequently utilized words and phrases. These are standard features utilized in most text mining tasks. References to self and others are likewise captured with POS these terms have been identified in previous research as being clear inside suicidal communication.

Features representing sentiment affective and passionate features and levels of the terms utilized inside the text. These were incorporated on account of the particularly emotive nature of the assignment. Feelings, for example, fear, anger and general aggressiveness are particularly prominent in suicidal communication [1].

Parts of Speech we used to the Stanford Part-Of-Speech (POS) Tagger8 to dole out each word in a Tweet a POS mark. Examples are things (broken down into singular, plural, proper), verbs (specifying tenses, for example, present, past and present participle), first versus 3rd person references, adjective and adverbs, pronouns (personal, possessive), just as other labels representing conjunctions, determiners, cardinal numbers, symbols, and interjections. For every one of POS we considered the frequency of each in a Tweet as a feature.

Other Structural Features For this we considered the consideration of invalidations in the sentence, the specific utilization of a first person pronoun (either singular or plural), and external communication features, for example, the incorporation of a URL in a tweet or a notice symbol (demonstrating a re-tweet or reply).

General Lexical Domains These features represent general lexical categories, for example, home, religion, psychology, humanism, and so on. These were extracted utilizing Word Net Domains marks.

Affective Lexical Domains These are a set of categories specifically related to domains representing 'affective' concepts. These incorporate concepts representing states of mind, circumstances inspiring feelings, or enthusiastic responses, for example, euphoria, anger, grief, bitterness, excitement, surprise, love, disdain, and happiness; yet considerably more specific sub-categories, for example, congeniality, belligerence, terrible temper, unrest, and trepidation; and opposites, for example, positive-negative concern, negative fear, positive-negative suspense, self-regard, self awareness, self-pity, and self-deprecation. These are very appropriate for the specific language we are exploring in this examination.

Sentiment Score Using SentiWordNet10 each words is doled out a score somewhere in the range of zero and one for both positivity and cynicism. The whole all words in a Tweet were utilized as features.

Words The most frequently utilized words and n-grams in terms of (first 100) unigrams, bigrams and trigrams contained in the training set.

Keyword list We likewise incorporated every one of the 62 keywords derived from the Web form text that were utilized for the pre-filtering search (for example 'asleep and never wake', 'don't have any desire to try anymore', 'end everything', 'isn't worth living', 'my life is pointless', 'slaughter myself', 'to live any more", 'need to end it', 'need to disappear', 'need to kick the bucket', etc..). Every one of the search terms was incorporated as individual features together with one worldwide binary feature representing the consideration of any of them in a Tweet.

The dataset were then used to measure the performance of two machine classifiers –Prism and ELM in classifying suicide-related text. These classifiers were picked because of their popularity, just as their properties: The following area shows the performance results of the individual classifiers for example the standard classification measure scores: Precision (P), Recall (R), F-measure (F) and Accuracy (A), for both the binary and multi-class datasets

V. PROPOSED ALGORITHM

5.1. Existing Algorithm1: Prism -

In 1987, Cendrowska is first introduced to the prism algorithm [6]. The main aim is to induce modular relegation rules directly from the training set. The algorithm surmises that all the attributes are categorical. When there are perpetual attributes they can first be converted to categorical one. Alternatively the algorithm can be elongated to deal with perpetual attributes. Prism utilizes the ‘take the first rule fires’ conflict resolution strategy when the resulting rules are applied to the unseen data, so it is consequential that as far as possible the most consequential rules are engendered first.

The algorithm engenders the rules concluding each of the possible classes in turn. Each rule is engendered term by term with each term of the form 'attribute = value '. The attribute/value pair integrated at each step is opted to maximize the probability of the target 'outcome class' [9]. The basic Prism algorithm is clearly presented in Algorithm 1 given below.

Algorithm 1 (Classical Prism Algorithm)

Input: A training dataset with n classes C_{i}, i = 1,2,3...........n

Output: Generated rules for all classes
Method: The rules are generated in the following steps:

1. For each class Ci start with the complete training set each time
2. Compute the probability of each attribute/value pair for the class, Ci
3. Select the pair with the largest probability and create a subset of the training set comprising all the instances with the selected attribute/value combination for each class, Ci
4. Repeat steps 2 and 3 for this subset until a subset is reached that contain only instances of Ci.
5. The rule is induced by the conjunction of all the attribute/value pairs selected.
6. Remove all instances covered by this rule from the training set.
7. Repeat step 2 through 6 until all instances of Ci have been removed
Move to step 1 until all classes are verified.

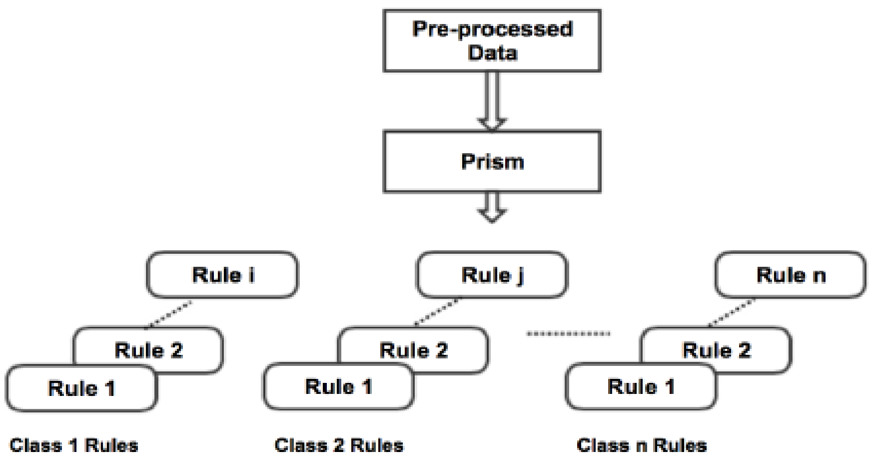

Figure 2. Prism work flow

Furthermore, for its application, the algorithm in particular, the algorithm was applied for identification of contact lenses types, and the results showed that Prism not only outperformed ID3 (a decision tree learning algorithm) in classification accuracy but also produced a smaller number of simpler rules. Another example of the Prism algorithm application to classification problems is the study carried out by They used Prism along with other techniques using specifically multimodal features to come up with a multi-media data mining framework that effectively detects soccer goal shots.

5.2. Proposed Algorithm: Extreme Learning Machine -

ELM algorithm is utilized for data relegation quandaries; depends on three parameters [11]. They are (i) number of obnubilated neurons, ii) the input weights and (iii) the partialness values. These are needed to be optimally chosen. Neural networks are mostly used in complex nonlinear mappings directly from the input sample. It has the disadvantage of more learning time. The cognition phase of ELM is consummated in less than seconds for many datasets The conventional learning algorithms for example feed forward back propagation network algorithm takes very long time to train the network. The ELM has better generalization performance than the gradient predicated learning e.g. Back propagation algorithm. Classical learning algorithms have problems of local minima, improper learning rate and over fitting etc. which is evaded by some issues like weight decay and early ceasing methods.

One key principle of the ELM is that one may desultorily optate and fine-tune the obnubilated node parameters. ELM is pristinely developed for the single-obnubilated layer victual forward neural networks (SLFNs) and then elongated to the "generalized" SLFNs. After the hidden node parameters are chosen randomly, SLFN becomes a linear system where the output weights of the network can be analytically determined using simple generalized inverse operation of the hidden layer output matrices. One of the salient feature of ELM is that the weights from the input layer to the hidden layer are randomly generated The paper further proves the random feature mapping theory rigorously.

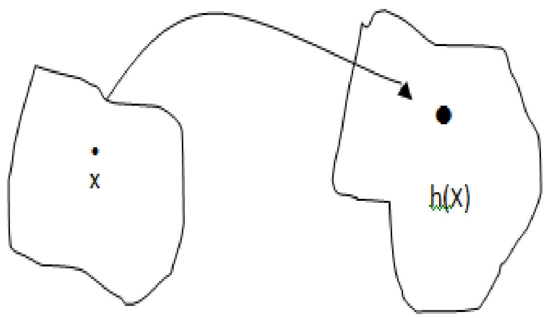

Figure 3. ELM random feature mapping : h(x)

The hidden layer output function (hidden layer mapping, ELM feature space): $h(x) = [G(a_1, b_1, x), \ldots, G(a_L, b_L, x)]$

The output functions of hidden nodes are limited to

1. Sigmoid: $G(a_i, b_i, x)=g(a_i.x+b_i)$
2. RBF: $G(a_i, b_i, x)=g(b_i\|x-a_i\|)$
3. Fourier Series: $G(a_i, b_i, x)= \cos(a_i.x+b_i)$

Conventional Arbitrary projection is just a categorical case of ELM desultory feature mapping (ELM feature space) when linear additive obnubilated node is utilized. After the desultory nonlinear feature mapping in the obnubilated layer, the rest of ELM can be considered as a linear system. Consequently, ELM has a closed form of solution due to the simple network structure and desultory obnubilated layer weights. The essence of the linear system utilized by ELM is to minimize the training error and the norm of connection weights from the obnubilated layer to the output layer at the same time [8]. Hence ELM has a good generalization performance according to the feed forward neural network theory [As a consequence, ELM has some desirable features, such as that hidden layer parameters need not be tuned. Advantage of this proposed method is quick learning speed, excellent generalization performance and in addition with unified framework for categorization

Arbitrary Projection: $G(a_i, b_i, x)=a_i.x$ ELM functions for multifaceted network are the ELM can perform different operations like feature, compression, learning, regression, clustering and classification.

ELM Algorithm

1. Separate the training set into two non-overlapping subsets for learning and validation.
2. Randomly assign hidden node parameters (c_i, a_i), $i=1,\ldots,\tilde{N}$.
3. Calculate the hidden layer output matrix H using the learning subset.
4. Calculate the statistical relevance for the hidden nodes using the statistical measures (□ ^{2} or IG) then sort them in descending order.
5. For each relevance threshold □ $_i$ (i =1,2,…. q).
6. Select S* according to min (AIC).
7. Retrain network S^* with the whole training set.
- Calculate the hidden layer output matrix H* using the training set.
- Calculate the output weight $\beta^*:\beta^*=(H^*)^{\dagger}T$.
8. Evaluate the performance of S* on unseen testing data set.

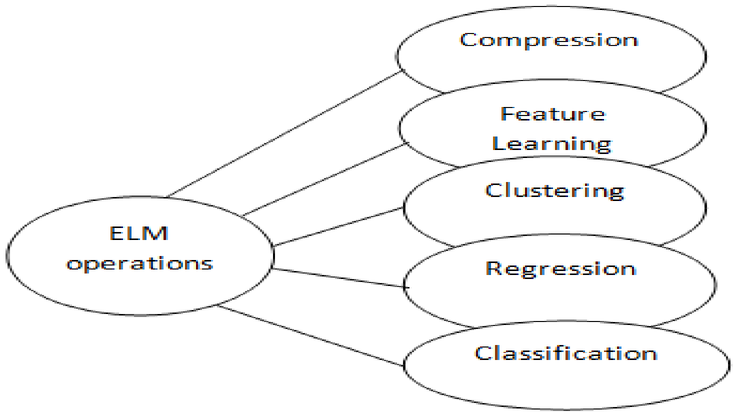

Figure 4. ELM operations

VI. Result & analysis

In this section we report the results of the experiments, i.e. the performance of the machine learning algorithms when applied to the three datasets, using the standard classification scores, which consist of the Precision (P), Recall (R) and F-measure (F). The results per class for the binary dataset, which consists of the suicide and flippant classes, showed that the top F-measure value of 0.67 has been achieved by the Prism algorithm and 0.79 has been archived by ELM The F-measure achieved by the ELM algorithm belongs to the Suicide, which is the majority class (156 instances) of the two classes. For the other machine learning algorithms, the best F-measure core

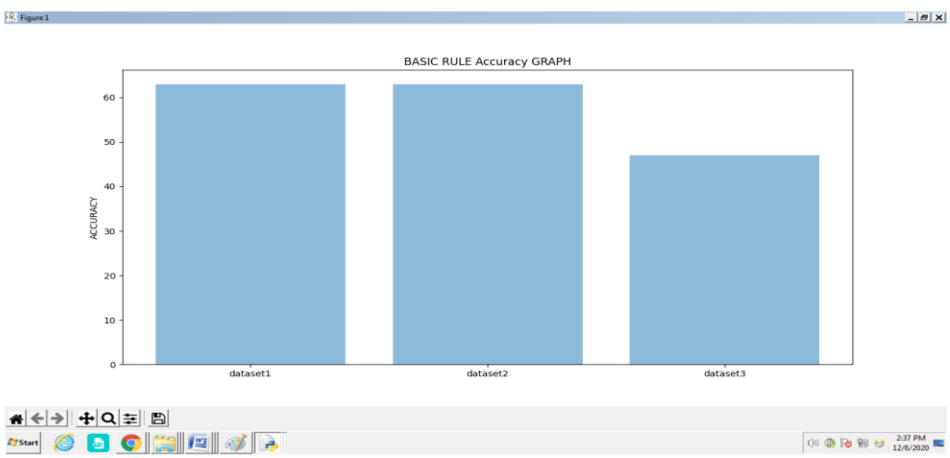

Figure 5. Basic Rule Accuracy

Table -1 Basic rule Accuracy

DATASET	PARAMETER	RESULT
TWITTER DATASET1	ACCURACY	63
TWITTER DATASET2	ACCURACY	61
TWITER DATASET3	ACCURACY	47

Figure 6. Prism Rule Accuracy

Table -2 Prism rule Accuracy

DATASET	PARAMETER	RESULT
TWITTER DATASET1	ACCURACY	64
TWITTER DATASET2	ACCURACY	62
TWITER DATASET3	ACCURACY	60

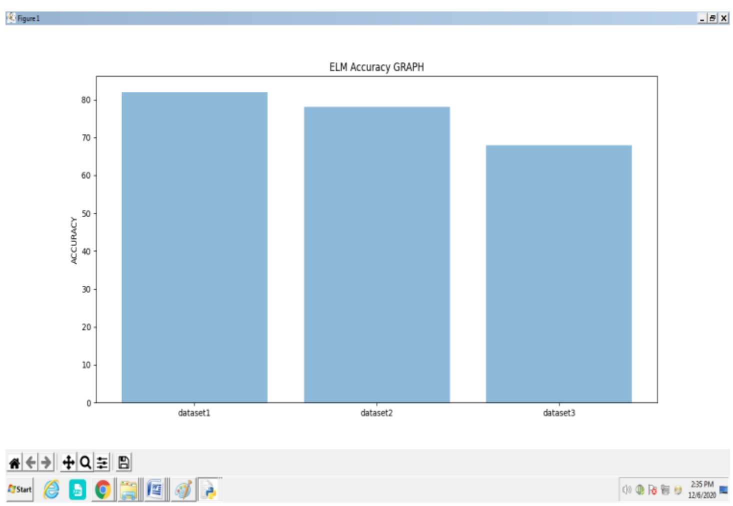

Figure 7. ELM Rule Accuracy

Table -3 ELM rule Accuracy

DATASET	PARAMETER	RESULT
TWITTER DATASET1	ACCURACY	82
TWITTER DATASET2	ACCURACY	81
TWITER DATASET3	ACCURACY	67

Table -4 Evaluation Metricies REPO

CLASSIFIER	MEASURE	SUCIDE	FLIPPANT
PRISM	PRECESION RECALL F1-SCORE	**93** **69** **79**	**75** **95** **84**
BASIC RULE	PRECESION RECALL F1-SCORE	**59** **80** **68**	**70** **45** **54**
PRISM RULE	PRECESION RECALL F1-SCORE	**62** **72** **67**	**67** **55** **51**

IV.CONCLUSION

The application of machine learning methods is getting more popular and a portion of the strategies, both popular and less popular, have indicated their different strengths when applied to suicide short informal text. The point of the investigation was to compare the classification performance of the ELM machine learning algorithm with more popular reasonable and reliable machine learning strategies. The result of the examination indicated that the ELM algorithm has performed better than the other algorithms when applied to different datasets of suicide short texts.

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