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A Comparison Between Twitter Based Naïve Bayes and Artificial Neural Network Comment Classification Algorithms

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Abstract

Machine learning has a wide range of uses, and one of its key uses is classification. A new observation is classified to determine which category it belongs to. Classifiers are the common name for machine learning classifiers. A classifier's task is to use training data provided to it to determine the relationship between a given input variable and a specific group that has already been identified by the system. Perceptron, Naive Bayes, Decision Tree, Logistic Regression, K-Nearest Neighbor, Artificial Neural Networks/Deep Learning, and Support Vector Machine are a few of the techniques used for training classifiers. However, every algorithm has unique benefits and drawbacks. As a result, it is necessary for us to determine which technique between naive bayesian classifiers and artificial neural networks Perform best for classifying tweets. Naive Bayes classifiers are Bayes theorem-based classifiers. The Nave Bayes algorithm is based on the assumption that for a training comment, C the classifier computes the probability that the comment should be categorized under Ki, where Ki is the ith category. On the other hand, an artificial neural network is a mathematical model that attempts to mimic the composition and operation of biological neural networks. Separating the problem's classes using just training data is the aim of supervised classification algorithms. The Artificial Neural Network Showed the highest precision of 0.97 in the regular Twitter data while the Naive Bayes model Showed the highest precision (0.85) in the data on hate speech. However, both algorithms have a recall of 0.96 in the weighted average data.

1. Introduction

There are several machine learning techniques, with classification emerging as the most important. Classification is the challenge of determining which of a set of categories a fresh opinion belongs to in machine learning and statistics [1] [2]. Machine learning classifiers are also referred to as "Classifiers" in general. Machine learning classifiers employ training data to determine the relationship between a given input variable and a specific class. It can correctly identify the class of a new observation when properly taught. Both supervised and unsupervised machine learning algorithms are available. To the category of supervised learning, classification belongs. Algorithms for unsupervised machine learning do not know the desired result. Other fields where categorization is used include those for loan approval, disease diagnosis, threat detection, and so forth. These machine learning methods are always being improved. Text classification is the process of computationally classifying and categorizing opinions expressed in a text with the intention of identifying whether the author has a good, negative, or neutral attitude toward a given topic, product, etc [3]. Perceptron, Naive Bayes, Decision Tree, Logistic Regression, K-Nearest Neighbor, Artificial Neural Networks/Deep Learning, and Support Vector Machine (SVM) are some of the most well-liked algorithms used to train classifiers [4]; [5]; [6]; [7]; [8]; [9]. The dilemma of which algorithm is more ideal for the specific problem one is seeking to solve arises from the fact that each of the aforementioned algorithms has advantages and weaknesses and that there is no one optimum algorithm among them for every use-case. Using the Nave Bayes algorithm and the artificial neural network technique for comment classification, this effort aims to determine which Machine Learning classifier or algorithms performs the best for sentiment analysis. There are literature reviews that, for example, demonstrate the efforts of scholars in Twitter sentiment analysis. In order to integrate it with [10] conducted a comparison of Twitter sentiment analysis techniques for live applications using Python. [11] Focused on sentiment analysis for twitter accounts using machine learning, and they compared sentiment analysis methods by using SVM to analyze political viewpoints. As far as we know, no researcher has compared the performance of a support vector machine with an artificial neural network when it comes to categorizing comments in a Twitter dataset. Through comparison of Naive Bayes and artificial neural networks, this study tries to identify the best machine learning technique for identifying comments.

2.0. Comment Classification Algorithms

According to published research, there are four different types of classification algorithms: association-based, rule-based, and probability-based (e.g., Naive Bayes), and tree-based [12]; [13]; [14]; [15]; [16]; [17]; [18]. However, we can essentially categorize these classification issues into binary classification and multi-class classification. Identifying email spam is a nice example of binary classification. Non-spam emails are mapped to 0, whereas spam emails are mapped to 1. Another example of a multi-class categorization is handwritten character recognition, which has classes ranging from 0 to 9. The methods for classifying comments are shown below:

i. Decision tree classifiers: The decision tree serves as the decision tree classifier's fundamental building element. It transforms weak learners into powerful ones. It is a solid categorization strategy even though it does have some uncertainties. [19]; [20]; [21]; [22].
ii. Probabilistic classifier: A probabilistic classifier can predict the probability distribution of an input over a number of classes. When used alone or in combination with other classifiers to create ensembles, probabilistic classifiers produce meaningful classifications [23]; [24]; [31].
iii. Rule-based classifier: Classifiers that employ rules and guidelines for classifying things. Further classifications of rule-based classifiers include exhaustive rules and two-way mutually exclusive rules. Classifiers contain mutually exclusive rules in mutually exclusive rules [25]. Exhaustive rules classifiers have exhaustive rules, according to [26]. However, basic rules could not be viewed as incompatible [27]; [28].

Table 1 shows the related literature:

Table 1: Related Works

SN	References	Methodology	Weekness	Strength
1.	[6]	Context-graph	Most lexicons do not take into account the fact that a word might convey several emotions	Constructing domain-specific sentiment lexicons with local context for words.

			depending on the prediction domain.	
2.	[10]	Created a web service to integrate it with marketpro.	Low accuracy	Since it is web-based, many people can access it.
3.	[29]	Long-short term memory	The baseline method outperformed the LSTM approach.	The Nave Bayes algorithm demonstrated the exceptional outcome.
4.	[30]	Comparing the BiGRU RNN network with other neural networks such as CNN, LSTM, and Hybrid CNN+LSTM.	Not all classifiers are investigated.	The BiGRULA outperformed the other three network models in terms of accuracy on the test dataset.

The literature that is most closely relevant to our work is included in Table 1. A concept based on a context-graph was put out that can be used to create domain-specific sentiment lexicons utilizing the local context of a word [6]. It was discovered that the model produced superior results to broad lexicon. [10] design a web service to integrate "marketpro" with comparative study of twitter sentiment analysis techniques for live applications. In an effort to bring natural language research up to speed with neural approaches. A neural network models for natural language processing can review these models from the standpoint of natural language processing research. A technique of selecting an appropriate algorithm and its optimal parameters for a given dataset was created and another model was created to predict the optimal parameter for a specific algorithm based on the history of datasets (existing knowledge). As part of their work on machine learning-based sentiment analysis for Twitter accounts. A Sentiment Analysis methods for the analysis of political viewpoints by using supervised machine learning algorithms like Naive Bayes and support vector machines (support vector machine). 2019 saw the development of sentiment analysis methods using Twitter data science. The researchers investigate how people discuss current events on Twitter. [29] used deep learning and conventional machine learning to conduct sentiment analysis experiments on the Lithuanian Internet comment dataset. The Nave Bayes Multinomial technique showed that the LSTM method performed worse than the baseline yet produced the greatest results. Lemma unigrams, replaced emotions, and repaired diacritics were all employed. In the research, CNN underperformed the support vector machine and Naive Bayes, but the accuracy disparity was only marginal. Deep learning showed promising results when used on tiny datasets, yet traditional machine learning techniques were superior when compared to them By changing the deep learning approaches' parameters and gathering and preparing more training data, the researchers in this study were unable to close the gap between traditional and deep learning approaches. The performance of Naive Bayes, K-Nearest Neighbor, and Support Vector Machine in sentiment analysis is compared in [30]. From Twitter, two sizable text datasets describing consumer attitudes were gathered. The study demonstrated that Naive Bayes performed dominantly across all datasets. To enhance the performance of the deep learning algorithms that were examined, the study did not use any optimization approaches. The majority of these lexicons do not take into account the fact that a word might communicate distinct sentiments in different predication domains, which introduces mistakes in the sentiment inference. [31] also evaluated the performance of single classifiers (SMO, MLP, kNN and Decision Tree) and ensembles (Bagging, Boosting, Stacking and Voting) in SDP considering major performance metrics using Analytic Network Process (ANP) multi-criteria decision method. Decision tree ranked highest in single classifiers with 0.0410.

Another approach was used by [32], who looked into the recently developed capsule networks (CapsNets), which are gaining a lot of attention for their outstanding performance gains on image analysis over CNNs and, in some cases, a notable improvement on sentence classification and sentiment analysis. Based on CNNs and RNNs utilized in sentence categorization, a superior alternative to the proposed well-tuned "CapsNet" model can be developed. When combined with a topic model (lda2vec) and an attention mechanism for sentiment analysis, the proposed bidirectional gated recurrent unit neural network model (BiGRULA) outperformed other neural networks such as CNN, LSTM, and Hybrid CNN+LSTM, as well as support vector machine, Naive Bayes (NB), and Maximum Entropy (ME), which had the best accuracy values among n-gram methods, and with word2vec. In a study conducted by [33], it was discovered that feature-based and tree kernel models perform better than the unigram baseline. The most significant features for the feature-based method, according to feature analysis, are those that integrate the prior polarity of words with their part-of-speech tags. Using the recently proposed cutting-edge unigram model as its baseline, two classification tasks saw an overall improvement of over 4%.

A research on Twitter sentiment analysis using machine learning algorithms on Python was conducted by [34]. They described the methodology they used and the models they used. Numerous scholars, as mentioned had suggested various ways for doing sentiment analysis as well as numerous algorithms. However, understanding the comment's class will assist us to better grasp the commenter's comments. In this study, we will look for the ideal algorithm to employ when categorizing Twitter comments.

2.1 Comparison Between Artificial Neural Network and Naïve Bayes

A classification technique with a probabilistic foundation is the Bayes algorithm. Bayesian classification is based on the Bayes theorem, whose fundamental idea is based on the concept for a training remark C. Using the rule of conditional probability, the classifier determines the likelihood that the comment should be categorized under each category, where Ci is the ith category. One of the most popular classification methods is Naive Bayes (NB), which just needs a little amount of data and training to predict the constraints needed for classification.

Naïve Bayes Algorithm

Function TRAIN NAÏVE BAYES(D,C) returns log p(c) and p(w|c)
For each class c ϵ C   #Calculate P(c) terms
N_{goc} =number of documents in D
N_c = number of documents from D in class c
Logprior[c] ←log$\frac{Nc}{Ndoc}$
V←vocabulary of D
Bigdoc[c] ←append (d) for d ϵ D with class c
For each word w in V, #Calculate p(w/c) terms
Count(w,c) ←# of occurrences of w is bigdoc[c]
Loglikelihood[w,c] ←log$\frac{count(w,c)+1}{\sum w' \, in \, v(count(w',c)+)}$
Return logprior, loglikelihood, V

A mathematical simulation of the structure and operations of biological neural networks is known as an artificial neural network. The artificial neuron, which is a straightforward mathematical model (function), serves as the fundamental building block of every artificial neural network [28]. There are three (3) sets of rules in an artificial neural network: multiplication, summation, and activation [9]; [35]; [36].

Artificial Neural Network

begin
Objective function $f(x)$,x=$(x_i\ldots..,x_d)^T$
Generate an initial population of n host nests xi(i=1,2,…,n), each nest containing a random solution;
While(t<MaxGeneration) or (stop criterion);
Get a cuckoo randomly by Levy flights;
Evaluate its quality/fitness F*i* ;
Choose a nest among n(say,j) randomly;
if(*F*i>*F*j),
Replace *j* by the new solution;
end
By using levy flights, a portion (po) of inferior nests are replaced by fresh random solutions;
Keep the top solutions (or clusters of top solutions), rank the solutions, and select the top one right now;
the future generation with the best options available today;
end while
return the best nest;
end

Table 2 shows the advantages and the disadvantages of artificial neural network algorithms and support vector machine algorithm:

Table 2: Pros and Cons of the Algorithms

S\no.	Algorithms	Advantages	Disadvantages
1.	Artificial Neural Network	1.The network as a whole stores information 2. It is the capacity to make do with limited information. 3. It's fault tolerance. 4. The distributed memory of the artificial neural network. 5. Network issues do not instantly result in destruction. 6. It has the ability to analyze data in parallel.	1. Hardware reliance exists. 2. The network's behavior is illogical. 3. There isn't a set rule that governs the formation of an artificial neural network. 4. The network's difficulties in displaying issues. 5. It is unclear how long the network will last.
2.	Naïve Bayes	1. A Naive Bayes classifier outperforms other models whenever the independent predictor's assumption is true. 2. Naive Bayes needs fewer training examples. 3. Naive Bayes is simpler to use.	1. Naive Bayes implicitly presume that each characteristic is independently determined by hand. 2. The model will assign a zero probability and be unable to generate a prediction if a categorical variable in the test data set contains a category that was not observed in the training data set.

3.0. Experimental Artificial Neural Networking

In our experiment, we carried out an empirical evaluation of both Naive Bayes and artificial neural network algorithms for comment classification.

A. DATASET

• Utilizing a Twitter dataset of 1MB in size, we test the performance of our suggested recommendation method using the Naive Bayes algorithm and an artificial neural network.

B. EXPERIMENTAL DESIGN

We plan to conduct three distinct experiments as part of our experimental design. These are the experiments:

i. Using a 1MB-sized Twitter dataset, a comment categorization system based on the Naive Bayes technique is used.

ii. Employing a 1MB-sized Twitter dataset and an artificial neural network-based comment classification system.

C. EVALUATION MATRICS

The most common metrics employed in evaluation [37] are precision, recall, and f-measure. Recall is a measure of absoluteness or completeness, while precision is a measure of accuracy or correctness. Below is a description of the formulas.

1. Precision = $\frac{TruePositives}{TruePositives+FalsePosittives}$ (1)
2. Recall = $\frac{True\ Positive}{True\ Positive+False\ Negative}$ (2)
3. F1= $(\frac{2}{recall-1+precision-1}) = 2.\frac{precision.recall}{precision+recall}$ (3)

D. EVALUATION STRATEGY

We have used 70% of the dataset as a training set and the remaining 30% as a testing set to validate our methodology. The Twitter dataset has been used in our experiments. Three times, we went through this process, choosing a different test set from each of the separated groups each time.

4.0 Result and Discussion

This section contains the comparison findings from our experiment using Twitter datasets.

4.1 Experimental Result

[3] achieved an accuracy of approximately 80% using Maximum Entropy, and SVM, but when n-gram and bigram model were utilized. The researchers were able to note that Ensemble and hybrid-based Twitter sentiment analysis algorithms tended to perform better than supervised machine learning techniques, as they were able to achieve a classification accuracy of approximately 85%. According to the regular Twitter data used in our research, artificial neural networks have the highest precision (0.97). In the data on hate speech, the naive Bayes model offers the maximum precision (0.85). In the macro average data, the naive Bayes model has the highest precision (0.90). In the weighted average data, the artificial neural network has the highest precision (0.96). For the average twitter data, Support Vector Machines and Naïve Bayes have the highest recall of 0.99. In the data on hate speech, the artificial neural network had the highest recall (0.65). In the macro average data, the artificial neural network has the best recall (0.81). In the weighted average data, the recall for each of the two techniques is 0.96. The average f1-score for all algorithms in the common Twitter data is 0.98. In the hate speech data, an artificial neural network has the highest f1-score (0.67). The macro average data's f1- score for artificial neural networks is 0.82. In the weighted average data, an artificial neural network has the highest f1-score (0.96). The results of comparing artificial neural network with Naïve Bayes, two algorithms.

Tables 3 and 4 in the following tables display the experimental results, which are depicted graphically in Figure 2. Precision, recall, and F-Measure are used to gauge the effectiveness of the performance.

Table 3: Naïve Bayes

Algorithms	Precision	Recall	F1-score	Support
Normal	0.96	0.99	0.98	8940
Hate-Speech	0.85	0.41	0.56	649
Accuracy			0.96	9589
Macro avg	0.90	0.70	0.77	9589
Weighted avg	0.95	0.96	0.95	9589

Table 4: Artificial Neural Network

Algorithms	Precision	Recall	F1-score	Support
Normal	0.97	0.98	0.98	8940
Hate-Speech	0.69	0.65	0.67	649
Accuracy			0.96	9589

Macro avg	0.83	0.81	0.82	9589
Weighted avg	0.96	0.96	0.96	9589

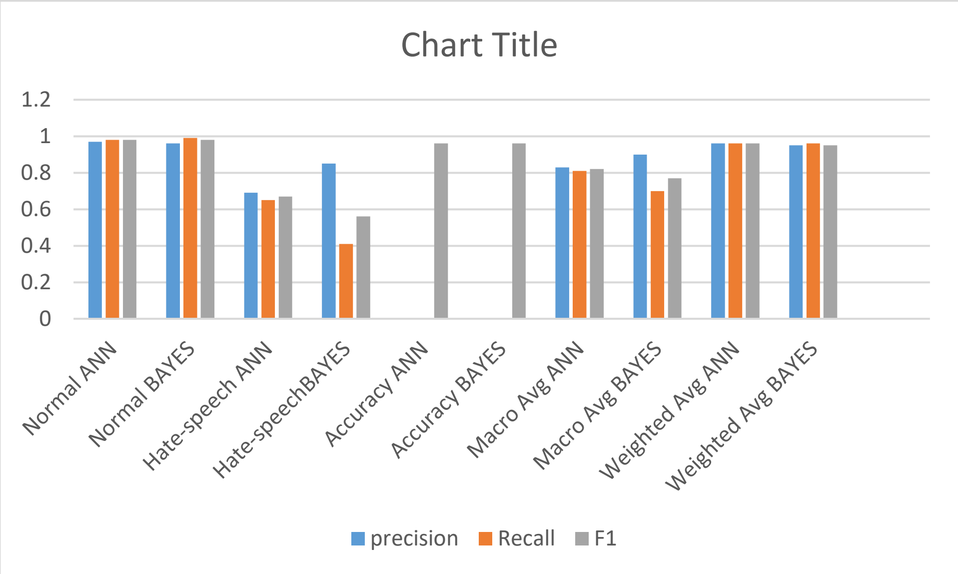

Figure. 2: Comparison result of support vector machine and artificial neural network in comment classification

5. Conclusion

The work's introduction and a literature review on machine learning, comment classification algorithms, as well as their strengths and weaknesses, were covered in paper. Next, we compared the naive Bayes algorithm and artificial neural network algorithm, which are both used for comment classification. The system's outcome and analysis are offered. Artificial Neural Network has the highest precision of 0.97 in the regular Twitter data. The nave Bayes model has the highest precision (0.85) in the data on hate speech. The naive Bayes model has the highest precision (0.90) in the macro average data. The artificial neural network has the highest precision (0.96) in the weighted average data. Support vector machines and naive Bayes have the highest recall of 0.99 for the typical twitter data. The artificial neural network has the highest recall (0.65) in the data on hate speech. The artificial neural network has the highest recall (0.81) in the macro average data. All two algorithms have a recall of 0.96 in the weighted average data. All algorithms in the standard Twitter data have a f1-score of 0.98. An artificial neural network has the greatest f1-score of 0.67 in the hate speech data. Artificial neural networks have a f1-score of 0.82 in the macro average data. The artificial neural network has the greatest f1-score of 0.96 in the weighted average data. We suggest adding more algorithms in the future to our comparison of different comment classification techniques.

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