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# Naïve Bayes Alpha Parameter Optimization with Ant Colony for Clinical Text Classification

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***Abstract***: *This study addresses the challenges of text classification in domain-specific Natural Language Processing (NLP) within the medical field, which differs significantly from general NLP due to the presence of complex medical jargon and informal language in clinical documents. The primary objective of this research is to develop and evaluate a cancer-related text classification model by integrating the Naïve Bayes algorithm with Laplacian smoothing and optimizing its alpha parameter using Ant Colony Optimization (ACO). Specifically, the study aims to determine whether ACO can effectively identify the optimal alpha value that enhances the classification performance of the Naïve Bayes model. Experimental results demonstrate that with an alpha value of 0.27, the proposed model achieves an accuracy of 81.05%. This indicates that the combination of ACO and Naïve Bayes significantly improves classification efficiency and accuracy. The findings contribute to more accurate interpretation of clinical cancer-related texts, supporting better-informed decision-making in medical contexts*

***Keywords:*** *Classification, NLP, Naïve Bayes, ACO, Medical Text*

## 1. Introduction

Text classification is an important part of Natural Language Processing (NLP), one of its many components, which mainly deals with the structure and categorization of textual data. It is fundamental when solving problems that deal with text data [1], [2]. Natural language processing (NLP) has been applied with advantages on data processing in many domains including medical. Natural language processing (NLP) has multiple applications in medicine, one of which is the analysis of patient care–related textual materials. Examples of these documents are primary care notes, physical exam note entries, radiological reports, progress notes and clinical histories [3].

Unlike other sectors, the use of NLP for applying text classification to the medical field presents unique challenges. We can infer that medical documents would be a good candidate for natural language processing models to struggle with since there are potentially numerous obfuscating and or rare phrases used within the documents themselves. Second, due to the narrative nature of medical records, it is more challenging to extract meaningful information. Third, the documents are informal language and NLP models struggle to figure out what is being said [4].

Requirements (both eligible and ineligible participants) are a basic needs of clinical studies. These requirements are often expressed in free text format, making it difficult for humans to interpret. This means that they must be explicitly defined in order to enable their correct computer interpretation [5]. Globally, text classification based techniques have been used by the analysts for classifying narrative clinical reports into specific categories that include supervised,

unsupervised, semi-supervised, ontology-based, rule-based techniques as well as other machine learning models such as transfer , reinforcement and multi-view learning model respectively [6].

The naive bayes classifier is a widely used text categorization method. Naive Bayes (NB) is a specific case of Bayesian networks, and the generic concept is rooted in conditional probability as embodied in Bayes' theorem. Supervised learning classification models can be simple to understand, are fast to apply on a dataset, and feature inherent noise tolerance, making them suitable for various domains—text classification, spam filtering, or sentiment analysis. Naive bayes is incremental in nature, which means in future we can add more training data and without retraining classifier from new dataset save computational costs [7].

Naive Bayes is the system of probability-based classification of data. However, one of the challenges it can encounter is zero probability, which occurs when a feature appears in the test data but not present in the training set. A common solution to this issue is Laplacian smoothing; by adding the same positive constant, typically 1 or a small positive number, to every frequency [8], [9], this effectively prevents zero probability. In the naive bayes framework, a parameter alpha regulates the level of smoothing. This value manages the amount of adjustment applied in the probability calculation [8], [10]The larger the alpha, the more the probabilities smooth out — reducing risk of overfitting. Conversely, a smaller alpha reduces smoothing and then the model can react more firmly to variations in data.

We proposed in this paper to optimize the alpha value of Naïve Bayes classifier by Ant Colony Optimization (ACO) method. It is well known that ACO, especially its better variations of them, are able to solve complex multimodal optimization problems where tens of thousands or more combinations of feasible variables must be processed [11]. ACO is used for feature selection and it greatly increases the accuracy of classification that was inspired from the ants where they find the easiest way to get food with a shortest route between their nest and food.

An iterative process is employed to address the high dimensionality and complexity inherent in text data, where feature concatenation also necessitates appropriate scaling. The primary goal of this research is to enhance both the speed and accuracy of clinical text classification specifically within Cancer Clinical Trials. Achieving this improvement has the potential to uncover novel clinical insights and contribute valuable medical knowledge.

Although text classification has been widely applied in the biomedical domain, previous studies have rarely focused on the combined optimization of model parameters and smoothing techniques—especially in the context of Naive Bayes classifiers for cancer clinical trial texts. To address this research gap, this study explicitly aims to optimize the smoothing parameter alpha in the Naive Bayes model by leveraging Ant Colony Optimization (ACO). The novelty of this work lies in the innovative integration of ACO to fine-tune the smoothing parameter, an approach that, to the best of our knowledge, has not been previously applied to clinical text classification in oncology.

## 2. Method

The primary objective of this study is to enhance cancer text classification using the Naïve Bayes algorithm through the innovative application of the Ant Colony Optimization (ACO) method to identify the optimal α (alpha) value. The α value plays a crucial role in Laplace smoothing within Naïve Bayes classification, addressing the issue of zero probability for words unseen in the training data. By leveraging the ACO approach, we aim to determine the most suitable alpha value that maximizes classification model accuracy and overall performance.

To ensure reliable and accurate classification, comprehensive text preprocessing is performed prior to model training. This preprocessing pipeline includes the following steps:

1. Data cleaning
   Removal of irrelevant characters, punctuation, numbers, and symbols to reduce noise in the textual data.
2. Tokenization
   Splitting text into individual tokens (words or terms) for analysis.

3. Stopword removal
   Eliminating common words (e.g., "the," "and," "is") that carry little semantic meaning and do not contribute to classification.
4. Stemming and Lemmatization
   Reducing words to their base or root form to unify different variations of the same word (e.g., “cancerous” to “cancer”).
5. Vectorization
   Transforming processed tokens into numerical features suitable for input into the Naïve Bayes classifier.

This study seeks to provide new insights into the importance of selecting an appropriate α value for Naïve Bayes, directly impacting the model’s ability to handle unseen words and make accurate predictions. Optimizing text classification using the ACO approach to adjust the α value is expected to demonstrate improved adaptability and generalization capabilities, leading to enhanced text categorization outcomes.

### 1.1. Dataset Information

The data used in this study is sourced from clinicaltrials.gov. The original dataset was processed by combining eligibility criteria information with the study's conditions and interventions. Subsequently, the data was transformed into a list of clinical statements with brief labels, where two features were extracted: the labels "Eligible" or "Not Eligible." An example of the data to be used can be seen in Table 1 below.

**Table 1**. Example of Clinical Trial Data

| No | Text | Label |
|---|---|---|
| 1 | recombinant CD40-ligand . melanoma skin diagnosis and no active cns metastases by ct scan or mri | Eligible |
| 2 | Liposomal doxorubicin . colorectal cancer diagnosis and cardiovascular | Eligible |
| 3 | BI 836909 . multiple myeloma diagnosis and indwelling central venous cateder or willingness to undergo intra venous central line placement | Eligible |
| 4 | Immunoglobulins . recurrent fallopian tube carcinoma diagnosis and patients are allowed to receive but are not required to receive two additional cytotoxic regimens for management of recurrent or persistent disease with no more than one non platinum non taxane regimen | Eligible |
| 5 | Paclitaxel . stage ovarian cancer diagnosis and patients must have recovered from the effects of recent surgery radiotherapy or other therapy | Eligible |
| 6 | Antibodies | Eligible |
| 7 | Hormones . prostate cancer diagnosis and imaging examinations including emission computed tomography ect positron_emission tomography pet computed tomography ct and magnetic resonance imaging mri revealed non regional lymph node metastasis bone metastasis or visceral metastasis | Eligible |
| 8 | Bendamustine Hydrochloride . diffuse large cell lymphoma diagnosis and no previous treatment | Eligible |
| 9 | Nivolumab . recovered from all toxicities associated with prior treatment to acceptable baseline status for laboratory toxicity see below limits for inclusion or national cancer institute common terminology criteria for adverse events nci ctcae version doc three grade of zero or one except for toxicities not considered safety risk alopecia or vitiligo | Eligible |
| …… | ……. | …… |

| No | Text | Label |
|---|---|---|
| 992 | Asparaginase . nasal and nasal type nk cell lymphoma diagnosis and disagreement on blood sample collection | Not Eligible |
| 993 | Antibodies . stage iiib ovarian cancer diagnosis and patients with history of abdominal fistula or perforation within the past twelve months | Not Eligible |
| 994 | Cortisol succinate . b cell lymphoma unclassifiable with features intermediate between diffuse large cell lymphoma and burkitt lymphoma diagnosis and patients who have had more than one cycle of prior chemoimmunotherapy for diagnosis of nhl are not eligible note | Not Eligible |
| 995 | Nivolumab . stage iv bladder urothelial carcinoma diagnosis and the subject has had evidence within two years of the start of study treatment of another malignancy which required systemic treatment | Not Eligible |
| 996 | Prednisolone . other prior or concurrent malignancy except for carcinoma in situ of the cervix or basal cell skin cancer | Not Eligible |
| 997 | BB 1101 . multiple myeloma diagnosis and poems syndrome polyneuropathy_organomegaly endocrinopathy monoclonal protein and skin changes | Not Eligible |
| 998 | 3-Iodobenzylguanidine . neuroblastoma diagnosis and concurrent palliative radiotherapy to localized painful lesions | Not Eligible |
| 999 | Selenious Acid . prostate cancer metastatic disease diagnosis and more than one prior chemotherapy | Not Eligible |
| 1000 | Oxaliplatin . leukocytes less_than one five nl or platelets less_than one00 nl except due to lymphoma | Not Eligible |

### 2.1. Laplacian Smoothing

In Naïve Bayes, probabilities are calculated based on the frequency of feature occurrences in the training data[12][13]. However, if a certain feature does not appear in a specific class during training, its probability becomes zero. When calculating the probability of new data containing this unseen feature, the overall probability becomes zero regardless of other features[14]. This issue can be resolved using the Laplacian smoothing techniqu[15]. Laplacian smoothing involves adding a small positive constant (often referred to as 'alpha' or 'k') to the numerator and denominator of the probability calculation. This ensures that no probability becomes zero.

$$P(\text{feature}_i \mid \text{class}) = \frac{(\text{count}(\text{Feature}_i, \text{class}) + \alpha}{(\text{count}(\text{class}) + \alpha * \text{number\_of\_features}}$$

Where:
- $P(\text{feature}_i \mid \text{class})$ is the probability of feature i given the class.
- $\text{count}(\text{feature}_i, \text{class})$ is the number of occurrences of feature i in the class.
- count(class) is the total number of instances in the class.
- alpha is the smoothing parameter (usually set to 1).
- number_of_features is the total number of features.

In the Naïve Bayes, we also add the parameter α in numerator and denominator of probability calculation to make sure that probabilities will never be equal to zero. That also deals with the problem of zero probabilities, a common problem in text classification where no training set instance for a class has had certain features [16]. A higher α value leads to heavier smoothing, resulting in more uniform probabilities and lower overfitting risk. On the other hand, a lower value of α will provide light smoothing and permits the model to capture variations in the data. The Ant Colony Optimization (ACO) algorithm is used in this study to identify the optimal α, which minimizes classification errors on the text dataset applied.

2.2. Feature Selection for α Using ACO

Ant Colony Optimization (ACO) - Naïve Bayes chooses α to be the best value of smoothing parameter α, which is not affecting zero probability as a result of words that are completely absent in training data. Ant Colony Optimization (ACO) algorithm is a metaheuristic based on the food searching behaviour of ant colonies [17]. Through cooperation and communication between them depositing pheromones along their paths, these ants are able to find the shortest path linking its nest with a source of food. This pheromone trail is information for the deliberately following ants to decide which way to go. This mechanism enables an ant colony to find the best solution as a collective by using the pheromone different journeys leave as trails [18]. Phenomenon trails evaporate over time in order to prevent premature convergence or stuck on less optimal paths. Doing so entices the ants to continue exploring to find optimize routes in a complex solution space[19]. This is why ACO becomes one of the most efficient optimization algorithms to address a number of complex optimization problems. To find the best α in the Naïve Bayes classifier, we use Ant Colony Optimization (ACO), through the optimization of a given objective function aimed at minimizing errors in classification.

**2.2.1. Classification Error Function**

$$f(\alpha) = \sum y_i \neq y'_i$$

Where :

- f(α) is the classification error function value for a specific α\alphaα value.
- $y_i$ is the actual label of the iii-th data point.
- $y'_I$ is the predicted label of the *i*-th data point by the Naïve Bayes algorithm with α

**2.2.2. Error Rate Function**

$$\text{error\_rate}(\alpha) = \frac{\sum y_i \neq y'_i}{N}$$

Where :

- error_rate(α) is the classification error rate for a specific α value.
- *N* is the total number of data points in the dataset.

**2.2.3. F1-Score Function**

$$\text{f1}_{\text{score}(\alpha)} = \frac{2 * (\text{precision}(\alpha) * \text{recall}(\alpha))}{(\text{precision}(\alpha) + \text{recall}(\alpha))}$$

Where :

- f1_score(α) is the F1 score for a specific α value.
- precision(α) is the classification precision for the α value.
- recall(α) is the classification recall for the α value.

The steps involved in optimizing the α value in Naïve Bayes can be seen in the following Figure 1.

The above diagram is a framework systematically designed to enhance Naive bayes model via Ant Colony Optimization (ACO) for classification of clinical trial datasets. This methodology consists of two basic stages: data preparation and the application of model training and parameter optimization based on ACO.

1. Prepare data and train the model
   First, the clinical trial data is pre-processed to get it ready for the ML tasks. These steps include:
   a. Text Preprocessing
      This stage involves cleaning and standardizing textual data to remove inconsistencies and ensure uniformity for later stages.

b. Text Vectorization
This involves converting the text-based information into formats that a computer can work with (number based, of course).

The dataset is then split into training and testing subsets after the preprocessing to sufficiently evaluate a model. The training data are used to train the Naive Bayes model, and the performance was assessed by 10-Fold Cross-Validation, which ensures reliable and generalized performance. The second step also tunes hyperparameters to improve the model's prediction power. The testing data on the other hand is to assess the model performance metrics like accuracy, precision, and recall validating its efficiency in classifying clinical trial data.

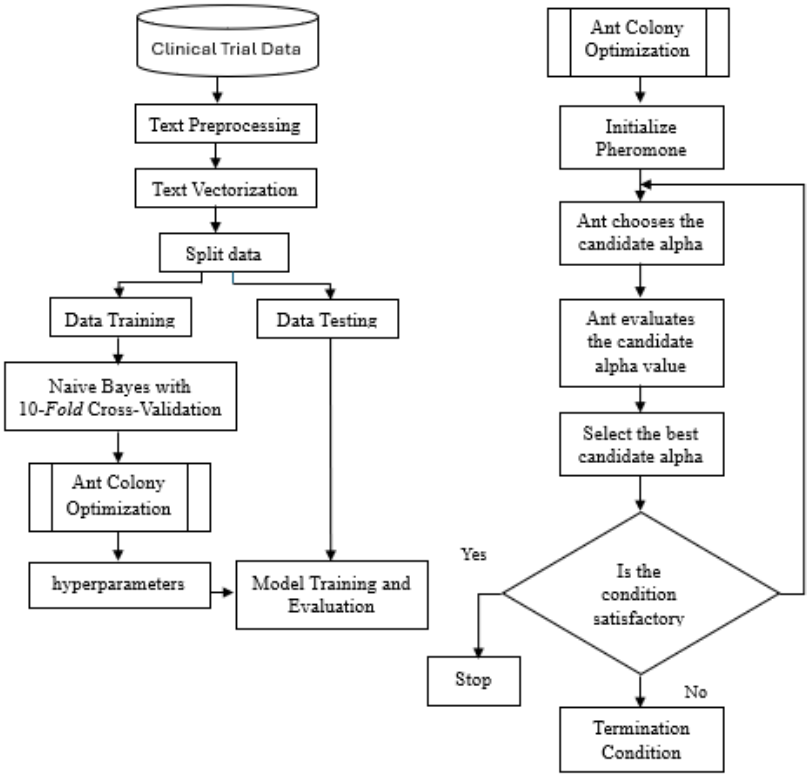


**Figure 1.** Naïve Bayes Optimization with Ant Colony

2. Ant Colony Optimization for Parameter Optimization
In phase two, ACO is used to determine the alpha value of Naive Bayes algorithm. From here on, we adopt a more structured iterating process as follows:
a. Pheromone Initialization
ACO AlgorithmThe ACO algorithm performs initialization of pheromone trails, which indicate, which alpha value is more desirable.
b. Candidate Alpha Selection
Since ants independently choose a candidate alpha, the candidate selection is performed probabilistically based on pheromone levels.
c. Evaluation of Performance
Next, these chosen alpha values are used on the Naive Bayes Model and evaluate its performance with accuracy,Error rate,Precision or Recall metrics.
d. Update pheromone information
The pheromone trails are updated depending on the evaluation results to maximize promising alpha values in future iterations.
e. Convergence Check
The algorithm: Verifies that the conditions for stopping (for example, a certain level of accuracy achieved) has been satisfied. The optimisation ends if the criteria are fulfilled or continues to the next iteration of the algorithm.

3. Final Model Evaluation

Upon identifying the optimal alpha value through ACO, the optimized Naive Bayes model is finalized and evaluated on the testing dataset. This evaluation ensures the model's effectiveness and suitability for real-world applications in clinical trial data classification. ACO Naive Bayes provides a systematic solution to the problems of medical text classification. The methodology optimally determines the alpha value, which increases accuracy and reliability to the model. Our framework exposes its capabilities for improving clinical trial applications in medical text analytics, as this could facilitate data interpretation and enhance decision-making processes in healthcare contexts.

## 3. Results and Discussion

This study emphasizes the alpha, a main parameter which is unit used to smooth probabilities and remove data sparsity problem for collapses Naive Bayes classification model, they search best value of this parameter. With these results, we can see that when changing the alpha to 0.27 our model gets a massive boost with accuracy as high as 81.05% clearly showing where it improves on visualisation. This improvement emphasizes the importance of alpha tuning, refining the models ability to handle unseen features and maintain solid classification performance.

As illustrated in the confusion matrix table 2, a more comprehensive analysis reveals the capabilities of the model. The matrix shows 808 True negatives, 813 true positives, 180 false negatives and 199 false positives. The results highlight the precision and recall of the model which come out to be 0.8187 and 0.8034 respectively, indicating that the model is able to classify data with accuracy while being sensitive enough to not miss out on any positive cases. The analysis shows that alpha should be chosen correctly to get the best precision-recall trade off for reliable classification on this dataset.

**Table 2.** Confusion Matrix of Naïve Bayes Optimization

| | | **Actual Value** | |
|---|---|---|---|
| | | Eligible | Not Eligible |
| **Predicted Value** | Eligible | 808 | 180 |
| | Not Eligible | 199 | 813 |

The graph showing the relationship between the alpha parameter and the accuracy of the Naive Bayes model with Ant Colony optimization can be seen in Figure 2 below

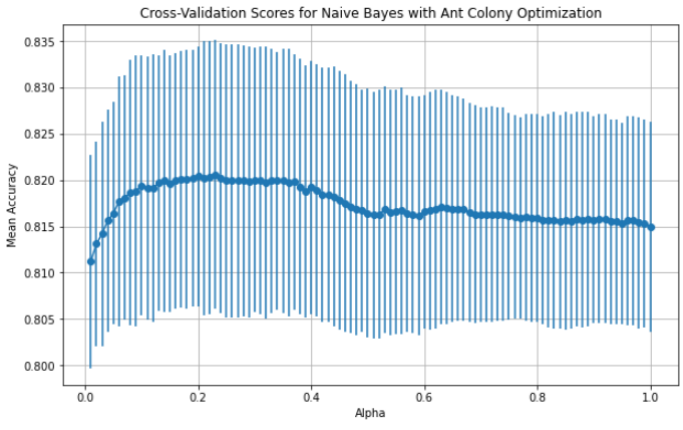


**Figure 2**. Graph of the relationship between the alpha parameter and the accuracy of the Naive Bayes model

The average accuracy of the Naive Bayes model against different values of alpha is shown in Figure 2. Error bars are also included here, which indicate the uncertainty associated with the accuracy estimates. Initially, the accuracy improves with increasing alpha value and achieves a peak level at an alpha value around 0.2. However after this point the accuracy starts to decrease slowly, showing that higher alpha values are providing diminishing returns. As the error bars also show, although the accuracy is mostly stable throughout a wide range of alpha values, there is an extreme fluctuation at both ends. These stable results imply that the model is relatively robust to small changes in alpha but becomes increasingly sensitive as alpha approaches the values of both extremes tested.

From these observations, we can conclude that the best alpha value for Naive Bayes model optimized from Ant Colony Optimization algorithm is about 0.2. This number represents the point at which the mean accuracy is at its peak and shows that this is where the model balances predictive power with stability. Thus, an alpha value near 0.2 is selected that only achieves the best classification results and is consequently a vital tuning parameter in this regard.

### 3.1 Discussion

The optimization of the alpha parameter using Ant Colony Optimization (ACO) significantly contributes to enhancing the model's accuracy by systematically exploring the parameter space and avoiding local optima that traditional grid search methods might miss. This optimization technique mimics the foraging behavior of ants, effectively balancing exploration and exploitation in the search process. Despite the improved performance, the study is limited by the scope of the dataset used and the potential variability in clinical text, which may affect the generalizability of the results. Furthermore, comparisons with previous studies are limited due to the novelty of integrating ACO for smoothing parameter tuning in Naive Bayes within cancer clinical text classification. Future work should consider larger and more diverse datasets and compare other metaheuristic optimization techniques to further validate and improve the approach.

## 4. Conclusions

In this work we highlight the importance of text classification in the development of NLP based applications in medicine. It is aimed to overcome the challenging scenario off processing medical documents, which includes numerous medical terms and informal terminologies. Using a Naive Bayes classifier for text classification, Laplcian smoothing is implemented to eliminate zero probability problem utilised solely in the context of clinical text classification problem specific to Cancer Clinical Trials. In addition,the study is also the first one to apply Ant Colony Optimization (ACO) to identify the optimal alpha values with a view of improving accuracy, interpretability,and innovation potential of clinical models..

The aim of this research is to improve supervised text classification approach for cancer-related text by coupling Naive Bayes with ACO for optimal parameter selection. The results described here show that alpha set to 0.27 provides a very strong performance, yielding an accuracy of 81.05%. Deep analysis showcases the importance of alpha hyperparam in tuning the final quality of the model, achieving an outstanding precision of 0.8187 and a recall score of 0.8034. Such metrics highlight the need of adjusting alpha parameter in order to strike a balance between precision and recall that would be favorable in medical text classification tasks.

ACO has been combined with Naive Bayes to illustrate the significance of finding a balance between improving efficiency while ensuring accuracy in cancer text classification models. Interestingly, the best solution as measured by average model performance has an alpha value of roughly 0.2. This result validates the impact of new optimization strategy here and establishes a new benchmark in the medical text classification task.

These models can potentially serve as a basis for highly accurate and adaptive modeling applied in medical texts — particularly cancer related ones. It advocates an evidence-based approach toward clinical decision-making through more granular interpretation of clinical data and also establishes the groundwork for future advances in Natural Language Processing (NLP)

applications within healthcare. This work may take a lead in the tuning of ML algorithms for other heterogeneous complex clinical datasets and thus increase, in general, the applicable domain of the proposed algorithm on medicine.

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