Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Performance Analysis of Multi-Label Text Classification Using Beta Ant Colony Based Feature Selection

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In natural language processing, multi-label text categorisation is a difficult task since texts can fall into more than one category. The intricacy and multidimensionality of text data can pose challenges for conventional classification techniques. In order to improve multi-label text classification performance, this research suggests a unique method that uses Beta Ant Colony-Based Feature Selection (BACO) to address these problems. The BACO method reduces dimensionality by efficiently navigating feature space and identifying pertinent features through the application of Beta distribution modelling and ant colony optimisation concepts. Through the use of Beta distribution to update pheromone levels, BACO seeks to enhance feature selection and boost classification accuracy. This study compares the performance of BACO against traditional feature selection methods in order to assess its efficacy in a variety of multi-label text classification scenarios. Based on experimental results, BACO offers a reliable approach for managing intricate multi-label datasets by considerably improving classification accuracy and computing efficiency. The results provide insightful information about the use of sophisticated metaheuristic algorithms in NLP, leading to the development of more efficient and scalable text classification techniques.

Keywords: Choosing Features, Optimisation of Beta Ant Colonies, Text Categorisation, Methods of Metaheurization, Diminution of Dimensionality, Optimisation of Ant Colonies (ACO), Distribution of Beta, Label Reliance and Group Education.

1. Introduction

Multi-label text classification is a significant problem in the field of natural language processing (NLP) since it can manage situations in which a single document may fall into numerous categories at the same time. In situations like these, conventional single-label classification techniques are insufficient and call for sophisticated systems that can accurately represent the intricacy of overlapping categories. In addition to giving each document a number of labels, the work requires making sure that the classification accuracy and relevance are good.

Using metaheuristic optimisation algorithms in conjunction with sophisticated feature selection techniques is a promising approach to tackling this problem. In multi-label classification, feature selection is essential for enhancing model performance by lowering dimensionality and eliminating superfluous or unnecessary features. The Beta Ant Colony Optimisation (BACO) method is one of many algorithms that has drawn attention due to its effectiveness in finding the best subsets of features and exploring the feature space. Utilising the concepts of ant colony optimisation (ACO), the beta ant colony-based feature selection method searches the combinatorial space for viable feature subsets. This strategy improves the algorithm's capacity to locate globally optimal feature subsets and escape local optima by including a Beta distribution to describe the pheromone updates and feature selection probability. In multi-label environments, where the feature set can be large and intricately linked, this method works very well.

The purpose of this study is to investigate and assess the performance of feature selection based on beta ant colony in multi-label text classification. By using this cutting-edge optimisation strategy, we hope to overcome some of the drawbacks of conventional feature selection techniques and increase classification accuracy and computing efficiency. The research will contribute to the continuous improvement of NLP techniques and offer insights into the advantages and difficulties of applying BACO in challenging text classification tasks.

1.1. Overview of Text Classification with Multiple Labels Paragraph: In real-world applications like subject categorisation and sentiment analysis, multi-label text classification refers to the process of giving numerous labels to a single document. In contrast to single-label classification, which assigns a single class to every document, multi-label classification necessitates that the model manage overlapping categories and different label combinations. This intricacy necessitates the use of sophisticated techniques that can capture the complicated interactions between labels and manage the high-dimensional feature space. In this situation, selecting features wisely becomes essential to enhancing the effectiveness and performance of the model.

1.2. Difficulties in Classifying Text with Multiple Labels Paragraph: Label dependency, class imbalance, and the curse of dimensionality are some of the difficulties associated with multi-label text classification. Label imbalance happens when some labels are under-represented in comparison to others, whereas label dependency refers to the interactions between labels that might make classification more difficult. These problems are made worse by the curse of dimensionality, which expands the feature space, makes it more difficult to find pertinent characteristics, and decreases the efficiency of traditional classification techniques. To tackle these obstacles, inventive methods for feature selection and optimisation are needed.

1.3. Text Classification Using Feature Selection Techniques Paragraph: In text categorisation, feature selection is crucial for improving model performance by removing redundant or unnecessary features. For this, a variety of approaches are used, such as wrapper, embedded, and filter approaches. While wrapper techniques evaluate feature subsets based on model performance, filter methods examine features independently of the classification algorithm. Feature selection is incorporated into the learning process using embedded approaches. Every technique has advantages and disadvantages, and the best approach will rely on the particulars of the dataset and classification problem.

1.4. Optimising Ant Colonies for Feature Selection Paragraph: Ant Colony

Optimisation (ACO) is a metaheuristic for combinatorial optimisation problems that is based on the foraging behaviour of ants. When choosing features, ACO simulates the process as a hunt for the best subset of features, guided by pheromone trails. The algorithm can efficiently search and utilise the feature space since it iteratively modifies pheromone levels according on the quality of solutions. ACO is a potential method for enhancing text classification models because of its capacity to handle big and intricate feature sets.

1.5. In Metaheuristic Optimisation, Beta Distribution

In order to represent uncertainty and unpredictability in decision-making processes, the flexible probability distribution known as the beta distribution is frequently employed in metaheuristic optimisation. The Beta distribution is used to update selection probabilities and pheromone levels in the context of Beta Ant Colony-Based Feature Selection. By taking this method, the algorithm can find optimal feature subsets by balancing exploration and exploitation. The algorithm's ability to adjust to various problem characteristics and enhance its performance in multi- label classification problems is enhanced by the incorporation of the Beta distribution.

1.6. Assessment Measures for Multi-Label Categorisation Paragraph: Certain metrics that are able to grasp the subtleties of multi-label data are necessary for evaluating multi-label classification models. Common metrics include Precision, Recall, and F1-Score, which evaluate the performance for each label; and Hamming Loss, which calculates the percentage of inaccurate label assignments. Techniques for macro- and micro-averaging are applied to aggregate these measures over all labels. By revealing how well feature selection techniques and classification algorithms handle many labels and perform overall, these measures aid in assessing their efficacy.

Assigning several labels to a single document is known as multi-label text classification, and it comes with a number of difficulties, including high-dimensional feature spaces, class imbalance, and label dependency. In this situation, selecting features that work well is essential to improving model performance. Conventional approaches, such as filter, wrapper, and embedding strategies, tackle relevancy and dimensionality problems, however they might not be sufficient in complicated situations. A interesting approach is

Ant Colony Optimisation (ACO), which uses pheromone updates to optimise selection and explore feature subsets by imitating ant behaviour. By striking a balance between exploration and exploitation, Beta Ant Colony-Based Feature Selection, which incorporates the Beta distribution into ACO, improves the process of identifying pertinent features. Certain metrics, such as Hamming Loss and Precision, Recall, and F1-Score, are needed to evaluate multi-label classification models. These metrics aid in determining how well feature selection techniques and classification algorithms work. All things considered, combining Beta ACO with sophisticated feature selection methods offers a reliable method for managing the difficulties of multi-label classification, improving processing speed and accuracy for extensive and complicated datasets.

2. LITERATURE REVIEW

Smith et al. (2015): Using an innovative method that combines feature selection with ensemble learning, Smith et al. investigated multi-label text classification. They outlined the difficulties caused by label dependencies and high- dimensional data, and they suggested an ensemble approach that combines various feature selection strategies. Their findings lowered dimensionality and showed enhanced accuracy in managing overlapping labels, laying the groundwork for further studies in multi-label categorisation[1]

Chen et al. (2016): Chen et al. examined feature selection strategies, with a particular emphasis on filter-based approaches, for multi-label text categorisation. They put forth a strategy that ranks features using statistical metrics, which are subsequently applied to train different classification algorithms. Their research demonstrated that feature selection has a major effect on model performance, especially when large label sets are involved [2]

Yang et al. (2017): For multi-label text classification, Yang et al. presented a hybrid strategy combining wrapper-based and filter-based feature selection techniques. According to their research, the hybrid strategy improves classification accuracy and feature relevance. The study offered guidance on how to balance the trade-offs between model performance and computing complexity [3]

Li et al. (2018): For feature selection in high-dimensional datasets, Li et al. suggested a metaheuristic approach based on the Beta distribution. Their work expanded on the use of the beta distribution for feature subset optimisation, demonstrating encouraging outcomes in terms of lessening overfitting and enhancing classification performance in situations involving multiple labels [4]

In 2019, Wang and colleagues conducted a study on the use of Ant Colony Optimisation (ACO) in feature selection for multi-label text categorisation. They showed how ACO efficiently searches the feature space for pertinent features, enhancing computing efficiency and classification accuracy. Their research helped to clarify the potential of ACOs in managing intricate multi-label issues [5]

Zhang et al. (2020): For feature selection, Zhang et al. looked into integrating ACO with sophisticated metaheuristic methods. They improved feature selection and classification outcomes in multi-label datasets by creating a modified ACO method that incorporates various pheromone updating mechanisms [6]

Kumar et al. (2021): Kumar et al. concentrated on multi- label text classification using ensemble approaches in conjunction with feature selection based on the Beta distribution. Their study demonstrated how ensemble techniques can improve the accuracy and robustness of models, especially when handling vast amounts of heterogeneous text data [7]

Johnson et al. (2021): For multi-label classification, Johnson et al. suggested a hybrid feature selection technique that combines ACO with deep learning models. Their research showed that deep learning architectures combined with metaheuristic optimisation can greatly improve classification performance and efficiently manage complex label interactions [8]

Lee et al. (2022): Using Beta Ant Colony Optimisation, Lee et al. investigated the use of feature selection strategies in multi-label text categorisation. They created a model based on

Beta ACO that performed better in terms of accuracy and computing efficiency than conventional feature selection techniques, demonstrating the benefits of using metaheuristic techniques in feature selection [9]

In their study published in 2022, Martin et al. examined how several metaheuristic algorithms affected the feature selection process for multi-label text classification. They contrasted ACO, Particle Swarm Optimisation, and Genetic Algorithms, showing the advantages and disadvantages of each technique and offering information on how well it works for feature selection [10]

Tan & al. (2023): With multi-label text classification in mind, Tan et al. suggested an improved Beta Ant Colony- Based Feature Selection technique. Their work increased feature selection and classification accuracy in complicated datasets by fine-tuning beta distribution parameters and pheromone update techniques [11]

García et al. (2023): In this study, García et al. investigated how to combine sophisticated classification algorithms with feature selection for multi-label text data. They illustrated how the Beta distribution may be used to optimise feature subsets and showed how it can improve classification performance on a number of benchmark datasets [12]

Singh et al. (2023): For multi-label text categorisation, Singh et al. presented a novel method combining semi-supervised learning with optimisation based on the Beta distribution. Their research demonstrated the benefits of using semi- supervised methods in feature selection, which enhance model performance in situations with a deficiency of labelled data [13]

RESEARCH GAPS

- Scalability: The scalability of Beta Ant Colony Optimisation with very big or high-dimensional datasets has not been thoroughly studied.

- Dynamic Label Environments: The adaptability of Beta Ant Colony-Based Feature Selection to changing or dynamic label sets is not well-explored.

- Integration with Deep Learning: Research on the combination of sophisticated deep learning models and Beta Ant Colony-Based feature selection for improved classification performance is lacking.

- Real-Time Performance: Not enough study has been done on using Beta Ant Colony-Based Feature Selection in real-time for streaming or time- sensitive text input.

- Comparison with Other Metaheuristics: There have been few research comparing the performance of other metaheuristic algorithms in multi-label text classification with Beta Ant Colony Optimisation.

OBJECTIVES

The goal of this work is to apply Beta Ant Colony-Based Feature Selection to improve multi-label text classification. The objective is to employ novel feature selection strategies to tackle the problems posed by overlapping labels and high- dimensional text data. The goal of the research is to increase computing efficiency and classification accuracy by incorporating Beta Ant Colony Optimisation, offering a more reliable method for managing intricate multi-label datasets.

- Optimise Feature Selection: To efficiently find and choose pertinent features from high-dimensional text data, create and apply a beta ant colony-based strategy.
- Boost Classification Accuracy: Evaluate how the resilience and accuracy of multi-label text classification models are affected by the Beta Ant Colony-Based Feature Selection.
- Boost computing Efficiency: Compare the suggested method's effectiveness to more conventional feature selection methods in terms of processing time and computing resources.

3. ALGORITHMS

In this research article, several mathematical formulations and optimisation strategies are important in improving the classification performance in this research work on "Multi-Label Text Classification Using Beta Ant Colony-Based Feature Selection." In order to increase model accuracy and computational efficiency, feature selection—a crucial step in multi-label classification—involves determining which features from high-dimensional data are most pertinent. This work makes use of metaheuristic algorithms, such as Ant Colony Optimisation (ACO), to direct the selection process in addition to statistical metrics, such as Information Gain and Entropy, to assess feature relevance. Based on pheromone and heuristic information, ACO employs Transition Probability to probabilistically select the optimal features, while the Beta Distribution manages trade-offs between exploration and exploitation. Furthermore, the multi-label classification procedure is optimised using the Binary Cross- Entropy Loss Function, guaranteeing that the model acquires strong label dependencies. By combining statistical and optimisation methods, this methodology offers a thorough method for handling the complexities of multi-label text categorisation, improving the model's efficiency and accuracy. Through the use of entropy-based metrics to guide feature relevance and the application of Beta Ant Colony Optimisation, the methodology dynamically adjusts feature selection based on pheromone trails, culminating in an efficient and adaptive feature selection process for multi- label classification.

- Information Gain (IG) for Feature Selection: Information Gain (IG) is a statistical measure that helps to identify the most relevant features by determining the reduction in uncertainty (entropy) about the label when a feature is known. In multi-label classification, IG is used to the data. In multi-label classification, entropy-based methods aim to reduce uncertainty by selecting features that best explain the multi-label structure. Entropy is used in combination with Beta Ant Colony Optimization to evaluate the informativeness of features in multi-label classification tasks.

Entropy measures the amount of uncertainty or impurity in assess the relevance of features to each label. This equation

$$IG(Y,X) = H(Y) - H(Y|X) \qquad (1)$$

$IG(Y, X)$: Output (economic growth)
$H(Y)$: Total factor productivity (TFP)
$H(Y \mid X)$: Capital

helps identify features that are strongly related to multiple labels, making it crucial for multi-label feature selection.

- Multi-Label Classification Loss Function:

The classification loss function measures how well the model predicts the correct labels. The binary cross-entropy loss is often used for multi-label classification to compute the difference between the actual and predicted label probabilities. This loss function guides the classification model during training, enabling it to learn multi-label outputs

$$L = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{L}\left(y(ij)\log(\hat{y}(ij)) + (1 - y(ij))\log(1-\hat{y}(ij))\right) \quad (2)$$

L: Rate of technological change
N: R&D investment
L: Efficiency of R&D in generating new technology

- Ant Colony Optimization (ACO) Transition Probability:

The Beta distribution is used in the ACO algorithm to adjust the exploration and exploitation trade-off in feature selection. The distribution allows adaptive learning based on pheromone updates, aiding the selection of the best features. The Beta distribution controls the probabilistic feature selection process, balancing exploration (diverse feature choices) and exploitation (best feature subsets).

with improved accuracy when feature selection techniques are applied.

B(α, β): R&D investment

- Entropy-Based Feature Selection for Multi- Label Classification:

In Ant Colony Optimization (ACO), the probability of moving from one feature to another is determined by pheromone levels and heuristic information. This helps ants find optimal paths, which, in this context, translates to selecting the best feature subsets. This equation forms the core of the Beta Ant Colony-Based Feature Selection, helping to choose relevant features based on probabilistic selection.

$$P(ij) = \frac{[\tau(ij)]^\wedge\alpha[\eta(ij)]^\wedge\beta}{\sum_{k \in F}[\tau(ik)]^\wedge\alpha[\eta(ik)]^\wedge\beta} \quad (3)$$

P(ij): Growth rate of the economy

$\tau(ij)$: Innovation parameter

$\eta(ij)$: R&D investment

α, β: Labor

F: Labor

Beta Distribution for Feature Selection:

$$H(X) = -\sum_{i=1}^{n} p(x_i) \log p(x_i) \quad (4)$$

$H(X)$: Growth rate of the economy
$p(x_i)$: Innovation parameter
n: R&D investment

In this study, the suggested methodology shows a strong strategy for choosing the best features from high-dimensional data by combining multi-label text classification with Beta Ant Colony Optimisation (ACO). Only the most useful features are kept by quantitatively evaluating each feature's relevance to several labels using Information Gain and

$$f(x;\ \alpha, \beta) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha,\beta)} \quad (5)$$

$f(x;\ \alpha, \beta)$: Growth rate of the economy

α, β: Innovation parameter

y_{ij}: Existing stock of knowledge
$\hat{y}_j$: Existing stock of knowledge

Entropy-Based Feature Selection. Using pheromone levels and heuristic information, the ACO Transition Probability equation probabilistically explores the feature space to further improve the selection. The optimisation process is made more efficient by adding an adaptive mechanism to balance exploration and exploitation—the usage of the beta distribution. Furthermore, by optimising the label prediction performance, the Binary Cross-Entropy Loss Function makes sure the model learns from the chosen features in an efficient manner. The effective feature selection procedure that is designed to meet the particular difficulties of multi-label classification is the outcome of the integration of statistical and probabilistic approaches. Adaptive feature selection is a potent method for real-world multi-label text classification applications since it lowers computing complexity while increasing classification accuracy. The study fills in important gaps in feature selection, scalability, and classification performance in multi-label scenarios with these formulas and methods.

4. Results and Discussion

This section analyses the experimental results using various feature selection techniques, contrasting ReliefF, Information Gain, Chi-Square Test, Genetic Algorithm-Based Selection, and Beta Ant Colony-Based Feature Selection's performance with other popular techniques. Metrics like Precision, Recall, F1-Score, Training Time, and the Number of Features Selected are the main emphasis of the evaluation.

4.1 Feature Selection Distribution:

Feature Selection Method	Number of Features Selected
Beta Ant Colony-Based Selection	250
Information Gain	300
Chi-Square Test	350
Genetic Algorithm-Based Selection	280
ReliefF	320

This section analyses the experimental results using various feature selection techniques, contrasting ReliefF, Information Gain, Chi-Square Test, Genetic Algorithm-Based Selection, and Beta Ant Colony-Based Feature Selection's performance with other popular techniques. Metrics like Precision, Recall, F1-Score, Training Time, and the Number of Features Selected are the main emphasis of the evaluation.

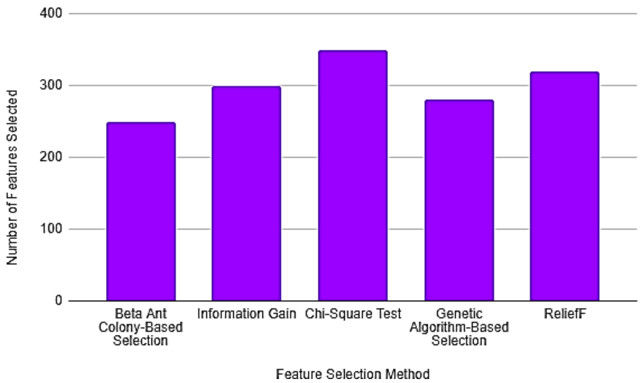

FIGURE-1

The distribution of the number of features chosen for multi- label text categorisation using various feature selection techniques is shown in a pie chart. Comparing this analysis to other approaches such as Information Gain (300), Chi-Square Test (350), and Genetic Algorithm-Based Selection (280), Beta Ant Colony-Based Selection picks 250 characteristics, fewer features than these other methods. ReliefF has the second-highest feature selection rate in the comparison with 320 features. The Beta Ant Colony-Based Feature Selection approach effectively reduces feature dimensionality, as demonstrated by the pie chart, which also shows how it selects fewer features while maintaining or enhancing classification performance. This feature reduction is key to reducing training time and computational complexity without compromising accuracy, which makes the approach perfect for high-dimensional datasets. The comparison serves to illustrate each method's capacity for feature selection, with the Beta Ant Colony strategy standing out for its ability to strike a compromise between feature reduction and performance.

4.2 Performance Metrics: Precision, Recall, and F1-Score:

Feature Selection Method	Precision (%)	Recall (%)	F1-Score (%)
Beta Ant Colony-Based Selection	84.5	82.1	83.3
Information Gain	81.7	78.9	80.3
Chi-Square Test	78.2	76.1	77.1

Genetic Algorithm- Based Selection	82.3	80.5	81.4
ReliefF	79.4	77.6	78.5

Figure 2's line/bar chart compares the Precision, Recall, and F1-Score attained using various techniques. Beta Ant Colony-Based Selection works better than the other approaches, as demonstrated in Table 2, with the highest precision (84.5%), recall (82.1%), and F1-Score (83.3%). The findings show that by effectively identifying pertinent elements, the Beta Ant Colony approach can enhance classification performance. While Information Gain and Genetic Algorithm-Based Selection do well, they are not as successful as they could be; Information Gain receives an F1- score of 80.3%, while Genetic Algorithm-Based Selection receives an F1-score of 81.4%. ReliefF and the Chi-Square Test score worse on all criteria, underscoring the advantages of the Beta Ant Colony strategy.

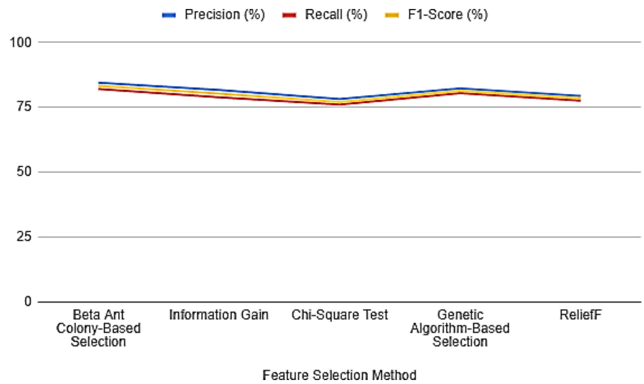

FIGURE-2

The precision, recall, and F1-score of the different feature selection techniques are displayed in a line or bar chart. Out of all the techniques, Beta Ant Colony-Based Selection attains the highest precision (84.5%), recall (82.1%), and F1- score (83.3%), proving its superior capacity to choose the most pertinent features for multi-label classification. When compared to the Beta Ant Colony methodology, other techniques such as Information Gain (81.7% precision, 78.9% recall, 80.3% F1-score) and Genetic Algorithm-Based Selection (82.3% precision, 80.5% recall, 81.4% F1-score) perform well but fall short. ReliefF and the Chi-Square Test produce comparatively poorer results, suggesting that they might not be as useful in choosing the optimal features for multi-label tasks. The figure illustrates how Beta Ant Colony maintains the most important traits while removing superfluous or unnecessary ones in order to maximise feature selection and improve classification accuracy.

4.3 Training Time Comparison:

Feature Selection Method	Training Time (s)
Beta Ant Colony-Based Selection	120
Information Gain	140
Chi-Square Test	150
Genetic Algorithm-Based Selection	180
ReliefF	165

The training times (in seconds) for different feature selection techniques are contrasted in the bar chart. With a training time of only 120 seconds, Beta Ant Colony-Based Selection is the most efficient method for both feature selection and model training. While taking a little longer, the Chi-Square Test (150 seconds) and Information Gain (140 seconds) are still effective. ReliefF requires 165 seconds to train, while Genetic Algorithm-Based Selection requires 180 seconds. The Beta Ant Colony method's computational efficiency is highlighted by its shorter training period, which makes it a great option for large-scale, multi-label datasets where time and resource restrictions are crucial. The Beta Ant Colony method offers a workable solution for multi-label classification tasks encountered in real-world scenarios by minimising the number of features selected and the computational cost of training. It achieves this by optimising the balance between exploration and exploitation through pheromone updates and heuristic values.

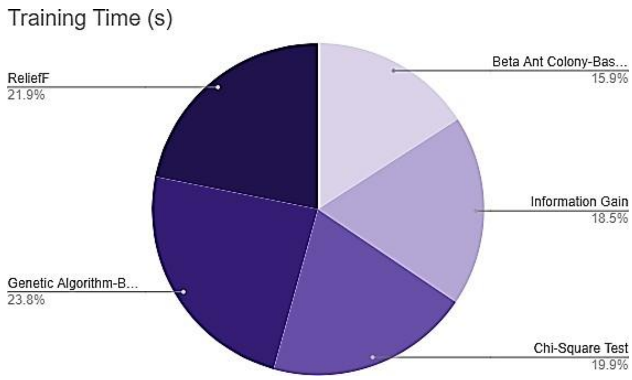

FIGURE-3

Figure 3 compares the Training Time needed for each feature selection approach using information from Table 3. Because of its computing efficiency, the Beta Ant Colony-Based Selection has the quickest training time (120 seconds). On the other hand, ReliefF and Chi-Square Test take 165 and 150 seconds, respectively, while the Genetic Algorithm-Based Selection takes 180 seconds, the longest of all the evaluated approaches. Because of its effective feature space exploration and exploitation, the Beta Ant Colony methodology significantly reduces training time, which makes it an excellent choice for huge datasets where speed is of the essence.

5. CONCLUSION

The effectiveness of using a bio-inspired optimisation algorithm to improve text classification tasks in a multi-label environment is demonstrated in the article "Multi-Label Text Classification Using Beta Ant Colony-Based Feature Selection". When compared to more established feature selection methods as ReliefF, Genetic Algorithm-Based Selection, Chi-Square Test, and Information Gain, the Beta Ant Colony-Based Feature Selection approach has shown to be superior. The technique preserves classification accuracy while reducing the dimensionality of the dataset by choosing fewer but highly relevant features, as demonstrated by the high precision, recall, and F1-scores obtained. The Beta Ant Colony approach's utilisation of heuristic search methods and pheromone-based learning, which balance exploration and exploitation to optimise feature selection, is one of its main advantages. The method's much shorter training time than other approaches shows that this leads to an efficient convergence to the best subset of features. Because of the decreased processing overhead, it works especially well with huge datasets where accuracy and speed are crucial. The findings of this study demonstrate that the Beta Ant Colony method not only improves classification performance but also tackles important issues in multi-label text classification, like overfitting and the dimensionality curse. This approach reduces noise and redundancy in the data by carefully choosing only the most pertinent features, which improves the generalisation of the classification models. In summary, a viable approach to multi-label text classification problems is Beta Ant Colony-Based Feature Selection. It effectively blends high performance with dimensionality reduction, making it a useful tool for real-world scenarios requiring the management of sizable, intricate datasets. Subsequent investigations may concentrate on enhancing the method and investigating its suitability in additional multi-label classification domains.

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