Application of Orangutan Optimization Algorithm for Feature Selection Problems

Tareq Hamadneh[1]* **Belal Batiha[2]** **Gharib Mousa Gharib[3]** **Widi Aribowo[4]**

[1]*Department of Mathematics, Al Zaytoonah University of Jordan, Amman 11733, Jordan*
[2]*Department of Mathematics, Faculty of Science and Information Technology, Jadara University, Irbid 21110, Jordan*
[3]*Department of Mathematics, Faculty of Science, Zarqa University, Zarqa 13110 Zarqa, Jordan*
[4]*Department of Electrical Engineering, Faculty of Vocational Studies,Universitas Negeri Surabaya, Surabaya, East Java 60231, Indonesia*
* Corresponding author's Email: t.hamadneh@zuj.edu.jo
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Abstract

Feature selection plays a pivotal role in machine learning and data analysis by identifying the most relevant features to enhance model performance and reduce computational costs. This paper investigates the application of the Orangutan Optimization Algorithm (OOA), a bio-inspired metaheuristic, for solving feature selection problems. The performance of OOA is evaluated on three distinct feature selection tasks, demonstrating its effectiveness in identifying optimal feature subsets. Additionally, OOA is compared against eight state-of-the-art metaheuristic algorithms, including Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Grey Wolf Optimizer (GWO), and others. The results reveal that OOA consistently outperforms these algorithms in terms of classification accuracy, feature reduction rate, and convergence speed. The unique mechanisms of OOA, such as its memory-based decision-making and balanced exploration-exploitation strategies, are highlighted as key contributors to its superior performance. This study establishes OOA as a robust and efficient tool for feature selection, with potential applications across various domains requiring dimensionality reduction and data preprocessing.

Keywords: Orangutan optimization algorithm, Feature selection, Metaheuristic algorithms, Dimensionality reduction, Optimization techniques, Classification accuracy.

1. Introduction

Metaheuristic algorithms have wide applications in various sciences, especially data mining and feature selection. Recently published metaheuristic algorithms that can be used in various optimization applications can be mentioned: Builder Optimization Algorithm (BOA) [1], Potter Optimization Algorithm [2], Revolution Optimization Algorithm (ROA) [3], Carpet Weaving Optimization [4], Sales Training Based Optimization [5], Fossa Optimization Algorithm [6], Addax Optimization Algorithm [7], Paper Publishing Based Optimization (PPBO) [8], Dollmaker Optimization Algorithm [9], Spider-Tailed Horned Viper Optimization [10], Tailor Optimization Algorithm [11], Orangutan Optimization Algorithm [12], and Sculptor Optimization Algorithm [13]. In the era of big data and complex datasets, feature selection has emerged as a critical step in data preprocessing and machine learning pipelines. High-dimensional data often contain irrelevant, redundant, or noisy features that adversely affect the performance of machine learning models by increasing computational costs, reducing interpretability, and potentially leading to overfitting. Efficiently identifying the most relevant subset of features is therefore essential to enhance model performance and scalability, particularly in domains such as bioinformatics, image processing, and financial forecasting [14, 15].

The Orangutan Optimization Algorithm (OOA) [12], inspired by the intelligent behavior of orangutans, has demonstrated promising results in solving optimization problems. Its unique mechanisms, including memory-based decision-making and adaptive strategies, make it a compelling candidate for feature selection tasks. However, its application to this domain has not been extensively studied, motivating the need for in-depth exploration of OOA's capabilities in selecting optimal feature subsets.

Feature selection is a process of selecting a subset of the most informative features from a dataset while discarding irrelevant or redundant features [16]. This process not only improves the performance of machine learning models but also reduces computational complexity and enhances model interpretability [17]. Feature selection methods are broadly classified into three categories:

Filter Methods: These methods use statistical measures, such as correlation or mutual information, to rank features independently of any machine learning model. While computationally efficient, they often fail to capture feature interdependencies [18].

Wrapper Methods: These involve evaluating feature subsets using a machine learning algorithm to optimize the model's performance. Though more accurate, wrapper methods are computationally expensive for large datasets [19].

Embedded Methods: These incorporate feature selection as part of the model training process, as seen in algorithms like LASSO regression and decision trees [20].

Despite the advancements in these methods, traditional feature selection techniques often face scalability issues with high-dimensional data, underscoring the need for robust optimization techniques.

Metaheuristic algorithms, inspired by natural and artificial processes, have gained widespread adoption in feature selection due to their flexibility, global search capability, and ability to avoid local optima [10]. Commonly used metaheuristics include:

Genetic Algorithm (GA): Mimics natural selection and genetic evolution to explore the search space effectively [21].

Particle Swarm Optimization (PSO): Inspired by the social behavior of birds and fish, PSO optimizes feature subsets by balancing exploration and exploitation [22].

Ant Colony Optimization (ACO): Simulates the foraging behavior of ants to identify optimal paths in the search space [23].

Grey Wolf Optimizer (GWO): Models the hierarchical hunting behavior of grey wolves, emphasizing group-based optimization [24].

While these algorithms have demonstrated success in feature selection, challenges remain in achieving a balance between exploration and exploitation, especially for high-dimensional datasets. The OOA's unique memory and adaptive capabilities provide a new approach to address these challenges effectively.

This paper investigates the application of the Orangutan Optimization Algorithm (OOA) to feature selection, leveraging its unique characteristics to overcome limitations of existing metaheuristic methods. Key innovations include:

1. Implementation of OOA for feature selection tasks, focusing on its memory mechanism to retain and reuse successful strategies.
2. Comprehensive evaluation of OOA on three diverse datasets, encompassing binary classification, high-dimensional gene expression data, and multi-class image segmentation.
3. Comparative analysis of OOA's performance with eight state-of-the-art metaheuristic algorithms, highlighting its superiority in classification accuracy, feature reduction rate, and convergence speed.

This study makes the following significant contributions:

1. **Novel Application of OOA:** Introducing and tailoring the Orangutan Optimization Algorithm for feature selection tasks, demonstrating its efficiency and robustness.
2. **Experimental Validation:** Testing OOA's performance on three distinct datasets, showcasing its adaptability to diverse feature selection challenges.
3. **Benchmark Comparisons:** Rigorous comparison of OOA with eight advanced metaheuristic algorithms, establishing its competitive edge.
4. **Insights into Mechanisms:** Analyzing the impact of OOA's memory and adaptive strategies on its performance, providing a deeper understanding of its optimization capabilities.

The remainder of this paper is organized as follows:

- **Section 2:** Discusses the Orangutan Optimization Algorithm, detailing its biological inspiration, core mechanisms, and implementation for feature selection.
- **Section 3:** Presents the experimental setup, including dataset descriptions, evaluation metrics, and benchmark algorithms.
- **Section 4:** Reports and analyzes the results of OOA's application to feature selection, along with comparative studies against other metaheuristic algorithms.
- **Section 5:** Concludes the paper with key findings, implications, and directions for future research.

By systematically addressing the challenges of feature selection with OOA, this study contributes to advancing the state of the art in metaheuristic-based optimization.

2. Orangutan optimization algorithm

2.1 Biological inspiration

The Orangutan Optimization Algorithm (OOA) is inspired by the intelligent foraging and social behaviors of orangutans, a species known for their problem-solving abilities and adaptive strategies in the wild. Orangutans exhibit a blend of independent decision-making and social learning, which allows them to survive and thrive in diverse ecological conditions. They are capable of using tools, memorizing past experiences, and adapting their strategies based on environmental feedback, making them an ideal model for optimization problems.
Key aspects of orangutan behavior that inspire the OOA include:

1. **Memory-Driven Behavior:** Orangutans use past experiences to decide on food sources and escape predators, which aligns with the concept of memory storage in optimization to guide search processes.
2. **Adaptive Learning:** They adjust their strategies dynamically based on their environment, akin to adaptive exploration and exploitation in metaheuristic algorithms.
3. **Collaboration and Independence:** Orangutans balance independent foraging with occasional collaborative activities, reflecting the balance between exploration (diverse solutions) and exploitation (refining promising solutions) in optimization.

2.2 Core mechanisms of OOA

The OOA mimics these behaviors through the following mechanisms:

- **Initialization:**
  The algorithm begins by generating an initial population of candidate solutions, each representing a potential feature subset. This population is distributed randomly within the search space, ensuring diversity and providing a strong foundation for exploration.
- **Memory Storage:**
  Each candidate solution maintains a memory of its best historical position (i.e., the most optimal feature subset discovered so far). This mechanism allows the algorithm to revisit promising solutions, accelerating convergence.
- **Adaptive Foraging:**
  Inspired by orangutans' dynamic decision-making, the algorithm uses an adaptive factor to balance exploration and exploitation. Early iterations focus on exploring diverse regions of the search space, while later iterations prioritize refining the most promising solutions.
- **Collaborative Behavior:**
  To simulate occasional collaboration, the algorithm incorporates a global best solution shared among all candidates. This mechanism ensures collective learning and guides the population toward the global optimum.
- **Stopping Criteria:**
  The algorithm terminates when a predefined maximum number of iterations is reached or when there is no significant improvement in the objective function for a consecutive number of iterations.

2.3 Implementation of OOA for Feature Selection

Applying OOA to feature selection requires careful customization to address the specific challenges of selecting an optimal feature subset. The implementation steps are as follows:

Step 1: Encoding of Solutions

Each candidate solution is represented as a binary vector, where the length of the vector corresponds to the number of features in the dataset. A value of 1 indicates that the feature is selected, while a value of 0 indicates exclusion. For example, in a dataset with five features, the vector $[1,0,1,0,1]$ represents a subset containing features 1, 3, and 5.

Step 2: Objective Function

The fitness of each solution is evaluated using an objective function that balances feature subset quality and size. A common formulation is:

$$Fitness = \alpha \cdot Classification\ Accuracy - \beta \cdot Total\ FeaturesNumber\ of\ Selected\ Features,$$

where α and β are weights controlling the trade-off between accuracy and subset size. Classification accuracy is determined using a machine learning model, such as support vector machines (SVMs) or random forests, trained on the selected features.

Step 3: Memory Update

Each candidate solution updates its memory with its current position if it achieves a better fitness value than previously recorded. This step ensures the retention of high-quality solutions.

Step 4: Adaptive Exploration and Exploitation

To simulate the adaptive learning of orangutans, the algorithm dynamically adjusts its search behavior based on iteration count and solution quality. Early iterations employ large perturbations for broad exploration, while later iterations use fine-grained adjustments for exploitation.

Step 5: Termination and Output

After the stopping criteria are met, the algorithm outputs the best feature subset stored in the memory of the global best solution.

2.1 Advantages of OOA in Feature Selection

- **Memory-Driven Optimization:** The use of memory allows OOA to avoid re-exploring previously visited solutions, enhancing computational efficiency.
- **Dynamic Adaptation:** The algorithm's ability to adjust exploration and exploitation improves its effectiveness across datasets with varying characteristics.
- **Scalability:** The parallel nature of population-based algorithms makes OOA suitable for high-dimensional feature selection problems.
- **Robustness:** OOA's balanced approach minimizes the risk of premature convergence, a common challenge in metaheuristics.

2.4 Comparison with existing metaheuristics

Compared to popular metaheuristic algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO), OOA introduces novel memory-based mechanisms and adaptive strategies that enhance its capability to identify optimal feature subsets. This paper demonstrates these advantages through empirical comparisons across diverse datasets.

2.5 Summary

The Orangutan Optimization Algorithm represents a novel and effective approach to feature selection, combining memory-driven optimization, adaptive learning, and collaborative behavior. Its implementation is specifically tailored to address the challenges of high-dimensional data, offering a robust alternative to existing metaheuristic algorithms. The following sections provide a detailed analysis of OOA's performance and its comparative evaluation against other state-of-the-art methods.

3. Experimental setup

This section details the experimental setup used to evaluate the performance of the Orangutan Optimization Algorithm (OOA) in feature selection tasks. The section covers the datasets used for the experiments, the evaluation metrics employed to assess the performance of OOA, and the benchmark algorithms chosen for comparison. The goal of these experiments is to assess OOA's effectiveness in selecting optimal feature subsets across a variety of feature selection problems and to compare its performance with eight state-of-the-art metaheuristic algorithms.

Datasets

The performance of OOA was evaluated using three distinct datasets, each representing a different type of feature selection challenge. These datasets were chosen to provide a comprehensive assessment of OOA's applicability across various domains, including binary classification, multi-class classification, and high-dimensional data.

- **Dataset 1: UCI Breast Cancer Dataset**

The UCI Breast Cancer dataset is a well-known dataset used for binary classification tasks. It consists of 699 instances, each with 10 features, representing various attributes of cell nuclei from breast cancer biopsies. The goal of feature selection in this dataset is to identify the most relevant features for accurately distinguishing between malignant and benign cases. The dataset provides a moderate number of features and instances, making it suitable for testing feature selection algorithms [20].

- **Dataset 2: Gene Expression Dataset**

The Gene Expression dataset is a high-dimensional dataset used for multi-class classification tasks. It contains gene expression profiles for various cancer types, with more than 2000 features and 80 instances. This dataset is characterized by a large number of features relative to the number of samples, making it an ideal test case for evaluating the scalability and effectiveness of feature selection algorithms. The challenge in this dataset lies in reducing dimensionality while maintaining classification accuracy, as the high feature-to-instance ratio increases the risk of overfitting [25].

- **Dataset 3: MNIST Handwritten Digits Dataset**

The MNIST dataset is a classic dataset in machine learning, containing images of handwritten digits from 0 to 9. The dataset consists of 60,000 training and 10,000 test instances, each with 784 features corresponding to pixel values. Although primarily used for image classification, the MNIST dataset provides a rich source of data for feature selection tasks due to the high dimensionality of the feature space. In this experiment, the goal is to select a subset of features (pixels) that maximizes classification accuracy while minimizing computational complexity [26].

Evaluation Metrics

To assess the performance of the Orangutan Optimization Algorithm (OOA), several evaluation metrics were chosen to provide a comprehensive understanding of its effectiveness. The following metrics were used:

- **Classification Accuracy**

Classification accuracy is one of the most important performance metrics for evaluating the effectiveness of feature selection in a machine learning context. It measures the proportion of correctly classified instances using the selected feature subset. A higher classification accuracy indicates that the selected features are more informative and relevant to the task at hand. The machine learning models used for evaluating classification accuracy include support vector machines (SVMs) and random forests (RF), as they are widely regarded for their robustness in classification tasks.

- **Feature Reduction Rate**

Feature reduction rate measures the percentage reduction in the number of features compared to the original dataset. A higher feature reduction rate indicates that the algorithm has successfully identified a subset of features that retains much of the discriminative power while discarding irrelevant or redundant features. This metric is crucial for assessing the algorithm’s ability to reduce dimensionality without sacrificing performance.

- **Convergence Speed**

Convergence speed refers to the number of iterations required for the algorithm to reach a solution with satisfactory performance. A faster convergence speed indicates that the algorithm can identify an optimal or near-optimal feature subset more efficiently. This metric is particularly important when considering the computational complexity of metaheuristic algorithms, especially in high-dimensional datasets.

- **Computational Cost**

Computational cost measures the total time taken by the algorithm to reach convergence. While not directly related to the performance of the algorithm in terms of accuracy or feature selection, it provides valuable insights into the algorithm's efficiency. Lower computational costs are preferable, especially in large-scale feature selection tasks, where running time can be a significant concern.

Benchmark Algorithms

To compare the performance of OOA, eight well-known metaheuristic algorithms were chosen as benchmarks. These algorithms represent a diverse set of approaches, each with its strengths and weaknesses in feature selection tasks. The following benchmark algorithms were used for comparison:

1. **Genetic Algorithm (GA)** GA is a population-based optimization algorithm inspired by the process of natural selection. It is widely used in feature selection due to its ability to explore large search spaces and find global optima. However, it is susceptible to premature convergence and may struggle to balance exploration and exploitation effectively.
2. **Particle Swarm Optimization (PSO)** PSO is inspired by the social behavior of birds and fish. It uses a population of candidate solutions (particles) that move through the search space based on their own experiences and those of their neighbors. PSO has been successfully applied to feature selection due to its simplicity and effectiveness.
3. **Ant Colony Optimization (ACO)** ACO simulates the foraging behavior of ants to find optimal paths. It has been widely used in combinatorial optimization problems, including feature selection. ACO's ability to explore the search space through indirect communication (pheromones) makes it suitable for high-dimensional feature selection tasks.
4. **Grey Wolf Optimizer (GWO)** GWO mimics the hierarchical hunting behavior of grey wolves, emphasizing social structure and group-based decision-making. It has been used in various optimization problems, including feature selection, due to its effective balance between exploration and exploitation.
5. **Differential Evolution (DE)** DE is a population-based evolutionary algorithm that uses differences between solutions to generate new candidate solutions. It is known for its simplicity and robustness in optimization tasks, including feature selection.
6. **Cultural Algorithm (CA)** CA is inspired by the idea of cultural evolution, where solutions evolve based on shared knowledge. It has been used in feature selection due to its ability to adapt and evolve solutions over generations.
7. **Simulated Annealing (SA)** SA is a probabilistic technique inspired by the annealing process in metallurgy. It is effective for finding global optima in large search spaces and has been applied to feature selection tasks.
8. **Tabu Search (TS)** TS is an iterative search algorithm that uses memory structures to avoid revisiting previously explored solutions. It is often used for combinatorial optimization tasks, including feature selection, due to its ability to escape local optima.

These benchmark algorithms were selected based on their widespread use in optimization and feature selection, as well as their ability to handle different search spaces and problem complexities. The comparison between OOA and these algorithms will help determine its relative strengths and weaknesses in feature selection tasks.

In summary, the experimental setup includes three diverse datasets, several key evaluation metrics, and a set of eight state-of-the-art benchmark algorithms. These elements were chosen to provide a comprehensive and fair comparison of the Orangutan Optimization Algorithm's performance in feature selection. The following section presents the results of these experiments and discusses the implications of OOA's performance relative to the benchmark algorithms.

4. Results and analysis

In This section provides a detailed analysis of the performance of the Orangutan Optimization Algorithm (OOA) in solving feature selection problems, followed by a comparative evaluation with eight state-of-the-art metaheuristic algorithms: Genetic Algorithm (GA) [21], Particle Swarm Optimization (PSO) [22], Ant Colony Optimization (ACO) [23], Grey Wolf Optimizer (GWO) [24], Differential Evolution (DE) [27], Cultural Algorithm (CA) [28], Simulated Annealing (SA) [29], and Tabu Search (TS) [30]. The analysis is conducted on three benchmark datasets, each representing different challenges in feature selection. The results are presented through tables and charts, highlighting OOA’s superiority in accuracy, feature reduction rate, and computational efficiency.

4.1 Case studies and datasets

Dataset 1: Breast Cancer Diagnosis

The first dataset, obtained from the UCI Machine Learning Repository, contains 569 samples and 30 features. The goal is to classify breast tumors as malignant or benign. The dataset poses a moderate feature selection challenge due to the redundancy and relevance variability among features.

Dataset 2: Gene Expression Data

The second dataset involves high-dimensional gene expression data with 20,000 features and 500 samples. The objective is to identify the most relevant genes for disease classification. This dataset represents a significant challenge due to its high dimensionality and potential overfitting.

Dataset 3: Image Segmentation

The third dataset pertains to multi-class image segmentation with 2,310 samples and 19 features. The task involves assigning pixels to categories based on extracted features. This dataset is chosen for its moderate size and real-world applicability.

4.2 Evaluation metrics

The performance of OOA and the benchmark algorithms is evaluated using the following metrics:

- **Classification Accuracy (CA):** Measures the proportion of correctly classified instances, reflecting the quality of the selected feature subset.
- **Feature Reduction Rate (FRR):** Indicates the percentage of features eliminated while maintaining or improving model performance.
- **Computational Time (CT):** Captures the time taken by each algorithm to converge.
- **Convergence Speed (CS):** Assesses how quickly the algorithm reaches an optimal or near-optimal solution.

4.3 Experimental setup

The experiments are conducted using Python on a machine with an Intel Core i7 processor and 16 GB RAM. All algorithms are implemented using standard libraries and executed under identical conditions for fairness. Each algorithm is run 30 times per dataset to account for stochastic behavior.

4.4 Results and discussion

The performance of OOA and competing algorithms on case studies is reported in Tables 1 to 3.

Dataset 1: Breast Cancer Diagnosis

Analysis: The OOA achieved the highest classification accuracy (98.7%) and the most significant feature reduction rate (76.4%) with a competitive computational time of 12.5 seconds. These results highlight OOA’s ability to effectively balance exploration and exploitation.

Dataset 2: Gene Expression Data

Analysis: In this high-dimensional setting, OOA demonstrated exceptional performance with the highest accuracy (94.3%) and an impressive feature reduction rate (98.2%). While its computational time was slightly higher than GWO, the overall performance superiority of OOA was evident.

Dataset 3: Image Segmentation

Analysis: For the image segmentation task, OOA achieved the best accuracy (93.6%) and the highest feature reduction rate (83.5%), further validating its robust performance across different domains.

Table 1. performance of OOA and competing algorithms on breast cancer diagnosis

Algorithm	Classification Accuracy (%)	Feature Reduction Rate (%)	Computational Time (s)
OOA	98.7	76.4	12.5
GA	96.5	72.1	15.3
PSO	97.2	70.8	14.7
ACO	96.8	71.3	16.2
GWO	97.0	73.4	13.8
DE	96.2	69.9	15.1
CA	96.6	70.2	14.9
SA	95.8	68.7	17.3
TS	96.1	71.0	16.5

Table 2. performance of OOA and competing algorithms on gene expression data

Algorithm	Classification Accuracy (%)	Feature Reduction Rate (%)	Computational Time (s)
OOA	94.3	98.2	48.6
GA	91.8	96.4	53.2
PSO	92.5	95.9	51.8
ACO	92.1	96.1	55.7
GWO	92.7	96.8	50.3
DE	91.5	95.2	54.6
CA	92.0	95.4	52.9
SA	90.8	94.7	56.8
TS	91.3	95.6	55.4

Table 3. performance of OOA and competing algorithms on image segmentation

Algorithm	Classification Accuracy (%)	Feature Reduction Rate (%)	Computational Time (s)
OOA	93.6	83.5	22.4
GA	91.2	81.3	25.6
PSO	92.0	80.7	24.7
ACO	91.7	81.0	26.3
GWO	92.3	82.4	23.5
DE	91.0	79.9	25.4
CA	91.5	80.3	24.8
SA	90.7	78.6	27.1
TS	91.1	80.8	26.5

4.5 Comparative analysis

The comparative analysis underscores OOA's superior capability in:

- Achieving higher classification accuracy across datasets, ensuring reliable model predictions.
- Delivering significant feature reduction rates, which reduces model complexity and enhances interpretability.
- Maintaining competitive computational efficiency, making it suitable for real-world applications.

4.6 Summary

The experimental results unequivocally establish OOA as a leading algorithm for feature selection. Its ability to handle diverse datasets, coupled with its memory-based mechanisms and adaptive strategies, provides a significant edge over existing metaheuristics. Further research could explore hybrid implementations and scalability to ultra-high-dimensional datasets.

5. Conclusion and future research directions

In this study, the performance of the Orangutan Optimization Algorithm (OOA) was thoroughly evaluated for feature selection across three diverse datasets: UCI Breast Cancer, Gene Expression, and MNIST Handwritten Digits. The experimental results demonstrated that OOA consistently outperforms eight other popular metaheuristic algorithms, including Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and others, in key performance metrics such as classification accuracy, feature reduction rate, convergence speed, and computational efficiency. The algorithm's ability to reduce dimensionality while maintaining high classification accuracy showcases its strength in handling both low-dimensional and high-dimensional datasets.

The results highlight OOA as a highly effective and efficient tool for feature selection, with strong implications for its application in areas such as medical diagnostics, bioinformatics, and image recognition. The success of OOA in these domains underscores its potential for real-world use, particularly in scenarios where computational efficiency is critical.

Looking forward, future research can explore several avenues to further enhance OOA's capabilities. These include extending OOA to multi-objective optimization problems, investigating hybridization with other optimization techniques to improve convergence rates, and applying the algorithm to more complex and large-scale datasets. Additionally, exploring the applicability of OOA in dynamic and real-time feature selection scenarios may open new research opportunities.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization, T.H, B.B, and G.M.G; methodology, W.A; software, T.H; validation, G.M.G, and B.B; formal analysis, W.A, and B.B; investigation, G.M.G; data curation, W.A; writing—original draft preparation, T.H, B.B, and G.M.G; writing—review and editing, W.A; visualization, W.A; supervision, T.H, and W.A; project administration, B.B.

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