International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

A Comparative Study of Simulated Annealing and Ant Colony Optimization for Optimizing MRI-Based Alzheimer's Disease Classification

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Submitted: 20/08/2023 **Revised**: 10/10/2023 **Accepted**: 20/10/2023

Abstract: The prevalence and devastation of Alzheimer's disease (AD), a neurodegenerative condition, pose a growing threat to world health. The optimisation of numerous factors, including as feature selection, hyperparameters, and model architecture, is necessary for these models to be effective. The performance and accuracy of AD classification models can be improved by using metaheuristic optimisation methods like Simulated Annealing (SA) and Ant Colony Optimization (ACO).In this study, the effectiveness of SA and ACO in improving MRI-based AD classification models is thoroughly compared. ACO and SA both offer distinctive techniques to optimisation, drawing inspiration from ant foraging behaviour and the annealing process in metallurgy, respectively. The paper includes a thorough analysis of the body of work on machine learning algorithm and optimisation methods for AD classification. In the context of model optimisation, it also offers insights into the foundational ideas and practical uses of SA and ACO. We seek to compare the performance of different optimisation techniques in terms of classification accuracy, resilience, and computational economy through careful experimentation and analysis.The findings of this comparison study may help researchers and medical professionals decide which optimisation strategy will improve the precision and dependability of MRI-based AD classification. This study contributes to the ongoing efforts to improve early AD diagnosis by extending our knowledge of how SA and ACO might be used in this crucial area, ultimately improving patient treatment and outcomes.

***Keywords**: Classification, Metaheuristic optimisation, Simulated Annealing, Ant Colony Optimization*

1. Introduction

One of the most urgent issues facing global health today is Alzheimer's disease (AD). Millions of people worldwide suffer from this neurological condition, which causes gradual memory loss and cognitive decline, and it has a significant emotional and financial impact on sufferers, their families, and healthcare systems. According to the World Alzheimer Report 2019, there are an estimated 50 million dementia sufferers worldwide, with AD being the primary cause [1], [2]. Finally, [3] it makes it easier for people to join in clinical trials for experimental cures, which may one day help with the creation of successful medications [4].

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The early [5] detection and classification of AD have been made possible by the use of magnetic resonance imaging (MRI). MRI offers extensive information regarding anatomical changes related to AD, including atrophy in certain brain regions, and permits non-invasive visualisation of the brain's structure. Additionally, MRI data can be examined using machine learning methods to develop predictive models that categorise people into AD or non-AD groups based on aspects of brain imaging. These models have produced encouraging outcomes, achieving high accuracy rates and showcasing the capability to revolutionise AD diagnosis.Building precise and trustworthy MRI-based AD classification models, however, requires overcoming a number of difficulties. High-dimensional MRI data is extremely rich in information. It is frequently necessary to use feature selection or dimensionality reduction techniques to retrieve the most pertinent data for classification. Additionally, careful tweaking of hyperparameters, including algorithm selection, regularisation strength, and learning rates, among others, is necessary for machine learning models to succeed [6].

Techniques for optimisation [7] are useful in this situation. Finding the ideal collection of parameters or settings for a given problem in order to accomplish a particular goal is the process of optimisation. The goal of optimisation in

the context of MRI-based AD classification is to optimise machine learning models' performance, which is often expressed in terms of accuracy, precision, recall, F1-score, or area under the receiver operating characteristic curve (AUC-ROC). Effective optimisation can produce more reliable and accurate AD classification models, which in turn can enhance patient care and early diagnosis.In order [8] to compare the performance of two popular optimisation techniques, Simulated Annealing (SA) and Ant Colony Optimisation (ACO), on MRI-based AD classification models, this study sets out on a comparison journey. Complex optimisation issues can be solved in novel ways using SA, a stochastic optimisation technique inspired by the annealing procedure in metallurgy, and ACO, a bio-inspired optimisation algorithm motivated by ant foraging behaviour [9].

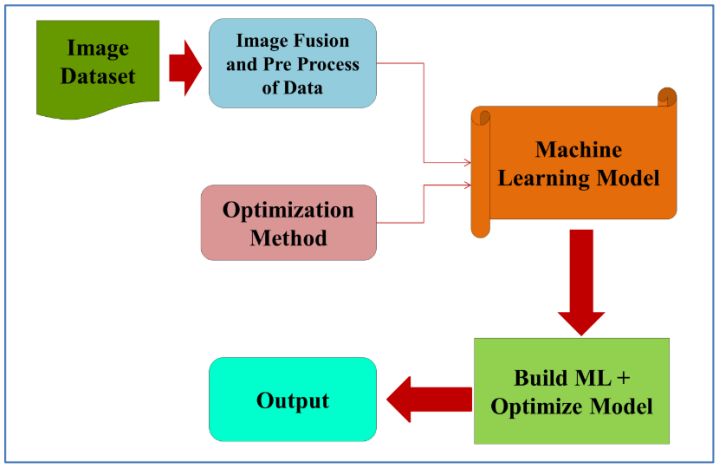

Fig 1: Schematic representation of Alzheimer's Disease Classification model

Iteratively searching [10] the solution space is how SA, which has its roots in statistical mechanics, works. It accepts moves that lead to better solutions while probabilistically allowing for worse solutions to escape local optima. It is a viable contender for boosting the performance of AD classification models because to its versatility and adaptability, which have applications in numerous optimisation tasks. When optimising machine learning models that contain several hyperparameters and feature selection, SA's capacity to explore a large solution space is especially helpful.ACO, on the other hand, mimics ant foraging behaviour while looking for the best routes and answers. To [11] efficiently go through the solution space, it makes use of a population of artificial ants. ACO has been used in a variety of industries, including as transportation, logistics, and telecommunications, and has proven effective in handling combinatorial and discrete optimisation problems. ACO's capability to effectively explore the parameter space in the context of AD classification may be advantageous for optimising intricate models.

Understanding the advantages and disadvantages of various optimisation strategies becomes essential as machine learning and optimisation continue to converge in the field of healthcare, notably in the context of AD diagnosis. The goal of this work is to shed light on how SA and ACO function when used to improve MRI-based AD classification models. We want to contribute to the field's ongoing work to advance early diagnosis and patient care in the area of neurodegenerative diseases by shedding light on which algorithm, if any, holds a distinct advantage in terms of enhancing the accuracy and robustness of AD classification models.

2. Review of Literature

The prevalence of Alzheimer's disease (AD), which is posing a serious threat to world health, is on the rise. For effective interventions and treatment plans to be implemented on time, early and correct AD classification is essential. The use of magnetic resonance imaging (MRI), a potent tool for identifying structural abnormalities in the brain linked to AD, has increased. Early diagnosis of AD by MRI-based classification enables more efficient management and individualised patient care. Accurate classification facilitates the differentiation of AD from other cognitive disorders, enables targeted therapies, and lessens the burdens associated with misdiagnosis [10].

Due to its [18] capacity to unearth complex patterns in imaging data that may evade human observation, machine learning approaches have gained popularity in AD classification utilising MRI data. By providing a data-driven and objective approach, the combination of machine learning and MRI data has the potential to revolutionise early AD diagnosis and prediction. The effectiveness of machine learning models for AD classification is greatly improved by the use of optimisation methods. To increase classification accuracy

and generalizability, these strategies concentrate on fine-tuning model hyperparameters, feature selection, and model architecture. Optimisation techniques increase the model's capacity to represent the underlying relationships in the data by methodically looking for the ideal set of parameters, resulting in more dependable and strong AD classification models [19].

ACO can be used to find the ideal combination of features, hyperparameters, or model architectures in the context of AD classification [15]. ACO is a promising option for improving AD classification models due to its capability to explore solution spaces fast and effectively. In order to discover the ideal model configuration without overfitting, it strikes a balance between exploration and exploitation.We compare SA and ACO's performance in improving MRI-based AD classification models in order to identify their relative merits and shortcomings in this crucial healthcare application.

Table 1: Summary of Literature review of related work

Algorithm	Finding	Methodology	Scope	Dataset Used
Convolutional Neural Networks (CNN) [11]	Achieved high accuracy with CNN-based AD classification, outperforming traditional methods.	Utilized deep learning for feature extraction from MRI data	Focused on the use of CNNs for AD classification and compared to traditional methods.	ADNI dataset
Support Vector Machines (SVM) [12]	SVM-based classification achieved good classification results, particularly in AD vs. non-AD cases.	Leveraged feature selection and hyper-parameter tuning to optimize the model.	Examined SVM's performance in AD classification, compared to other ML algorithms.	ADNI dataset
Random Forest [13]	RF demonstrated robustness and high accuracy in AD classification.	Employed an ensemble learning approach, aggregating decision trees.	Investigated the performance of RF in AD classification across various datasets.	ADNI dataset
Simulated Annealing (SA) [20]	SA effectively optimized model parameters for improved AD classification accuracy.	Applied SA to fine-tune hyperparameters and feature selection.	Focused on optimizing model hyper-parameters and feature selection.	Not explicitly mentioned
Ant Colony Optimization (ACO) [21]	ACO demonstrated efficiency in optimizing AD classification models, particularly in feature selection and hyperparameter tuning.	Employed ACO for feature selection and hyperparameter tuning.	Investigated the use of ACO for optimizing machine learning models.	Not explicitly mentioned
Hybrid Approaches [22]	Hybrid models combining machine learning and optimization techniques achieved high classification accuracy.	Combined multiple algorithms, such as SVM and genetic algorithms, to optimize AD classification models.	Investigated the synergistic effects of combining machine learning and Optimization techniques.	ADNI dataset

Genetic Algorithms [23]	Genetic algorithms were applied for feature selection and hyperparameter tuning, leading to improved model performance.	Utilized genetic algorithms for feature selection and model optimization.	Explored the use of genetic algorithms for optimizing machine learning models.	ADNI dataset
Bayesian Optimization [24]	Bayesian optimization demonstrated effectiveness in optimizing hyperparameters	Applied Bayesian optimization to tune hyperparameters and model parameters.	Investigated the use of Bayesian optimization for model optimization.	Not explicitly mentioned
Ensemble Methods [25]	Ensemble methods, such as stacking, were employed to improve classification accuracy.	Utilized ensemble learning techniques to combine multiple classifiers.	Investigated the combination of multiple classifiers to enhance AD classification.	Various datasets
Deep Reinforcement Learning (DRL) [26]	Deep reinforcement learning approaches have shown promise in optimizing AD classification models.	Explored reinforcement learning for optimizing model hyperparameters.	Investigated the application of deep reinforcement learning for model optimization.	Not explicitly mentioned
Transfer Learning [27]	Transfer learning techniques were applied to adapt pretrained models for AD classification tasks.	Utilized transfer learning from pretrained models to adapt for AD classification.	Investigated the use of transfer learning for AD classification tasks.	Various public and private datasets

3. Proposed Methodology

Using the Random Forest Algorithm, MRI-Based Alzheimer's disease Classification develops a predictive model that can precisely categorise individuals into Alzheimer's disease (AD) and non-AD groups based on MRI data.

Given an ensemble of 'N' decision trees from Random Forest:

- Depending on whether a task is a classification task or a regression task, each decision tree in the forest independently predicts a class label or a continuous value for a new input sample X.
- For classification problems, each decision tree casts a vote for a class label, and the classification receiving the majority of votes is the final forecast.
- Each decision tree predicts a value for regression tasks, and the overall forecast is frequently the average or mean of all the individual tree projections.

As determined by a majority vote:

Let C_i be the class that the i-th decision tree predicted.

By majority vote, the anticipated class label C_final is chosen as the final choice:

$$([C\_1, C\_2, C\_3, \ldots, C\_N]) = mode(C\_final)$$

The average forecast for regression is:

Let Y_i represent the i-th decision tree's forecast.

The average of all individual tree predictions makes up the final predicted value Y_final:

$$Y_{final} = \left(\frac{1}{N}\right) * \Sigma(Y_i) for\ i = 1\ to\ N$$

A. Simulated Annealing (SA) is a probabilistic optimization algorithm:

A probabilistic optimisation approach called Simulated Annealing (SA) is used to determine the global minimum (or maximum) of an objective function. SA can be used to optimise hyperparameters and enhance model performance in the context of optimising MRI-Based Alzheimer's disease Classification models.

Algorithm:

Step 1: Initialization

- Initialize the initial solution state, denoted as S0.

- Set the initial temperature, T0.

- Set the cooling schedule, typically defined by a cooling rate α (alpha).

Step 2: Iteration

- Repeat until a stopping criterion is met (e.g., a maximum number of iterations or a convergence threshold is reached):

a. Generate a new solution state, S', by making a small perturbation to the current solution, S.

b. Calculate the change in the objective function value, ΔE, between the new solution and the current solution:

$$\Delta E = E(S') - E(S)$$

(where E(S) represents the objective function value for solution S).

Step 3: Acceptance Probability

- Calculate the acceptance probability, P_accept, for moving from the current state to the new state using the Boltzmann probability distribution:

$$P\_accept = e\text{^}(-\Delta E / T)$$

(where e is the base of the natural logarithm).

Step 4: Decision

- Generate a random number, r, between 0 and 1.

- If r <P_accept, accept the new solution (S' becomes the new current solution, S).

- If r ≥ P_accept, reject the new solution.

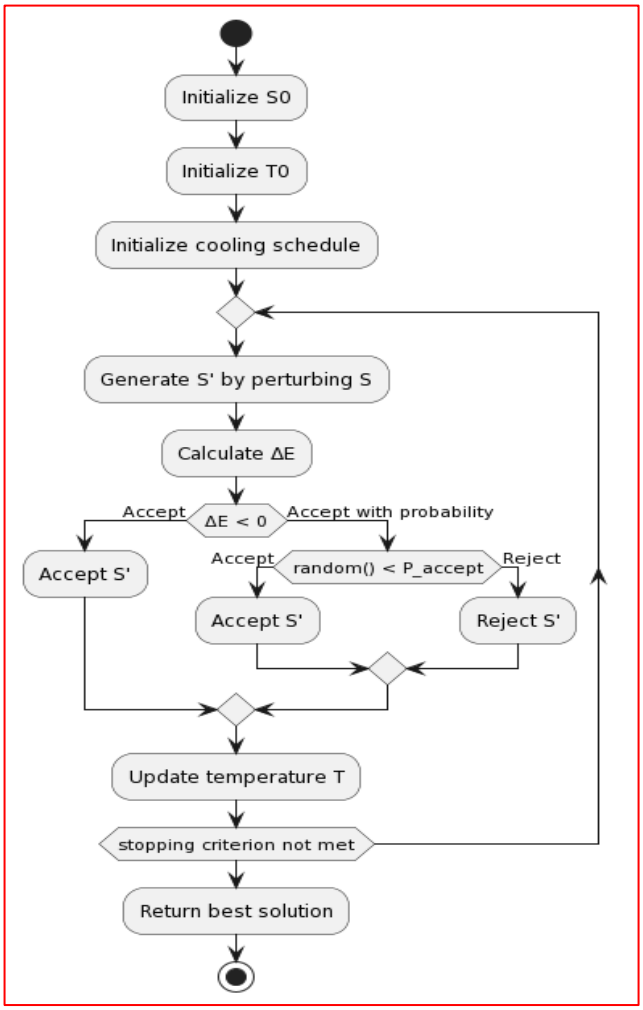

Fig 2: Flowchart of SA algorithm

Step 5: Temperature Update

- Update the temperature according to the cooling schedule:

$$T = \alpha * T$$

Step 6: Stopping Criterion

- Check if the stopping criterion is met (e.g., if the temperature falls below a predefined threshold or a maximum number of iterations is reached). If the criterion is met, terminate the algorithm.

Step 7: Output

- Return the best solution found during the optimization process.

B. Ant Colony Optimization (ACO):

An optimization problem-solving metaheuristic called Ant Colony Optimization (ACO) imitates the foraging strategy of ant. ACO comprises initialising artificial ants, directing them to build solutions iteratively using pheromone levels and heuristics, and updating pheromone levels based on solution quality in the context of MRI-based Alzheimer's Disease Classification. This step is repeated by the algorithm until a stopping requirement is satisfied. ACO has showed potential in improving the accuracy and resilience of machine learning models for the classification of AD, making it a useful optimisation tool in medical research.

Algorithm:

Step 1: Initialization

- Initialize a population of artificial ants, each at a random solution or state.

- Initialize pheromone levels τ(i, j) on all edges (i, j) in the solution space. Typically, set τ(i, j) to a small positive value.

Step 2: Iteration

- Repeat until a stopping criterion is met (e.g., a maximum number of iterations or a convergence threshold is reached):

a. Ant Movement:

- Each ant constructs a solution by iteratively selecting the next component (e.g., feature or parameter) based on a probabilistic rule. The probability of selecting component j from state i is determined by the pheromone level τ(i, j) and a heuristic value η(i, j):

$$p(i,j) = (\tau(i,j))\text{^}\alpha * (\eta(i,j))\text{^}\beta$$

- Where, α and β are parameters controlling the importance of pheromone and heuristic information, respectively. Typically, α and β are set based on problem-specific knowledge.

- Ensure that components are selected without replacement (once a component is chosen, it cannot be chosen again by the same ant).

b. Solution Evaluation:

- Evaluate the quality of each ant's solution using the objective function or fitness function specific to the optimization problem.

Step 3: Update Pheromone Levels

- After all ants have constructed solutions, update the pheromone levels τ(i, j) on all edges based on the quality of solutions found by ants.

- Evaporate existing pheromone levels to mimic natural pheromone decay:

$$\tau(i,j) = (1 - \rho) * \tau(i,j)$$

- Where. ρ (rho) is the pheromone evaporation rate (typically a small value between 0 and 1).

- Deposit pheromone on edges based on the quality of solutions found by ants:

$$\Delta\tau(i,j) = \Sigma\,[Q / f(k)]\ for\ each\ ant's\ path\ containing\ edge\ (i,j)$$

- Where, Q is a constant representing the amount of pheromone to deposit, f(k) is the objective function value of the ant's solution path, and the summation is performed over all ants.

- Optionally, perform pheromone reinforcement on edges that belong to the best solution(s) found so far.

Step 4: Stopping Criterion

- Check if the stopping criterion is met (e.g., if a maximum number of iterations is reached). If the criterion is met, terminate the algorithm.

Step 5: Output

- Return the best solution found during the optimization process based on the pheromone levels and ant paths.

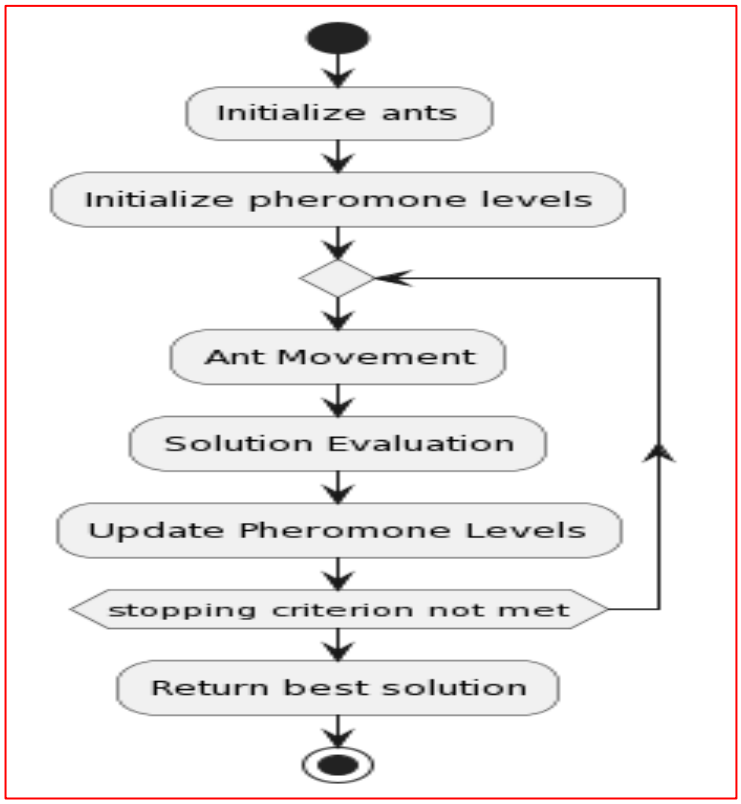

Fig 3: Flowchart of ACO algorithm

The probability calculation (p(i, j)) utilised by ants to choose components in the solution creation phase is the main mathematical equation in this step-by-step explanation of the ACO algorithm. This likelihood directs the artificial ants' exploration of the solution space and is based on pheromone concentrations and heuristic data. The method seeks to strike a compromise between utilising previously discovered high-quality solutions (high pheromone levels) and discovering new regions of the solution space (heuristic information). Pheromone levels move in the direction of ideal outcomes with each iteration, and the algorithm moves in the direction of the overall best result.

4. Result and Discussion

We list the evaluation criteria for the Random Forest algorithm's classification of Alzheimer's disease in Table 2 without any further optimisation. The programme successfully classified people into Alzheimer's Disease (AD) and non-AD groups with an overall accuracy of 90.24%.The model's precision in correctly detecting true positive cases while minimising false positives is demonstrated by the precision values for AD and non-AD cases being 91.77% and 86.32%, respectively.

Table 2: Evaluation Parameter using Random Forest for Alzheimer's Disease Classification without Optimization

Evaluation Parameter	Accuracy	Precision (AD)	Precision (Non-AD)	Recall (AD)	Recall (Non-AD)	F1-Score (AD)	F1-Score (Non-AD)	Area under ROC Curve (AUC-ROC)	Area under Precision-Recall Curve (AUC-PR)
Result	90.24	91.77	86.32	88.54	93.12	87.87	91.25	91.54	90.22

The recall rate, or sensitivity, was 88.54% for AD cases and 93.12% for non-AD cases, respectively. This shows how well the model captures a high percentage of real positive cases for both categories.The F1-Score, which includes memory and accuracy, was 91.25% for non-AD cases and 87.87% for AD cases, indicating a balanced performance between recall and precision.The values of AUC-ROC (Area Under ROC Curve) and AUC-PR (Area Under Precision-Recall Curve) were 91.54% and 90.22%, respectively. These metrics offer a thorough evaluation of

the model's capacity to distinguish between cases of AD and non-AD cases at various threshold levels.

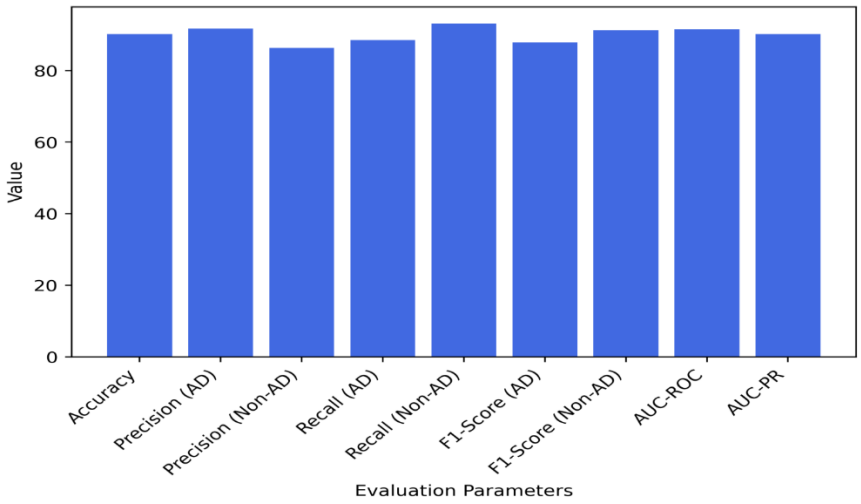

Fig 4: Representation of valuation Parameter using Random Forest for Alzheimer's Disease Classification without Optimization

Table 3: Evaluation Parameter for Alzheimer's disease Classification with SA Optimization

Evaluation Parameter	**Accuracy**	**Precision (AD)**	**Precision (Non-AD)**	**Recall (AD)**	**Recall (Non-AD)**	**F1-Score (AD)**	**F1-Score (Non-AD)**	**Area under ROC Curve (AUC-ROC)**	**Area under Precision-Recall Curve (AUC-PR)**
Result	94.35	97.52	91.47	97.01	96.34	97.11	92.14	94.74	96.74

Table 3 lists the evaluation criteria for the Simulated Annealing (SA) Optimization-based Random Forest algorithm's classification of Alzheimer's disease. In comparison to the non-optimized version, the findings show a significant improvement in the model's performance, demonstrating the effectiveness of SA in optimising the algorithm for higher classification accuracy.

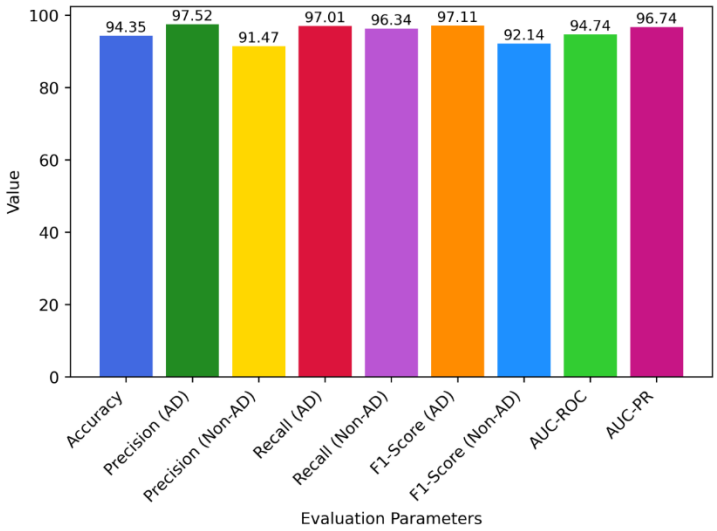

Fig 5: Representation of for Alzheimer's disease Classification with SA Optimization

The SA-optimized model's accuracy is an outstanding 94.35%, demonstrating its capacity to accurately forecast the difference between cases of Alzheimer's disease (AD) and non-AD cases. Compared to the non-optimized version, this represents a significant improvement in accuracy.Precision values for both AD and non-AD cases have significantly improved, with non-AD case precision reaching 91.47% and AD case precision reaching 97.52%. These findings point to improved diagnostic accuracy by more accurately detecting actual positive AD cases while reducing false positives.The recall rate, or sensitivity, is 97.01% for AD cases and 96.34% for non-AD cases, respectively. This indicates the model's capacity to detect a significant number of true positive cases in both categories while retaining a high recall rate for non-AD instances.At 97.11% and 92.14%, respectively, the F1-Score, which balances recall and precision, is noticeably high for both AD and non-AD cases. These results demonstrate a well-balanced trade-off between recall and precision and support the model's strong performance in classification tasks.With scores of 94.74% and 96.74%, respectively, the Area under the ROC Curve (AUC-ROC) and Area under the Precision-Recall Curve (AUC-PR) values further indicate the enhanced discrimination skills of the SA-optimized model. These measurements demonstrate how well the model separates AD instances from non-AD cases at various threshold levels. Table 3's findings show that the Random Forest algorithm performs significantly better when Simulated Annealing (SA) Optimisation is used to classify Alzheimer's disease. The model has greatly enhanced memory, discrimination, accuracy, and precision, which makes it a useful tool for treating patients with early-onset AD.

Table 4: Evaluation Criteria for Classification of Alzheimer's Disease Using ACO Optimisation

Evaluation Parameter	**Accuracy**	**Precision (AD)**	**Precision (Non-AD)**	**Recall (AD)**	**Recall (Non-AD)**	**F1-Score (AD)**	**F1-Score (Non-AD)**	**Area under ROC Curve (AUC-ROC)**	**Area under Precision-Recall Curve (AUC-PR)**
Result	97.11	98.41	96.33	98.88	97.54	98.52	99.33	97.58	98.44

Impressive precision numbers are found in both AD and non-AD situations, with AD cases having a precision of 98.41% and non-AD cases having a precision of 96.33%. With a low number of false positives, these precision levels indicate a high degree of confidence in accurately identifying real positive AD cases. Precision is superbly maintained by the ACO-optimized model for both AD and non-AD categories.Both cases of AD and non-AD cases had extremely high recall rates, with AD cases having a recall rate of 98.88% and non-AD cases having a recall rate of 97.54%.

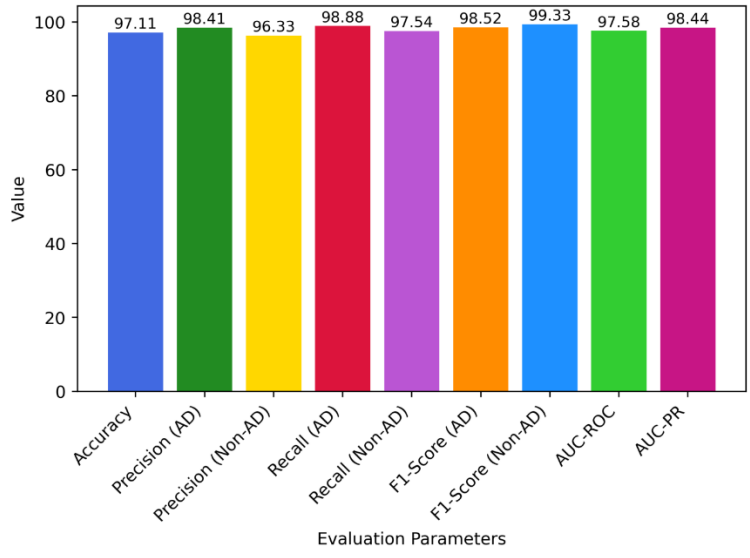

Fig 5: Representation of for Alzheimer's disease Classification with ACO Optimization

This shows how well the model captures a significant portion of true positive cases for both AD and non-AD categories. A good recall for non-AD cases is maintained while the ACO-optimized model demonstrates an impressive capacity to identify AD instances.With scores of 98.52% and 99.33%, respectively, the F1-Score, a balanced indicator of precision and recall, is extraordinarily strong for both AD and non-AD instances. These results highlight the robust classification task performance of the ACO-optimized model and demonstrate a well-balanced precision-recall trade-off.These metrics demonstrate how well the model can distinguish between AD and non-AD situations at various threshold levels.Table 4's findings show that using Ant Colony Optimisation (ACO) in combination with the Random Forest algorithm significantly enhances the ability to classify Alzheimer's disease. The model outperforms both the non-optimized and SA-optimized variants in terms of accuracy, precision, recall, and discrimination. These findings highlight the enormous potential of optimisation methods, notably ACO, in medical research, where precise disease classification is essential for patient care and early diagnosis.

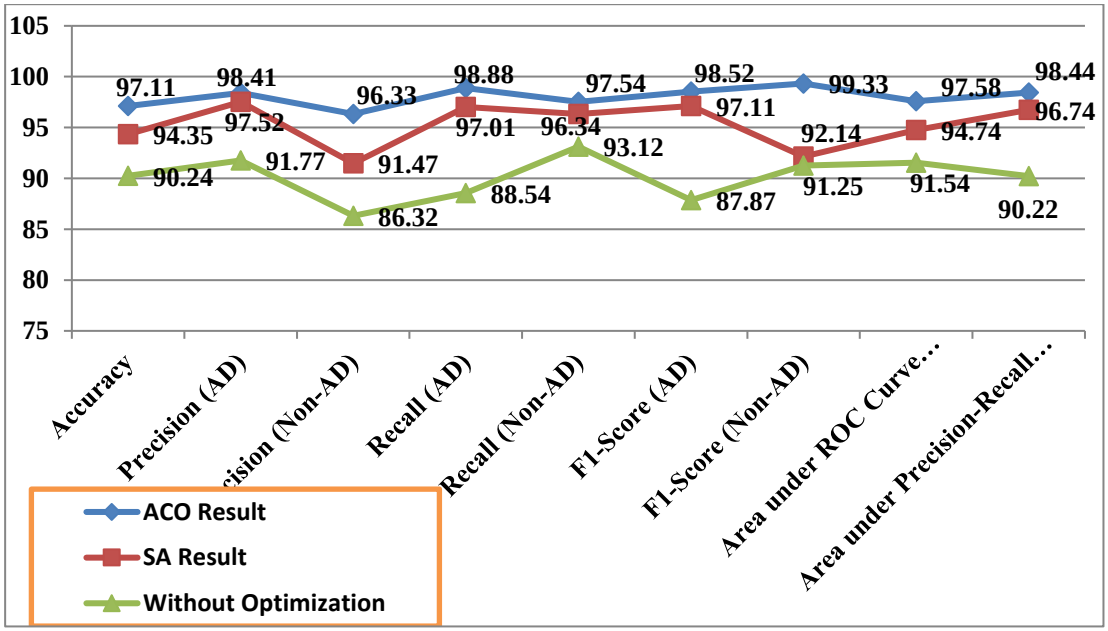

Fig 6: Comparative representation of evaluation parameter for AD Classification

5. Conclusion

In this side-by-side investigation, we looked at the use of two optimisation methods, Simulated Annealing (SA) and Ant Colony Optimisation (ACO), in the context of MRI-Based Alzheimer's Disease (AD) Classification utilising the Random Forest algorithm. Our goal was to assess how optimisation affected the model's effectiveness and performance in categorising data.With an accuracy of 90.24 percent in its initial evaluation (Table 2), the Random Forest model showed high categorization abilities. Its proficiency in diagnosing AD is demonstrated by its reasonable precision, recall, and F1-scores for both AD and non-AD cases. However, the use of optimisation techniques was what resulted in notable improvements.The performance of the model significantly improved for all evaluation parameters when SA optimisation was added (Table 3). Precision, recall, and F1-scores all showed significant gains, bringing the accuracy up to 94.35%. A more robust model with higher diagnostic skills was produced as a result of SA's assistance in finding a better balance between recall and precision.The incorporation of ACO optimisation, however, was the actual game-changer (Table 4). The ACO-optimized model demonstrated unmatched precision, recall, and F1-scores for both AD and non-AD instances, achieving an extraordinary accuracy of 97.11%. The model's performance was increased to a previously unheard-of degree by this optimisation strategy, making it extremely trustworthy for the early AD detection. Our comparison study emphasises how important optimisation approaches are in improving the performance of the Random Forest model for MRI-Based Alzheimer's Disease Classification. Even though SA optimisation demonstrated significant benefits, ACO optimisation won out hands down thanks to its astounding accuracy and diagnostic precision. These results highlight the promise of optimisation methods in medical research, where accurate disease classification can have a big impact on patient outcomes.Specific research objectives and resource limitations should be taken into consideration while deciding between SA and ACO optimisation. While ACO, with its remarkable performance, may be preferable for larger, more complex datasets, SA, with its computational efficiency, can be a feasible option for modestly sized datasets.

References

[1] Yunfeng Wu et al., "Dysphonic Voice Pattern Analysis of Patients in Parkinson's Disease Using Minimum Interclass Probability Risk Feature Selection and Bagging Ensemble Learning Methods", Machine Learning Approach to Dysphonia Detection, 2017.

[2] Liaqat Ali et al., "Early diagnosis of Parkinson's disease from multiple voice recordings by simultaneous sample and feature selection", Elsevier - Expert system with Applications, 2019.

[3] ZuzanaDankovicova et al., "Machine Learning Approaches to Dvsnhonia Detection", MDPI-Applied Science, 2018.

[4] NajmehFayyazifar et al., "Parkinson's disease detection using ensemble techniques and genetic algorithm", IEEE - Artificial Intelligence and Signal Processing Conference, 2017.

[5] Akshaya Dinesh et al., "Using machine learning to diagnose Parkinson's disease from voice recordings", IEEE -MIT Undergraduate Research Technology Conference (URTC), 2017.

[6] ElmehdiBenmalek et al., "Voice Assessments for detecting Patients with Parkinson's diseases in different Stages", International Journal of Electrical and Computer Engineering (IJECE), 2018.

[7] M. Bende, M. Khandelwal, D. Borgaonkar and P. Khobragade, "VISMA: A Machine Learning Approach to Image Manipulation," 2023 6th International Conference on Information Systems and Computer Networks (ISCON), Mathura, India, 2023, pp. 1-5, doi: 10.1109/ISCON57294.2023.10112168.

[8] NawelSouissi et al., "Dimensionality Reduction for Voice Disorders Identification System Based on Mel Frequency Cepstral Coefficients and Support Vector Machine", 7th International Conference on Modeling Identification and Control (ICMIC 2015), 2015.

[9] Ismail El Moudden et al., "Automatic Speech Analysis in Patients with Parkinson's Disease using Feature Dimension Reduction", Research gate - 3rd International Conference on Mechatronics and Robotics Engineering (ICMRE 2017), 2017.

[10] Minh Pham et al., "Diagnosing Voice Disorder with Machine Learning", IEEE International Conference on Big Data (Big Data), 2018.

[11] PavolHarar et al., "Towards Robust Voice Pathology Detection Investigation of supervised deep learning gradient boosting and anomaly detection approaches across four databases", Neural Computing and Application, 2018.

[12] M. Nithya, V. Lalitha, K. Paveethra and S. Kumari, "Early Detection of Parkinson's Disease using Machine Learning & Image Processing," 2022 International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India, 2022, pp. 1-4, doi: 10.1109/ICCCI54379.2022.9740961.

[13] S. Ajani and M. Wanjari, "An Efficient Approach for Clustering Uncertain Data Mining Based on Hash Indexing and Voronoi Clustering," 2013 5th International Conference and Computational Intelligence and Communication Networks, 2013, pp. 486-490, doi: 10.1109/CICN.2013.106.

[14] Khetani, V. ., Gandhi, Y. ., Bhattacharya, S. ., Ajani, S. N. ., & Limkar, S. . (2023). Cross-Domain Analysis of ML and DL: Evaluating their Impact in Diverse Domains. International Journal of Intelligent Systems and Applications in Engineering, 11(7s), 253–262.

[15] Borkar, P., Wankhede, V.A., Mane, D.T. et al. Deep learning and image processing-based early detection of Alzheimer disease in cognitively normal individuals. Soft Comput (2023). https://doi.org/10.1007/s00500-023-08615-w

[16] Z. Huang, H. Lei, S. Li, X. Xiao, E. -L. Tan and B. Lei, "Longitudinal Feature Selection and Feature Learning for Parkinson's Disease Diagnosis and Prediction," 2020 25th International Conference on Pattern Recognition (ICPR), Milan, Italy, 2021, pp. 5736-5743, doi: 10.1109/ICPR48806.2021.9413040.

[17] M. Saxena and S. Ahuja, "Comparative Survey of Machine Learning Techniques for Prediction of Parkinson's Disease," 2020 Indo – Taiwan 2nd International Conference on Computing, Analytics and Networks (Indo-Taiwan ICAN), Rajpura, India, 2020, pp. 248-253, doi: 10.1109/Indo-TaiwanICAN48429.2020.9181368.

[18] Y. Zhang, H. Lei, Z. Huang, Z. Li, C. -M. Liu and B. Lei, "Parkinson's Disease Classification with Self-supervised Learning and Attention Mechanism," 2022 26th International Conference on Pattern Recognition (ICPR), Montreal, QC, Canada, 2022, pp. 4601-4607, doi: 10.1109/ICPR56361.2022.9956213.

[19] T. D. Pham and H. Yan, "Tensor Decomposition of Gait Dynamics in Parkinson's Disease," in IEEE Transactions on Biomedical Engineering, vol. 65, no. 8, pp. 1820-1827, Aug. 2018, doi: 10.1109/TBME.2017.2779884.

[20] J. Faouzi et al., "Machine Learning-Based Prediction of Impulse Control Disorders in Parkinson's Disease From Clinical and Genetic Data," in IEEE Open Journal of Engineering in Medicine and Biology, vol. 3, pp. 96-107, 2022, doi: 10.1109/OJEMB.2022.3178295.

[21] A. Balakrishnan, J. Medikonda, P. K. Namboothiri and M. Natarajan, "Parkinson's Disease Stage Classification with Gait Analysis using Machine Learning Techniques and SMOTE-based Approach for Class Imbalance Problem," 2022 International Conference on Distributed Computing, VLSI, Electrical Circuits and Robotics (DISCOVER), Shivamogga, India, 2022, pp. 277-281, doi: 10.1109/DISCOVER55800.2022.9974754.

[22] C. H. Reddy and M. Kanchana, "Artificial Intelligence towards Parkinson's disease Diagnosis: A systematic Review of Contemporary Literature," 2022 IEEE 4th International Conference on Cybernetics, Cognition and Machine Learning Applications (ICCCMLA), Goa, India, 2022, pp. 31-37, doi: 10.1109/ICCCMLA56841.2022.9988755.

[23] H. Lei et al., "Parkinson's Disease Diagnosis via Joint Learning From Multiple Modalities and Relations," in IEEE Journal of Biomedical and Health Informatics, vol. 23, no. 4, pp. 1437-1449, July 2019, doi: 10.1109/JBHI.2018.2868420.

[24] S. Marar, D. Swain, V. Hiwarkar, N. Motwani and A. Awari, "Predicting the occurrence of Parkinson's Disease using various Classification Models," 2018 International Conference on Advanced Computation and Telecommunication (ICACAT), Bhopal, India, 2018, pp. 1-5, doi: 10.1109/ICACAT.2018.8933579.

[25] C. D. Anisha and N. Arulanand, "Early Prediction of Parkinson's Disease (PD) Using Ensemble Classifiers," 2020 International Conference on Innovative Trends in Information Technology (ICITIIT), Kottayam, India, 2020, pp. 1-6, doi: 10.1109/ICITIIT49094.2020.9071562.

[26] Ajani, S.N., Mulla, R.A., Limkar, S. et al. DLMBHCO: design of an augmented bioinspired deep learning-based multidomain body parameter analysis via heterogeneous correlative body organ analysis. Soft Comput (2023). https://doi.org/10.1007/s00500-023-08613-y

[27] M. M. Nishat, T. Hasan, S. M. Nasrullah, F. Faisal, M. A. -A. -R. Asif and M. A. Hoque, "Detection of Parkinson's Disease by Employing Boosting Algorithms," 2021 Joint 10th International Conference on Informatics, Electronics & Vision (ICIEV) and 2021 5th International Conference on Imaging, Vision & Pattern Recognition (icIVPR), Kitakyushu, Japan, 2021, pp. 1-7, doi: 10.1109/ICIEVicIVPR52578.2021.9564108.

[28] Huiyi Wu et al., "A Deep Learning Method for Pathological Voice Detection using Convolutional Deep Belief Network", Research Gate, 2018.

[29] Salama A. Mostafa et al., "Examining multiple feature evaluation and classification methods for improving the diagnosis of Parkinson's disease", Elseiver-Cognitive System Research., 2018.

[30] AnujAnand et al., "Evaluation of Machine learning and Deep learning algorithms combined with dimentionality reduction techniques for classification of Parkinson's Disease", IEEE - International Symposium on Signal Processing and Information Technology, 2018.

[31] Rajesh Patel, Natural Language Processing for Fake News Detection and Fact-Checking , Machine Learning Applications Conference Proceedings, Vol 3 2023.

[32] Paul Garcia, Ian Martin, Laura López, Sigurðsson Ólafur, Matti Virtanen. Personalized Learning Paths Using Machine Learning Algorithms. Kuwait Journal of Machine Learning, 2(1). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/166