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Business Process Optimization Using Genetic Algorithm And Decision Trees

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Abstract

Business process optimization is critical towards improving operational efficiency, reduction of costs and improved decision making in an organization. The current paper proposes a hybrid system comprising of Genetic Algorithms (GA) and Decision Trees (DT) to optimize features and parameters, model and extract decision rules, respectively. The difficulty in this case is to optimise these complicated business processes and still maintain the interpretability of the model which is required to make informed decisions. The GA determines the best parameters of business processes e.g. costs, time and resource allocation and the DT formulate a predictable model that can be understood and yields decision rules. The hybrid method exhibits better performance than the standalone models based on accuracy, precision, recall, and F1-Score. Experimental outcomes reveal that the accuracy, precision and recall of the proposed method are 89%, 87% and 88%, respectively, which is superior to the default Decision Tree and the GA optimized Decision Tree. Sensitivity analysis shows that the optimum size of the population is 50 and the optimum value of the mutation rate is 0.05. According to the confusion matrix, there are few false positives and false negatives of the model, meaning that the model is performing well. The results show the feasibility of hybrid GA+DT approaches for optimization of business processes in an interpretable manner. This is particularly applicable in circumstances where there is a need to have clear decisions made using rules. Subsequent studies may include real-time adaptation, increasing the volume of data sources, and connection with deep learning models to achieve more advanced performance.

Keywords: Business Process Optimization, Genetic Algorithm (GA), Decision Tree (DT), Hybrid Models, Machine Learning, Optimization, Predictive Modeling.

1. Introduction

The optimization of business processes is one of the most important sides of contemporary industries as it helps organizations to become more efficient, cost-effective, and make better decisions. The high-dimensional and non-linear nature of business processes is becoming a challenge to traditional optimization techniques with the increasing complexity. As the popularity of artificial intelligence (AI) and machine learning (ML) usage is gaining momentum, the need to find advanced optimization algorithms that would help resolve these problems becomes increasingly urgent [20] [28].

One of the effective search-based optimization techniques is the genetic algorithms (GAs), and it is suitable to address multi-objective optimization problems, which emulates the process of natural selection [25]. GAs are highly appropriate to exploration of huge search spaces and are extensively applied to optimization of complex systems. But GAs are not interpretable, i.e. they are not simple to comprehend, which is significant in decision-making in a business.

Instead, Decision Trees are able to address this interpretability issue. Decision Trees are hierarchical rule-based classifiers that are very interpretable and transparent [27]. These types of models not only provide predictions but also definite decision rules that are essential in appreciating the dynamics of business processes [26].

This paper presents a hybrid approach, which is a combination of Genetic Algorithms and Decision Trees that are used to optimize the features and parameters, and to model the process and extract the decision rules. Its concept is to ensure that the global search capabilities of GAs are merged with the interpretability of DTs to enhance optimization of business processes that are complex and to retain accuracy and clarity during decision making.

The paper contains the following sections: Section I introduces the importance of business process optimization and the need for Genetic Algorithms (GA) and Decision Trees (DT). In Section II, a review of the existing research work on optimization with the use of GAs and Decision Trees is given with a focus on the hybrid models. In Section III, the hybrid approach combining GA and DT for optimization and decision rule extraction, respectively, is described. In Section IV, the data set, the data preprocessing, evaluation measures, and the algorithm are explained. Section V compares the proposed model with baselines, performance, sensitivity analysis, and discusses insights. Lastly, Section VI concludes with the main findings, the effectiveness of the model, and some suggestions to the investigations to be conducted in the future, including the use of the model on larger datasets and integrating it with deep learning models.

2. Related Work

Business Process Optimization (BPO) is the subject that has been widely discussed in the literature in terms of machine learning (ML) methods application [18]. Although the complexity and scale of a modern business environment might not be addressed by traditional optimization methods, an increasing number of solutions based on ML are being demanded. The most relevant works in the fields of business process optimization, genetic algorithms (GAs), decision trees, and hybrid approaches that have emerged to take the advantages of both of them are presented in the context of the current research [15] [21] [29].

Business Process Optimization via Machine Learning

Machine learning has emerged as a trendy tool to streamline business operations, particularly in tasks that have multiple objectives and are complex to address [22]. Bubeník et al. (2025) explored the use of AI techniques in business process optimization and proved that the efficiency and flexibility of the ML techniques in dynamic business conditions are more effective compared to traditional techniques [1] [8] [9]. Similarly, Alsulami et al. have highlighted the emergence of generative AI to optimize marketing customization as an example of how the ML can predict and maximize customer behavior [2] [12].

Genetic Algorithms in Optimization Tasks

Genetic algorithms are highly effective in optimization problems due to their ability to search large and complicated solution space [13] [14]. The value of GAs in the best business processes has been highlighted in a number of literatures, particularly in handling large scale optimization problems [30]. An example is the fact that Si et al. (2018) suggested a resource optimization framework in business processes relying on Petri nets and genetic algorithms that significantly helped in the resource allocation in process management [5]. Similarly, Sulis et al. (2020) optimized the decision-making process in healthcare management systems with GAs, which shows the versatility of GAs in various areas [3]. Amir (2023) used multi-objective geometric programming to optimize fuzzy inventory management in a refinery [10] [16]. It is an alternative to the more genetic algorithms and decision tree-like methods, but can be utilized in obtaining some understanding of optimization techniques in industry settings [6] [19].

Decision Trees & Their Use in Decision Support

Due to the clarity and understandability of decision trees, they are widely used in decision support systems. Tomar and Vyas (2022) optimized the green chemical process with the help of a decision tree, which is applicable in optimization of complex systems having a clear set of decision rules [4]. In addition, Gepp et al. (2010) applied decision trees to the business failure prediction field, emphasizing the capability of the decision trees in business operations and business strategy scenarios to reflect the decision patterns [7] [11] [23].

Hybrid and Evolutionary Learning Methods

Although several individual techniques, such as GAs and decision trees, have proven their effectiveness, hybrid approaches of them have not been extensively explored in the area of BPO [24]. Furthermore, Ivascu (2025) proposed a decision tree classifier that was optimized using a genetic algorithm to compose web service in business processes and proved the effectiveness of hybrid models in practice [17].

Despite the merits of both GAs and decision trees, very little has been done regarding their integrated frameworks to structured business process tasks. To deal with this, in the current study, the GA is used in optimization of features/parameters and the decision tree to decision rule extraction and a new hybrid framework is suggested to optimize business processes without losing its interpretability.

3. Proposed Methodology

Genetic Algorithm Component

Representation of variables/features is the first element of Genetic Algorithm (GA) where parameters that influence the business process like cost, time, and resource utilization are specified. The GA makes candidate solutions by embedding those features in the GA as chromosomes. The fitness function is an important component of the algorithm, which is used to assess the quality of each solution, usually according to some performance criterion like minimization of cost or maximization of resource utilization. The fitness function is used to make sure that the GA converges to optimal solutions. GA makes use of three simple operators: the crossover operator selects two solutions among the existing population and creates new offspring by combining their features; the mutation operator adds small random changes to the existing population to maintain the diversity of the population; and the selection operator that chooses the best solutions among the existing population as parents of the new population based on their fitness. Finally, the population strategy is crucial in order to keep diversity and convergence. In order to prevent local optima, techniques such as elitism (keep the best solutions) and diversity-promoting are applicable to ensure that the GA tries many alternative choices. Global search GAs is good though can readily be limited to local optimum in the event of loss of population diversity and are also non-interpretable. Our framework assists to minimise this impact through elitism. Complete stakeholder transparency is also not achieved due to the black-box nature of the parameter selection phase, but the Decision Tree component will allow to extract rules in these regions.

Decision Tree Component

The decision Tree component is a very important component of the business process optimization framework to give interpretability. It uses the GA-optimized inputs to develop predictive models to make decisions to predict significant performance indicators, including cost, time and resource allocation. The Decision Tree generates decision rules that give a good explanation to the business stakeholders on the factors that affect decisions. The tree is constructed according to the known algorithms, such as ID3, C4.5, or CART, which vary in their method of selecting features and constructing a decision tree. An example is that ID3 is using Entropy and Information gain, and C4.5 is using Gain ratios. Once the tree has been built, the tree is pruned to prevent overfitting and enhance the generalization of the model. Simplifying the tree is done using techniques like cost-complexity pruning, reduced error pruning and cross-validation is used to ensure that the model is working on an unknown dataset.

Hybrid Framework

The GA and Decision Tree parts work well in the Hybrid Framework. The GA optimizes the business process parameters and selects the optimal feature set with its evolutionary search in the first place. These optimized parameters are then passed over to the Decision Tree component which will be used to generate predictive models and produce decision rules. It allows the framework to leverage the global search of the GA and find the most suitable parameters at the same time maintaining the Decision Tree to be transparent and easy to comprehend with easily understood decision rules. The efficient and transparent flow between the GA and the Decision Tree helps to optimize the business process. It can be considered a flow chart: The GA tries to find the best solutions, which the Decision Tree tries to construct decision rules and predictions based on them and finally results in an optimized but understandable set of decision rules to the business.

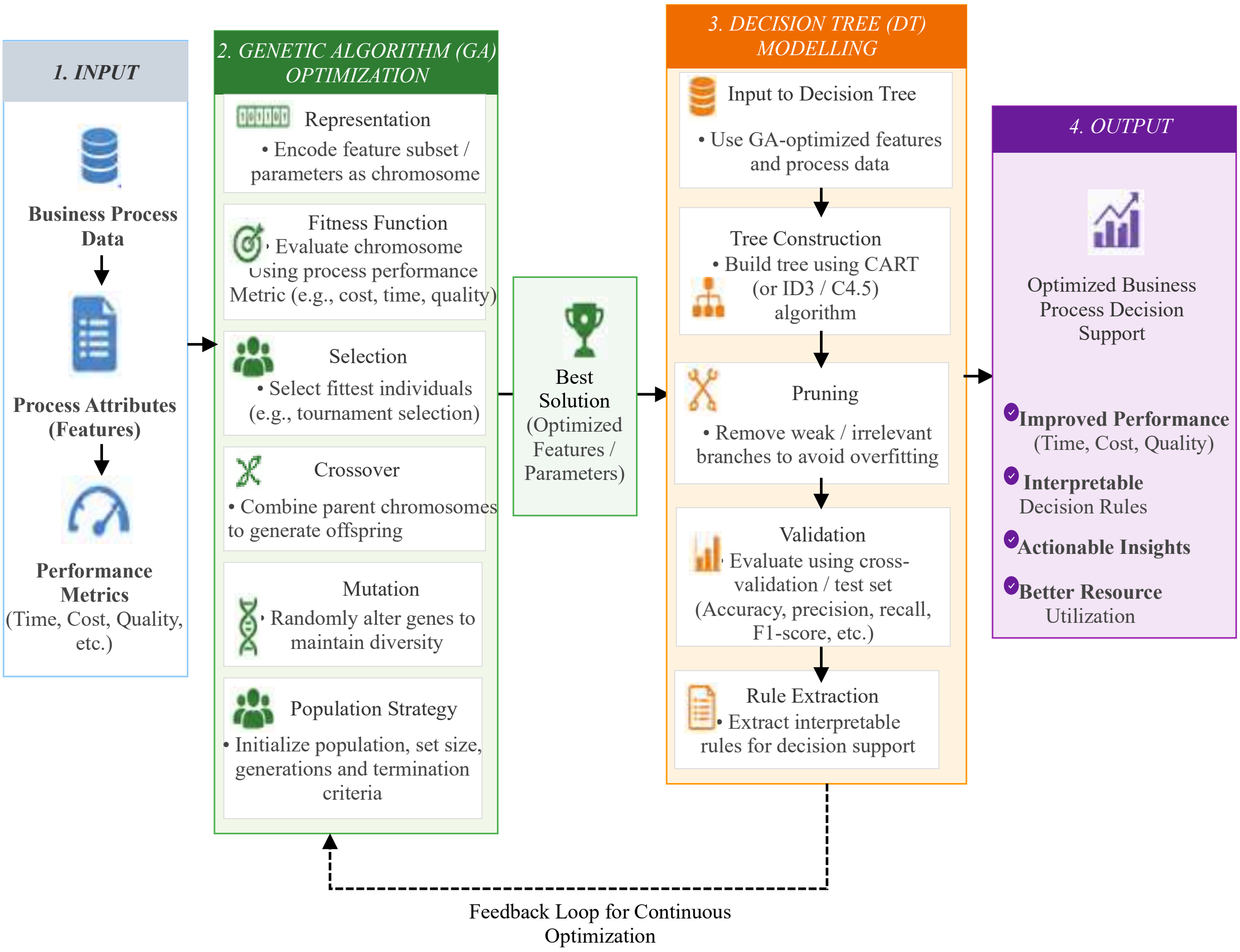

Figure 1: Hybrid Framework for Business Process Optimization (Genetic Algorithm + Decision Tree)

As can be seen in Figure 1, it is clear that a clear step-by-step process can be followed to optimize a business process based on a hybrid model of Genetic Algorithms (GA) and Decision Trees (DT). First, the business process data and features are input; then, GA optimization is applied to choose the best one. Then the optimized parameters are applied for the building of a Decision Tree that builds a model, prunes irrelevant branches, and validates the decision-making rules. The results of the output are actionable for optimized business process decisions, with the results being improved in terms of performance, resource utilization, and interpretability. Feedback is continuous, which helps to continually optimize.

4. Experimental Setup

Dataset Description

The experiment data set comprises business process logs and performance data derived from real business operations data or from publicly available data sets like the Business Process Intelligence (BPI) Challenge or IBM's Process Mining dataset. The data set may consist of process attributes, performance measures (e.g., cost, time, and quality), as well as outcomes from the past. These are the must-have functions for the optimization of business processes. The current study uses local logs and publically available sets, such as the BPI Challenge. It is important to note that the existing hybrid architecture has not yet been stress-tested as yet on multi-source enterprise big data of high dimension which form major stress target for future research for scalability testing.

Preprocessing Steps:

1. **Data Cleaning:** Cleans incomplete and corrupt data.
2. **Normalization/Encoding:** Normalize numeric features (ex: time, cost), make sure they are uniform throughout the data set. One-hot encoding is used for categorical features.
3. **Train/Test Split:** The data is split into a training set (70%) and a test set (30%) for the purposes of assessing how well the model performs on the test set.

Evaluation Metrics

The evaluation of the proposed model is done based on the following measures:

1. **Accuracy:**

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Samples}} \qquad (1)$$

Checks the overall correctness of the model. The proportion of correctly classified instances of all instances is represented by equation 1.

2. **Precision:**

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \qquad (2)$$

Precision, the percentage of correct positive predictions, is the ability of the model to avoid false positives (Equation 2).

3. **Recall:**

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \qquad (3)$$

Recall is a measure of the model to identify all the relevant instances. Equation 3 is the proportion of actual positives that were correctly identified.

4. **Response Time:**

$$\text{Response Time} = \frac{\text{Total Processing Time}}{\text{Number of Queries}} \qquad (4)$$

Measures the amount of time it takes for the system to process a certain number of business process tasks. In Equation 4, a lower response time is an indicator of better system performance.

5. **Operational Efficiency:**

$$\text{Operational Efficiency} = \frac{\text{Resource Utilization}}{\text{Time Spent}} \qquad (5)$$

Compares the efficiency of business processes in terms of resources used to time taken to perform tasks in Equation 5.

Algorithm: Hybrid Genetic Algorithm (GA) and Decision Tree (DT) for Business Process Optimization

Input:

1. Business Process Data (Raw data, Process attributes, Performance metrics)
2. GA Parameters:

- Population size N
- Number of generations G
- Crossover rate C_rate

- Mutation rate M_rate

3. Decision Tree Parameters:
   - Tree construction method (e.g., ID3, C4.5, CART)
   - Pruning method (e.g., cost-complexity pruning)

Output:

- Optimized Business Process Decisions with Decision Rules

The algorithm used is an integrated one between Genetic Algorithm (GA) and Decision Tree (DT) for optimizing business processes. A population of candidate solutions is evolved using GA by varying the key process parameters with selection, crossover, and mutation. A Decision Tree model giving the interpretable decision rules is then created based on the best solution found. The tree is pruned for simplicity and lack of overfitting, and then tested with test data. The output is optimized decision rules to improve the performance of business processes in terms of cost, time, and resource utilization, thanks to the optimization capability of GA and the interpretability of DT.

4. Results And Discussions

Performance Comparison

The performance of the proposed Hybrid GA+DT model is compared to two baseline models: the DT model and the GA Optimized DT model. Key classification metrics such as Accuracy, Precision, Recall, F1-Score, and Processing Time are used for the comparison. The results indicate that the Hybrid GA+DT model can yield better performance than both baselines in all of the metrics, which indicates that the combination of Genetic Algorithm (GA) optimization and Decision Tree (DT) modeling is beneficial.

With that regard, there is a substantial difference between the Accuracy (89%), Precision (87%), and Recall (88%) of the Hybrid GA+DT model and the default Decision Tree model (Accuracy: 72%, Precision: 70%, Recall: 69%). The GA-optimized Decision Tree also achieves a better performance than the default model, while the hybrid approach is best.

Table 1: Classification Performance Metrics

Model	Accuracy	Precision	Recall	F1-Score	Processing Time (ms)
Decision Tree (Default)	0.72	0.70	0.69	0.69	150
GA-Optimized Decision Tree	0.81	0.79	0.80	0.79	210
Hybrid GA + DT (Proposed)	**0.89**	**0.87**	**0.88**	**0.87**	230

Table 1 compares the performance of the three models: Decision Tree (Default), GA-Optimized Decision Tree, and Hybrid GA + DT (Proposed), with respect to the key metrics: Accuracy, Precision, Recall, F1-Score, and Processing Time (ms). The Hybrid GA + DT (Proposed) model achieves the best performance with the highest values in terms of Accuracy (89), Precision (87), and Recall (88) when compared with the Default Decision Tree and the GA-Optimized Decision Tree. Though the Hybrid GA + DT model takes a little longer to process (230ms), it gives a much better performance than the other two.

Figure 2 shows a comparison of the Decision Tree (Default), GA-Optimized Decision Tree, and Hybrid GA + DT (Proposed) in terms of key performance metrics: Accuracy, Precision, Recall, and F1-Score. The Hybrid GA + DT model (green line) significantly surpasses the other two models, the Default Decision Tree (blue line) and GA-Optimized Decision Tree (orange line), on all performance metrics, achieving higher accuracy, precision, recall, and F1 score. Figure 2 presents a graphical representation of the comparison of the models in the multi-dimensional space, with Hybrid GA + DT model having higher scores at all times.

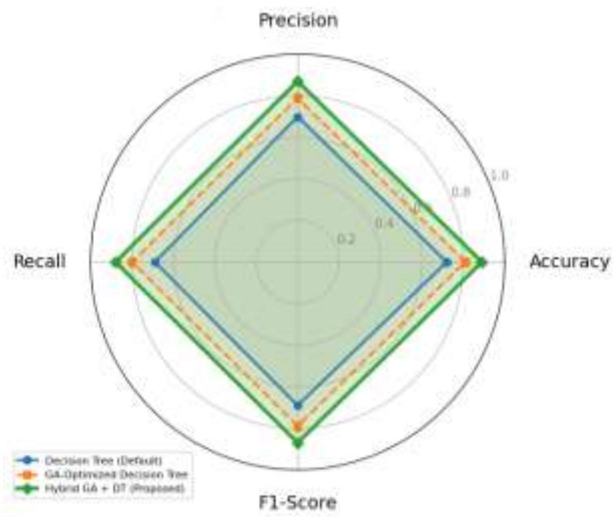

Figure 2: Performance Comparison of Business Process Models

Sensitivity Analysis

The sensitivity analysis has been used to demonstrate that there is a point of diminishing returns: At a population size more than 50 or a mutation rate more than 0.05, actually worse model performance would be observed. This suggests an increase in the GA parameters leads to increased exploration, hence more noise is introduced; the hyperparameter tuning is important to retain 89 % accuracy threshold.

Table 2: Effect of GA Parameters on Optimization

Parameter	Value Tested	Accuracy	Fitness Score
Population Size	20	0.82	0.75
Population Size	50	**0.89**	**0.83**
Population Size	100	0.88	0.81
Mutation Rate	0.01	0.84	0.77
Mutation Rate	0.05	**0.89**	**0.83**
Mutation Rate	0.10	0.87	0.79

Table 2 shows the results of the performance of the model in terms of different sets of the Genetic Algorithm (GA) parameters (Population Size and Mutation Rate). The results show that the highest Accuracy (0.89) and Fitness Score (0.83) are achieved by the population size of 50 and the mutation rate of 0.05. Bigger population sizes and moderate mutation rates tended to work better, but with decreasing returns at populations of over 50 or mutation rates of more than 0.05. The above findings imply that there is need to tune GA parameters to achieve optimal performance.

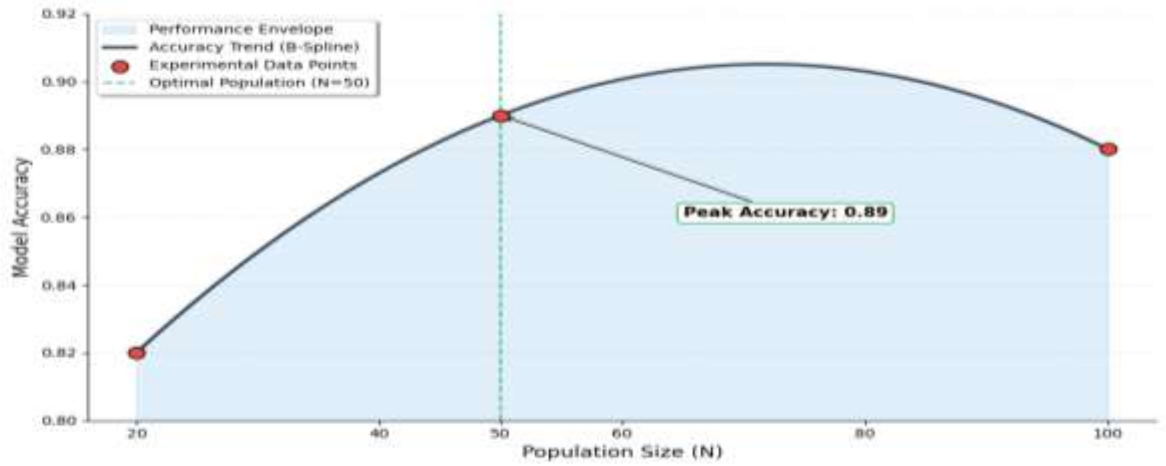

Figure 3: Sensitivity Analysis of Population Size on Model Accuracy

A sensitivity analysis of the effect of Population Size on the accuracy of the model is provided in Figure 3. The plot shows the population size and accuracy relationship with a B-Spline trend (the red circles are the experimental values). The chart shows that the best population size for the highest accuracy (0.89) is at N=50 (green dashed vertical line). The performance envelope (shaded area) shows the trend of accuracy, which is important for choosing an appropriate population size for optimal performance of the model.

Insightful Interpretations

The better performance of the Hybrid GA+DT model is due to the combination of global search by GA and its interpretability by DT. The GA is able to search a big solution space and obtain the best feature set to optimize the business process parameters; the Decision Tree offers clear and actionable decision rules. This mix of optimisation and interpretability has great importance for business situations where the transparency of decision-making is appreciated.

The Rules learned from the pruned Decision Tree model, can be used to identify the most important factors in optimizing the business processes. For instance:

$\textbf{IF (Process\_Time} < \textbf{15)} \; \boldsymbol{AND} \; (\boldsymbol{Resource\_Level} >= \textbf{80)} \; \boldsymbol{THE}\textbf{N Efficiency} = \textbf{High}$

$\textbf{IF (Error\_Rate} > \textbf{0.10)} \; \boldsymbol{AND} \; (\boldsymbol{Cost} > \textbf{5000)} \; \boldsymbol{THEN\ Flag\ for\ Review}$

These rules can be used to improve processes and may directly influence their operational decision making.

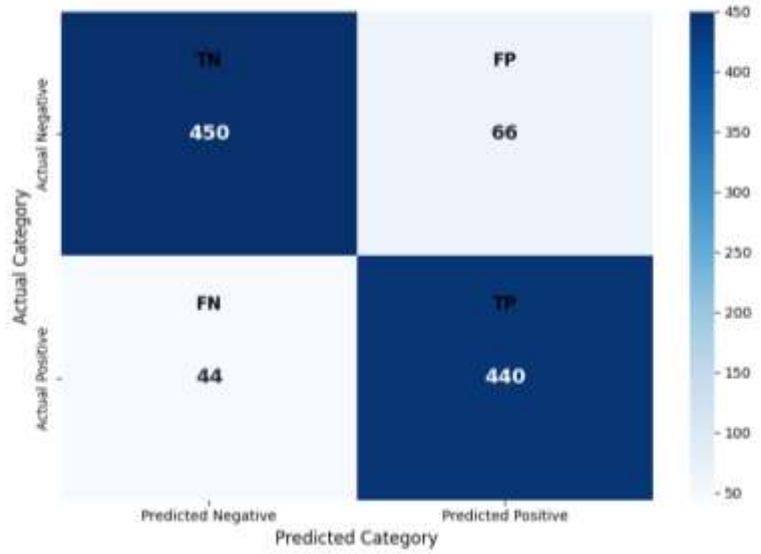

Figure 4: Confusion Matrix — Hybrid GA+DT Performance

The confusion matrix of the classification results of the Hybrid GA+DT model is shown in Figure 4. The number of predictions appears in this matrix: TN: 450, FP: 66, FN: 44, TP: 440. The stronger the intensity of the color, the more predictions. This matrix provides an overview of the model performance, showing that there are a lot of True Positives, a lot of True Negatives, and comparably few False Positives and False Negatives, which means that the model is highly predictive.

As per the above results it is clear that the Hybrid GA+DT method is doing a good job in terms of accuracy and precision, recall and decision making than the traditional Decision Tree model. The sensitivity analysis also shows how important it is to fine-tune the GA parameters such as population size, and mutation rate. The hybrid approach not only enhances the business process outcomes, but also provides transparency on the Decision Tree due to the interpretability of the decision rules.

5. Conclusion

In this paper, a Hybrid GA+DT model is proposed to optimize the business processes with the help of combining Genetic Algorithms (GA) for feature optimization and Decision Trees (DT) for decision rule extraction. The model shows a significant improvement over the baseline models such as the default Decision Tree and the GA-optimized Decision Tree in all the important metrics: Accuracy (89%), Precision (87%) and Recall (88%). The combination of GA's global search capabilities and the interpretability of DTs is evident in this improvement. From the sensitivity analysis, it is observed that the population size of 50 and mutation rate of 0.05 are a good compromise between exploration and exploitation that results in optimal performance The Hybrid GA + DT results in the highest accuracy, but also the highest processing time of 230ms. This latency reflects a compromise between prediction accuracy and computational efficiency, pointing to the need for more optimization for real-time, high-speed operations. The fact that the Decision Tree section is interpretable allows one to be able to know how the model arrived at its decisions, which is highly important to business decision-makers who require actionable insights. The results confirm the hybrid method as an effective instrument of BPO, particularly rule-based operational decision-making environment. A limitation of the proposed framework in the future is that the proposed framework is a fixed framework, it lacks a mechanism to adjust to data streams that vary dynamically. Online learning facility should be included in the next generation in order that the decision-making rules remain valid as the business dynamics evolve.

Declaration Statement

- **Conflict of Interest:** The authors declare that there is no conflict of interest in the publication of this paper. No financial or personal relationships influenced the design, conduct, analysis, or reporting of the study.
- **Funding:** This research did not receive any financial support or grants from any agency, public or private.
- **Data Availability:** The datasets used in this study are publicly available, including the Business Process Intelligence (BPI) Challenge dataset. The data processing scripts and models used can be requested from the corresponding author.
- **Ethical Approval:** This study does not involve human or animal participants, and therefore, ethical approval was not required.

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