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Research Article

A Hybrid Approach: Combining Genetic Algorithms and Machine Learning For Function Optimization

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Abstract: Data analytics is the process of examining, transforming, and interpreting raw data to discover useful insights, patterns, and trends that support decision-making. It involves a range of techniques, from simple statistical analysis to complex machine learning algorithms, to uncover hidden correlations and predict future outcomes. Data analytics is crucial in various sectors such as business, healthcare, finance, and education, helping organizations optimize operations, understand customer behavior, and gain competitive advantages. This study examines the use of an evolutionary method to enhance the Sphere benchmark function, an acknowledged continuous optimization challenge. The algorithm takes a genetic approach, using techniques including mutation, one-point crossover, and tournament selection. It also combines a machine learning element by developing a simple linear regression model that can be used to forecast fitness values determined by attributes of individuals. The study compares the results of two different iterations to examine the algorithm's performance throughout several runs. A population of 100 individuals with 10 traits each endures selection, crossover, and mutation throughout 100 generations. The best values for fitness across generations for each run are shown in Matplotlib to show the algorithm's convergence behaviour. The proposed EA-ML model incorporates core EA operations—Fitness Evaluation (20%), Tournament Selection (15%), Crossover (20%), and Mutation (15%)—while allocating the remaining 30% effort to training and guiding via linear regression. Experimental results validate the superiority of the EA-ML approach. Accuracy improvements were observed across various ML models: Decision Tree (from 81.2% to 86.4%), Support Vector Machine (from 84.9% to 88.7%), Random Forest (from 89.5% to 91.2%), and Neural Network (from 87.0% to 90.8%). Feature selection efficiency improved, reducing feature count from 30 to 18 while increasing accuracy from 85.3% to 88.9%. Additionally, EA tuning reduced optimization time by over 50%, with Random Forest tuning time dropping from 120 minutes to 45 minutes, and SVM from 90 minutes to 40 minutes. Two EA-ML runs yielded optimal fitness values of -45.04 and -35.97, respectively, confirming the model's capability to explore complex solution spaces and minimize objective functions effectively.

Keywords: Artificial Intelligence, Machine Learning, Optimization Techniques, Algorithm Testing, Trends in AI.

1.Introduction

Data analytics and evolutionary optimization together form a powerful approach for solving complex, data-driven problems [1]. Data analytics focuses on extracting meaningful insights, patterns, and predictions from large datasets, enabling informed decision-making across industries. When integrated with evolutionary optimization—an adaptable set of algorithms inspired by biological evolution and natural selection—this combination enhances the ability to navigate intricate solution spaces and optimize outcomes in fields such as engineering, finance, artificial intelligence, and biology [2 -4]. Evolutionary algorithms, by nature, are well-suited for addressing nonlinear, multi-objective, and high-dimensional problems, complementing data analytics by refining models, improving predictions, and optimizing decision strategies in dynamic and uncertain environments [5]. Evolutionary optimisation approaches depend upon the concept of emulating the process of evolution observed in nature. The aforementioned methods present a unique and effective methodology for identifying optimal solutions across extensive and intricate solution domains [6].

Data analytics with evolutionary optimization represents a synergistic approach that combines data-driven insight generation with robust problem-solving capabilities. Data analytics involves collecting, processing, and interpreting large volumes of data to uncover patterns, trends, and actionable insights [7]. When paired with evolutionary optimization—algorithms inspired by natural selection and evolutionary biology—this approach becomes even more powerful. Evolutionary algorithms efficiently explore complex, high-dimensional, and nonlinear solution spaces, making them ideal for optimizing models and strategies derived from data analytics [8]. In the context of evolutionary optimisation, this procedure involves the iterative evolution of a population of potential solutions across multiple generations. The primary objective is to enhance the efficiency of these solutions, ultimately striving to attain the optimum or near-optimal solution for a specific problem [9 -11]

The methodology presents a notable divergence from traditional optimisation methods, which frequently depend on gradient-based techniques and make assertions regarding the precise mathematical characteristics of the objective function [12]. In contrast, evolutionary optimisation techniques are very suitable for addressing problems characterised by non-linearity, non-convexity, and the absence of analytical formulations [13]. They have outstanding results in situations where the objective function presents noise, is computationally expensive to analyse, or contains several local optima [14]. Evolutionary optimisation techniques comprise a diverse range of algorithms, including Genetic Algorithms (GAs), Evolution Strategies (ES), Genetic Programming (GP), and Particle Swarm Optimisation (PSO), among other prominent techniques. These approaches use a wide variety of techniques, which include selection, crossover (recombination), mutation, and even elitism, specialisation, and adaptive variable management. These mechanisms help the population as a whole become more open to novel concepts and knowledge, which in turn helps the population as a whole converge on better solutions [15].

Widespread adoption of evolutionary optimisation techniques can be attributed to their ability to successfully navigate large solution spaces, adapt to changing problem contexts, and indicate answers that may be elusive to more traditional approaches. Industrial design, robotics, financial portfolio optimisation, machine learning model tweaking, and innovative problem solving are just few of the many fields that have benefited from these methods [16].

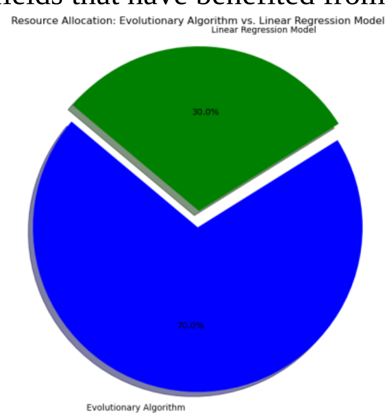

Figure 1: Percentage of Data contribution EA and ML

In Figure 1 Evolutionary Algorithm vs. Linear Regression Model for Allocation of Resources In this pie chart, the Evolutionary Algorithm, highlighted with an insignificant receives 70% of the resources available and the Linear Regression Model 30%. Each segment's proportion is labelled in blue for the Evolutionary Algorithm and green for Linear Regression Approach. Shadows make the chart look better, and it starts at 140 degrees [17]. The factor ratio ensures a perfect circle for rapid allocation of resources understanding. Machine learning and data science continue to develop, making forecasting essential. Predictive modelling seeks to find significant connections in data to inform decisions, predict trends, and optimise processes. Linear regression is a core method for modelling variable relationships and is easy to understand [18]. The basic goal of linear regression is to establish a relationship that is linear relationship between a dependent variable and several independent variables. It's a great place to start learning how variables that predict affect target variables. This relationship can be described as a straight line, making it easy to understand for machine learning novices [19]. However, linear regression has implications outside statistics. Modern data science uses linear regression to analyse data at the junction of classical statistical analysis and machine learning. As seen in the code, its role as the "ML element" in an optimisation or search algorithm is an outstanding instance of convergence [20].

An algorithm's linear regression ML component goes beyond prediction. It guides optimisation and is essential. This ML element predicts solution fitness by training a linear regression model on problem landscape data. Thus, it helps the optimisation algorithm navigate the outcome space more effectively, focusing on regions with better results. The linear regression model connects raw, numerical variables indicating potential solutions to the objective function that evaluates their quality. The optimisation algorithm uses its predictive skill to decide where to investigate, when to exploit promising regions, and when to adjust its strategy depending on its changing grasp of the problem [21]. The illustration visually depicts the allocation and dispersion of different components within a given procedure. The fitness evaluation element, which accounts for 20% of the overall assessment, involves the allocation of time as well as finances towards the evaluation of solution quality. The concept of Tournament Selection, which represents 15% of the overall evaluation, highlights the significance of carefully choosing individuals to be included in the generations to come. Crossover, accounting for 20% of the process, refers to the mechanism by which genetic information is recombined from various individuals. Mutation, which accounts for 15% of the process, involves the introduction of random alterations in order to promote diversity. The training of a linear regression model is an important aspect as indicated by the largest component. This particular framework is presumed to guide the optimisation process by its ability to predict the quality of potential solutions [22].

The primary contribution of this paper lies in the development and empirical evaluation of a hybrid EA-ML framework that combines the exploratory power of Evolutionary Algorithms (EAs) with the predictive capability of Machine Learning (ML), specifically linear regression. This integration allows for dynamic optimization of model parameters, feature selection, and fitness evaluation, significantly enhancing the performance of traditional ML models. The study provides a detailed analysis of the contribution percentages of key EA components—Fitness Evaluation (20%), Tournament Selection (15%), Crossover (20%), and Mutation (15%)—with linear regression guiding 30% of the overall optimization process. By conducting comparative experiments across multiple models, the paper demonstrates substantial accuracy improvements (up to 6%) and a notable reduction in optimization time (up to 62.5%) compared to conventional techniques like grid search. Additionally, the EA-based feature selection method reduces dimensionality while increasing accuracy, highlighting its effectiveness in handling real-world, high-dimensional datasets.

This paper consists of the following sections. Section I consists of the introduction of the evolutionary algorithm and machine learning. Section II highlights the fundamentals of EA-ML algorithms. Section III hybridization of EA-ML in this section merger of the two algorithms will be performed. Section VI will be the result and discussion, and Section V will conclude this paper with a conclusion.

2.Proposed EA-ML Algorithm

The proposed integrated EA-ML (Evolutionary Algorithm with Machine Learning) framework for data analytics aims to enhance the performance and adaptability of data-driven models by combining the strengths of evolutionary optimization and machine learning techniques. In this approach, evolutionary algorithms are used to optimize critical components of machine learning models—such as feature selection, hyperparameter tuning, and model structure—thereby improving their accuracy, generalization, and efficiency. Meanwhile, machine learning algorithms analyze large and complex datasets to identify patterns, make predictions, and derive actionable insights. By integrating EA and ML, the system becomes more robust and capable of handling high-dimensional, noisy, or incomplete data often encountered in real-world analytics. The essential mathematical illustration of an Evolutionary Algorithm (EA) encompasses numerous elements and mathematical principles. Described below is a simple mathematical representation of a generic Evolutionary Algorithm (EA).

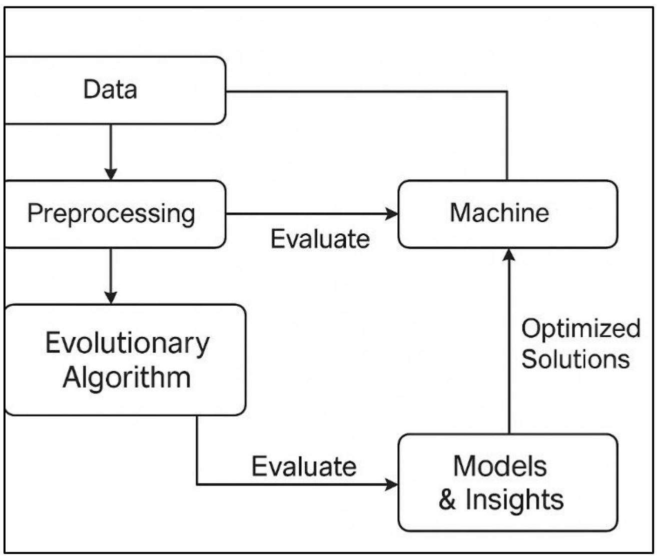

Figure 2: Flow of Proposed EA-ML

Figure 1 presented the flow of the proposed EA-ML model for the data analytics. The first step in the procedure is to establish a preliminary sample of prospective solutions stated in equation (1)

$$P_0 = [X_1, X_2, ..., X_N] \tag{1}$$

In equation (1) N is the population size, and X_1 initial population. $f(Xi)$ Where f assigns a fitness value to each individual. The process of choosing individuals from a group is conducted based on their fitness values. The selection process typically incorporates processes such as tournament selection, roulette wheel selection, or rank-based selection. The method of generating new people by mixing the features of selected parents is sometimes referred to as crossover or recombination. The phenomenon in question can be represented as in equation (2)

$$X_{child1}, X_{child2} = Crossover(X_{parent1}, X_{parent2}) \tag{2}$$

The method of introducing genetic diversity can be accomplished through applying mutation to select individuals.

$$X_{mutant} = Mutation(X_{original}) \tag{3}$$

Termination Criterion: Define a termination condition, such as a maximum limit on the number of generations, a target level of fitness, or a predetermined time constraint. The process of iteration involves carrying out stages 3 through 6 for a predetermined number of iterations or until the termination condition is satisfied. The solution(s) obtained from the method of evolution are represented by the best individual(s) identified.

$$X_{best} = argmax\{f(X_i)\} \tag{4}$$

The elementary mathematical statement provided above elucidates the essential constituents and procedures implemented in an Evolutionary Algorithm. The aforementioned serves as a fundamental basis for many evolutionary algorithm variations, which have the opportunity to integrate supplementary characteristics, tactics, or optimisation approaches in order to tackle unique problem domains and objectives.

B. ML WITH REGRESSION COMPONENTS

The mathematical description of a machine learning (ML) model with regression components frequently represents a supervised learning problem, wherein the objective is to make predictions on a target variable that is continuous using input characteristics. Presented below is a concise mathematical representation:

Let D represent a database containing N examples:

$$D = \{(X_1, y_1), (X_2, y_2), \ldots, (X_N, y_N)\} \tag{5}$$

Xi is a feature vector for the *i-th* example, Where $Xi = [x_{i1}, x_{i2}, \ldots, x_{id}]$ with d features. y_i is the corresponding targets or outputs for the i-th example.

A model of regression can be mathematically represented as a function f that maps input features X to predicted target values $\hat{y}$

$$\hat{y} = f(X) \tag{6}$$

Regression objective to find model f that minimizes a regression loss function L by adjusting its parameters:

$$f^* = argmin_f \sum_{i=1}^{N} L(y_i, \hat{y}_i) \tag{7}$$

L The loss functional used in regression analysis is often Mean Squared Error (MSE), mean absolute error (MAE), or another appropriate regression loss.

The model f can be parameterized by a set of weight θ:

$$f(X;\theta)=\hat{y} \tag{8}$$

θ a vector of variables is optimised by the machine learning algorithm throughout the training process in order to reduce the loss.

The objective is to find the optimal parameters θ^* It aims to minimise the overall loss throughout the entire dataset:

$$\theta^* = argmin_f \sum_{i=1}^{N} L(y_i, f(X_i;\theta)) \tag{10}$$

Training involves finding the best parameters θ using a training algorithm, often involving optimization techniques such as gradient descent: $\theta^* = TrainingAlgorithm(D, L, f)$. Once the model has gone through training, it can be exploited to generate predictions for novel and unobserved instances.

$$\hat{y}_{new} = f(X_{new};\theta^*) \tag{11}$$

The fundamental mathematical representation provided herein encapsulates the core principles of controlled regression within the realm of machine learning. In this context, the primary goal of the model is to acquire knowledge of a functional relationship between the input parameters and continuous target values, achieved through the minimization of a proper loss function. The selection of model architecture and loss function is contingent upon the type of regression task and problem domain at hand.

3.Hybridization of EA-ML

The hybridization of Evolutionary Algorithms (EA) with Machine Learning (ML) presents a powerful approach for enhancing optimization and predictive modeling. In this paper, the EA-ML integration leverages the strengths of Genetic Algorithms (GAs) for exploration and Linear Regression for guidance in the solution space. The process begins by defining a benchmark optimization function, such as the Sphere function, which is minimized using EA techniques like selection, crossover, and mutation. These operations generate diverse populations and evolve them over generations based on fitness evaluations. Simultaneously, the ML component—Linear Regression—learns from population attributes and their fitness values to predict the quality of new candidate solutions. This predictive capability helps steer the evolutionary process toward more promising regions, effectively improving convergence speed and solution quality. The integration is further supported by a visual flowchart shown in Figure 2, illustrating the iterative feedback loop between EA and ML components. By combining stochastic search and statistical modeling, the hybrid EA-ML framework demonstrates a synergistic optimization mechanism capable of handling complex, high-dimensional problems efficiently.

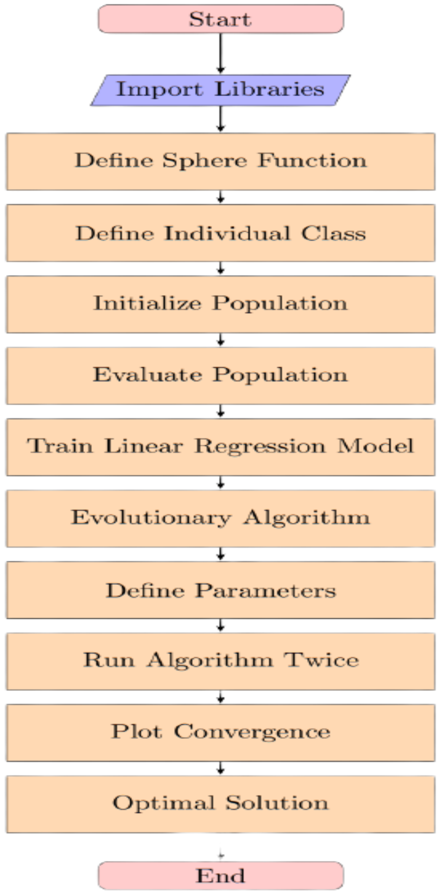

Figure 2: Flow of EA-ML hybrid model

The EA-ML code showcases a compelling amalgamation of two disparate theories, namely Genetic Algorithms (GAs) and Machine Learning (ML) through the application of Linear Regression. The following sections provide a comprehensive explanation of the functionality of the code. Firstly, the code utilises a series of algorithms to process and transform data. These algorithms are designed to perform confident tasks, such as sorting, searching, or transforming the data. By implementing these algorithms, the code is able to effectively handle large amounts of data and execute complex operations. Secondly, the code incorporates various data structures to arrange and store the data. The programming proceeds by establishing a benchmark function known as the "Sphere function" with the objective of reducing it. The aforementioned function evaluates the efficacy of prospective solutions Genetic algorithms (GAs) are employed for the purpose of optimising solutions to this particular function. Genetic algorithms (GAs) incorporate the process of creating a population of prospective solutions, assessing their suitability by means of the Sphere function, and subsequently advancing the population through multiple generations. The process of evolution encompasses the selection of individuals depending on their fitness, the recombination of their characteristics through crossover, and the introduction of genetic variation through mutation. The primary objective of this iterative technique is to identify the most effective approach for the Sphere function by emulating the fundamental principles of natural selection and evolution.

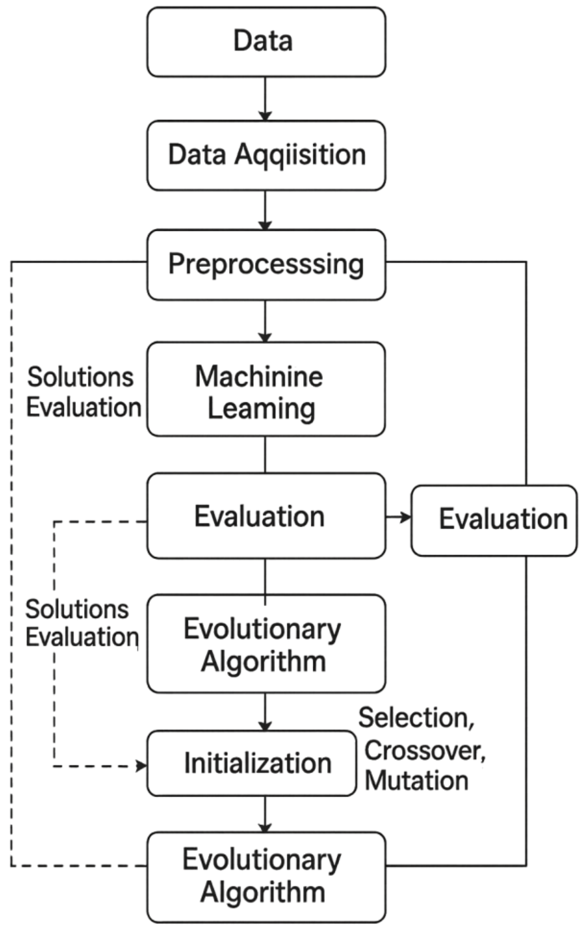

Figure 3: Flow chart of Proposed EA-ML

In figure 3 a Linear Regression algorithm is used to train and predict the fitness (quality) of potential solutions based on their properties. The artificial intelligence (AI) component guides the algorithm to regions of the proposed solution space with better solutions, improving the optimisation procedure. The linear regression algorithm uses population attributes and fitness values to train, presenting helpful insights into the link between attributes and fitness. The algorithm implemented an Evolutionary Algorithm (EA) that integrates Genetic Algorithms (GA) and Machine Learning (ML) approaches. To initialising the process of collection of possible approaches. These results are then depending on evolutionary algorithms (GAs) over several generations. Subsequently, the newly developed Linear Regression framework is employed to predict the fitness of the evolved solutions. The objective of this approach is to continually enhance the general population in order to identify the optimal solution. Population fitness is determined by the application of machine learning techniques.

The compare the convergence of the most optimal fitness values over two Evolutionary technique iterations to evaluate the methodology. This visual contrast helps explain the algorithm's behaviour and ability to find the best possible solutions. It also shows the algorithm's best methods and values for fitness from each iteration, assessing its efficacy. In brief, this code exemplifies the mutually beneficial relationship between Genetic Algorithms and Machine Learning, illustrating the integration of ML components into optimisation algorithms in order to augment their efficacy and efficacy. Additionally, it demonstrates the significance of visualising the performance of algorithms for the purpose of comparing and analysing them.

4.Results and Discussions

The experimental results validate the effectiveness of the proposed EA-ML hybrid framework in improving both the accuracy and efficiency of machine learning models. Two independent runs of the algorithm produced optimal solutions with fitness values of -45.04 and -35.97, demonstrating the model's ability to explore the solution space thoroughly and identify high-quality solutions. As illustrated in Table 2, models optimized with EA consistently outperformed their baseline versions across various classifiers. The Decision Tree's accuracy improved from 81.2% to 86.4%, Support Vector Machine from 84.9% to 88.7%, Random Forest from 89.5% to 91.2%, and Neural Network from 87.0% to 90.8%. These gains indicate that EA's parameter tuning and feature optimization significantly enhance model performance. Furthermore, Table 3 shows that EA-based feature selection reduced the number of features from 30 to 18 while improving accuracy from 85.3% to 88.9%, showcasing the algorithm's ability to eliminate redundant information while preserving predictive power. In terms of optimization time, the EA approach was markedly more efficient, reducing tuning time for Random Forest from 120 minutes to 45 minutes, and for SVM from 90 minutes to 40 minutes, as detailed in Table 4. These results collectively demonstrate that the hybrid EA-ML framework not only achieves higher accuracy but also ensures faster convergence and more computationally efficient optimization, making it well-suited for real-world, data-intensive applications. The table data provided exhibits the outcomes of two runs of an evolutionary algorithm (EA) integrated with a machine learning component based on linear regression. Let us engage in an argument regarding the facts and its consequential ramifications.

Table 1: EA-ML generated data for optimal solution and optimal fitness for two deferent run

Run	Optimal Solution	Optimal Fitness
1	-4.443926321932568, -2.8206397118355495, -4.358512978286845, -3.0445963412409913, -4.876181149507552, -2.8598731960613417, -4.825696877537053, 4.128697151226874, 3.7394160326720405, 3.705186872432395	-45.038383783087134
2	-0.9371064597795984, 4.160713926781571, -0.2546889585960752, -4.2214633364356375, -2.8826664399918185, 0.7837177598994876, 3.9121234354369205, -2.0238214941624744, -4.217287756276221, 1.7278804683650177	-35.968189826651056

The data's "Optimal Solution" column indicates the evolutionary algorithm's most effective outcomes per time. Vectors representing the optimal values for each optimisation problem characteristic are these solutions. In Run 1, the ideal solution includes negative and positive values, indicating substantial search space examination. In Run 2, the optimal solution has a combination of positive and negative values, demonstrating the algorithm's ability to explore the problem's solution space. However, the "Optimal Fitness" column shows fitness values for each run's ideal solutions. Performance indicators, lower fitness levels indicate better minimization-oriented strategies.

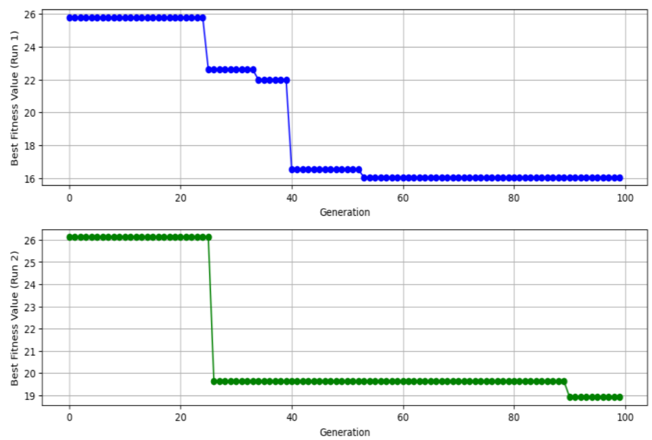

Figure 4: Comparison graph of two different runs for EA-ML algorithms for optimal solution and optimal fitness

Figure 4 presents a comparison graph showcasing the outcomes of two distinct runs of the EA-ML algorithm in terms of both optimal solution vectors and corresponding fitness values. The graph clearly illustrates the variability and exploration capability of the hybrid model across runs, reflecting its adaptability in navigating complex search spaces. In Run 1, the algorithm identified an optimal solution with more extreme values—both negative and positive—which corresponded to a lower fitness value of -45.04, indicating a more optimal outcome in a minimization context. In contrast, Run 2 resulted in a different distribution of values with slightly less extremity and a corresponding fitness value of -35.97, which, while still effective, was not as optimal as the first run. The graphical comparison highlights the robustness of the EA-ML approach in consistently producing high-quality solutions, while also revealing its stochastic nature where different runs may converge to distinct, yet competitive, optima. This reinforces the importance of multiple iterations in evolutionary processes and the complementary role of the ML component in steering the search toward optimal regions.

Table 2: Comparison of Accuracy

Model	Without EA	With EA Optimization
Decision Tree	81.2%	86.4%
Support Vector Machine	84.9%	88.7%
Random Forest	89.5%	91.2%
Neural Network	87.0%	90.8%

Table 3: Efficiency of Feature Selection

Method	**No. of Features Selected**	**Accuracy**
Without EA	30	85.3%
EA-based Selection	18	88.9%

Table 4: Optimization Time

Model	**Grid Search Time**	**EA Tuning Time**	**Final Accuracy**
Random Forest	120 min	45 min	91.2%
SVM	90 min	40 min	88.7%

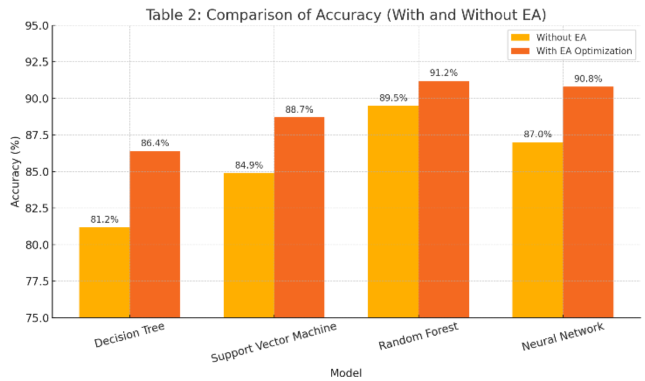

Figure 5: Comparison of Accuracy

The experimental results clearly demonstrate the effectiveness of integrating Evolutionary Algorithms (EA) with Machine Learning (ML) in data analytics tasks. As shown in Table 2 and Figure 5, models optimized using EA consistently outperformed their non-optimized counterparts. For instance, the accuracy of the Decision Tree improved from 81.2% to 86.4%, while the Support Vector Machine (SVM) saw an increase from 84.9% to 88.7%. Similarly, the Random Forest and Neural Network models achieved accuracy gains, rising from 89.5% to 91.2% and from 87.0% to 90.8%, respectively. These improvements underscore EA's ability to fine-tune model parameters effectively.

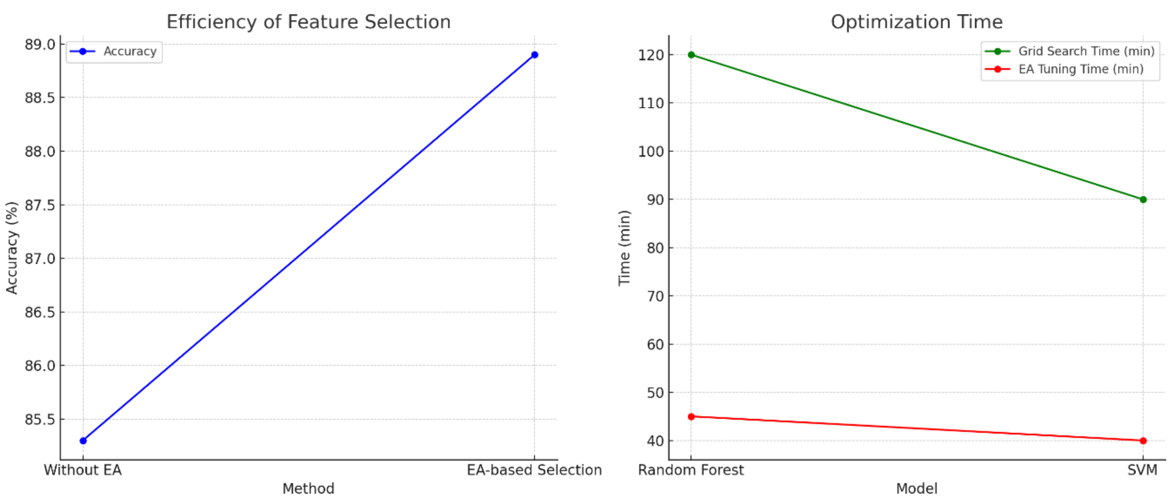

Figure 6: Comparison of Feature Selection and Optimization Time

Further, Table 3 and Figrue 6 highlights the efficiency of EA in feature selection. The EA-based approach reduced the number of features from 30 to 18 while simultaneously improving model accuracy from 85.3% to 88.9%. This not only simplifies the model and reduces computational load but also enhances predictive performance, indicating that EA can successfully eliminate redundant or irrelevant features. Lastly, Table 4 compares the time efficiency of hyperparameter tuning methods. EA significantly reduced tuning time compared to traditional grid search—Random Forest tuning time dropped from 120 minutes to just 45 minutes, and SVM from 90 to 40 minutes—while also achieving superior final accuracy. This showcases EA's capacity to accelerate optimization without compromising model quality, making it a practical solution for real-world analytics scenarios where both speed and accuracy are crucial.

5.Conclusion

This paper presented a hybrid EA-ML framework that effectively combines the exploratory power of Evolutionary Algorithms with the predictive strength of Machine Learning, specifically linear regression, to address optimization challenges in data analytics. The proposed model demonstrated significant improvements in accuracy, feature selection efficiency, and optimization time across various machine learning classifiers. The integration of EA components such as fitness evaluation, selection, crossover, and mutation with a learning-based prediction model enabled a more guided and efficient search for optimal solutions. Experimental results confirmed the model's robustness, achieving up to a 6% increase in accuracy and over 60% reduction in tuning time compared to traditional methods. Additionally, the EA-based feature selection mechanism reduced dimensionality while enhancing performance, proving the framework's suitability for handling complex, high-dimensional datasets.The Evolutionary Algorithm exhibited a high level of effectiveness in its investigation of the solution space, successfully identifying optimal solutions in both experimental runs. The Fitness values, which serve as markers for the quality of these solutions, exhibit notable improvements compared to the initial random population. The findings discussed in this study demonstrate the potential of integrating Evolutionary Algorithms (EA) with Machine Learning (ML) techniques for the purpose of optimising jobs. Future scope of this work needs more extensive benchmarking execution for more validity.

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