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FACILITATE THE PROCESS OF A HOLONIC MANUFACTURING SYSTEM BASED ON THE WHALE OPTIMIZATION ALGORITHM WITH RANDOM FOREST

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BSTRACT

Current manufacturing systems face considerable challenges due to technological development and customer demand for products that grow nowadays. This growth requires manufacturing systems to improve and adapt their techniques, methods, and strategies. There have been many advancements in holonic control architectures, but there has not been much progress in holonic control methodologies. The optimization and decision-making in the control systems need to adjust to a particular manufacturing system, features of processing technologies, transportation infrastructure, and production environment. Thus, this paper focuses on facilitating and improving the process of decision-making in a holonic manufacturing control unit by applying data mining methods such as data preprocessing and Random Forest (RF). In addition, we used one of the swarm intelligence optimization algorithms for Feature Selection (FS) purposes, the Binary version of the Whale Optimization Algorithm (BWOA). Afterwards, apply the subset generated by feature selection to the random forest classifier and grid search technique to get the best prediction for decision-making purposes. The experiment result for the three datasets was glass identification with 93.2 % accuracy, car evaluation dataset with 98.8 % accuracy, and grape dataset with 100% accuracy. Therefore, combining the grid search technique and random forest followed by feature selection using BWOA yields promising results compared to other algorithms.

KEYWORDS: Holonic Manufacturing System, Random Forest, Grid Search, Binary Whale Optimization algorithm

1. INTRODUCTION

The influence of users on planning and production activities is growing substantially in the modern manufacturing sector. Large-scale complexity on the production line and a wide range of manufactured goods are the outcomes of the influence's continued growth (Wullink et al., 2002). Current manufacturing structures deal with rapid changes and disruptions of the products. Thus, their control necessitates systematic modification and a good level of flexibility. Holonic manufacturing is a dispersed control standard that has the potential to solve these difficulties. It has built on the notion of autonomous and cooperating entities known as holons (Derigent et al., 2021). The concept of holonic systems came from the writings of the thinker A. Koestler, who used the phrase to characterize his studies of the behaviour of social and biological systems (Giret, 2009; Leitão, 2008). The Greek term (holos) means (whole), and the suffix (on) designates a neutron or proton as a component are the origins of the word Holon. He discovered that through establishing stable intermediate holons, many social and biological systems develop, expand, and adjust to complex and changing contexts (Colombo et al., 2006). A quality of autonomy exists in every Holon. It has enough development and capability to operate on its own. Holon likewise holds a cooperative trait that enables them to rely on the shared structure of other holons. They cooperate to achieve the group's overarching objectives. More details can be found in the paper (Valckenaers, 2020).

Holon's internal architecture has a control unit, an inside database, and communication/negotiation. Figure (1) displays a schematic illustration of a Holon's inner architecture. The control module is in charge of directing holons toward achieving individual or collective goals. The control unit contains information and algorithms that allow the Holon to analyze its condition, be dynamic in the environment, and be ready for the best decision on the next step. Therefore, push the Holon towards its goal by improving its inner performance measure. The internal architecture contains a database that stores information about the holonic architecture, completing activities, and desired environment for appropriately analyzing and executing prospective tasks (Ahmed and Abdulazeez, 2015).

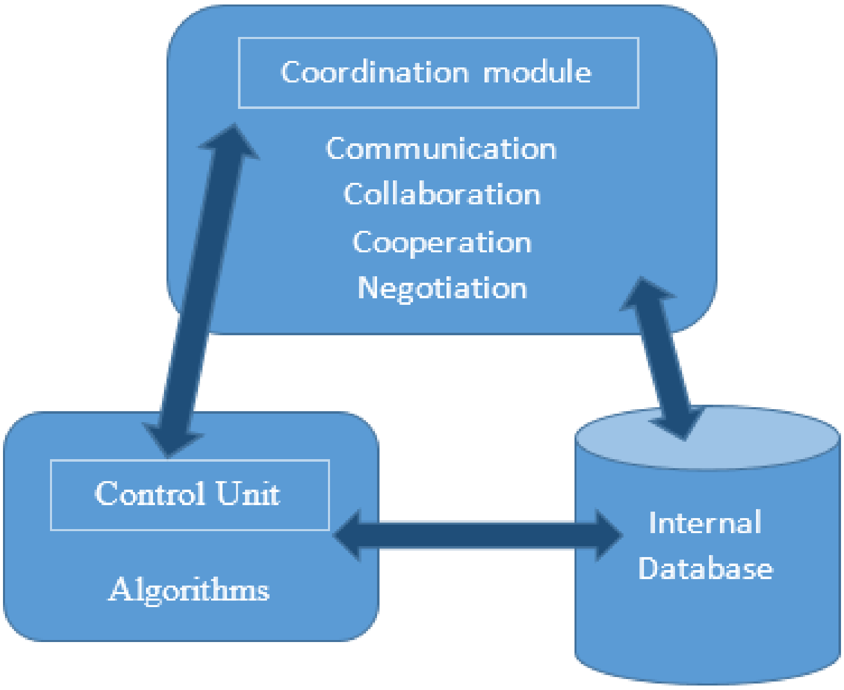

Fig. (1): Holon Internal Architecture by (Ahmed and Abdulazeez, 2015)

Furthermore, (Ahmed and Abdulazeez, 2015) proposed a new unit (FS) for holonic inner architecture. Their work involved two main steps. First, they used a Bee Algorithm (BA) to generate a subset of features and evaluated them using the Artificial Neural Network (ANN) algorithm. Second, they utilized the ANN again to perform a classification task for decision-making purposes in Figure (2).

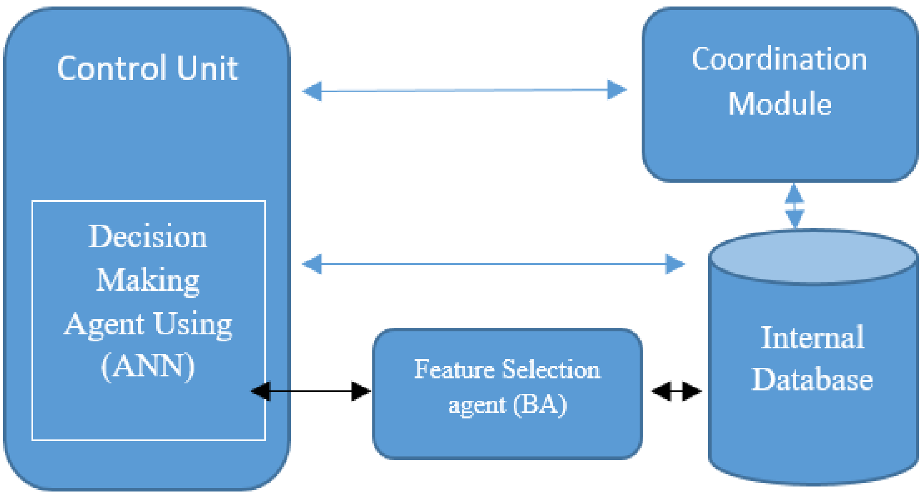

Fig. (2): Holon Internal Architecture proposed by (Ahmed and Abdulazeez, 2015)

Therefore, this paper suggests using different algorithms by applying the random forest algorithm for classification and decision-making combined with grid search techniques to tune the RF parameters and utilizing the BWOA for FS, as shown in Figure (3).

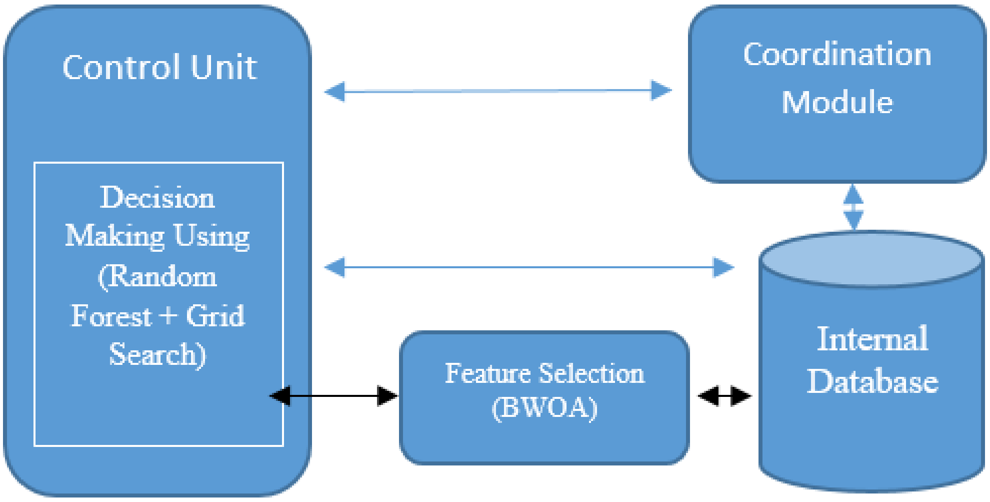

Fig. (3): Holon Internal Architecture Proposed by this Paper

The following section explains the HMS's background. Section three briefly states this paper's methods employed, and section four discusses and monitors the results obtained throughout the experiment.

2. HOLONIC MANUFACTURING SYSTEM BACKGROUND

HMS deals with all aspects of the manufacturing system, including the products, materials, workplaces, employees, operators, gear, machines, and controls. These components are Holons with autonomous and cooperative qualities (Derigent et al., 2021). The holonic manufacturing system (HMS) consortium created a set of definitions to clarify and direct the transformation of holonic principles into a production setting, as shown below:

Holon: An autonomous and cooperative manufacturing process building block for converting, transferring, storing, and verifying data and physical items. The Holon involves a data processing element and, in some scenarios, a physical processing component. A Holon sometimes belongs to some other Holon.

Autonomy: An entity's ability to devise and control the implementation of its plans in either or both tactics.

Cooperation: the process through which a group of entities forms and implements mutually satisfactory goals.

Re-configurability: the potential of a manufacturing unit's role to be easily changed quickly and cost-effectively.

Holarchy: a structure of holons that works together to attain a common purpose. It establishes the essential principles for holons' collaboration and thus restricts their autonomy.

According to (Wang and Haghighi, 2016; Christensen, 1994), there are two main parts of holonic architecture consisting of physical processing and information processing components that later became the general architecture for holonic systems see Figure (4). The first part includes physical processing separated into two components: physical processing itself, hardware conducting the manufacturing activity, and optional physical processing. Worker-order, planning, and scheduler holons are examples of holons that do not include a physical processing component. The second is control, which is a controller that regulates hardware activities. The information processing part is made up of three modules:

- The Holon's decision-making kernel controls the Holon's capacity for reasoning.
- The inter-holon interface facilitates interactions and communication with some other holons.
- The human-machine interface handles input (operational commands) and output (status monitoring) data for humans.

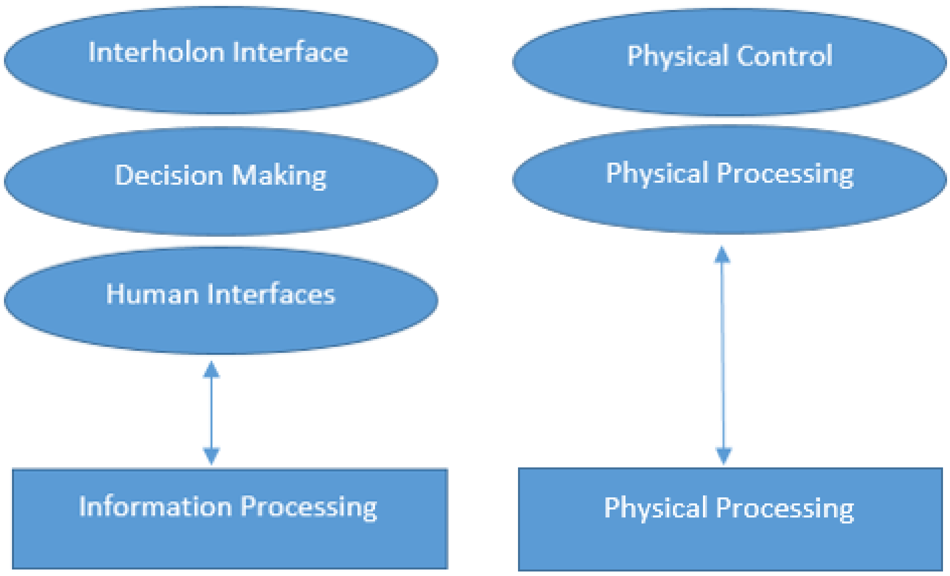

Fig. (4): Holon General Architecture by (Wang and Haghighi, 2016)

The industrial firms related to the research community (Van Brussel et al., 1998) explain that three largely separate manufacturing problems exist. One is resource factors, such as operating the machine at its best speed and optimizing its capacity. Two are product and method-related technology elements, such as which procedures must be conducted to obtain a good quality product. There are three logistical considerations, such as client requests and deadlines. The investigators concluded that there are three different sorts of fundamental holons based on this analysis: the HMS basic reference architecture formed as a resource, production, and ordering holons. Each of them is in charge of a different area of industrial control, such as logistics, technical planning, or resource capacities. These fundamental holons are systematically utilizing object-oriented principles such as aggregation and specialization. Staff holons can provide expert knowledge for the fundamental holons. These enable the employment of centralized algorithms for the integration of legacy systems.

A resource Holon consists of a physical component, such as a manufacturing program's production supply, and an ingredient for information handling that manages the resource. It gives nearby holons functioning and manufacturing capability. It contains the strategies for allocating the production resources for the information and guidelines for organizing, employing, and managing these resources to boost output. An abstract of the production methods is factory, shop, equipment, incinerators, conveyors, pipes, parts, building supplies, instruments, instrument containers, storing space, staff, energy, ground interplanetary, and many more.

A product Holon covers the product and procedure information required to ensure the accurate and adequate production of the product. It includes reliable and informed data on the product's progress sequence, operator needs, layout, procedure tactics, bill of ingredients, and quality guarantee approaches.

As reasoning, it holds the product type's model rather than the product state model of a single physical product example generated. It serves as a data provider to other HMS holons.

In the manufacturing scheme, a task is represented by an order Holon. It is responsible for doing the allocated tasks precisely and on time. It oversees the production of the actual product, the model of the product's standing, and entirely logistical data handling linked to the assignment. A client order, a make-to-stock order, a prototype order, and a maintenance and repair order. It can frequently be a workpiece with a specific control behaviour through the factory, such as negotiating with other resources and creating components.

3. RESEARCH METHODS AND DESIGN

This section states the algorithms and tools employed within the study and explains the design of the proposed methodology for a holonic manufacturing system.

3.1 RapidMiner Tool

It is a data extraction, text analysis, and predictive analytics software program. The software enables individuals to input raw data, such as datasets and written content, which is evaluated extensively and wisely. The RapidMiner tool version used in this research is 10.1.

As labelled in Figure (5), the dataset can be imported into the repository section. The process section is the workstation of the program where operators and data can be placed and designed. To change the operator setting, one can click on the operator, and the setting will be available in the Parameters section. Furthermore, the Operator section contains numerous data mining and statistics algorithms, techniques, and other data manipulation tools.

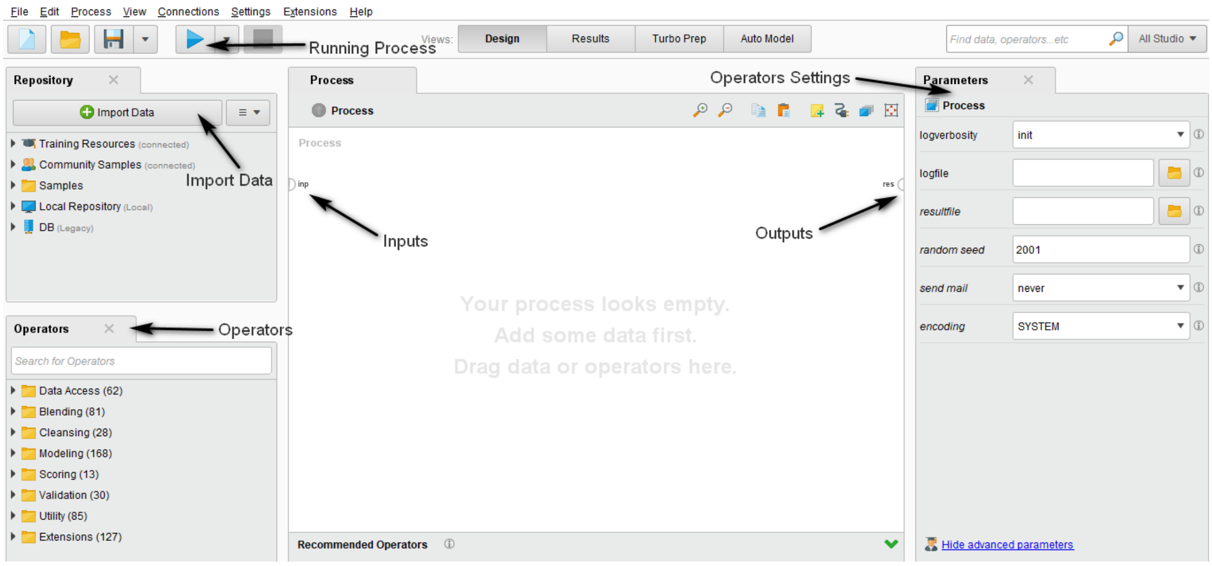

Fig. (5): Rapid Miner Tool Interface

3.2 Data Collection and Preparation

In this paper, we tested our methodology on three benchmark datasets from the UCI Machine Learning Repository. Table (1) shows the features of glass identification, car evaluation, and grape datasets. The glass identification dataset contains ten features involving the ID index and 214 samples. The dataset involves seven types, but one type has no records; only six types exist. The car evaluation dataset contains six features and 1728 samples. The label class attribute consists of four categories. The grape dataset has thirteen features and 178 records with three class types.

Table (1): Datasets Features

Features \ Datasets	Glass Identification	Car Evaluation	Grape
Feature 1	ID	Buying	Alcohol
Feature 2	RI	Maint	MalicAcid
Feature 3	Na	Doors	Ash
Feature 4	Mg	Persons	AlcalinityOfAsh
Feature 5	AL	LugBoot	Magnesium
Feature 6	Si	Safety	Total_Phenols
Feature 7	K		Flavanoids
Feature 8	Ca		NonFlavanoidPhenols
Feature 9	Ba		Proanthocyanins
Feature 10	Fe		ColorIntensity
Feature 11			Hue
Feature 12			DilutedWines
Feature 13			Proline

In RapidMiner, the process started by importing the datasets into Rapid Miner Studio. After that, one can drag the dataset into the working station. The remove duplicates operator removes all the duplications in the datasets. The glass identification dataset has only one duplicate record. The car evaluation and grape datasets have unique rows. Then, normalizing the data between zero and one using the normalize operator makes the data gap or range more proportionate. The normalized operator did not work for the car evaluation dataset since it has a nominal data type. Ultimately, the dataset was split into 80% for training the model and 20% for testing model performance using the split data operator. Figure (6) shows that the splitting type stratification method was selected. Stratification means that 80% of each class type splits for the training dataset and 20% split for the testing dataset.

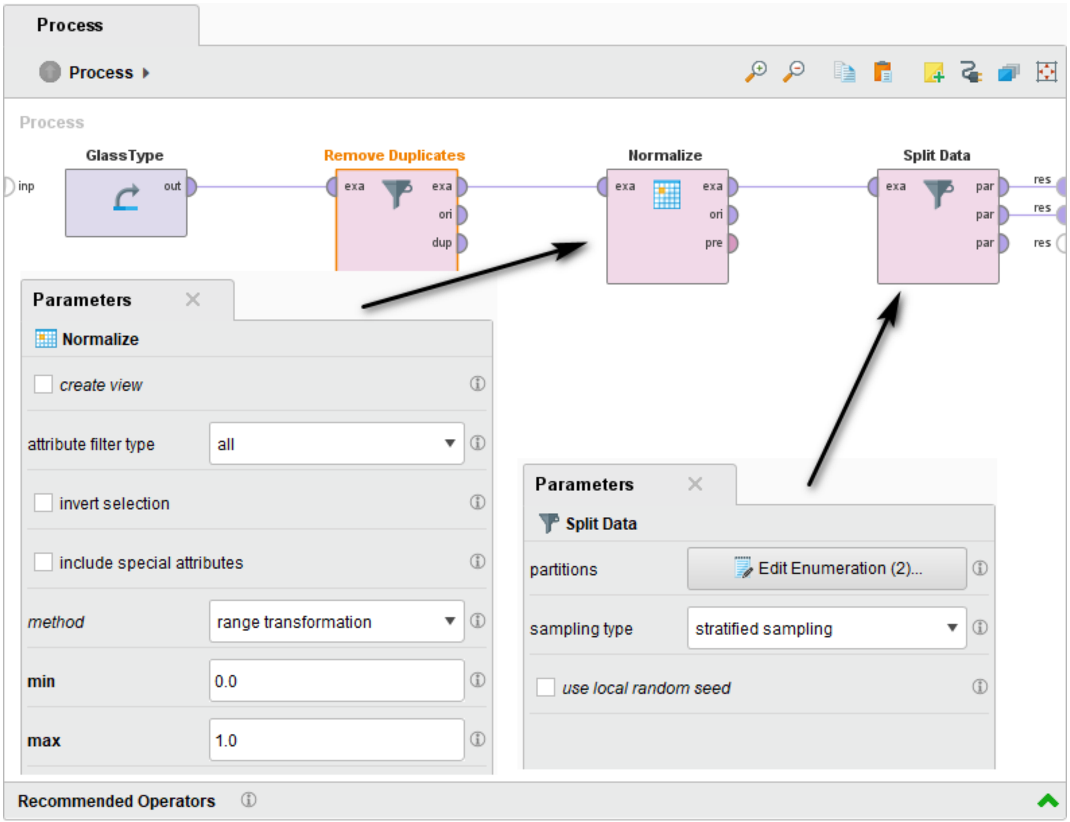

Fig. (6): Dataset preparation phase using Rapid Miner tool

3.3 Whale Optimization Algorithm

An optimization algorithm that is nature-inspired. The binary form of whale optimization is a new feature selection procedure constructed on Humpback whale hunting strategies, which include three steps: surrounding prey, spiral bubble-net assaulting, and searching for prey. Figure (7) shows that it produces several humpback whales and scatters them randomly in the search area. Throughout the first stage, the location of every humpback whale is assessed, and the best individuals are chosen. The other whales aim to improve their places about the top whale. The second phase is for humpback whales to launch an attack using a bubble-net approach. There are two ways for bubble-net invasion: shrinking encircling and spiral changing location. In reality, this process is identical to the exploitation phase, wherein every whale recommends a selection of characteristics. In the third step, or exploration phase, humpback whales look for prey randomly based on their position. More details about the whale optimization algorithm's equation and implementation can be found in the papers (Sharawi et al., 2017; Hussien et al., 2017; Mirjalili and Lewis, 2016).

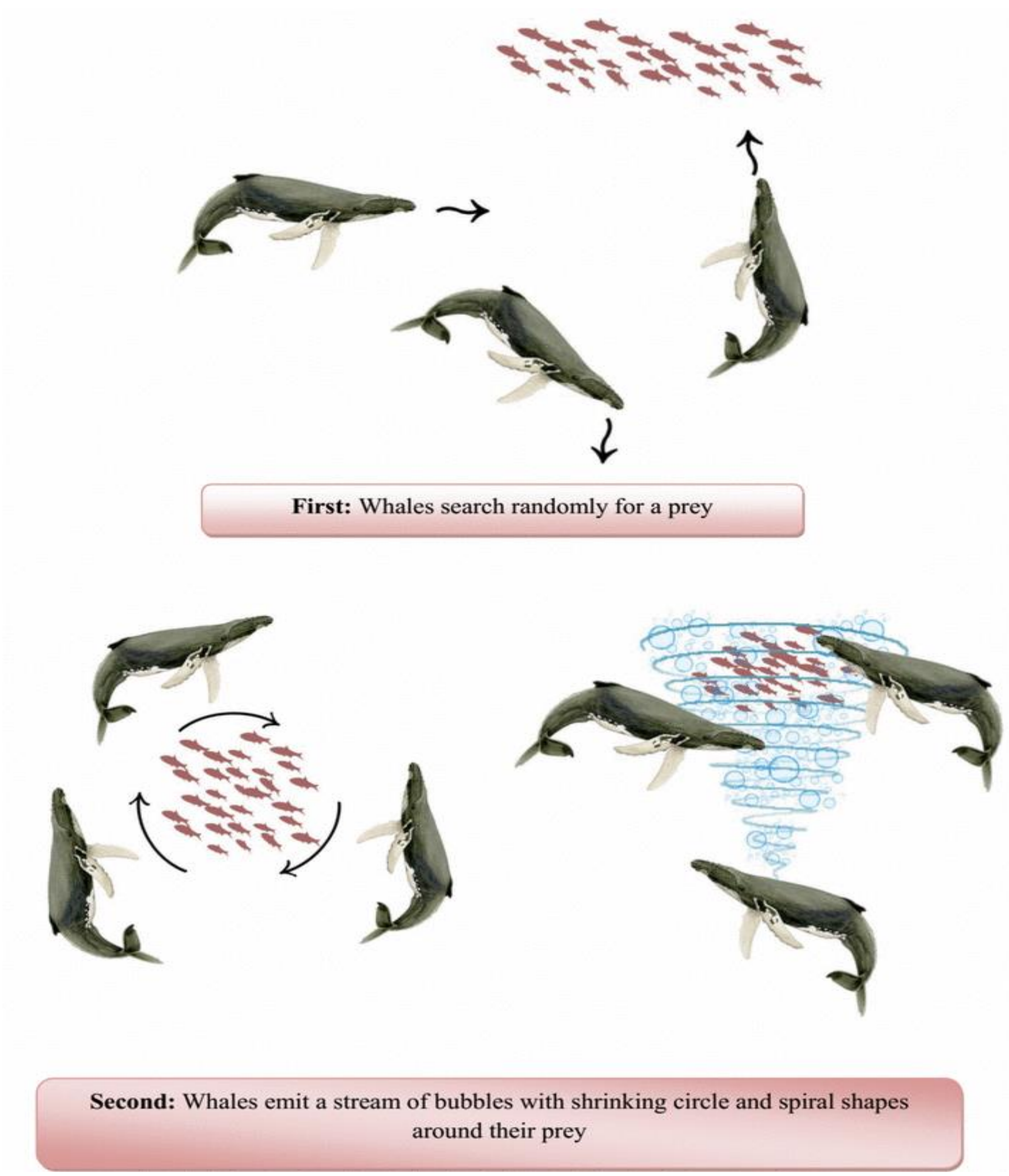

Fig. (7): Whale optimization Algorithm Mechanism by (Abdel-Basset et al., 2019)

Transforming the WOA into the BWOA requires modifying the initial algorithm to function with binary-encoded variables rather than continuous variables. Binary optimization, such as FS, deals with problems where variables can only take binary values (0 or 1) rather than continuous values. Multiple functions like hyperbolic tangent or sigmoid convert continuous variables into binary encoded variables. This research employs the KNN algorithm as a fitness function for transforming a continuous variable into a binary variable. The code for implementing the fitness function is provided in Figure (8).

```
function cost = jFitnessFunction(feat,label,X,opts)
% Default of [alpha; beta]
ws = [0.99; 0.01];

if isfield(opts,'ws'), ws = opts.ws; end

% Check if any feature exist
if sum(X == 1) == 0
  cost = 1;
else
  % Error rate
  error     = jwrapper_KNN(feat(:,X == 1),label,opts);
  % Number of selected features
  num_feat = sum(X == 1);
  % Total number of features
  max_feat = length(X);
  % Set alpha & beta
  alpha     = ws(1);
  beta      = ws(2);
  % Cost function
  cost      = alpha * error + beta * (num_feat / max_feat);
end
end
```

Fig. (8): Implementation Code of Fitness Function for the BWOA

The FS phase started by employing the binary version of the whale optimization algorithm in the Matlab Library. Split the dataset by 80:20 stratify. Setting five whales for searching with 100 iterations as stopping criteria. Using the K-Nearest Neighbor (KNN) classifier with K equal five as a fitness function to evaluate the subset of selected features by BWOA.

3.4 Random Forest (RF)

Random forest is a widely used model capable of performing either regression or classification problems. RF algorithm developed by (Breiman, 2001), some of his ideas came through the work of other researchers. The name is related to selecting a random part of data and features, and it builds multiple trees, which is why it is called a random forest. To increase performance and solve the overfitting problem, it randomly generates several decision trees accomplished on separate regions with replacement and without pruning, thus decreasing the correlation between trees. Random forest selects the qualities randomly to generate a certain number of trees with various attributes. In decision trees, test data examines a single generated tree instead of a random forest, where the test data is evaluated on entirely generated trees, and the best result is allocated to that occurrence. The more trees in the forest, the sturdier it will be. The random forest model will deliver the maximum accuracy of the forest containing a sophisticated number of trees. In addition, it can tolerate missing data. Random forest accepts categorical variables, and it employs the Gini index indicator to determine the purity and impurities of variables.

3.5 Grid Search

The grid search technique is a tuning approach to find the best model hyper-parameters values. It is an extensive search executed on a model's specified parameter values. The model is referred to as an estimator. It can help save time, effort, and money. The grid search operator takes in training and testing data and can house multiple operators. When a classifier is placed within the operator, as depicted in Figure (9), its parameters become accessible within the settings of the grid search operator, as shown in Figure (10).

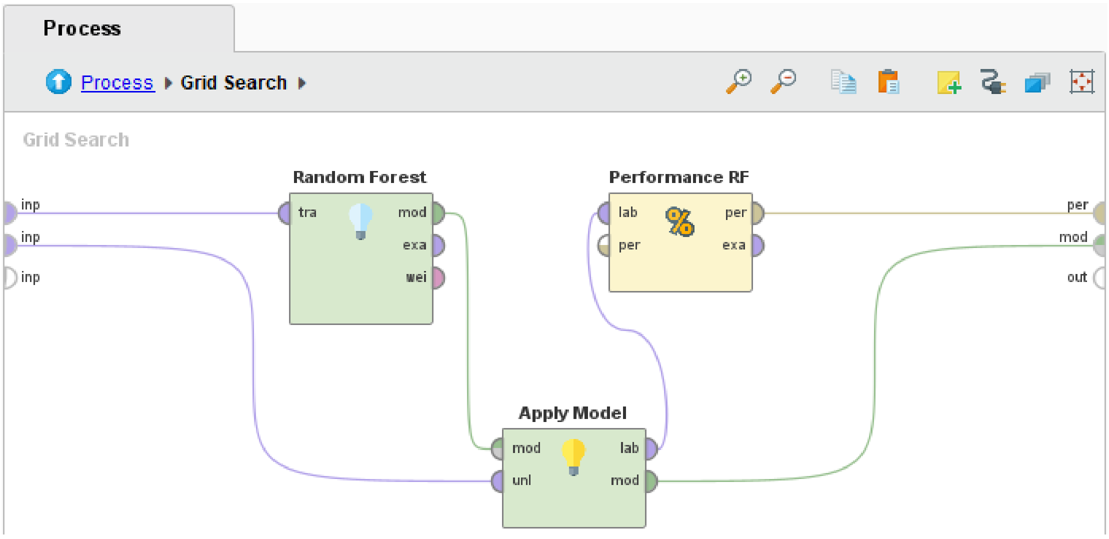

Fig. (9): Grid Search Operator Workspace

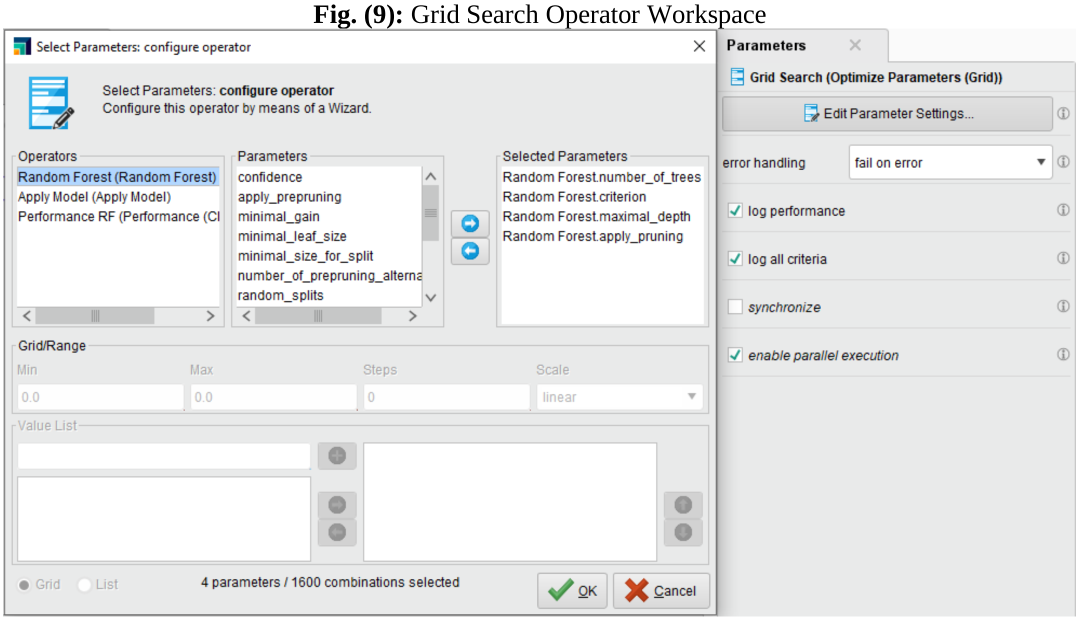

Fig. (10): Grid Search Operator Configuration

3.6 Random Forest Tuned Parameters

This research involved adjusting RF parameters using the grid search method. The parameters included the number of trees, maximum depth, criterion, and the decision to apply pruning, which can be observed in Figure (10) within the Selected Parameters panel. The values for the number of trees and maximum depth ranged from 1 to 20, while the criterion had two options: Gini index and Information Gain. The pruning option could be set as either true or false. Consequently, 1600 unique combinations were generated from these four parameters.

3.7 Random Forest and Grid Search Design

This section will explain the experiment structure of one of the datasets since the structure design for all the datasets is the same.

As shown in Figure (11), the select role operator renamed to (Train Class Role, Test Class Role) can modify the role of the attributes. The select attributes operator, renamed to (Train attributes and Test Attributes) can select all or some features from the dataset to participate in the process. The grid search operator sets the range values for any model parameters. It also holds the training and testing inputs from the dataset example set. The RF operator trains in the training input example set, and then the apply model operator applies the testing input example set and then passes the output to the performance operator to calculate the result.

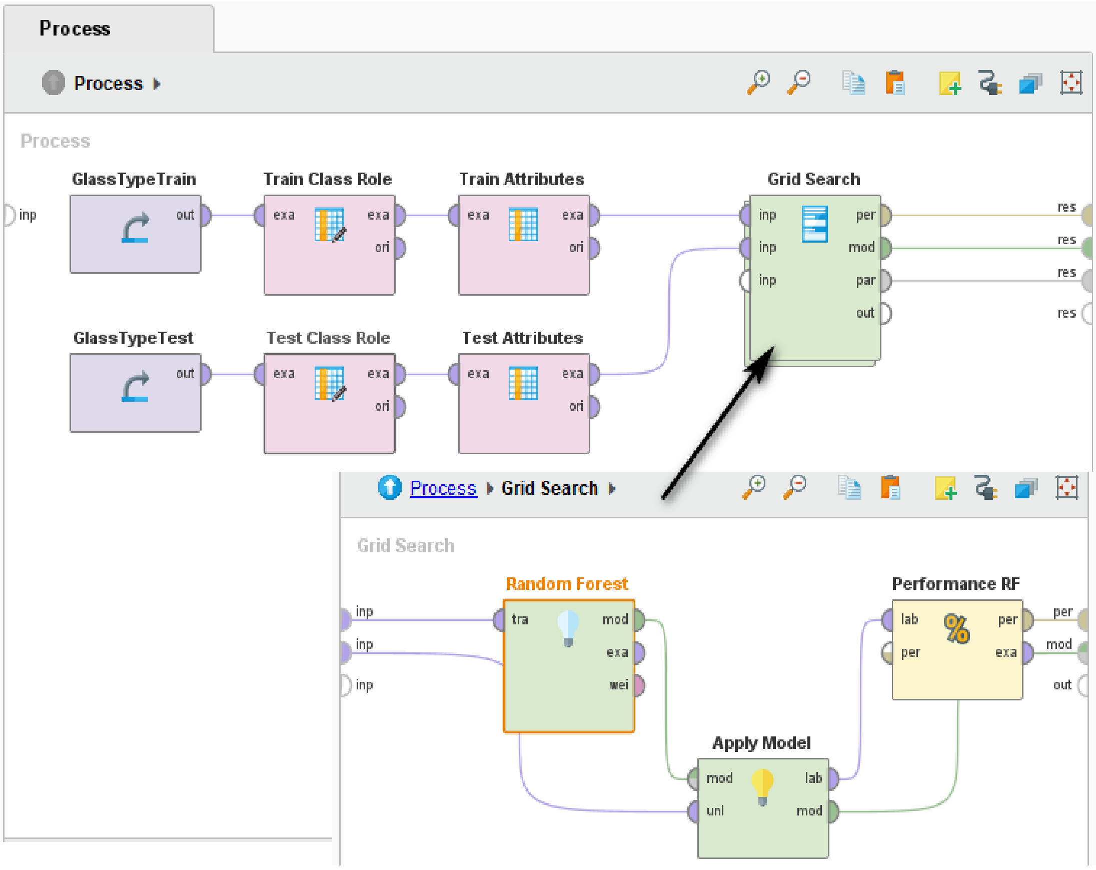

Fig. (11): RF and Grid Search Structure in RapidMiner for Glass Identification Dataset

3.8 Proposed Methodology

In this study, as depicted in Figure (12), the experiment started by preprocessing the data, which involved data cleaning for duplication and normalizing to make the gap or range of data more proportionate. Subsequently, the data is split into stratification mode, with 80% for training and 20% for testing. The next step was to generate feature subsets using BWOA and feed them to the random forest model. The random forest parameters (number of trees, maximum depth, criterion, and pruning) are tuned utilizing the grid search technique. The random forest model prediction helps Holon make appropriate decisions.

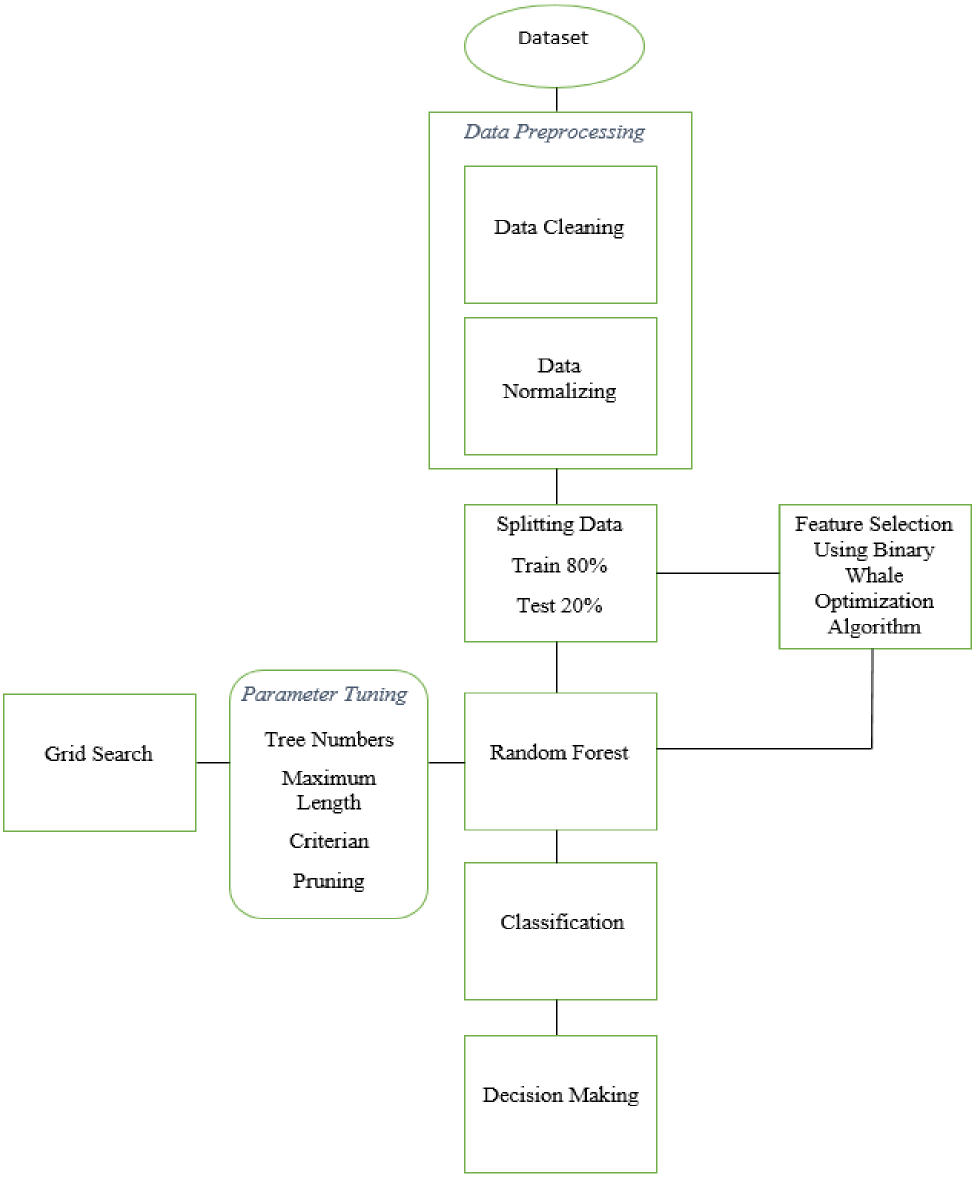

Fig. (12): Proposed Methodology

4. RESULT AND DISCUSSION

This study conducted experiments using three standard benchmark datasets. The outcomes and discourse are examined independently for each dataset. The data preprocessing was conducted, including tasks like data cleansing and normalization using data mining methods. The binary whale optimization algorithm was employed to select optimal features. Subsequently, the Random Forest (RF) algorithm was applied to classify each dataset. Furthermore, a comparative analysis was performed, contrasting the results with other algorithms employed in previous studies on the same datasets.

4.1 Feature Selection Results using BWOA

In the case of the Glass Identification Dataset, The BWOA selected six features, namely RI, Mg, Al, K, Ba, and Fe, out of a total of nine. The KNN model evaluated the fitness of this feature combination and yielded an accuracy of 80.95%. In the case of the Car Evaluation Dataset, after running the process multiple times, BWOA suggested using all features. The KNN fitness function for the selected feature combination is 93.04%. Furthermore, the study performed feature selection seven times for Grape Dataset, and the results for (3, 5, 6, 7, 8, 9, 10, and 12) feature combinations are displayed in Table (2).

Table (2): Feature Selection Attributes for Grape Dataset

Features \ Feature Combination	3	5	7	8	9	10	12
Alcohol	1	1	1	1	1	1	1
MalicAcid	1	0	1	1	1	1	1
Ash	0	0	1	1	0	1	1
AlcalinityOfAsh	0	0	1	1	1	1	1
Magnesium	0	1	0	0	1	1	1
Total_Phenols	0	0	0	0	0	0	1
Flavanoids	0	1	1	1	1	1	1
NonFlavanoidPhenols	0	1	1	0	1	1	1
Proanthocyanins	0	0	1	1	0	1	1
ColorIntensity	0	0	0	1	1	1	1
Hue	0	0	0	0	1	1	1
DilutedWines	0	1	0	1	1	0	1
Proline	1	0	0	0	0	0	0
Fitness Function Percentage	97.1	85.7	94.2	100	94.2	91.4	91.4

The first column represents feature names, the second to the eighth column represents the feature selection combination, and the last row is the fitness function rate of each feature selection combination. The digit 1 means that the feature participated in the combination, and the digit 0 means that the feature was not selected.

4.2 Classification Result on the Glass Identification Dataset

As shown in the confusion matrix in Figure (13), the performance accuracy is 93.02 % with all the attributes. Then, the FS subset (RI, Mg, Al, K, Ba, and Fe) that BWOA generated was applied. The result was still 93.02 % accuracy, as shown in Figure (14). In this case, the benefit of FS is that it reduced nine attributes into six, and the result is still the same.

accuracy: 93.02%

	true One	true Two	true Three	true Five	true Six	true Seven	class precisi...
pred. One	14	0	1	0	0	0	93.33%
pred. Two	0	15	0	1	0	1	88.24%
pred. Three	0	0	2	0	0	0	100.00%
pred. Five	0	0	0	2	0	0	100.00%
pred. Six	0	0	0	0	2	0	100.00%
pred. Seven	0	0	0	0	0	5	100.00%
class recall	100.00%	100.00%	66.67%	66.67%	100.00%	83.33%	

Fig. (13): RF and Grid Search performance with all attributes on the Glass Identification dataset accuracy: 93.02%

	true One	true Two	true Three	true Five	true Six	true Seven	class precisi...
pred. One	14	1	0	0	0	0	93.33%
pred. Two	0	14	1	1	0	0	87.50%
pred. Three	0	0	2	0	0	0	100.00%
pred. Five	0	0	0	2	0	0	100.00%
pred. Six	0	0	0	0	2	0	100.00%
pred. Seven	0	0	0	0	0	6	100.00%
class recall	100.00%	93.33%	66.67%	66.67%	100.00%	100.00%	

Fig. (14): RF and Grid Search performance with six features on the Glass Identification dataset

Table (3) shows that the RF algorithm has yet to be previously evaluated using this specific dataset. While more than relying solely on a single metric for model comparison is required, given that previous researchers exclusively discussed the accuracy metric, this study will concentrate on accuracy for comparison. The classification outcome of the RF algorithm, fine-tuned using the grid search technique, exemplifies the superior nature of this approach when contrasted with alternative algorithms illustrated in Table (3). The Multilayer Perceptron algorithm employed by (Arora, 2012) achieved the highest accuracy of 85% among other algorithms on this dataset. The margin of accuracy disparity between the proposed approach and the highest attained by alternative algorithms is 7.2%, underscoring the efficacy of this experimentation.

Table (3): Comparing the Proposed Methodology Result with Other Algorithms on the Glass Identification Dataset

Paper	Algorithm	Accuracy
This paper	BWOA (FS) + RF (Classifier) + Grid Search (hyperparameter tuning)	93.02 %
(Kulluk et al., 2012)	SGHS	80.95 %
(Aldayel, 2012)	KNN + Hidden Naive Bayes	80.3738 %
(Arora, 2012)	J48	81 %
	Multilayer Perceptron	85 %
(Aitkenhead, 2008)	Co-evolving Decision Tree	82.4 %
(Zhong and Fukushima, 2007)	v-K-SVCR	72.86 %
(Athitsos and Sclaroff, 2005)	Boosting NN	75.6 %
	Allwein	74.8 %
	Naïve KNN	73.2 %
(Jiang and Zhou, 2004)	Neural Network + KNN (NNEE)	67.94 %
(Krawiec, 2002)	C4.5 Decision Tree	66.39

4.3 Classification Result on the Car Evaluation Dataset

The dataset's performance assessment involves utilizing all features, as recommended multiple times by BWOA. The visualization in Figure (15) illustrates the confusion matrix for RF results. The outcomes are encouraging, achieving an accuracy of 98.84%, a recall of 92.86%, and a precision of 95.79%. When considering the diagonal elements of the confusion matrix representing accurately identified samples (summing up to 170 out of 172 test samples), the accuracy is 98.84%, calculated by dividing 170 by 172.

accuracy: 98.84%

	true unacc	true acc	true vgood	true good	class precision
pred. unacc	121	0	1	0	99.18%
pred. acc	0	38	0	0	100.00%
pred. vgood	0	0	5	1	83.33%
pred. good	0	0	0	6	100.00%
class recall	100.00%	100.00%	83.33%	85.71%	

Fig. (15): RF and Grid Search performance with all attributes on the Car Evaluation dataset

The study approach outperformed alternative algorithms shown in Table (4). Conducting experiments on the car evaluation dataset with grid search tuning RF model resulted in a noteworthy enhancement of the model's accuracy. Although (Ramanathan and Sharma, 2017) reported a comparable accuracy of 98% in their experiment. However, if they had included additional metrics such as recall and precision, the comparison would have been better to declare the superior approach.

Table (4): Comparing the proposed methodology with other algorithm's results on the Car Evaluation dataset

Paper	Algorithm	Accuracy
This paper	BWOA (FS) + RF (Classifier) + Grid Search (hyperparameter tuning)	98.84 %
(Chen et al., 2020)	Random Forest	93.31 %
	KNN	86.34 %
	SVM	93.3 %
	LDA	88.08 %
(Khashman, and Sadikoglu, 2019)	neural Network based on the backpropagation (BPNN)	85.07 %
(Ramanathan and Sharma, 2017)	SMK (SVM based multi knowledge-based system)	98 %

4.4 Classification Result on the Grape Dataset

The comparison of this dataset is different since other authors tested their algorithms with various feature selections, as shown in Table (5). (Ahmed and Abdulazeez, 2015) conducted their experiment seven times with the same algorithms but different feature combinations, and (Shokouhifar and Sabet, 2010) used three algorithms. The performance of our methodology is better compared to (Shokouhifar and Sabet, 2010) algorithms. On the other hand, the performance of the proposed algorithms compared to (Ahmed and Abdulazeez, 2015) algorithms is very similar for feature number five and lower for feature number eight but better for all other features.

Table (5): Comparing the proposed methodology with other algorithm's results on the Grape dataset

(Ahmed and Abdulazeez, 2015)			(Shokouhifar and Sabet, 2010)			This paper		
Algorithm	**Features**	**Accuracy**	**Algorithm**	**Features**	**Accuracy**	**Algorithm**	**Features**	**Accuracy**
HFSBA	3	96.726 %	GA	6	93 %	BWOA (FS) + RF (Classifier) + Grid Search (hyperparameter tuning)	3	97.2 %
	5	97.569 %	ACO	5	94.44 %		5	97.22 %
	7	99.131 %	ABC	5	96.66 %		7	100 %
	8	99.375 %					8	97.22
	9	99.242 %					9	100 %
	10	97.916 %					10	100 %
	12	95.833 %					12	100 %

4.5 Integrating the RF Algorithm into the HMS

The RF algorithm outperformed other algorithms on each dataset represented within this research, meaning that it is significant to integrate this algorithm for Holon's internal architecture. Integrating Holon's internal architecture with the random forest can provide several benefits. This research will showcase these benefits from various aspects through a scenario considering the datasets used within this research.

Scenario: In the context of a holonic manufacturing system for glass, car, or grape production, the Holon integrated with the proposed methodology will assist in making data-driven decisions regarding resource allocation, quality control, demand forecasting, customization and personalization, and collaborative decision-making. Analyzing the attributes of different products will enhance the system's ability to produce high-quality, customized products while developing collaborative decision-making among the Holons within the system.

4.5.1 Resource Classification and Allocation

The Holon will categorize manufacturing resources such as furnaces, cutting machines, and shaping tools based on their capabilities and compatibility with different glass types. For instance, Holon identifies that float-processed windows require specific temperature ranges in furnaces, leading to an optimized allocation of resources for each glass type.

4.5.2 Quality Control

The Holon analyzes glass samples' chemical composition and refractive index in real-time. By comparing these attributes against predefined quality standards, the system can classify products as high-quality or defective. Defective products can be flagged for further inspection or reprocessing, ensuring that only products meeting quality criteria proceed to the next stages.

4.5.3 Demand Forecasting

The Holon analyzes historical sales data to forecast demand for different types of cars with specific attributes. For instance, if a trend indicates increased demand for cars with attributes related to safety and maintenance, the HMS can adjust production volumes and resource allocation accordingly.

4.5.4 Customization and Personalization

Some customers may prefer cars with attributes suggesting better safety and higher seating capacity. The Holon will categorize these preferences and guide the assembly process. When a customer places an order, the system can quickly categorize their preferences and ensure that the car is assembled with the requested attributes.

4.5.5 Collaborative Decision Making

The Holon will help other holons within the system understand the characteristics of different grape batches. For example, an accurate decision based on classifying grape using attributes like MalicAcid, Ash, AlkalinityOfAsh, Flavanoids, and NonFlavanoidPhenols can aid holons in collaboratively deciding how to blend batches to create unique grape juice blends with specific flavour profiles.

5. CONCLUSION

In this paper, we have worked on the holonic manufacturing system control methodologies rather than the holonic control architecture. Proposed a new approach to facilitate the process of the holonic manufacturing system by combining the RF classifier and Grid Search technique. In addition, employed one of the swarm intelligence algorithms for feature selection purposes called the binary whale optimization algorithm. The study used three benchmark datasets from UCL machine learning respiratory: glass identification, Car evaluation, and grape datasets. The experiment shows that the RF algorithm outperformed other algorithms with 93.02 % accuracy with and without FS for the glass identification dataset.

On the other hand, the performance for the car evaluation dataset is 98.84 % accuracy with all the features since the BWOA suggested using all features. As for the grape dataset, the proposed methodology is better in most cases and lower by 2.155 % in one case. These results indicate that the methodology is well-suited for integration into holonic manufacturing systems, as it can significantly enhance and streamline decision-making. The combination of BWOA and other classification algorithms is an open issue.

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